INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS & SOCIAL SCIENCES

Vol 15, Issue 9, (2025) E-ISSN: 2222-6990

Scenario Analysis of AI Adoption among Employees in Abu Dhabi Transportation Department

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DOI Link: http://dx.doi.org/10.6007/IJARBSS/v15-i9/26440

Published Date: 03 September 2025

Abstract

As public sector organisations increasingly adopt Artificial Intelligence (AI) technologies to enhance service delivery, employee acceptance has emerged as a critical success factor. This study investigates staff readiness to embrace AI within the Abu Dhabi Transportation Department, employing a scenario analysis approach to explore perceptions across three key dimensions: system availability factors (SAF), user satisfaction attributes (USA), and behavioural intention to use AI (BIU). Data were collected through a structured questionnaire administered to 29 employees. Findings indicate a strong positive orientation toward AI adoption, with all mean scores exceeding 4.5. Specifically, SAF recorded a mean of 4.76, USA achieved 4.77, and BIU reached 4.71. These results place the organisation within the Optimistic Scenario, suggesting that employees view AI technologies as reliable, efficient, and valuable to their daily operations. High satisfaction levels appear linked to the successful integration of AI systems supported by dependable infrastructure, targeted training initiatives, and clear operational benefits such as real-time decision-making and improved efficiency. The study highlights that employees' trust in AI systems and recognition of their practical advantages significantly influence their behavioural intention to adopt the technology. These insights emphasise the importance of continuous investment in digital infrastructure, tailored training programs, and proactive management of technical challenges to sustain positive employee perceptions and support long-term AI integration. By identifying the factors that shape acceptance, this research offers practical guidance for policymakers and managers aiming to foster effective AI adoption in the public transportation sector.

Keywords: AI Adoption, Scenario Analysis, System Availability, User Satisfaction, Behavioural Intention

Introduction

The rapid urban development and economic expansion in the United Arab Emirates have further intensified the pressure on the country's transportation infrastructure. According to Badawi and Habib (2023), the development of new residential and commercial areas has

aggravated traffic congestion, necessitating innovative urban planning and transportation management strategies. In rapidly expanding cities such as Abu Dhabi and Dubai, the existing infrastructure often struggles to accommodate rising population levels and the increasing number of vehicles on the roads. In addition, sustainability presents a major concern, as high carbon emissions from conventional vehicles contribute significantly to environmental challenges. Although the United Arab Emirates has made progress in promoting green transportation initiatives, further efforts are needed to reduce the environmental impact of expanding transportation networks.

Transportation systems play a fundamental role in modern societies by enabling the movement of people and goods, which supports both economic growth and social development (Lewis and Jago, 2017). However, managing these systems has become increasingly complex because traditional methods struggle to meet the demands of rapidly growing urban areas (Barceló and Beuthe, 2022). The complexity arises from the enormous volume of transportation data, the unpredictability of human behaviour, and the interconnected nature of transportation components (Helbing and Johansson, 2014). Furthermore, rapid urbanization and technological advancements add additional challenges, making it more difficult to effectively manage transportation networks (Kwan, 2017). These challenges are particularly evident during real-time decision-making in response to traffic incidents or sudden spikes in demand, where conventional approaches often prove inadequate, resulting in operational inefficiencies (Rybski and González, 2022).

To address these challenges, Artificial Intelligence (AI) is emerging as a transformative tool within the transportation sector. AI enhances operational efficiency, improves service delivery, and optimizes decision-making processes (Li et al., 2020). In government transportation departments, AI adoption plays a crucial role in managing complex transportation networks, enhancing public service delivery, and ensuring the sustainability of urban mobility (Zhou et al., 2021). However, successful AI adoption depends on several important factors, including the perceived availability of AI systems, users' satisfaction with AI-supported services, and employees' intention to use AI in their daily tasks (Dwivedi et al., 2021).

To overcome these challenges, transportation authorities increasingly rely on AI technologies to improve both efficiency and effectiveness (Gomes et al., 2023). AI systems can analyse vast amounts of data, detect patterns, and support real-time decision-making. These capabilities allow AI to address the limitations of traditional transportation management approaches (Gomes et al., 2023). For example, AI can transform conventional traffic sensors into smart agents capable of detecting accidents and predicting congestion patterns (Bean, 2017). In Abu Dhabi, AI has already been applied to optimize traffic signals, reduce congestion, and lower carbon emissions through platforms such as Google's AI technology (Wam, 2024).

