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Validating the Mediating Role of User Satisfaction in Artificial Intelligence Adoption within Abu Dhabi's Public Transportation System

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Abstract

Artificial Intelligence (AI) is increasingly recognized as a transformative tool for improving efficiency, sustainability, and decision-making in public transportation. However, its adoption is shaped not only by technical system availability but also by behavioural and user-related factors, highlighting the importance of user satisfaction in ensuring successful implementation. This study develops and validates a comprehensive framework that examines the mediating role of user satisfaction in AI adoption within Abu Dhabi's public transportation sector. A quantitative research design was employed, with data collected through a structured questionnaire distributed to employees of the Abu Dhabi Department of Transport and affiliated public transportation entities. Using a convenience non-probability sampling technique, 325 valid responses were obtained from full-time employees across operational, technical, supervisory, and managerial roles. The framework was validated using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS. The analysis included reliability and validity testing, measurement and structural model assessment, path analysis, predictive relevance, model fit evaluation, and mediation analysis. The results confirm that system availability significantly influences both user satisfaction and behavioural intention to adopt AI, with satisfaction partially mediating this relationship. The validated model explained 73.9% of the variance in behavioural intention, underscoring the importance of reliable, accessible, secure, and user-friendly AI systems supported by appropriate training and responsive support. This user-centred framework provides practical insights for policymakers and transport authorities, positioning satisfaction as a critical driver of sustainable AI adoption.

Keywords: Artificial Intelligence Adoption, User Satisfaction, System Availability Factors, Public Transportation (Abu Dhabi)

1. Introduction

Transport networks are fundamental to modern society, enabling the efficient movement of people, goods, and services while contributing significantly to economic development, urban functionality, and social connectivity (Lewis & Jago, 2017). As urban populations expand and cities grow more complex, maintaining transport infrastructure has become increasingly challenging. These systems represent interdependent networks of roadways, public transport, vehicles, infrastructure, and human actors, all of which are influenced by rapidly changing external factors such as weather, emergencies, and economic fluctuations (Barceló & Beuthe, 2022).

Traditional transport management systems, which rely heavily on static models and historical data, are proving inadequate in addressing the dynamic nature of contemporary mobility. They often fail to provide real-time solutions during traffic congestion, accidents, or infrastructure breakdowns, where rapid, data-driven decision-making is essential (Kharrazi et al., 2016). The growing availability of real-time data from GPS devices, IoT sensors, and connected vehicles has further exposed the limitations of these conventional systems, which struggle to process and analyze large-scale, dynamic information effectively (Helbing & Johansson, 2014; Zannat et al., 2021). Rapid urbanization, rising vehicle ownership, and emerging mobility innovations such as ride-sharing, micromobility, and autonomous vehicles have introduced new challenges to transportation management, contributing to congestion, higher emissions, and declining safety standards (Kwan, 2017; Rybski & González, 2022).

Artificial intelligence (AI) has emerged as a transformative solution to these issues. AI systems, particularly those employing machine learning, computer vision, and predictive analytics, can process vast amounts of real-time data to identify patterns, forecast demand, and support adaptive decision-making (Gomes et al., 2023; Liu et al., 2022). Applications such as smart traffic lights, AI-based route optimization, predictive maintenance, and automated incident detection are revolutionizing the monitoring and management of transportation networks (Bean, 2017; Zhang et al., 2023). In Abu Dhabi, where rapid urban growth and rising car ownership place increasing pressure on transport infrastructure, AI-powered solutions are being introduced to improve traffic flow, enhance safety, and support sustainability goals (OECD, 2023; Chen et al., 2024).

However, in the effective adoption of AI within public transportation systems. High implementation costs, infrastructure constraints, regulatory gaps, and limited system design flexibility continue to hinder widespread integration (United Arab Emirates Government, 2024). Moreover, while AI technologies are technically capable of improving efficiency and sustainability, their success depends heavily on user acceptance and satisfaction. Without positive user experiences, even the most advanced systems risk underutilization and resistance.

Although studies have applied the Technology Acceptance Model (TAM) and related frameworks to transportation contexts, limited empirical research has examined AI adoption specifically within public transportation services in the UAE (Prayoonphan & Xu, 2019; Sánchez-Prieto et al., 2020; Ikhsan, 2020; Ahn & Park, 2022; Abduljabbar et al., 2019; Al

Shamsi & Davies, 2022; Al-Bulushi, 2023). More critically, existing studies have largely overlooked the mediating role of user satisfaction in explaining how AI system characteristics influence behavioural intention and adoption outcomes. This gap restricts policymakers and transport authorities from fully understanding the human factors that drive successful AI implementation.

