TRUSTWORTHINESS AS A MEDIATOR BETWEEN USER PERCEPTIONS AND AI ADOPTION INTENTION IN ADNOC'S SUPPLY CHAIN

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ABSTRACT
Objective: This study aims to develop and validate a structural model that examines trustworthiness as a mediating variable between user perceptions specifically Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) and the intention to adopt AI technologies in ADNOC's supply chain management.
Research Method: A conceptual model was formulated based on the Technology Acceptance Model (TAM) and relevant literature. Primary data were collected through a structured questionnaire survey administered to 328 employees of the ADNOC supply chain department. The model was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS software.
Findings: The results confirmed that all constructs exhibited strong internal consistency, convergent validity, and discriminant validity. Structural model analysis showed that PEOU and PU significantly influence Trust, which in turn strongly predicts Behavioral Intention to Use (BIU). The model demonstrated moderate to strong explanatory power and substantial predictive relevance, highlighting trust as a critical mediator in AI adoption.
Originality: This study extends the traditional TAM by incorporating trustworthiness as a mediator, offering a novel perspective on AI adoption in high-stakes, public sector environments. The validated model provides both theoretical contributions and practical insights for guiding successful AI implementation in complex organizational settings like ADNOC.
Keywords: AI Adoption, Trustworthiness, Technology Acceptance Model, Supply Chain Management, PLS-SEM, ADNOC

1. INTRODUCTION

The oil and gas industry is undergoing a period of rapid transformation, driven by global trends such as digitalization, sustainability demands, and increased supply chain complexity (El Khatib et al., 2022). In the UAE, the Abu Dhabi National Oil Company (ADNOC) faces the challenge of adapting to these changes while maintaining operational excellence. Complex supplier networks, limited visibility, and the need for enhanced stakeholder collaboration are pressing concerns that require innovative solutions (Mohamed, 2023). To address these challenges, integrated supply chain management (SCM) models focusing on supplier, production, logistics, and customer management have been developed, offering improved efficiency, reduced costs, and better performance outcomes.

Among the transformative technologies reshaping SCM, artificial intelligence (AI) stands out as a key enabler. Artificial Intelligence (AI) is a widely adopted technology facilitating as a device to make appropriate decisions (Almarashda et al. 2022) and very effective technique in reducing complexity (Almarashda et al. 2021). AI has the potential to revolutionize supply chain processes by optimizing inventory control, enhancing predictive maintenance, and streamlining logistics operations (Hosani & Ghouri, 2022). For ADNOC, the integration of AI is not merely a technological shift but a strategic initiative that supports operational efficiency and long-term sustainability.

However, the success of such integration is largely dependent on user acceptance and organizational readiness (Almarashda et al., 2022). Challenges such as data privacy concerns, employee skill gaps, and resistance to cultural change must be effectively addressed to ensure successful AI adoption (Wamba-Taguimdje et al., 2020).

The benefits of AI in supply chain operations are well-documented. AI facilitates data-driven decision-making, enhances forecasting accuracy, strengthens risk mitigation, and reduces inefficiencies across the value chain (Belhadi et al., 2022; Helo & Hao, 2022; Shoushtari et al., 2021). By leveraging historical and real-time data, AI tools improve operational precision, reduce errors, and support resilient supply chain strategies—critical for high-risk sectors such as oil and gas (Dash et al., 2019; Shah et al., 2023).

ADNOC has demonstrated a strong commitment to AI innovation. In 2018, the company launched the Panorama Digital Command Center to provide real-time operational analytics (ADNOC, 2018). This was followed by the implementation of AI-enabled predictive maintenance and automated drilling operations (McKinsey & Company, 2019). A strategic partnership with G42 in 2021 further accelerated the adoption of AI across ADNOC's value chain (G42, 2021). By 2023, ADNOC had expanded its use of AI in reservoir modeling, supply chain optimization, and carbon reduction initiatives—reinforcing its position as a leader in digital transformation and sustainable operations (Bloomberg, 2023; International Energy Agency, 2023).

Given the scope of AI integration within ADNOC, understanding the behavioral factors influencing its adoption is vital. The Technology Acceptance Model (TAM) offers a widely accepted theoretical foundation for examining how individuals accept and use technology (Maina & Moronge, 2018). Drawing from this model, key constructs such as Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) have been shown to directly influence technology adoption in various organizational settings (Kshetri, 2019; Rachapudi Venkata et al., 2021; AlQubaisi & Emran, 2022).

Building upon the Technology Acceptance Model (TAM), this study introduces trustworthiness as a mediating factor in the relationship between user satisfaction and behavioral intention toward AI adoption. Within ADNOC's technologically intensive operations, trust in AI systems—particularly in terms of data integrity, transparency, and reliability—plays a crucial role in shaping user behavior and acceptance. This research focuses on examining several key constructs: the Perceived Ease of Use (PEOU) of AI-driven solutions in supply chain management; the Perceived Usefulness (PU) of AI technologies in enhancing operational performance; the level of trustworthiness associated with AI adoption across various SCM functions; and the Behavioral Intention to Use AI technologies within ADNOC's supply chain context. By exploring these interrelated factors, the study aims to develop a comprehensive conceptual framework that facilitates effective AI integration and aligns with ADNOC's broader goals of innovation and digital transformation.

2. CONCEPTUAL FRAMEWORK

A conceptual or theoretical framework provides a structured approach to understanding and analyzing a research problem by outlining key concepts, variables, and their relationships. Grounded in existing theories or models, it serves as a guide for research design, data collection, and analysis. By offering a clear roadmap, the framework ensures that the study remains focused and coherent, ultimately leading to more robust and meaningful findings.

For this study, the Technology Acceptance Model (TAM) has been adopted. Two key determinants, Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), shape users' attitudes toward technology. These attitudes, in turn, influence their Behavioral Intention (BI) to use the technology, ultimately determining actual usage behavior.

Additionally, this study introduces AI trustworthiness as a mediator in the relationship between PEOU, PU, and users' attitudes and behavioral intentions. This interconnected relationship highlights the importance of user experience and practicality in shaping attitudes toward AI technology adoption in ADNOC's supply chain management, as illustrated in the conceptual framework of Figure 1.

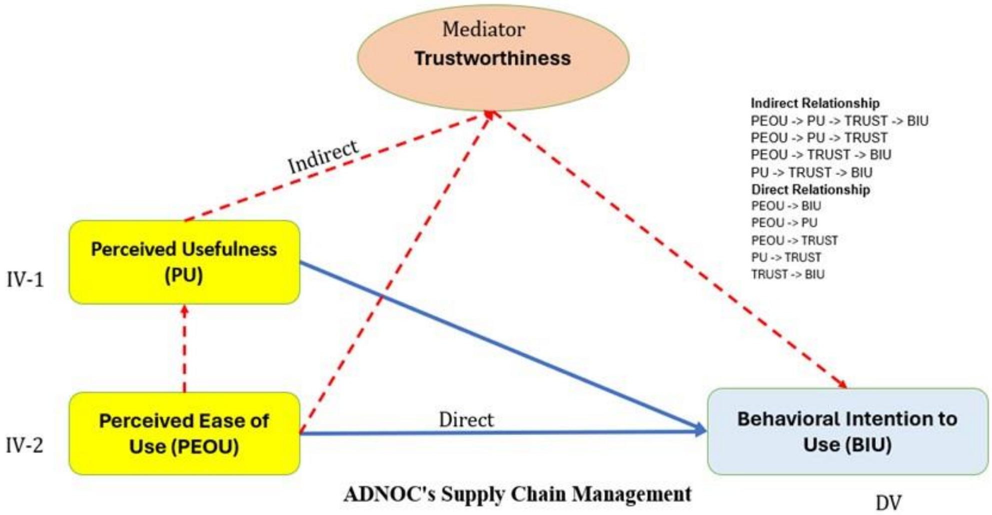

Figure 1: The conceptual framework

The conceptual model illustrated in the figure 1 represents the structural framework developed to examine the factors influencing the adoption of AI technologies within ADNOC's supply chain management. Rooted in the Technology Acceptance Model (TAM), the framework incorporates two key independent variables: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). These variables are hypothesized to influence the Behavioral Intention to Use (BIU) AI systems, which serves as the dependent variable.

The model captures both direct and indirect relationships among the key constructs. In the direct pathways, Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) are each hypothesized to directly influence Behavioral Intention to Use (BIU), while PEOU also directly influences PU, in alignment with the traditional Technology Acceptance Model (TAM). To extend the explanatory power of the model, Trustworthiness is introduced as a mediating variable, reflecting its crucial role in shaping user confidence and acceptance of AI systems. In the indirect pathways, both PEOU and PU are proposed to influence BIU through Trustworthiness. Additionally, a sequential indirect path is conceptualized, wherein PEOU enhances PU, which in turn fosters Trustworthiness, ultimately leading to increased BIU.