Despite these advances, integrating AI into transportation systems still faces several obstacles. These include limitations in system design, financial constraints, regulatory gaps, and the need for reliable digital infrastructure (United Arab Emirates Government, 2024). Furthermore, although many prior studies have applied the Technology Acceptance Model to transportation systems, these studies rarely focus on AI adoption within public transportation

services (Prayoonphan and Xu, 2019; Sánchez-Prieto et al., 2020; Ikhsan, 2020; Ahn and Park, 2022; Abduljabbar et al., 2019; Al Shamsi and Davies, 2022; Al-Bulushi, 2023). There is also a lack of research addressing employee and user acceptance of AI-powered tools, such as AI-driven chatbots for public transport information and AI algorithms designed to optimize route planning and service scheduling. Understanding these factors is crucial to enhancing both user experience and operational efficiency.

In Abu Dhabi, despite ongoing efforts to integrate AI into transportation operations, limited research exists on the acceptance of AI adoption among employees working within the transportation department. Gaining a better understanding of employee acceptance, satisfaction, and perceived benefits of AI-powered tools is essential for achieving sustainable and successful AI implementation within the transportation sector in the United Arab Emirates.

To address this gap, this study applies scenario analysis to assess AI adoption among employees in the Abu Dhabi Transportation Department. Scenario analysis is a strategic planning technique used to identify and evaluate possible future outcomes under different conditions (Van der Heijden, 2005). This study focuses on three key dimensions: System Availability Factors, User Satisfaction Attributes, and Behavioural Intention to Use AI. These dimensions reflect technological reliability, employees' satisfaction with AI tools, and their willingness to adopt AI. All three constructs are aligned with the core principles of the Technology Acceptance Model (Venkatesh and Davis, 2000.

Literature Review

Artificial Intelligence (AI) refers to the ability of machines to perform tasks that typically require human intelligence, such as learning, reasoning, and decision-making (Russell & Norvig, 2021). In the transportation sector, AI is playing a pivotal role in transforming how people and goods move across cities and regions. Its growing influence is evident through the integration of advanced technologies that are becoming essential to the development of modern transportation systems.

The use of AI in public sector transport management has expanded significantly in recent years. Cities around the world are increasingly adopting smart technologies to improve operational efficiency, optimize traffic flow, and enhance service delivery (Kumar et al., 2020). AI tools such as predictive traffic control, fleet management systems, and real-time event detection have become vital for transportation authority's striving to reduce congestion, increase safety, and maintain reliable public transportation networks (Chen et al., 2019). These applications underscore the growing reliance on AI to manage transportation infrastructure at a more intelligent and responsive level.

Several key forms of AI are widely used in the transportation industry. Machine learning is applied to forecast traffic conditions and improve route planning, which helps minimize delays. Computer vision enables autonomous vehicles to identify and respond to their surroundings, improving the safety of self-driving systems. Natural language processing supports virtual assistants in guiding users through transportation systems more efficiently. In addition, robotics enhances the precision and speed of logistics and warehouse operations (Yuan et al., 2022; Gkartzonikas & Gkritza, 2019). These technologies are not just

supplementary improvements. They are foundational to the design and operation of intelligent transportation networks.

The impact of AI in transportation is both profound and far-reaching. It offers the potential to improve traffic efficiency, reduce travel time, and significantly increase safety on the roads. By minimizing human error, which is responsible for the majority of traffic accidents, AI contributes to saving lives and reducing injuries (Litman, 2020). Furthermore, AI supports the dependability of public transportation systems, lowers energy consumption, and aids in building environmentally sustainable urban environments (Shladover, 2018; Chen et al., 2020). Embracing AI is not merely a technological choice. It represents a strategic vision for building smarter and more resilient cities.