The intention of this study is to address these gaps by proposing and validating a comprehensive framework that examines the mediating effect of user satisfaction on AI adoption in Abu Dhabi's public transportation system. By extending TAM to incorporate AI-specific constructs and positioning user satisfaction as a central mediating variable, the study provides a structured and empirically testable approach to understanding adoption dynamics. The research contributes theoretically by refining technology adoption models with a satisfaction-based mediation perspective, and practically by offering insights to support user-centred, intelligent, and sustainable transportation development in Abu Dhabi and the wider UAE.

2. Conceptual Framework

The conceptual framework for this study is grounded in three complementary theories that collectively explain the mediating role of user satisfaction in artificial intelligence (AI) adoption within Abu Dhabi's public transportation system. The Socio-Technical Systems Theory (STS) provides the foundation for analyzing system availability by emphasizing the interdependence of technical reliability and human needs. It highlights dimensions such as resilience, scalability, sustainability, and inclusivity, which are critical for ensuring that AI-enabled transport systems remain dependable and adaptable to diverse operational contexts (Baxter & Sommerville, 2011; Mumford, 2006).

Building on this, the Technology Acceptance Model (TAM) explains how employees' perceptions of usefulness and ease of use shape their behavioural intentions to adopt AI technologies (Davis, 1989; Venkatesh & Davis, 2000). In the Abu Dhabi context, TAM is particularly relevant, as employees' attitudes toward efficiency, innovation, and commuter experience determine the success of AI integration in public services (Dahi & Ezziane, 2015). TAM therefore underpins the construct of Behavioural Intentions Attitudes (BIU), clarifying how organizational, individual, and societal benefits influence adoption.

The Unified Theory of Acceptance and Use of Technology (UTAUT) extends TAM by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). These dimensions directly inform the construct of User Satisfaction Attributes (USA), situating satisfaction as the critical mediator between system availability and behavioural intention. For instance, user-friendly interfaces, training support, and responsive communication enhance satisfaction, which in turn strengthens employees' willingness to embrace AI technologies (Alhassan, Sammon, & Daly, 2021). Together, STS, TAM, and UTAUT provide a holistic foundation: STS anchors the framework in technical realities, TAM explains adoption drivers, and UTAUT situates satisfaction as the bridge between system availability and behavioural intention (Baron & Kenny, 1986; Hayes, 2013).

Within this framework, System Availability Factors (SAF) represent the independent construct. Availability encompasses reliability, redundancy, scalability, maintenance, data accessibility, cybersecurity, environmental resilience, and user accessibility. These factors ensure confidence in AI systems and lay the groundwork for satisfaction and adoption (Abduljabbar et al., 2019; Xu et al., 2021; Santoso & Surya, 2024; Lv, Lou, & Singh, 2020; Mnyakin, 2023).

User Satisfaction Attributes (USA) serve as the mediating construct, capturing employees' perceptions of usability, support, and empowerment when interacting with AI technologies. Satisfaction is shaped by ease of use, training and learning support, system customizability, responsiveness to feedback, communication and support services, engagement and collaboration, and productivity enhancement (Abduljabbar et al., 2019; Santoso & Surya, 2024; Xu et al., 2021; Lv, Lou, & Singh, 2020; Mnyakin, 2023). When employees interact with AI systems that are dependable, adaptive, and responsive to their operational requirements, their satisfaction increases, which in turn fosters trust and strengthens behavioural intention.

Finally, Behavioural Intentions Attitudes (BIU) form the dependent construct, reflecting employees' willingness to adopt AI technologies. These intentions are influenced by attitudes toward operational efficiency, service quality, data-driven decision-making, cost reduction, innovation, competitiveness, user experience, and sustainability (Abduljabbar et al., 2019; Lv, Lou, & Singh, 2020; Xu et al., 2021; Santoso & Surya, 2024; Mnyakin, 2023). Positive attitudes toward these outcomes drive adoption and long-term integration of AI in public transport. The conceptual framework is as illustrated in Figure 1.