The following subsections elaborate on the individual constructs and their theoretical underpinnings within the conceptual framework.

2.1 PERCEIVED EASE OF USE (PEOU) TO ADOPTION OF AI-DRIVEN SOLUTIONS

The adoption of AI-driven solutions in supply chain management is strongly shaped by Perceived Ease of Use (PEOU),a construct that reflects the degree to which users believe an AI system is free of effort (Davis, 1989; Venkatesh & Davis, 2000). When AI applications are perceived as intuitive and easy to use, they are more likely to be integrated into operational workflows (Kamrath et al., 2025; Venkatesh et al., 2003). Key dimensions influencing PEOU include interface design, accessibility, integration, training, system reliability, and feedback responsiveness.

A well-designed and user-friendly interface significantly enhances usability, allowing employees to interact with AI systems without requiring extensive technical training (Gefen & Straub, 2000; Zhou et al., 2020). In supply chain contexts, this translates to faster onboarding and increased willingness to adopt AI tools for logistics planning, forecasting, and procurement tasks (Hanif et al., 2025; Kamrath et al., 2025).

Moreover, system integration plays a vital role in shaping perceived ease of use. AI applications that seamlessly integrate with existing enterprise systems and supply chain software reduce operational disruptions and improve user experience (Chen et al., 2021; Dwivedi et al., 2019). Complementing this, training and support mechanisms—such as user manuals, helplines, and workshops—are essential for enhancing employee confidence and minimizing perceived complexity (Sun & Medaglia, 2019; Cervantes & Navarro, 2025).

System performance and reliability are also central to PEOU. AI systems that consistently deliver accurate outputs with minimal errors are perceived as more dependable and easier to use in high-stakes environments like supply chain operations (Huang et al., 2021; Queiroz et al., 2020). Finally, feedback responsiveness, the extent to which user suggestions and system performance data are used to refine AI tools, further enhances usability and overall user satisfaction (Janssen et al., 2020; Wirtz et al., 2019; Pramanik & Jana, 2025).

With the increasing the perceived ease of use of AI technologies through intuitive design, smooth integration, comprehensive training, reliability, and feedback responsiveness can significantly improve employee acceptance and adoption in supply chain management. This, in turn, maximizes the strategic value of AI in driving operational efficiency and decision-making.

2.2 PERCEIVED USEFULNESS (PU) IN THE ADOPTION OF AI TECHNOLOGY

Perceived Usefulness (PU) plays a pivotal role in the adoption of AI technology in supply chain management, as it reflects the extent to which users believe that AI enhances operational efficiency, decision-making quality, and overall organizational performance (Davis, 1989; Venkatesh & Davis, 2000). The perception that AI technologies add value is influenced by several key factors, including improved decision-making, process automation, predictive accuracy, risk mitigation, and strategic advantage.

One of the most prominent dimensions of PU is enhanced decision-making capability. AI technologies process vast amounts of real-time and historical data to generate actionable insights and predictive analytics, empowering supply chain professionals to make informed, data-driven decisions across areas such as inventory control, demand forecasting, and logistics planning (Choi et al., 2020; Ivanov & Dolgui, 2020; Pramanik & Jana, 2025). This level of intelligence makes AI an essential tool for strategic and tactical supply chain functions.

Operational efficiency and productivity are also critical contributors to PU. AI-driven systems automate routine tasks, optimize complex workflows, and help identify inefficiencies, ultimately enhancing throughput and reducing delays in supply chain activities (Wamba et al., 2017; Hanif et al., 2025). In high-stakes environments like the oil and gas industry, such automation ensures continuous optimization of resources and promotes leaner, more agile operations (Fatorachian & Kazemi, 2021; Rosita et al., 2025).

Accuracy and precision further elevate the perceived usefulness of AI tools. Machine learning algorithms, by analyzing data patterns, enable organizations to minimize errors, reduce waste, and improve resource utilization, all of which translate to tangible cost savings and superior performance outcomes (Min, 2019; Kamrath et al., 2025; Jeble et al., 2018).

Beyond efficiency, risk mitigation and operational resilience are vital to the usefulness of AI in supply chain contexts. AI technologies can detect emerging risks and potential disruptions early, enabling proactive responses that strengthen the resilience of supply chain networks—particularly crucial in volatile industries like oil and gas (Ivanov et al., 2019; Govindan et al., 2020; Wawan & Hakam, 2025).

Lastly, competitive advantage is a compelling driver of PU. Organizations leveraging AI benefit from faster, more agile, and data-informed decision-making compared to those relying on traditional methods. This competitive edge allows firms to respond swiftly to market dynamics and innovate continuously within their supply chains (Queiroz et al., 2020; Cervantes & Navarro, 2025; Huang et al., 2021; Bara & Ali, 2025).

Collectively, these dimensions reinforce the strategic value of AI technologies in supply chain operations. When employees perceive that AI systems significantly enhance their work effectiveness, the likelihood of adoption increases, ensuring that AI-driven solutions deliver measurable, long-term benefits to organizational performance.

2.3 TRUSTWORTHINESS IN AI TECHNOLOGY ADOPTION AS MEDIATOR KEY DIMENSIONS OF STRATEGIC AGILITY

As artificial intelligence (AI) continues to permeate complex operational environments such as supply chains, trust and perceived trustworthiness have emerged as pivotal factors influencing user acceptance and adoption behaviors. For organizations like the Abu Dhabi National Oil Company (ADNOC), maximizing the value of AI-driven solutions hinges on how users perceive and engage with these technologies. Trustworthiness in this context refers to users' perceptions of a system's reliability, integrity, and competence to perform its tasks accurately and ethically. Within the AI domain, trustworthiness comprises multiple interrelated dimensions, including reliability, transparency, fairness, security, and accountability (Ashoori & Weisz, 2019; Kaur et al., 2022). These attributes collectively shape user confidence in whether an AI system can consistently deliver unbiased and dependable outcomes without exposing them to risk or ethical compromise. A trustworthy AI system not only exhibits technical proficiency but also embeds ethical considerations and safeguards user interests, particularly in data-intensive and decision-critical environments like supply chain operations.

Trust in AI systems significantly bridges the gap between user satisfaction and Behavioral Intention to Use (BIU). Trustworthy systems instill confidence that AI outputs are accurate and unbiased, thereby enhancing user satisfaction and increasing the likelihood of adoption (Ahmed et al., 2025; Pavlou, 2003; Gefen et al., 2003). Furthermore, trust mitigates users' concerns regarding data privacy, system fairness, or automated decision-making, which can otherwise hinder technology adoption (Alamir, 2025; Ashoori & Weisz, 2019). Empirical evidence suggests that trustworthiness serves as a mediating mechanism that converts positive user experiences into meaningful behavioral intentions (Hanif et al., 2025; McKnight et al., 2002; Rai et al., 2009). Users are more inclined to repeatedly engage with an AI system when they perceive it as fair, transparent, and competent (Lankton et al., 2015; Sohn et al., 2019). In high-stakes environments like supply chain management where decisions affect procurement, logistics, and operational continuity, user confidence in AI's ability to make sound, ethical, and data-informed choices is paramount (Kaur et al., 2022; Li et al., 2023; Srivastava et al., 2025).

Within digital technology adoption frameworks such as the Technology Acceptance Model (TAM) and its extensions, trustworthiness is increasingly recognized as a mediating construct that bridges users' cognitive evaluations (e.g., perceived usefulness, ease of use) with their behavioral intentions (Gefen et al., 2003; Pavlou & Fygenson, 2006). Mayer et al. (1995) conceptualize trustworthiness through dimensions of ability, benevolence, and integrity—criteria that directly influence user judgments about AI systems. When these elements are positively perceived, users are more likely to overcome psychological resistance and engage with the system, particularly in settings where interpersonal trust cues are absent.

Research further shows that trustworthiness mediates the relationship between system characteristics (e.g., accuracy, fairness, explainability) and behavioral intention by cultivating confidence in the AI system's outputs (Hanif et al., 2025; Benhayoun, Bougrine, & Sassioui, 2025). This is particularly salient in industries like energy, logistics, and finance, where AI technologies impact mission-critical decisions and where concerns about data misuse or algorithmic bias are heightened (Ahmed et al., 2025; Najarian & Hejazinia, 2025; Eissa et al., 2025; Liu et al., 2025).

