INTERNATIONAL JOURNAL OF SUSTAINABLE CONSTRUCTION ENGINEERING AND TECHNOLOGY
ISSN: 2180-3242 e-ISSN: 2600-7959

IJSCET

Vol. 15 No. 2 (2024) 175-188
https://publisher.uthm.edu.my/ojs/index.php/ijscet

Framework of the Mediation Effect of Artificial Intelligence Usage on the Relationship Between Innovation Factors and Organisational Performance

Shamma Ebraheem Esmaeel Saleh Alhosani[1], Edie Ezwan Mohd Safian[1*]

[1] *Faculty of Technology Management & Business, Universiti Tun Hussein Onn Malaysia, MALAYSIA*

*Corresponding Author: edie@uthm.edu.my
DOI: https://doi.org/10.30880/ijscet.2024.15.02.015

Article Info

Received: 10 March 2024
Accepted: 10 March 2024
Available online: 26 March 2024

Keywords

Mediation effects, artificial intelligence usage, innovation factors, organisational performance

Abstract

This paper details a study focused on establishing a framework to examine how Artificial Intelligence Usage mediates the relationship between innovation factors and organizational performance. Before constructing the framework, a Partial Least Squares Structural Equation Modelling (PLS-SEM) mediation model was formulated using SmartPLS software. This model encompasses innovation factors categorized into three groups: marketing, management, and process, treated as independent constructs, while organizational performance serves as the dependent construct, with artificial intelligence usage acting as the mediator. Data for constructing the model were gathered through a questionnaire survey administered to 129 employees of ADNOC, selected via convenient random sampling. The constructed model underwent rigorous assessment of its inner and outer components until meeting predefined fitness criteria. Subsequently, a bootstrapping procedure was employed for hypothesis testing to ascertain the significance level of each relationship path, facilitating the determination of mediation effects. The framework emerged from the results of these mediation effects, indicating that process innovation achieved partial mediation, management innovation achieved full mediation, while marketing innovation showed no mediation effect. This framework is poised to aid ADNOC employees in integrating innovation factors with artificial intelligence usage to enhance organizational performance.

1. Introduction

Since the early 2000s, the UAE government has implemented new public management measures (Alsaqri, 2018). The term “new public management” refers to approaches to managing public organizations that were established in the 1980s to bring managerial skills from the private sector into the public sector (Elbanna & Abdel-Maksoud, 2020). New public management emphasizes key characteristics of innovation such as resource efficiency, private-sector management methods, performance assessment, and contract-based compensation. The UAE government has introduced new managerial techniques in its public organizations as part of public management reforms. Particularly, it has increased the utilization of strategic performance assessment systems across public organizations in its effort to reform public management. Additionally, it has instituted governmental excellence awards to evaluate the work of its government agencies (Alsaqri, 2018). The UAE government encourages public organizations to compete for such awards annually, placing pressure on competing public organizations to meet award assessment requirements. Nonetheless, research on the factors that drive organizational performance in the UAE's oil sector is relatively scarce and provides limited insight into innovation within these businesses. The United Arab Emirates (UAE) stands among the top ten global oil producers and actively engages with the UNDP (United Nations Development Program) (EIA, 2017). Despite the government's inclination towards fostering innovation and technology adoption, significant technological and financial risks pose substantial systemic barriers to the swift advancement of new technologies within the oil and petroleum industry in the United Arab Emirates (ENR, 2019). This dynamic significantly impacts organizational performance, hindering the organization's ability to keep pace with market trends favouring innovative AI solutions. Considering the benefits of novel AI technologies, the UAE government continues to place a high focus on developing public organizations with new innovations, especially state-of-the-art technologies. Organizational performance is measured by enhancing numerous capabilities that assist firms in addressing critical organizational innovation traits to obtain a competitive edge and provide superior services (Van de Weerd et al., 2016). However, in an era of ongoing transition, organizational work processes are regularly reinvented to survive in a dynamic environment driven by technological innovation and AI advancement (Ryan & Ali, 2013). This necessitates ongoing research by scholars to identify the variables of innovation that can affect organizational performance, particularly concerning AI innovation technologies. One of the key objectives of this research is to examine the structural relationship between the three constructs of innovation factors, organizational performance, and AI technologies. Put another way, the ever-changing landscape of innovation and AI technologies requires continuous research on the impact and relationship of these two aspects on organizational performance.