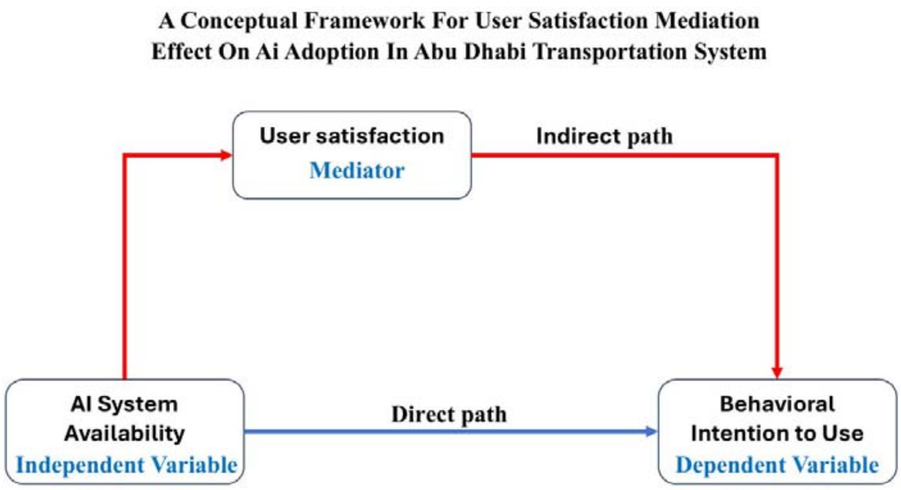

Figure 1. Conceptual framework

Based on this conceptual framework of figure 1, the proposed hypotheses are as follow:

H1: system availability positively influences user satisfaction;

H2: user satisfaction positively influences behavioural intention to adopt AI; **H3:** system availability directly influences behavioural intention to adopt AI;

H4: user satisfaction mediates the relationship between system availability and behavioural intention.

3. Validating the Conceptual Framework

The conceptual framework presented in Figure 2 was validated using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS software. PLS-SEM was selected due to its strong suitability for theory development and exploratory research, particularly when analysing complex models with small to medium sample sizes (Hair et al., 2019; Hair et al., 2022; Ringle et al., 2015). In addition, PLS-SEM is appropriate in situations where data may not meet the stringent assumptions required by covariance-based SEM approaches, such as multivariate normality and large sample size requirements.

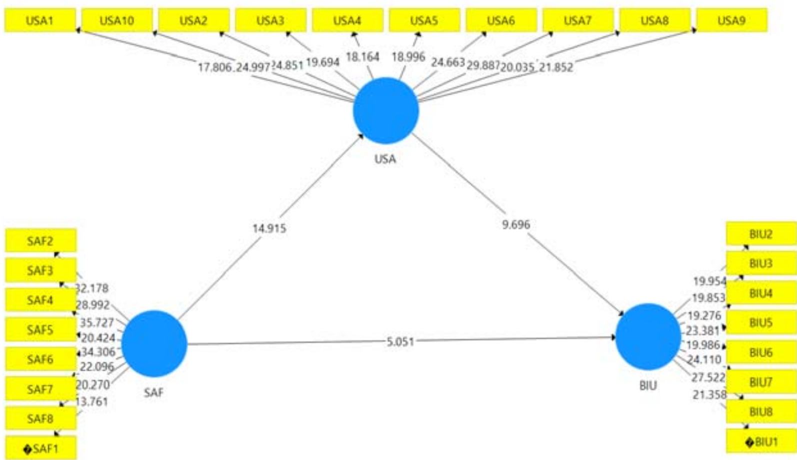

Figure 2. Validated model of the framework

The following subsections present the assessment outcomes of the measurement and structural models, together with the results of hypothesis testing for all proposed path relationships within the conceptual framework.

3.1 Measurement Model Assessment

The measurement model was evaluated to ensure construct reliability, convergent validity, and discriminant validity. Reliability was assessed using Cronbach's Alpha and Composite Reliability (CR), while convergent validity was examined through the Average Variance Extracted (AVE). Discriminant validity was tested using both the Fornell-Larcker criterion (Fornell & Larcker, 1981) and the Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2015).