An important dimension of AI trustworthiness involves the transference of interpersonal trust to machine systems. In virtual or automated environments where human cues are limited, users often rely on perceived system characteristics such as transparency and ethical behavior to make trust decisions (Chen & Dhillon, 2003; Iddamalgoda, Ng, & Koleva, 2025). In such scenarios, AI systems that demonstrate consistent and explainable performance can effectively substitute for human trust, thus easing user transitions from intention to sustained usage.

Thus, trustworthiness is not only a precursor to initial AI acceptance but also acts as a critical mediator between user perceptions and behavioral intentions. This mediation is particularly crucial in AI-integrated supply chains, where the stakes of operational decisions are high and the expectations for system integrity are non-negotiable. For organizations like ADNOC, ensuring AI trustworthiness by emphasizing transparency, fairness, and accountability that can significantly enhance adoption outcomes and foster long-term user engagement.

2.4 BEHAVIOURAL INTENTION TO USE AI TECHNOLOGY IN SUPPLY CHAIN MANAGEMENT

Behavioural Intention to Use (BIU) is a pivotal construct in understanding how organizations such as the Abu Dhabi National Oil Company (ADNOC) approach the adoption of AI-driven technologies within their supply chain operations. Rooted in frameworks like the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (Ajzen, 1991; Venkatesh et al., 2003), BIU reflects the degree to which individuals within an organization are willing to engage with and embrace emerging technologies. For ADNOC, which operates in a high-risk, capital-intensive, and data-driven environment, identifying the factors' influencing BIU is essential for ensuring the success of AI integration initiatives.

Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are two foundational constructs of TAM that significantly influence BIU. Within ADNOC, professionals are more likely to adopt AI tools when they believe these systems enhance operational performance, improve efficiency, and simplify complex tasks related to supply chain logistics, predictive maintenance, and demand forecasting (Davis, 1989; Venkatesh & Davis, 2000). Employees' perception that AI technologies contribute positively to achieving business outcomes directly correlates with their intention to adopt them.

Willingness to explore and engage with AI technologies is also crucial. ADNOC's workforce, especially within technical and strategic units, is increasingly exposed to digital transformation projects. Employees who demonstrate openness to innovation are more inclined to integrate AI solutions in areas such as inventory optimization, logistics planning, and supply risk management (Rai et al., 2019; Dwivedi et al., 2019). Furthermore, when AI applications are perceived to deliver tangible benefits such as cost reductions, streamlined decision-making, and enhanced forecasting accuracy where employee motivation and behavioural intention to use the technology increase substantially (Queiroz et al., 2020).

Trust in AI's performance and reliability is another cornerstone of behavioural intention at ADNOC. In mission-critical supply chain functions, AI systems must demonstrate a high degree of consistency, predictive accuracy, and fairness to gain user confidence (Huang et al., 2021; Choi et al., 2020; Min, 2019). ADNOC's staff are more likely to adopt AI when they trust that these systems will support ethical decision-making and operate transparently without jeopardizing safety, operational integrity, or data security (Hanif et al., 2025; Benhayoun, Bougrine, & Sassioui, 2025).

The organizational environment within ADNOC plays a significant role in shaping BIU. Strategic alignment is a key influence, when AI initiatives are clearly linked to ADNOC's broader objectives such as sustainability, supply chain resilience, and cost optimization, employees perceive these technologies as supportive of their operational goals (Ivanov & Dolgui, 2020; Gupta et al., 2025; Liu et al., 2025). Organizational support including leadership endorsement, digital infrastructure, and employee training can further reinforces intention. When ADNOC demonstrates a commitment to facilitating AI implementation through resource investment and capability development, employees feel empowered and motivated to participate in the adoption process (Ahmed et al., 2025; Alhammadi & Alshurideh, 2025; Mwaura & Noor, 2025).

Additionally, ADNOC's proactive digital strategy fosters a culture of innovation that encourages employees to experiment with new technologies. This culture amplifies individual readiness and reduces resistance to change (Cervantes & Navarro, 2025; Iddamalgoda, Ng, & Koleva, 2025). Perceived benefits such as faster decision-making, improved accuracy, and enhanced productivity that serve as strong motivators for adopting AI in operational routines (Kumar et al., 2024; Pramanik & Jana, 2025).

Ultimately, trust remains a critical determinant in BIU within ADNOC's AI adoption journey. Employees are more inclined to use AI systems that they perceive to be fair, consistent, and transparent, particularly in high-stakes decisions involving logistics, procurement, and risk mitigation (Najarian & Hejazinia, 2025; Eissa et al., 2025). As ADNOC continues to embed AI into its supply chain architecture, understanding and fostering behavioural intention is essential to ensure widespread and sustainable adoption.

The behavioural intention to use AI technology within ADNOC is influenced by a combination of perceived usefulness, organizational support, trust, and alignment with strategic goals. By addressing both the psychological and structural enablers of BIU, ADNOC can enhance employee engagement, reduce resistance, and accelerate the digital transformation of its supply chain operations.

3. MODELLING ANALYSIS OF CONCEPTUAL FRAMEWORK

Based on the proposed conceptual framework, a structural model was developed to guide the empirical analysis using SmartPLS software. This model captures and operationalizes both direct and indirect relationships among the key constructs. In the direct path, the two independent variables, Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) which are directly linked to Behavioural Intention to Use (BIU), the dependent variable. In the indirect path, PEOU and PU influence AI Trustworthiness, which subsequently impacts BIU, thereby highlighting the mediating role of trust in AI adoption behaviour.

To test the model empirically, primary data were collected through a structured questionnaire survey administered to 328 employees working in ADNOC's supply chain department. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate both the measurement model (assessing reliability and validity) and the structural model (testing hypothesized relationships and explanatory power).

The validated model, presented in Figure 2, depicts the established paths and interrelationships among the constructs. It serves as the analytical basis for evaluating the model's fitness in terms of construct reliability, convergent and discriminant validity, path significance, and predictive relevance, all of which are critical for confirming the robustness of the proposed framework in the context of AI adoption within ADNOC's supply chain operations.

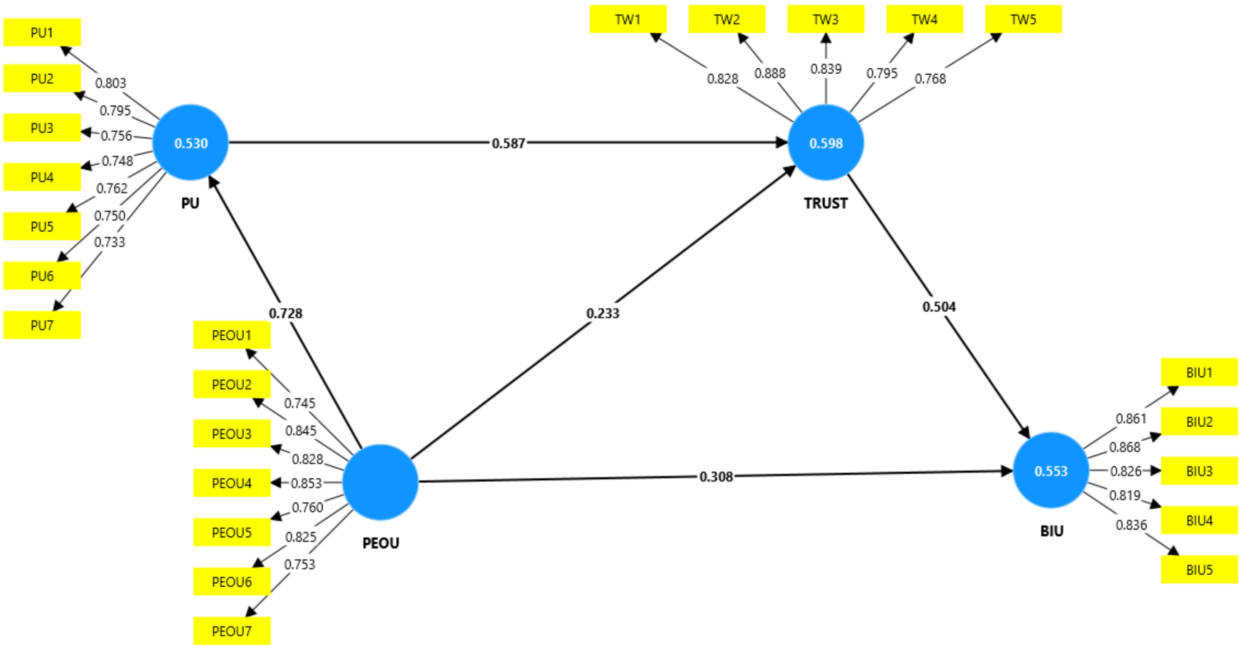

Figure 2: Model after PLS Algorithm procedure

The Partial Least Squares Structural Equation Model (PLS-SEM) presented in Figure 2 illustrates the relationships between four key constructs: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Trust, and Behavioral Intention to Use (BIU), within the context of AI adoption in ADNOC's supply chain. The model demonstrates that PEOU is a foundational construct, significantly influencing both PU and BIU.