To enhance organizational performance, the UAE government would need to proactively address the challenges posed by innovation stemming from technological advancements, thereby ensuring proper training for its employees. Kolbjrnsrud et al. (2016) highlighted how innovations, particularly those related to technology and AI, are reshaping organizational work processes. In today's world, technological advancements have become a critical factor in enhancing organizational effectiveness (Rajapathirana & Hui, 2018). However, such arguments require empirical studies, which is the primary aim of this research, especially considering the UAE government's encouragement for public organizations to adopt the latest innovations and AI technology to improve their services and performance. Consequently, the current study needs to examine organizational innovation characteristics and their impact on organizational performance, with AI serving as a mediating variable.

Few studies have utilized data from the understudied UAE public sector to address the issue of creative resources/capabilities impacting organizational performance in the UAE, as highlighted by Elbanna and Abdel-Maksoud (2020). Endeavors to explore this topic could enhance our comprehension of the factors influencing organizational success across diverse contexts. Organizational performance remains a central theme in innovative management, garnering both empirical and theoretical attention across various regions worldwide.

To sum up, while the UAE has placed greater emphasis on innovation within public organizations, there has been limited research conducted in this area. ADNOC, one of the world's largest oil companies, is still under investigation regarding its utilization of innovation to enhance performance. Additionally, the past few years have witnessed significant advancements in organizational innovation, particularly in the adoption of technologies. The ongoing evolution of innovation necessitates continuous investigation into its impact on organizational performance, which is the primary focus of this research. Although innovation has been examined by various scholars, there is a need for a conceptual model tailored to the UAE context. This research's novelty lies in identifying the dimensions of innovation factors that influence organizational performance, which have not been integrated in previous studies. Furthermore, employing AI as a mediator aligns with the research's objectives, particularly as the UAE government is actively promoting the use of AI technologies to enhance public sectors. This positions AI as a crucial factor in strengthening the relationship between innovation dimensions and organizational performance. Finally, there is limited understanding of innovation within large oil organizations like ADNOC in the UAE, a gap this research aims to address through empirical investigation.

2. Literature Review

2.1 Innovation Factors

The innovation factors are clustered into three groups namely marketing innovation; Management Innovation; and Process Innovation.

2.1.1 Marketing Innovation Factors

Marketing and innovation are interconnected concepts, each relying on the success of the other for optimal outcomes. Marketing innovation, specifically, integrates marketing activities into the innovation process, playing a pivotal role in ensuring and enhancing innovation success (Drucker, 2015). All actions in innovation management that contribute to the market success of new products and services fall under the umbrella of marketing innovation. It involves effectively marketing new products or services to meet customer demands, anticipate future needs, and identify emerging market opportunities.

Marketing innovation, through strategic market mix and selection, focuses on addressing customer demands and preferences, resulting in significant enhancements across product, price, promotion, and distribution strategies (Ganzer et al., 2017). As Yusheng & Ibrahim (2019) note, marketing innovation encompasses differentiation in product, promotion, distribution, market, and pricing strategies. Consequently, marketing innovation entails the implementation of new strategies that lead to substantial changes in product development, packaging, promotion strategies, market positioning, and pricing.

According to the Organisation for Economic Co-Operation and Development (2005), the objective of marketing innovation is to fulfil customer needs by creating new markets and repositioning products to increase sales. Hence, regular implementation of marketing innovation is essential for organizations to compete effectively and efficiently (Wu et al., 2023).

2.1.2 Management Innovation Factors

The second group pertains to management innovation, which involves an organization's management fostering innovation by empowering employees, as those with greater control over their job tend to exhibit more innovative tendencies (Ollila & Yström, 2020). However, experts suggest that the level of management support and empowerment directly impacts individuals' ability to innovate (Grass et al., 2020), emphasizing the importance of employees not feeling isolated in their pursuit of innovation.