However, despite the many advantages, public attitudes toward AI in transportation remain divided. While a growing number of people appreciate the convenience and innovation that AI brings, others express concerns about safety, privacy, and control. These concerns are legitimate, but they can be addressed. Research indicates that when AI systems are developed with transparency, guided by ethical standards, and supported by strong regulatory oversight, public trust and acceptance tend to rise significantly (Zhang et al., 2021; Shariff, Bonnefon, & Rahwan, 2017). Building public confidence through clear communication and responsible innovation is essential to the successful integration of AI in this sector.

System Availability in Technology Adoption

System availability factors (SAF) are an important aspect impacting AI adoption since it impacts whether employees perceive AI systems to be dependable, functional, and regularly available when needed (Davis, 1989). AI-based tools in the transportation sector, such as predictive traffic management systems, automated fleet tracking, and real-time route optimisation, must be readily available to create confidence and encourage widespread adoption among employees (Sharma et al., 2022). When AI solutions perform seamlessly with no downtime and give real-time, accurate insights, employees are more inclined to rely on them for decision-making and operational efficiency.

Previous research has shown that perceived system availability has a direct impact on technology acceptability and users' behavioural intentions to engage with advanced technologies (Alharbi, 2020). Employees that believe AI systems will be accessible and operational with few errors are more likely to integrate them into their daily tasks, resulting in better adoption rates and increased productivity. In contrast, unreliable AI systems with frequent downtimes, technical malfunctions, or variable performance can cause dissatisfaction, lost trust, and reluctance to adoption. Thus, establishing a strong infrastructure, ongoing system maintenance, and timely technical assistance is critical for sustaining AI adoption in the workplace (Zhou et al., 2021). In the context of Abu Dhabi's transport department, providing highly available AI-driven solutions with proactive monitoring and rapid issue resolution will be critical to preserving employee confidence and maximising the long-term success of AI integration (Abu Hammad et al., 2023).

User Satisfaction in AI Adoption

User satisfaction (USA) is an important factor of technology adoption, especially in organisations where employees rely on digital technologies to improve efficiency and

productivity (DeLone & McLean, 2003). In the public sector, satisfaction with AI-powered solutions such as automated scheduling, predictive maintenance, and AI-driven reporting systems is critical to ensure long-term adoption and engagement with the technology (Iqbal et al., 2021). Employees that see these AI-driven services as dependable, effective, and user-friendly are more inclined to incorporate them into their regular workflows, leading to higher adoption rates and overall workplace productivity.

Dissatisfaction with AI technology might result from technical errors, system complexity, or insufficient training (Petter, DeLone, & McLean, 2008). Employees may struggle to adopt AI if they see numerous system faults, lack faith in the technology, or see the system as cumbersome rather than advantageous. To ensure that employees can use AI technologies effectively, organisations must prioritise user-centric design, ongoing technical support, and thorough training programs. In the context of Abu Dhabi's transport department, aligning AI tools with employee needs and demonstrating clear operational benefits such as improved decision-making, increased efficiency, and reduced workload which can significantly enhance user satisfaction and drive long-term adoption (Abu Hammad et al., 2023).

Behavioural Intention to Use AI

Behavioural intention (BIU) is critical in determining the effective use of AI technology within organisations, particularly in the public sector. It represents employees' propensity to embrace and use AI-powered solutions into their regular operations (Venkatesh et al., 2003). According to the Technology Acceptance Model (TAM) and its extended versions, perceived usefulness and simplicity of use have a substantial impact on employees' BIU, hence moulding their overall attitude towards AI adoption (Davis, 1989). Employees are more likely to use AI when they understand how technology may improve efficiency, automate monotonous work, and deliver important insights (Alsheibani et al., 2020).

Furthermore, various organisational elements help to develop favourable behavioural intents for AI adoption. A supportive organisational culture, leadership commitment, and planned training programs foster an atmosphere in which employees feel comfortable utilising AI tools (Al-Muwil et al., 2020). Leadership support ensures that staff have the required direction, resources, and incentives to successfully migrate to AI-integrated workflows. Furthermore, well-designed training programs assist bridge the skill gap, allowing employees to gain a better knowledge of AI's functions and benefits (Al-Muwil et al., 2020). These elements work together to increase employees' desire to adopt AI, resulting in successful adoption and long-term sustainability of AI technology in public sector organisations.