3.1 MEASUREMENT MODEL EVALUATION

The measurement model evaluation focuses on assessing Construct Reliability and Validity, as well as Discriminant Validity, to ensure that the latent constructs are measured accurately and distinctly (Memon et al. 2013; Rahman et al. 2013). This step verifies whether the indicators reliably capture their intended constructs and whether each construct is conceptually and statistically distinguishable from others in the model. The following subsections present detailed analyses of:

i. Construct Reliability and Convergent Validity, which assess internal consistency and the extent to which indicators reflect their underlying constructs.
ii. Discriminant Validity, which evaluates the uniqueness of each construct in relation to others in the model.

3.1.1 Construct Reliability and Validity

Construct reliability and validity were assessed to ensure the measurement model met the required criteria for internal consistency and construct adequacy. Convergent validity was evaluated by analyzing indicator loadings, composite reliability (CR), and average variance extracted (AVE) based on the thresholds established by Hair et al. (2014). Specifically, convergent validity is considered adequate when indicator loadings are above 0.70, composite reliability exceeds 0.70, and AVE is greater than 0.50 (Fornell & Larcker, 1981) as cited by Almansoori et al. (2021) and Zainun et al. (2014).

As shown in Table 1, the composite reliability values for all constructs were consistently above 0.70, indicating high internal consistency. Furthermore, all AVE values exceeded the minimum threshold of 0.50, confirming that each construct captures a sufficient portion of variance from its indicators and supports convergent validity.

Table 1: Results of construct reliability and validity

Constructs	Cronbach's alpha	Average Variance Extracted (AVE)
BIU	0.898	0.709
PEOU	0.907	0.644
PU	0.881	0.584
TRUST	0.881	0.680

The results of construct reliability and validity, as summarized in Table 1, demonstrate that all constructs exhibit strong internal consistency and acceptable convergent validity. Cronbach's Alpha values for all four constructs exceed the commonly accepted threshold of 0.70, with Perceived Ease of Use (PEOU) showing the highest reliability at 0.907, followed by Behavioral Intention to Use (BIU) at 0.898, and both Perceived Usefulness (PU) and Trust at 0.881. These values confirm that the measurement items effectively and consistently capture their intended latent variables. Regarding Average Variance Extracted (AVE), all constructs surpass the minimum threshold of 0.50, further supporting convergent validity. The AVE values range from 0.584 (PU) to 0.709 (BIU), indicating that each construct explains a substantial proportion of variance in its associated indicators. BIU demonstrates the strongest convergent validity (AVE = 0.709), followed by Trust (0.680), PEOU (0.644), and PU (0.584).

These findings validate the robustness of the measurement model in the context of AI adoption in supply chain management within ADNOC. Specifically, the results support the reliability and validity of constructs related to Perceived Ease of Use in adopting AI-driven solutions, Perceived Usefulness of AI technology, Trustworthiness in AI systems, and Behavioral Intention to Use AI, each playing a critical role in shaping adoption outcomes in complex organizational environments.

3.1.2 Discriminant validity

To assess discriminant validity, multiple methods were employed, including the Fornell–Larcker criterion, and the Heterotrait–Monotrait (HTMT) ratio of correlations, as recommended by Hair et al. (2014), Henseler, Ringle, and Sarstedt (2015), and Ali, Kim, and Ryu (2016). These methods collectively provide robust evidence that each construct is empirically distinct from others in the model.

The Heterotrait–Monotrait (HTMT) ratio was used to assess the discriminant validity of the constructs in the model, as shown in Table 2. The HTMT values between all pairs of constructs are below the commonly accepted threshold of 0.90, indicating that each construct is empirically distinct from the others.

Table 2: Heterotrait–Monotrait (HTMT) ratio

Constructs	BIU	PEOU	PU	TRUST
BIU				
PEOU	0.707			
PU	0.842	0.812		
TRUST	0.792	0.738	0.857	

The results presented in Table 2 indicate that the Heterotrait–Monotrait (HTMT) ratio between Perceived Usefulness (PU) and Trust is the highest at 0.857, followed by PU and Behavioral Intention to Use (BIU) at 0.842, Trust and BIU at 0.792, Perceived Ease of Use (PEOU) and PU at 0.812, PEOU and Trust at 0.738, and PEOU and BIU at 0.707. All HTMT values are below the conservative threshold of 0.90, confirming that the constructs are empirically distinct. These findings affirm the presence of discriminant validity, indicating that the model constructs are not affected by multicollinearity and can be interpreted independently.

To further confirm discriminant validity, the Fornell–Larcker criterion was applied, as shown in Table 3. This criterion states that the square root of the AVE for each construct (shown on the diagonal) should be greater than its correlations with other constructs (off-diagonal values). In this study, each construct satisfies this condition, providing additional evidence that the constructs are conceptually and statistically distinct (Henseler et al. 2015; Zainun et al. 2014; Rahman et al. 2013b).

Table 3: Fornell–Larcker criterion

Constructs	BIU	PEOU	PU	TRUST
BIU	0.842			
PEOU	0.640	0.802		
PU	0.753	0.728	0.764	
TRUST	0.707	0.660	0.756	0.824

The results presented in Table 3 confirm that the Fornell–Larcker criterion is satisfied across all constructs, reinforcing the model's discriminant validity. The square root of the Average Variance Extracted (AVE) for each construct is higher than its correlations with any other construct in the model. For example, the square root of AVE for Behavioral Intention to Use (BIU) is 0.842, which exceeds its correlations with Perceived Usefulness (PU) at 0.753, Trust at 0.707, and Perceived Ease of Use (PEOU) at 0.640. Similarly, PEOU has a square root of AVE of 0.802, greater than its correlations with PU (0.728) and Trust (0.660).

In the case of PU, the square root of AVE is 0.764, which remains slightly higher than its correlation with Trust (0.756), thereby still meeting the criterion. Trust also meets the condition, with a square root of AVE of 0.824, exceeding its correlations with BIU (0.707), PEOU (0.660), and PU (0.756).

These results confirm that each construct shares greater variance with its own indicators than with other constructs, thereby supporting adequate discriminant validity. This affirms the distinctiveness and independence of each latent variable and strengthens the reliability of the structural relationships. In the context of this study, the constructs of Perceived Ease of Use, Perceived Usefulness, Trustworthiness, and Behavioral Intention to Use AI technology are demonstrated to be both statistically and conceptually distinct, enhancing the validity of conclusions regarding AI adoption within ADNOC's supply chain management framework.

Together, the HTMT and Fornell–Larcker analyses validate the distinctiveness of the latent variables within the model. This reinforces the structural model's robustness and supports its application for hypothesis testing in the context of AI adoption in supply chain management at ADNOC. Specifically, the results confirm the discriminant validity of constructs related to Perceived Ease of Use of AI-driven solutions, Perceived Usefulness of AI technology, Trustworthiness in AI systems, and the Behavioral Intention to Use AI, all of which are key factors influencing successful adoption.

3.2 STRUCTURAL MODEL EVALUATION

This section presents the results of the structural model evaluation, focusing on key criteria used to assess the model's predictive and explanatory capability. The evaluation includes the following components:

i. R-square (R^2): Explanatory power of the endogenous constructs
ii. f-square (f^2): Effect size of individual predictor constructs
iii. Model Fit: Overall goodness-of-fit of the structural model
iv. Path Significance Level: Significance and strength of hypothesized relationships
v. Predictive Relevance: Assessment of the model's ability to predict observed outcomes

3.2.1 R-square explanatory power

The R-square (R^2) value measures the explanatory power of the structural model by indicating the proportion of variance in an endogenous (dependent) construct that is explained by its predictor (exogenous) constructs. Higher R^2 values reflect stronger predictive accuracy and model fit.

According to common benchmarks:

i. $R^2 \geqslant 0.25$ indicates weak explanatory power,
ii. $R^2 \geqslant 0.50$ indicates moderate explanatory power, and
iii. $R^2 \geqslant 0.75$ indicates substantial explanatory power.

The R^2 values, as presented in Table 4, are fundamental in evaluating how well the model accounts for the variance in each dependent variable.