While employees play a crucial role in formulating and developing innovative ideas, literature suggests that they require adequate time, materials, and financial resources for new and innovative ideas to flourish (Lei et al., 2020). Therefore, it falls upon management to ensure that the organizational environment fosters innovation and that employees are equipped with the knowledge of how to innovate in their roles.

2.1.3 Process Innovation Factors

Process innovation involves the introduction of new or enhanced tools, equipment, materials, and technologies that directly impact the goods produced by innovators, subsequently offered in the market. While product and process innovations differ, Möldner et al. (2020) define process innovation as something novel developed by a company to meet customer needs.

Process innovation encompasses the creation of entirely new or improved manufacturing or production processes, aiming to achieve greater output with fewer inputs. Sjödin et al. (2020) characterize this as eco-efficiency on a broader scale. It involves introducing new or significantly improved production processes and distribution methods for the end product, a concept gaining traction in recent years (Rogers et al., 2006).

Within the spectrum of transformation lies various types of process innovation, ranging from incremental to radical. Given its incorporation of equipment, methods, or software, process innovation holds significant importance. Its objectives include cost reduction, value enhancement, and product quality improvement (Tidd & Bessant, 2020).

Process innovation has the potential to be highly strategic, allowing companies to create unique offerings or showcase their business in a superior manner compared to competitors. Its application can provide a valuable competitive edge (Trantopoulos et al., 2017).

2.2 Artificial Intelligent (AI) Usage Factors

There are various factors that influence the adoption of innovative technologies in businesses, including the utilization of AI-related innovations to enhance productivity. For example, AI breakthroughs and new technologies are being leveraged to influence customers, thereby improving organizational performance (Grgecic et al., 2015). Conversely, innovative technologies are designed to attract customers, necessitating a greater focus on their values and behaviours during the planning process for implementing any technological innovation in the firm.

The technical factor stands out as one of the most critical aspects of adopting AI-related innovative technologies to enhance organizational performance. Organizational technical variables, such as distinct stakeholder groups, technological characteristics, and incongruity within and among stakeholder groupings, are instrumental in promoting organizational success, as indicated by Olesen (2014). Thus, to enhance organizational success, IT-related innovations must prioritize technical features. According to Oliveira et al. (2014), factors such as technological preparedness, high managerial support, and organizational size influence the successful application of AI breakthroughs, such as cloud computing, to improve organizational performance. Therefore, successful implementation of AI-related innovations to assist organizational performance necessitates a comprehensive understanding of the organization’s technical capabilities.

Furthermore, at the organizational level, social aspects influencing the performance of new AI technologies have been studied from various perspectives. Strong regulatory pressures, such as laws and procedures, as well as everyday operational challenges, such as work culture, can impede the performance of revolutionary AI technologies in the company, while social traits, such as professional readiness, can have a positive impact (Choudrie & Zamani, 2016). Additionally, various external variables, such as business demand and strategic acceptance, along with internal considerations like funding for top management and group size, have been shown to influence the performance of innovative technologies, including AI technologies, in the organization (Oliveira et al., 2014).

Moreover, human factors may influence the organization's adoption of AI-related technologies. Many researchers have explored the perspectives of individuals with diverse objectives at the individual level. Understanding of AI technology, according to Aggarwal et al. (2015), is a key factor in implementing such technological breakthroughs in the workplace. Furthermore, the technological capabilities of the system influence the organization's activities when it comes to implementing AI-related advancements (Kummer et al., 2017). Hence, if the human aspect or individuals' technological abilities and expertise are not considered, the deployment of AI-related innovations in organizations may not contribute to improving organizational performance.

Additionally, organizational characteristics at the managerial, group, and company levels affect the organization's adoption of AI advancements. For instance, the costs associated with transitioning from old to new technologies have been explored from various angles, suggesting that businesses may not fully benefit from such innovative technologies (van de Weerd et al., 2016). The team atmosphere is a crucial organizational variable related to the adoption of AI technologies, with research indicating that having a shared goal, support for innovation, and an environment of participatory interaction and feedback can alter cognitive perceptions and enhance the use of AI technologies (van de Weerd et al., 2016). Furthermore, the organizational climate, culture, management policies, and top management's approach may all influence the performance of AI-related technology in the business (Oliveira et al., 2014).