Methodology

This pilot study adopts a quantitative research design, using a structured questionnaire to collect data from 29 employees of the Abu Dhabi Transportation Department. The primary objective is to assess employees' behavioural intention to use Artificial Intelligence (AI) technologies to enhance their work environment and ultimately improve transportation services in Abu Dhabi. The study focuses on two major factors influencing behavioural intention: system availability and user satisfaction. The questionnaire included items designed to measure system availability factors, which reflect employees' perceptions of the reliability, functionality, and overall accessibility of AI systems. These systems include

predictive traffic control, route optimization tools, and fleet tracking technologies (Pan et al., 2019). It also addressed user satisfaction attributes, capturing employees' experiences with AI-supported services such as intelligent scheduling, predictive maintenance, and AI-powered dashboards (Cheng et al., 2022). Additionally, the questionnaire assessed behavioural intention to use AI, which indicates employees' willingness to adopt and actively engage with AI tools in their daily tasks (Venkatesh et al., 2003).

To explore how potential future developments and uncertainties may affect AI adoption, the study integrates scenario analysis as a strategic evaluation tool (Rosenbaum et al., 2018; Borgonovo, 2017). Scenario analysis is a widely recognized approach in technology adoption research that enables the examination of multiple plausible futures shaped by variables such as technology performance, user satisfaction, and organizational preparedness (Van der Heijden, 2005). This method helps policymakers and organizations anticipate challenges, identify key success factors, and formulate targeted strategies to support AI adoption (Schoemaker, 1995). In the context of Abu Dhabi's transportation sector, scenario analysis is essential for predicting adoption trends and designing informed interventions. It provides a structured way to assess criteria for AI integration, evaluate workforce readiness, and understand how different conditions may influence the implementation process (Gausemeier et al., 1998). By combining survey data with structured models of technology adoption, this approach promotes data-driven decision-making. Scenario analysis also highlights enablers such as leadership support, employee training, and robust technological infrastructure, ensuring alignment between AI adoption initiatives and organizational goals (Ringland, 2006). As AI continues to transform transportation systems, scenario analysis strengthens planning, risk management, and the long-term success of implementation efforts (Bradfield et al., 2005).

The analysis follows a structured four-step approach. The first step involves establishing threshold values based on prior studies, expert consultations, or validated scales from technology adoption literature. This provides a consistent and meaningful reference point for interpretation. The second step calculates mean scores for each construct measured in the study, including system availability, user satisfaction, and behavioural intention to use AI. These scores form the basis for developing future scenarios. In the third step, a scenario matrix or visual representation is created. Different combinations of high, medium, and low mean scores are used to construct distinct and plausible adoption scenarios. The fourth and final step is the interpretation of these scenarios by comparing the construct scores with the predefined thresholds. This analysis draws on previous research to ensure the findings are both evidence-based and theoretically sound. This systematic approach enables organizations to anticipate how fluctuations in system performance and user satisfaction might influence AI adoption. It equips decision-makers with valuable insights into likely adoption pathways and provides a foundation for developing strategies that promote readiness and acceptance (Bood and Postma, 1998; Rosenbaum et al., 2018; Borgonovo, 2017).

To interpret the questionnaire results, the study applies a five-point Likert scale along with predefined thresholds. As outlined in Table 1, a mean score below 3.0 is considered poor, whereas a score of 4.5 or higher is classified as excellent. These threshold values offer a clear framework for evaluating and understanding the data in a meaningful conte.

Table 1
Predefined Threshold for Mean Scores

Mean Score	Interpretation	Source
4.5 - 5.0	Excellent	Joshi et al., 2015 / Vagias, 2006
4.0 - 4.49	Good	Joshi et al., 2015
3.5 - 3.99	Moderate	Vagias, 2006
3.0 - 3.49	Low	Sekaran & Bougie, 2016
Below 3.0	Poor	Boone & Boone, 2012

Based on Table 1, the scenario analysis can be classified into three distinct scenarios. The first is the Optimistic Scenario (Excellent Adoption Potential), where all mean scores fall within the range of 4.5 to 5.0, indicating excellent perceptions and a high likelihood of successful AI adoption. The second is the Moderate Scenario (Mixed Adoption Potential), which occurs when one or more mean scores fall within the range of 3.5 to 4.49. This reflects moderate to good perceptions, suggesting the presence of certain concerns or reservations that could potentially hinder AI adoption. Finally, the Pessimistic Scenario (Low Adoption Potential) arises when one or more mean scores fall below 3.5, indicating low or poor perceptions. This scenario signals significant barriers to AI adoption, such as dissatisfaction with system performance or resistance from users.