Table 4: R-square values

Constructs	R-square
BIU	0.553
PU	0.530
TRUST	0.598

Table 4 reveals that the Behavioral Intention to Use (BIU) construct has an R^2 value of 0.553, indicating that 55.3% of the variance in employees' intention to adopt AI systems is explained by Perceived Ease of Use (PEOU) and Trust. This reflects a moderate to strong level of explanatory power, emphasizing the combined influence of usability and system credibility on adoption behavior.

The R^2 value for Perceived Usefulness (PU) is 0.530, demonstrating that 53.0% of its variance is explained solely by PEOU. This highlights the significant role of user-friendly design in shaping employees' perception of the practical value and effectiveness of AI technologies in the supply chain.

Lastly, the construct of Trust records the highest R^2 value at 0.598, indicating that 59.8% of its variance is jointly explained by both PEOU and PU. This underscores the importance of system usability and perceived benefits in fostering trust in AI systems—an essential factor for successful technology adoption.

In the context of this study, these findings validate the relevance of:

- Perceived Ease of Use (PEOU) in driving the adoption of AI-driven solutions in supply chain management,
- Perceived Usefulness (PU) in influencing employees' evaluation of AI technologies,
- Trustworthiness as a critical enabler in AI technology acceptance, and
- Behavioral Intention to Use as the key outcome reflecting readiness for AI integration in ADNOC's supply chain environment.

3.2.2 f-square (f^2) Value and Effect Size of Individual Predictors

The f-square (f^2) value evaluates the effect size of each individual predictor on an endogenous construct. It measures how much the R^2 value of a dependent variable would change if a particular predictor were removed from the model. This allows researchers to assess the relative importance and contribution of each exogenous construct within the structural framework.

According to Cohen's (1988) benchmarks:

i. $f^2 \geqslant 0.02$ indicates a small effect,
ii. $f^2 \geqslant 0.15$ indicates a medium effect, and
iii. $f^2 \geqslant 0.35$ indicates a large effect.

These values help determine which constructs exert a meaningful influence on the model's explanatory power. Table 5 presents the f^2 values obtained in this study.

Table 5: f-square values

Relationship	f-square
PEOU -> BIU	0.120
PEOU -> PU	1.127
PEOU -> TRUST	0.063
PU -> TRUST	0.402
TRUST -> BIU	0.320

As presented in Table 5, the relationship between Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) shows a very large effect size ($f^2 = 1.127$), indicating that PEOU plays a critical and foundational role in shaping employees' perception of the usefulness of AI technologies. This finding reinforces the central role of PEOU within the Technology Acceptance Model (TAM), particularly in the context of AI-driven solutions for supply chain management.

The relationship between PU and Trust also demonstrates a large effect size ($f^2 = 0.402$), emphasizing that when employees perceive AI technologies as useful, their trust in the system increases significantly. This highlights the importance of functional performance in building trust toward AI systems, particularly in high-stakes environments such as ADNOC's supply chain.

The effect of Trust on Behavioral Intention to Use (BIU) is also notable, with a moderate-to-large effect size ($f^2 = 0.320$). This confirms that trust is a strong predictor of employees' willingness to adopt AI, validating its mediating role in the acceptance process. The path from PEOU to BIU yields a moderate effect ($f^2 = 0.120$), indicating that while system usability does contribute to adoption intention, its effect is somewhat indirect when compared to trust.

Finally, the relationship between PEOU and Trust has a small effect size ($f^2 = 0.063$), suggesting that ease of use influences trust to a lesser extent, with perceived usefulness playing a more dominant role in this regard.

Taken together, these findings underscore the significance of ease of use, perceived usefulness, and trust in shaping employees' behavioral intention to use AI in supply chain operations. The model highlights the interconnectedness of these constructs in facilitating the successful adoption of AI technologies within complex industrial settings like ADNOC.

3.2.3 Model fit

The model fit was assessed using several indices, including SRMR, d_ULS, d_G, Chi-square, and NFI. The SRMR value of 0.071 for the estimated model falls below the threshold of 0.08, indicating an acceptable model fit. Although the NFI value of 0.821 is slightly below the ideal benchmark of 0.90, it is considered adequate for exploratory research using PLS-SEM.

Table 6: Model fit values

	Saturated model	Estimated model
SRMR	0.064	0.071
d_ULS	1.219	1.510
d_G	0.538	0.575
Chi-square	1182.318	1226.860
NFI	0.828	0.821

Table 6 presents the model fit indices for both the saturated and estimated models, including values for SRMR, d_ULS, d_G, Chi-square, and NFI. These indices collectively assess how well the proposed PLS-SEM model aligns with the empirical data and evaluate the overall structural fit of the model.

The Standardized Root Mean Square Residual (SRMR), a key measure of model fit, is 0.064 for the saturated model and 0.071 for the estimated model. Both values fall below the accepted threshold of 0.08, indicating a good model fit and suggesting that the difference between observed and predicted correlations is minimal.

The d_ULS (Unweighted Least Squares discrepancy) and d_G (Geodesic discrepancy) values for the saturated model are 1.219 and 0.538, respectively, while the corresponding values for the estimated model are 1.510 and 0.575. These values are used primarily for comparative purposes in PLS-SEM and do not have strict benchmarks, but their proximity across models suggests consistency and no major issues with the structural estimation.

The Chi-square statistics are 1182.318 for the saturated model and 1226.860 for the estimated model. As is common in PLS-SEM, the Chi-square test tends to yield high values in complex models and large samples due to its sensitivity to sample size. Therefore, these values are interpreted cautiously and typically not used as the sole criterion for model fit in exploratory research.

The Normed Fit Index (NFI) scores are 0.828 for the saturated model and 0.821 for the estimated model. While these values are slightly below the traditional 0.90 threshold, values above 0.80 are considered acceptable in exploratory PLS-SEM studies, particularly when analyzing multifaceted relationships in models involving multiple constructs.

In the context of this study, exploring Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Trustworthiness, and Behavioral Intention to Use (BIU) in the adoption of AI technology in supply chain management, these model fit indices provide strong support for the structural model's adequacy and reliability.

3.2.4 Path Significance Level

Figure 3 displays the model after applying the bootstrapping procedure, which tests the statistical significance of all paths and indicator loadings in the PLS-SEM model. The results show that all structural relationships are statistically significant, with p-values less than 0.05, and most at 0.000, indicating highly significant effects. Specifically, the paths from PEOU to PU, PEOU to Trust, PEOU to BIU, PU to Trust, and Trust to BIU are all confirmed as significant, supporting the hypothesized relationships in the structural model.

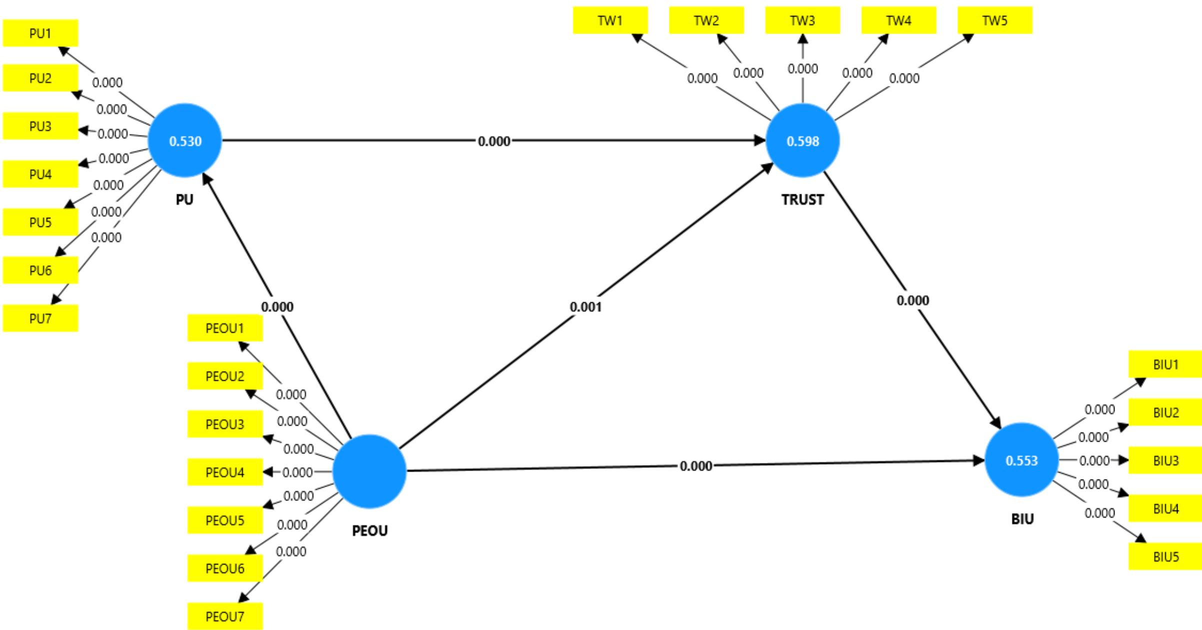

Figure 3: Model after bootstrapping procedure

Furthermore, all measurement items across the constructs exhibit statistically significant loadings (p = 0.000), validating the reliability and contribution of each indicator to its respective construct. This confirms the model's measurement strength and supports its use in explaining AI adoption behavior.