The results confirmed strong reliability and validity across all constructs. Cronbach's Alpha values exceeded the threshold of 0.7, with BIU at 0.897, SAF at 0.914, and USA at 0.923, indicating high internal consistency (Nunnally & Bernstein, 1994). Composite Reliability values were similarly robust (BIU = 0.917; SAF = 0.930; USA = 0.935), confirming that the indicators collectively represented their constructs with precision (Dijkstra & Henseler, 2015). AVE values for BIU (0.580), SAF (0.625), and USA (0.592) all surpassed the recommended threshold of 0.5, demonstrating adequate convergent validity (Fornell & Larcker, 1981).

Discriminant validity was also established. The Fornell-Larcker criterion confirmed that each construct shared more variance with its own indicators than with other constructs, while HTMT ratios were all below 0.90, further verifying that the constructs were conceptually distinct (Henseler et al., 2015). These results ensured that SAF, USA, and BIU were empirically separable, thereby strengthening the credibility of the mediation model.

3.2 Structural Model Assessment

Following the validation of the measurement model, the structural model was assessed to evaluate the hypothesized relationships among the constructs. Key parameters included path coefficients, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2), alongside overall model fit indices such as SRMR and NFI (Hair et al., 2019).

The results demonstrated substantial explanatory power. The R^2 value for BIU was 0.739, indicating that 73.9% of the variance in behavioural intention was explained by SAF and USA combined. The R^2 value for USA was 0.521, showing that system availability accounted for 52.1% of the variance in user satisfaction. These values confirm the predictive strength of the model and highlight the dual-pathway effect of SAF: a direct influence on BIU and an indirect influence mediated through USA. This finding aligns with the Information Systems Success Model (DeLone & McLean, 2003) and supports prior studies emphasizing system quality as a determinant of satisfaction (Wixom & Todd, 2005; Helm et al., 2020).

3.3 Hypothesis Testing

Hypothesis testing was conducted using the bootstrapping procedure in SmartPLS, which provided robust estimates of path significance (Ramayah et al., 2018). The results confirmed all hypothesized relationships as in table 1.

Table 1. Results of hypotheses testing

Hypothesis	**Path Relationship**	**Path Coefficient**	**p-value**	**Result**
H1-direct	SAF → USA	0.722	< 0.001	Supported
H2-direct	USA → BIU	0.602	< 0.001	Supported
H3-direct	**SAF → BIU**	0.317	< 0.001	Supported
H4-indirect	**SAF → USA → BIU**	—	< 0.001*	Mediation Supported

Note. * The indirect effect was tested using bootstrapping and found to be statistically significant.

The results presented in Table 1 validate the proposed conceptual framework. Specifically, system availability (SAF) has a significant direct effect on behavioural intention to use (BIU) and also exerts an indirect effect through user satisfaction (USA). The significance of both the direct path (SAF → BIU) and the indirect path (SAF → USA → BIU) indicates that user satisfaction partially mediates the relationship between system availability and behavioural intention. This suggests that while system availability directly influences adoption intentions, its impact is further strengthened when users perceive higher levels of satisfaction (Hair, 2014).

3.4 Summary of Validation

The validation process confirms that the conceptual framework is both theoretically sound and empirically robust. The constructs exhibit strong reliability, validity, and discriminant properties, while the structural model demonstrates substantial explanatory power. The mediation analysis highlights the critical role of user satisfaction in translating system-level availability into positive behavioural intentions. This validated framework provides valuable insights for both theory and practice. Theoretically, it extends TAM and UTAUT by embedding satisfaction as a mediating construct (Venkatesh et al., 2003). Practically, it offers guidance for policymakers and transport authorities in Abu Dhabi, emphasizing the need to balance technical system reliability with user-centric design and support to foster successful AI adoption in public transportation.

4. Application of Validated Framework

Based on the validated conceptual framework in the earlier section, this study provides practical and strategic guidelines for enhancing Artificial Intelligence (AI) adoption within Abu Dhabi's public transportation system. The empirical results confirmed that System Availability Factors (SAF) exert both direct and indirect effects on Behavioural Intention to Use (BIU), with User Satisfaction Attributes (USA) playing a significant mediating role. These findings reinforce the view that successful AI adoption is not solely a technical endeavour but also a user-centred process, consistent with established information systems and technology adoption theories.