Findings and Discussions

Apart from the demographic section, the questionnaire focused on three main sections: the System Availability Factors (SAF), the User Satisfaction Attributes (USA), and the Behavioural Intention to Use AI (BIU). Specifically, the questionnaire included 8 factors under SAF, 10 attributes under USA, and 8 attitudes under BIU. Data was collected from 29 employees of the Abu Dhabi Transportation Department, with each item measured using a 5-point Likert scale. The mean scores for each item, derived from the survey responses, are presented in Figure 1.

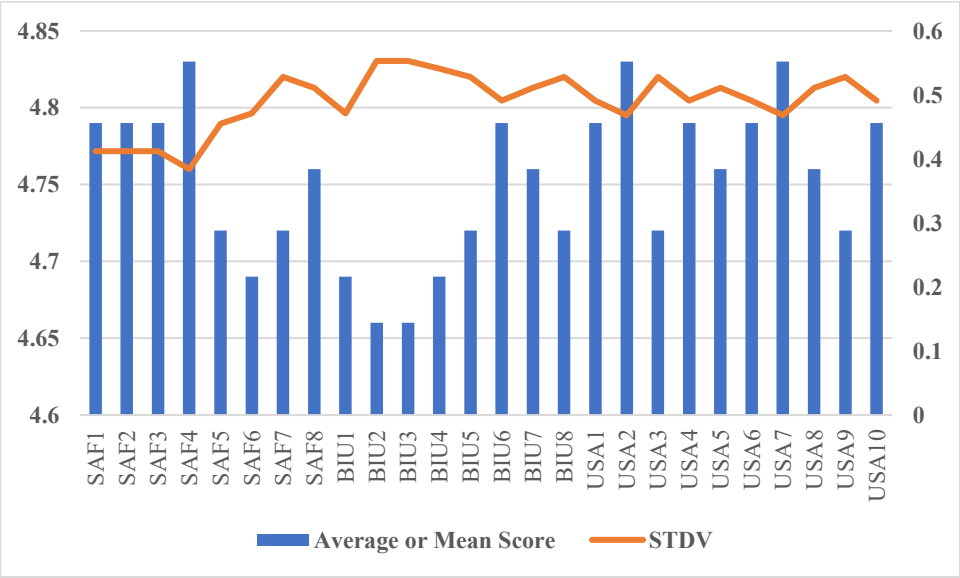

Figure 1: Mean score of each item

Figure 1 indicates that the mean scores for all items exceed 4.5, which clearly reflects a strong acceptance and positive outlook toward AI adoption among employees of the Abu Dhabi Transportation Department. As a result, this places the organization firmly within the

Optimistic Scenario, where employees perceive AI systems as reliable, functional, and effective. This positive perception enhances both their satisfaction and their willingness to adopt these technologies. Moreover, this finding is consistent with previous research, which has emphasized that technological reliability and user satisfaction are critical drivers of successful technology adoption (Venkatesh & Davis, 2000; Dwivedi et al., 2021).

In addition, when considering the item groups, the analysis revealed that the System Availability Factors (SAF) group achieved a mean score of 4.76, the User Satisfaction Attributes (USA) group recorded an mean score of 4.77, and the Behavioural Intention to Use AI (BIU) group obtained an mean score of 4.71. According to the predefined thresholds, these scores collectively place all three groups within the Optimistic Scenario, confirming the strong positive perceptions toward AI adoption among employees.

This favourable outlook may be attributed to the successsful integration of AI tools into daily operations, supported by adequate training, reliable infrastructure, and visible benefits such as improved operational efficiency and real-time data insights (Cheng et al., 2022). Furthermore, employees' willingness to adopt AI could also be influenced by organizational support and a clear understanding of how AI can enhance job performance (Pan et al., 2019). However, maintaining this positive adoption climate requires continuous investment in AI infrastructure, while simultaneously addressing potential technical issues and ensuring ongoing training and user engagement (Schwarz, 2006).