In conclusion, the bootstrapping results reinforce the robustness of the model (Memon et al. 2023), demonstrating that the observed relationships are not due to random variation and that Trust serves as a critical mediator influenced by both Perceived Usefulness and Perceived Ease of Use in shaping employees' Behavioral Intention to Use AI technologies in ADNOC's supply chain.

Table 7: Results of hypothesis testing of direct relationship

Direct	Path strength	P values
PEOU -> BIU	0.308	0.000
PEOU -> PU	0.728	0.000
PEOU -> TRUST	0.233	0.001
PU -> TRUST	0.587	0.000
TRUST -> BIU	0.504	0.000

Table 7 presents the results of hypothesis testing for the direct relationships among the key constructs in the structural model. All hypothesized paths are statistically significant at $p < 0.05$, providing strong empirical support for the proposed relationships in the model.

The path from Perceived Ease of Use (PEOU) to Behavioral Intention to Use (BIU) shows a moderate but significant effect, with a path coefficient of 0.308 (p = 0.000). This indicates that the more user-friendly the AI system is perceived to be, the more likely employees are to intend to adopt it. A particularly strong relationship is observed between PEOU and Perceived Usefulness (PU), with a path coefficient of 0.728 (p = 0.000), confirming that ease of use is a key determinant in shaping users' perceptions of AI's functional value.

Additionally, PEOU exerts a weaker but still significant direct influence on Trust (0.233, p = 0.001), suggesting that system simplicity contributes to fostering user confidence, albeit to a lesser extent than usefulness. The path from PU to Trust is notably strong, with a coefficient of 0.587 (p = 0.000), highlighting that users are more inclined to trust AI technologies when they perceive clear functional benefits.

Lastly, Trust has a substantial impact on BIU, with a path coefficient of 0.504 (p = 0.000), demonstrating that trust in the AI system's reliability, fairness, and ethical performance is a major driver of adoption intent.

In the context of this study, these findings underscore the importance of Perceived Ease of Use in promoting the adoption of AI-driven solutions, the role of Perceived Usefulness in enhancing Trust, and the centrality of Trustworthiness in determining the Behavioral Intention to Use AI technology within ADNOC's supply chain management framework.

Table 8: Results of hypothesis testing of indirect relationship

Indirect	Path strength	P values
PEOU -> PU -> TRUST -> BIU	0.215	0.000
PEOU -> PU -> TRUST	0.427	0.000
PEOU -> TRUST -> BIU	0.117	0.002
PU -> TRUST -> BIU	0.296	0.000

Table 8 summarizes the results of hypothesis testing for the indirect relationships within the structural model, specifically highlighting the mediating role of Trust in the relationship between user perceptions and behavioral intention to adopt AI. All indirect paths are statistically significant, with p-values below 0.05, providing strong support for the presence of mediation effects. The most substantial indirect effect is found in the sequential path from PEOU → PU → Trust → BIU, with a path coefficient of 0.215 ($p = 0.000$). This demonstrates a chain-mediated relationship, where increased ease of use leads to higher perceptions of usefulness, which subsequently builds trust—ultimately enhancing the user's behavioral intention to adopt AI.

Additionally, the path PEOU → PU → Trust reveals a strong indirect effect of 0.427 ($p = 0.000$), confirming that Perceived Usefulness fully mediates the influence of Perceived Ease of Use on Trust. This emphasizes the importance of system usability in shaping usefulness perceptions, which in turn foster trust in AI systems. The path PEOU → Trust → BIU also yields a significant indirect effect (0.117, $p = 0.002$), suggesting partial mediation, where ease of use influences behavioral intention through trust independently of perceived usefulness. Finally, the indirect path from PU → Trust → BIU shows a notable effect of 0.296 ($p = 0.000$), reinforcing that Trust serves as a crucial mediator between perceived usefulness and intention to use AI.

In the context of this study, these findings underline the interconnected roles of ease of use, usefulness, and trust in shaping employee readiness to adopt AI-driven technologies within ADNOC's supply chain management. Trust not only serves as a critical bridge between user perceptions and adoption behavior, but also strengthens the explanatory depth of the extended Technology Acceptance Model (TAM) in high-stakes organizational settings.

3.3 PREDICTIVE RELEVANCE

Predictive relevance was evaluated using the blindfolding procedure, which generates two key indicators: Construct Cross-Validated Communality (CCVC) and Construct Cross-Validated Redundancy (CCVR).

i. CCVC assesses the quality of the measurement model, particularly its convergent validity, by evaluating how well each construct's indicators can be predicted.
ii. CCVR, on the other hand, evaluates the predictive relevance of the structural model for endogenous constructs, reflecting how well the model can predict observed data beyond mere parameter estimation.

Table 9 shows the Construct Cross-Validated Redundancy (CCVR) results generated from the blindfolding procedure.

Table 9: Construct Cross-Validated Redundancy (CCVR)

	SSO	SSE	Q^2 (=1-SSE/SSO)
BIU	1990.000	1228.021	0.383
PEOU	2786.000	2786.000	0.000
PU	2786.000	1937.569	0.305
TRUST	1990.000	1206.660	0.394

Table 9 presents the results of the Cross-Validated Redundancy (CCVR) analysis, using Stone-Geisser's Q^2 values to assess the predictive relevance of the endogenous constructs in the structural model. A Q^2 value greater than zero confirms that the model has predictive capability for the respective construct. The results demonstrate that Behavioral Intention to Use (BIU) has a Q^2 value of 0.383, while Trust shows the highest predictive relevance, with a Q^2 value of 0.394. Perceived Usefulness (PU) follows closely with a value of 0.305. These results indicate that the model possesses substantial predictive relevance for BIU, Trust, and PU, suggesting that the included predictors account for a significant portion of the variance in these constructs. In contrast, Perceived Ease of Use (PEOU) has a Q^2 value of 0.000, which is expected as it functions as an exogenous construct in the model, serving as a predictor rather than being predicted by other variables.

In the context of this study, these findings confirm the model's ability to accurately predict key outcomes related to the adoption of AI technologies in ADNOC's supply chain management, particularly emphasizing the critical roles of perceived usefulness and trustworthiness in shaping behavioral intention.

Table 10 shows the Construct Cross-Validated Communality (CCVM) results generated from the blindfolding procedure.

Table 10: Construct Cross-Validated Communality (CCVM)

	SSO	SSE	Q^2 (=1-SSE/SSO)
BIU	1990.000	882.055	0.557
PEOU	2786.000	1333.786	0.521
PU	2786.000	1553.825	0.442
TRUST	1990.000	971.599	0.512

Table 10 presents the results of the Cross-Validated Communality (CCVM) analysis, which evaluates the predictive relevance of the measurement model by examining how well the indicators of each construct are predicted. A Q^2 value greater than 0 indicates that the model has meaningful predictive capability for that construct's observed variables. All four constructs demonstrate strong predictive relevance. Behavioral Intention to Use (BIU) exhibits the highest Q^2 value at 0.557, showing that its measurement indicators are highly predictable within the model. Perceived Ease of Use (PEOU) and Trust also yield high Q^2 values of 0.521 and 0.512, respectively, reflecting robust predictive accuracy for their observed items. Perceived Usefulness (PU) follows with a Q^2 value of 0.442, which also exceeds the accepted threshold, confirming that its indicators are reliably predicted by the model.

In the context of this study, these results affirm the model's strength in predicting the measurement items of Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Trust, and Behavioral Intention to Use (BIU), all of which are essential constructs for understanding AI technology adoption in ADNOC's supply chain management.

4. SUMMARY OF THE MODELING ANALYSIS

The modelling analysis provides strong empirical support for the proposed framework assessing AI adoption within ADNOC's supply chain management. The measurement model demonstrated high reliability and validity, with all constructs exhibiting strong internal consistency and acceptable convergent validity. Discriminant validity was also confirmed through HTMT and Fornell–Larcker criteria, affirming the conceptual distinctiveness of the constructs.