Transportation authorities and decision-makers should therefore prioritise strengthening AI system availability. The strong explanatory power of SAF in predicting BIU aligns with the modified Information Systems Success Model proposed by DeLone and McLean (2003), which emphasises system quality as a critical antecedent of system use and user satisfaction. Ensuring high levels of system reliability, scalability, maintenance and support, cybersecurity, and accessibility is essential for fostering employee trust and confidence in AI-enabled transportation systems. Similar conclusions were drawn by Abduljabbar et al. (2019) and Xu et al. (2021), who highlighted system availability and reliability as key determinants of AI adoption.

Beyond technical readiness, the validated mediation effect demonstrates that user satisfaction significantly amplifies the influence of system availability on behavioural intention. This finding is consistent with prior studies suggesting that system characteristics affect behavioural intention primarily through satisfaction and perceived usefulness (Wixom & Todd, 2005). The stronger indirect effect of SAF on BIU through USA underscores the importance of investing in user-oriented initiatives such as intuitive interface design, adequate training and learning resources, responsive technical support, and opportunities for system customisation. These factors enhance employees' perceptions of empowerment, productivity, and engagement, which are crucial for sustained AI usage.

The framework further highlights the importance of integrating technical excellence with human-centred design, particularly within the public sector. As noted by Riandi et al. (2021), user satisfaction mediates the relationship between system quality and user performance, reinforcing the need to align AI system design with user expectations and work practices. Similarly, Helm et al. (2020) emphasised that AI solutions must be not only functionally robust but also user-friendly and supportive to ensure continuous user involvement. This is especially relevant in public transportation systems, where employee acceptance directly affects service quality and operational efficiency.

Finally, the validated framework serves as a practical decision-support tool for policymakers and practitioners seeking to scale AI adoption sustainably within Abu Dhabi's transportation sector. By simultaneously enhancing system availability and user satisfaction, organisations can strengthen behavioural intention to use AI, promote innovation, and improve public service delivery outcomes. As highlighted by Santoso and Surya (2024) and Mnyakin (2023), user-centric design, trust, and satisfaction are essential for ensuring the long-term effectiveness and sustainability of AI implementations in public service environments. Overall, the framework offers a balanced and empirically grounded guideline for advancing AI adoption by aligning technological capability with human experience.

5. Conclusion

This study examined the mediating role of user satisfaction in Artificial Intelligence (AI) adoption within Abu Dhabi's public transportation system. By developing and empirically validating a conceptual framework grounded in socio-technical systems theory, the Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology (UTAUT), the research offers both theoretical and practical insights into the dynamics of AI adoption.

The findings confirm that System Availability Factors (SAF) exert significant direct and indirect effects on Behavioural Intention to Use (BIU), with User Satisfaction Attributes (USA) serving as a critical mediator. This dual-pathway effect demonstrates that successful AI adoption depends not only on technical robustness but also on the extent to which users perceive systems as reliable, usable, and supportive of their work practices. In particular, the mediation analysis highlights that satisfaction amplifies the influence of system availability, underscoring the importance of user-centred design, training, and responsive support mechanisms.

Theoretically, the validated framework extends existing technology adoption models by embedding satisfaction as a mediating construct. This refinement contributes to the broader literature on information systems success and technology acceptance, offering a more nuanced understanding of how system-level factors translate into behavioural outcomes. Practically, the framework provides policymakers and practitioners in Abu Dhabi with a decision-support tool for scaling AI adoption sustainably. By simultaneously enhancing system availability and user satisfaction, transport authorities can strengthen behavioural intention, promote innovation, and improve public service delivery outcomes.

Despite these contributions, the study has limitations. The empirical analysis was conducted within the specific context of Abu Dhabi's public transportation sector, which may restrict the generalisability of findings to other regions or industries. Additionally, reliance on self-reported survey data introduces potential biases related to perception and intention rather than actual usage behaviour.

Future research should extend this framework through comparative studies across Gulf cities and other global smart mobility hubs, as well as longitudinal investigations to capture changes in satisfaction and adoption over time. Incorporating sustainability outcomes—such as reductions in carbon emissions and improvements in commuter well-being—would further enrich the framework's relevance to broader urban development goals.

In conclusion, AI adoption in public transportation is both a technical and human-centred endeavour. By validating the mediating role of user satisfaction, this study provides a balanced and empirically grounded pathway for advancing AI-enabled mobility systems in Abu Dhabi, supporting the emirate's vision of building efficient, sustainable, and future-ready urban infrastructure.

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