Moreover, the scenario analysis highlights the importance of proactively monitoring these influencing factors over time to identify and mitigate potential adoption barriers before they emerge. This proactive approach not only supports sustained adoption but also helps the organization adapt to evolving employee expectations and technological advancements.

This finding is further supported by previous research, which highlights that System Availability and User Satisfaction are key determinants of Behavioural Intention to Use technology (Venkatesh & Davis, 2000; Pan et al., 2019; Cheng et al., 2022). Specifically, when employees perceive AI systems as reliable, functional, and consistently available, and when they are satisfied with the services and benefits provided by these systems, they are more likely to develop a strong behavioural intention to adopt and actively engage with AI technologies (Venkatesh et al., 2003).

Ultimately, the alignment of all three constructs within the Optimistic Scenario provides strong evidence for a high likelihood of successful AI adoption within the department. This finding supports the core principles of the Technology Acceptance Model (TAM), which asserts that perceived ease of use, which closely relates to system availability, and perceived usefulness, which reflects user satisfaction, directly predict behavioural intention (Davis, 1989). Therefore, when employees trust the reliability of AI systems and perceive clear benefits in using them, they become more motivated and ready to adopt these technologies, which eventually leads to higher adoption rates (Dwivedi et al., 2019; Rana et al., 2023).

Conclusion

This study used scenario analysis to anticipate AI adoption among Abu Dhabi Transportation Department personnel via a questionnaire survey. The study discovered that

employees are well accepted and have a good attitude on AI adoption by looking at System Availability Factors (SAF), User Satisfaction Attributes (USA), and Behavioural Intention to Use AI (BIU). With all item mean values greater than 4.5, the organisation falls into the Optimistic Scenario, indicating that employees believe AI systems are dependable, functional, and effective. This good perception, in turn, increases both user happiness and employees' willingness to use this technology. The investigation also indicated that SAF had a mean score of 4.76, USA had 4.77, and BIU had 4.71, all of which consistently reflect a positive attitude. These favourable opinions are most likely fuelled by the successful integration of AI technologies into daily operations, dependable infrastructure, proper training, and visible operational benefits like as increased efficiency and real-time insights. Furthermore, the results are consistent with the Technology Acceptance Model (TAM), which emphasises that perceived ease of use (related to system availability) and perceived usefulness (connected to user satisfaction) are important determinants of behavioural intention to embrace technology. In this situation, employees' faith in system stability and perceived benefits from AI significantly influence their desire to adopt these technologies, resulting in higher adoption rates. As a result, this study emphasises the importance of maintaining a supportive environment for AI adoption, which includes continuous investment in AI infrastructure, proactive resolution of technical issues, and ongoing training to sustain positive user perceptions and further improve AI adoption within the department.

Contributions

This work complements significantly to both the theoretical and practical knowledge of AI adoption in government transport departments by giving a data-driven road map for effective deployment. Through utilising scenario analysis, it provides a structured technique to measuring employee acceptability and attitudes towards AI integration. The findings suggest that employees see AI as reliable, functional, and successful, as demonstrated by important parameters such as System Availability parameters (SAF), User Satisfaction Attributes (USA), and Behavioural Intention to Use AI (BIU). Furthermore, the study confirms the significance of the Technology Acceptance Model (TAM) by demonstrating that perceived ease of use, linked to system availability, and perceived usefulness, linked to user pleasure, are important determinants of AI adoption. The results show an optimistic outlook for AI adoption, as all mean scores surpass 4.5, reflecting a high level of preparedness and favourable emotion among employees. Furthermore, the study emphasises the significance of strong infrastructure, sufficient training, and obvious operational benefits in pushing AI adoption. It makes practical advice to politicians and technology managers, emphasising the importance of continual investment in AI infrastructure, proactive resolution of technical difficulties, and regular training to maintain good user attitudes and enable long-term AI integration. This research is a crucial resource for the successful application of AI in government transport departments, as it provides both conceptual insights and practical recommendations.

Author Contributions

Shaikha Alblooshi as the author of this article and a PhD candidate, Mohd Hilmi Izwan Abd Rahim as the supervisor.

Acknowledgement

The authors would like to thanks UTHM for giving the opportunity to conduct and publish this study.

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