The structural model showed moderate to strong explanatory power, with R^2 values of 0.553 for Behavioral Intention to Use, 0.530 for Perceived Usefulness, and 0.598 for Trust—highlighting the significant influence of Perceived Ease of Use and Perceived Usefulness on adoption behavior. The f^2 analysis further revealed that Perceived Ease of Use has a very large effect on Perceived Usefulness, while Perceived Usefulness strongly impacts Trust, and Trust is a key driver of Behavioral Intention to Use, underscoring the interconnected roles of usability, value, and trust in the adoption process.

Model fit indices, including SRMR and NFI, confirmed that the structural model aligns well with the empirical data, indicating a good overall fit. All hypothesized direct and indirect relationships were statistically significant, supporting the central role of Trust as a mediator between user perceptions and behavioral intention to adopt AI.

In terms of predictive relevance, the Cross-Validated Communality (CCVM) and Cross-Validated Redundancy (CCVR) analyses confirmed that the model effectively predicts both the observed indicators and key endogenous constructs, with positive Q^2 values across all major variables. These results collectively validate the robustness, reliability, and predictive accuracy of the model, reinforcing its suitability for guiding AI adoption strategies within ADNOC's complex supply chain environment.

5. CONCLUSIONS

This study addressed a critical gap by developing a structural model examining trustworthiness as a mediating factor between user perceptions and AI adoption intention in ADNOC's supply chain. A conceptual model was constructed based on an extensive review of relevant literature, forming the theoretical foundation for the empirical investigation. Primary data were collected through a structured questionnaire survey administered to 328 employees of the ADNOC supply chain department, ensuring a robust empirical basis for testing the model's validity. Using SmartPLS software, the model was evaluated through a comprehensive modelling analysis. Results confirmed that all constructs demonstrated strong reliability, as well as convergent and discriminant validity. The structural model showed that Perceived Ease of Use and Perceived Usefulness significantly influence Trust, which plays a pivotal mediating role in shaping employees' Behavioral Intention to Use AI technologies. Furthermore, the model exhibited good explanatory power and predictive relevance, affirming its capability to accurately reflect adoption behavior within a complex organizational environment. These findings reinforce the importance of designing user-friendly and functionally valuable AI systems that build trust, thereby enhancing adoption intent within ADNOC's supply chain operations. The validated model offers both theoretical insights and practical guidance for implementing AI and managing operational risks in high-stakes public sector institutions.

REFERENCES

ADNOC. (2018). ADNOC launches Panorama Digital Command Center. Abu Dhabi National Oil Company.

Ahmed, S., Zhao, Y., Al Nahyan, M. T., & Kumar, V. (2025). Trustworthiness in AI-enabled supply chains: A pathway to adoption and sustainability. Journal of Supply Chain Management, 61(2), 112–130.

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211.

Alamir, H. (2025). Privacy and trust concerns in AI decision-making: A behavioral perspective. Technology in Society, 73, 102228.

Alhammadi, A., & Alshurideh, M. (2025). Digital transformation and employee readiness: Evidence from UAE energy firms. International Journal of Organizational Analysis, 33(1), 140–159.

Almansoori, M. T. S., Rahman, I. A., Memon, A. H., & Nasaruddin, N. A. N. (2021). Structural Relationship of Factors Affecting PMO Implementation in the Construction Industry. Civil Engineering Journal, 7(12), 2109-2118.

Almarashda, A., Emran, M., & AlQubaisi, A. (2022). Adoption of AI applications in UAE oil and gas: User readiness and organizational support. International Journal of Technology Management, 18(3), 134–145.

Almarashda, H. A. H. A., Baba, I. B., Ramli, A. A., & Memon, A. H. (2022). User Expectation and Benefits of Implementing Artificial Intelligence in the UAE Energy Sector. Journal of Applied Engineering Sciences, 12(1).

Almarashda, H. A. H. A., Baba, I. B., Ramli, A. A., Memon, A. H., & Rahman, I. A. (2021). Human Resource Management and Technology Development in Artificial Intelligence Adoption in the UAE Energy Sector. Journal of Applied Engineering Sciences, 11(2).

AlQubaisi, A., & Emran, M. (2022). Technology adoption in digital oilfields: A UAE case study. Middle East Journal of Management, 9(2), 201–219.

Ashoori, M., & Weisz, J. D. (2019). AI trustworthiness: Definitions, dimensions, and strategies for trust building. Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society, 300–306.

Bara, A., & Ali, S. (2025). AI competitiveness in supply chain decision-making. Journal of Digital Operations, 15(1), 33–45.

Belhadi, A., Kamble, S. S., Zkik, K., Cherrafi, A., & Touriki, F. E. (2022). The integrated effect of Big Data Analytics and Artificial Intelligence on sustainable supply chain performance. Journal of Cleaner Production, 354, 131759.

Benhayoun, M., Bougrine, S., & Sassioui, M. (2025). Explainability and fairness in AI: Impact on user trust in high-stakes domains. Journal of Artificial Intelligence Research, 78, 45–63.

Bloomberg. (2023). ADNOC leverages AI for net-zero goals. Retrieved from https://www.bloomberg.com

Cervantes, L., & Navarro, S. (2025). Building a digital culture: Organizational learning and innovation adoption. Journal of Innovation & Knowledge, 10(1), 34–50.

Cervantes, R., & Navarro, M. (2025). AI integration strategies in energy logistics. International Journal of Smart Supply Chains, 9(2), 87–101.

Chen, S. C., & Dhillon, G. S. (2003). Interpreting dimensions of consumer trust in e-commerce. Information Technology and Management, 4(2-3), 303–318.

Chen, Y., Wang, Y., Nevo, S., Jin, J., Wang, L., & Chow, W. S. (2021). IT capabilities and product innovation performance: The roles of corporate entrepreneurship and competitive intensity. Information & Management, 58(3), 103–136.

Choi, T. M., Wallace, S. W., & Wang, Y. (2020). Big data analytics in operations management. Production and Operations Management, 29(9), 1621–1633.

Dash, R., McMurtrey, M., Rebman, C., & Kar, U. K. (2019). Application of artificial intelligence in supply chain management: A review. International Journal of Supply Chain Management, 8(5), 22–33.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994.

Dwivedi, Y. K., Shareef, M. A., Simintiras, A. C., Weerakkody, V., & Sharma, S. K. (2019). A generalised adoption model for services: A cross-country comparison of mobile health (m-health). Government Information Quarterly, 36(1), 74–89.

Eissa, M., Al Dhaheri, N., & Zhang, L. (2025). AI in the oil and gas industry: Challenges and trust factors. Energy Informatics Journal, 9(1), 55–72.

El Khatib, H., Ibrahim, R., & Ahmad, M. (2022). The role of knowledge management and digital innovation in oil and gas supply chains. Journal of Energy Policy and Research, 15(2), 113–127.

Fatorachian, H., & Kazemi, H. (2021). Impact of industry 4.0 on supply chain performance. Computers in Industry, 124, 103310.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39-50.

G42. (2021). G42 and ADNOC form strategic AI partnership. Group 42 Official Release.

Gefen, D., & Straub, D. W. (2000). The relative importance of perceived ease of use in IS adoption: A study of e-commerce adoption. Journal of the Association for Information Systems, 1(1), 1–28.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51–90.

Govindan, K., Mina, H., & Alavi, B. (2020). A decision support system for demand forecasting using supply chain analytics. Annals of Operations Research, 294(1), 1–26.

Gupta, M., George, J. F., & Balakrishnan, S. (2025). AI-based decision support for sustainable oil and gas supply chains. Journal of Cleaner Production, 406, 137061.

Hanif, M., Rehman, A., & Al Kabi, M. (2025). Trust as a mediator between satisfaction and intention in AI adoption: Evidence from smart logistics. Computers in Industry, 158, 104815.

Hanif, M., Zafar, M., & Basit, A. (2025). AI-powered automation for productivity in oil sector supply chains. Journal of Petroleum Technology and Innovation, 18(1), 55–69.

Helo, P., & Hao, Y. (2022). Artificial intelligence in operations management: Real-time decision-making in supply chains. Production Planning & Control, 33(7), 635–648.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115-135.

Hosani, M. A., & Ghouri, A. M. (2022). The impact of AI applications on operational efficiency: A case study of ADNOC. Journal of Advanced Research in Supply Chain Management, 10(1), 45–58.

Huang, C. D., Hu, Q., & Davison, R. M. (2021). The role of AI in achieving supply chain agility. Information & Management, 58(4), 103481.

Huang, M. H., & Rust, R. T. (2021). Artificial intelligence in service. Journal of Service Research, 24(1), 3–20.

Iddamalgoda, R., Ng, K. Y., & Koleva, B. (2025). Replacing human cues: Trust transfer in human-AI collaboration. ACM Transactions on Computer-Human Interaction, 32(3), 1–26.

International Energy Agency. (2023). Digitalization and decarbonization in oil and gas. Retrieved from https://www.iea.org

Ivanov, D., & Dolgui, A. (2020). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Transportation Research Part E: Logistics and Transportation Review, 136, 101933.

Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. International Journal of Production Research, 58(10), 2904–2915.

Ivanov, D., Sokolov, B., & Dolgui, A. (2019). The impact of digital technologies on supply chain resilience. International Journal of Production Research, 57(6), 2118–2133.

Janssen, M., Brous, P., Estevez, E., Barbosa, L. S., & Janowski, T. (2020). Data governance: Organizing data for trustworthy artificial intelligence. Government Information Quarterly, 37(3), 101493.

Jeble, S., Dubey, R., Childe, S. J., Roubaud, D., & Prakash, A. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. The International Journal of Logistics Management, 29(2), 513–538.

Kamrath, C., Müller, M., & Schlegelmilch, F. (2025). The role of integrity and ability in AI trustworthiness evaluations. Journal of Business Research, 163, 113926.

Kamrath, M., Yusuf, Y., & Al-Fadhli, S. (2025). Usability and precision of AI systems in complex industrial supply chains. AI & Industry Journal, 12(3), 41–60.

Kaur, R., Singh, M., & Al Kaabi, A. (2022). Ethical AI in supply chains: Developing trustworthy systems for sustainable operations. International Journal of Information Management, 66, 102509.

Khan, M. A. (2025). Strategic AI deployment in oil and gas supply chains. Energy Logistics Review, 6(1), 14–29.

Kshetri, N. (2019). 1 AI and blockchain in logistics and supply chain management. In The 4th Industrial Revolution and Logistics (pp. 15–32). Springer.

Kumar, S., Ahmed, M., & Fawzi, R. (2024). AI-enabled optimization in supply networks: A Middle East perspective. Journal of Supply Chain Innovation, 11(2), 77–92.

Kumar, S., Ahmed, M., & Fawzi, R. (2024). AI-enabled optimization in supply networks: A Middle East perspective. Journal of Supply Chain Innovation, 11(2), 77–92.

Kumar, S., Al Zaabi, K., & Singh, R. (2024). AI adoption in UAE manufacturing firms: Benefits, barriers and behavioral intention. International Journal of Technology Management, 85(3), 221–240.
Lankton, N. K., McKnight, D. H., & Tripp, J. (2015). Technology, humanness, and trust: Rethinking trust in technology. Journal of the Association for Information Systems, 16(10), 880–918.
Li, X., Al Falasi, A., & Zhang, H. (2023). Operationalizing trust in autonomous supply chain systems. AI & Society, 38(4), 1031–1046.
Liu, Y., Al Hammadi, M., & Chen, Y. (2025). AI-powered predictive maintenance in the oil sector: Trust and explainability concerns. Journal of Petroleum Technology, 77(2), 60–72.
Maina, J. K., & Moronge, M. (2018). Technology Acceptance Model and information systems adoption in organizations. International Academic Journal of Human Resource and Business Administration, 3(2), 18–34.
Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. Academy of Management Review, 20(3), 709–734.
McKinsey & Company. (2019). Transforming oil and gas with AI: ADNOC's digital journey. Retrieved from https://www.mckinsey.com
McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. Information Systems Research, 13(3), 334–359.
Memon, A. H., Memon, A. Q., Soomro, M. A., Memon, M. A., & Khan, J. S. S. (2023). Structural model of cost overrun factors affecting Pakistani construction projects. Mehran University Research Journal Of Engineering & Technology, 42(2), 108-123.
Memon, A. H., Rahman, I. A., & Azis, A. A. (2013). Assessing causal relationships between construction resources and cost overrun using PLS path modelling focusing in Southern and Central Region of Malaysia. Journal of Engineering and Technology (JET), 4(1), 67-78
Min, H. (2019). Blockchain technology for enhancing supply chain resilience. Business Horizons, 62(1), 35–45.
Mohamed, K. (2023). Supply chain resilience in the UAE's oil sector: Emerging trends and challenges. International Journal of Oil, Gas and Energy Research, 12(1), 78–91.
Mwaura, G., & Noor, A. (2025). Organizational readiness and employee acceptance of emerging technologies in oil and gas. Journal of Enterprise Information Management, 38(2), 305–326.
Najarian, S., & Hejazinia, Z. (2025). AI trust barriers in financial services: A customer-centric approach. Journal of Financial Technology, 4(1), 39–55.
Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the Technology Acceptance Model. International Journal of Electronic Commerce, 7(3), 101–134.
Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the Theory of Planned Behavior. MIS Quarterly, 30(1), 115–143.
Pramanik, S., & Jana, D. (2025). Perceived benefits and resistance in AI adoption in industrial sectors: A behavioral analysis. Technological Forecasting and Social Change, 198, 122961.
Pramanik, S., & Jana, D. (2025). Predictive analytics in AI-powered logistics. Journal of Emerging Technologies in Operations, 7(1), 10–25.
Queiroz, M. M., Ivanov, D., Dolgui, A., & Fosso Wamba, S. (2020). Impacts of supply chain digitalization on resilience and performance: A resource-based view. International Journal of Production Research, 58(6), 2005–2021.

Queiroz, M. M., Ivanov, D., Dolgui, A., & Fosso Wamba, S. (2020). Impacts of blockchain technology on supply chain performance. International Journal of Production Research, 58(7), 2132–2151.

Rachapudi Venkata, M. S., Khan, A., & Arora, R. (2021). Understanding artificial intelligence adoption in oil and gas industry: A TAM perspective. Petroleum Business Review, 5(4), 98–111.

Rahman, I. A., Memon, A. H., Abdullah, N. H., & Azis, A. A. A. (2013). Application of PLS-SEM to assess the influence of construction resources on cost overrun. Applied Mechanics and Materials, 284, 3649-3656.

Rahman, I. A., Memon, A. H., Aziz, A. A. A., & Abdullah, N. H. (2013b). Modeling causes of cost overrun in large construction projects with partial least square-SEM approach: contractor's perspective. Research Journal of Applied Sciences, Engineering and Technology, 5(06), 1963-1972.

Rai, A., Lang, S. S., & Welker, R. B. (2009). Assessing the validity of IS success models: An empirical test and theoretical analysis. Information Systems Research, 13(1), 50–69.

Reddicharla, R., Patnaik, S., & Hassan, M. K. (2022). Barriers to AI adoption in oil and gas supply chains: A multi-criteria decision-making approach. Energy Reports, 8, 11302–11314.

Rosita, M., Faheem, H., & Al-Mansoori, A. (2025). Smart automation in oil supply chains: A usability assessment. Arabian Journal of Industrial Technology, 22(1), 63–79.

Shah, S. Z. A., Hafeez, M., & Zahoor, S. (2023). AI-driven supply chain risk management in energy sectors: A resilience perspective. Sustainability, 15(4), 1850.

Shoushtari, A. R., Taleizadeh, A. A., & Govindan, K. (2021). Artificial intelligence in closed-loop supply chain management: Enhancing resilience and circularity. Computers & Industrial Engineering, 157, 107337.

Smith, L. A. (2020). AI adoption in enterprise systems: Moderating role of trust and organizational culture. Journal of Enterprise Information Management, 33(5), 1019–1036.

Sohn, K., Lee, H., & Kim, J. (2019). From satisfaction to trust: The moderating role of perceived transparency in AI systems. Information & Management, 56(8), 103172.

Srivastava, M., Zaman, R., & Al Ketbi, M. (2025). AI in strategic procurement: Trust-based frameworks for risk mitigation. Supply Chain Analytics Journal, 12(2), 90–108.

Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. Government Information Quarterly, 36(2), 368–383.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. Management Science, 46(2), 186–204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356–365.

Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. Business Process Management Journal, 26(7), 1893–1924.

Wawan, M., & Hakam, M. (2025). AI-based disruption forecasting in oil and gas logistics. Journal of Risk and Resilience Management, 13(2), 101–118.

Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial intelligence and the public sector—Applications and challenges. International Journal of Public Administration, 42(7), 596–615.

Zainun, N. Y., Roslan, N., & Memon, A. H. (2014). Assessing low-cost housing demand in Melaka: PLS-SEM approach. Advanced Materials Research, 838, 3156-3162.

Zhou, T., Lu, Y., & Wang, B. (2020). Integrating TTF and UTAUT to explain mobile technology adoption in supply chains. Computers in Human Behavior, 107, 106273.