Thus, to enhance performance, organizations have increasingly focused on AI technology breakthroughs with innovative ideas. Various AI-related factors can either facilitate or hinder the success of these technological innovations, influencing organizational performance. Innovation tools related to marketing and management skills, innovation to support processes, and organizational structure support the implementation of new innovations, including AI technologies. These dimensions, when supported by the use of AI technologies, help organizations perform better, making AI a suitable mediator between innovation dimensions and organizational performance

2.3 Organizational Performance Factors

There exist several definitions of organizational innovation, each highlighting different aspects of innovation, ranging from processes to products, services, and organizational characteristics. The diversity in definitions underscores the need for an integrated understanding of innovation. For instance, Nandal et al. (2020) define innovation as the development, acceptance, and implementation of new ideas, processes, goods, or services. Similarly, West and Anderson (1996), as cited by Wong et al. (2009), describe innovation as the effective application of novel processes and products to benefit the business and its stakeholders. Hogan and Coote (2014) offer a broader perspective, viewing innovation as a multi-stage concept involving innovation as a process, a discrete item (e.g., products or services), and a characteristic of organizations.

The term "innovation" has gained widespread usage in both the public and private sectors, with Anwar et al. (2020) framing innovation as a multifaceted process involving individuals across the supply chain, communication networks, rules, and cognition. Encouraging creativity within organizations requires consideration of various factors, including the propensity for innovation, barriers to innovation, and available resources (Zhang et al., 2020).

Empirical evidence suggests that fostering innovation within organizations contributes to productivity, strategic process performance, organizational success, knowledge management, and financial performance (Saunila, 2020). Consequently, it is reasonable to assert that in order for businesses to thrive in the twenty-first century, they must adopt strategies that foster continuous organizational innovation to gain a competitive edge in the market.

In the quest for eco-friendly solutions, various forms of innovation, such as "green innovation," "environmental innovation," and "sustainable innovation," are commonly explored (Halila & Rundquist, 2011; Becker & Egger, 2013). Enhancing and advancing environmentally friendly processes, products, organizational models, and systems can contribute to the environmental well-being of future generations (Halila & Rundquist, 2011). Environmental innovation encompasses initiatives that introduce new products, services, or processes for long-term development (Doran & Ryan, 2014).

When organizations employ innovation to adapt to new market demands or challenges, or to address environmental concerns, they are said to be innovating. However, until recently, many managers and economists viewed achieving more with less as simply the cost of doing business (Doran & Ryan, 2014).

Today's environmental challenges have heightened the imperative for innovation to reduce overall environmental impact (Rennings & Zwick, 2002). Developing a robust innovation program and integrating it into

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regular management operations is a demanding task, requiring a deep understanding of sustainability (Halila & Rundquist, 2011). Various types of innovation, such as process innovation, marketing innovation, management innovation, and product innovation, warrant attention from firms. Implementing new ideas without evaluating their impact on organizational performance is only marginally successful (Cheng, Yang, & Sheu, 2014).

3. Modelling and Framework

This study adopted quantitative approach research involves the collection and analysis of numerical data to investigate relationships, patterns, and trends within a research topic. The empirical data were derived from a questionnaire survey among 129 employees of ADNOC, distributed using a convenient random sampling method. The respondents were required to rate each of the items in the questionnaire using 5-points Likert scale on the level of agreeability.

The gathered data served as the foundation for constructing a model within the SmartPLS software. Utilizing the Partial Least Squares (PLS) technique within the framework of Structural Equation Modelling (SEM), commonly referred to as PLS-SEM, the model in this study adopts a mediation approach. Here, the Artificial Intelligence construct assumes the role of mediator in the relationships between innovation factors and organizational performance.

3.1 Model Construction

Recent advancements have witnessed a notable surge in the utilization of multivariate statistical analysis techniques, with a particular emphasis on Structural Equation Modeling (SEM). SEM, categorized into covariance-based and variance-based forms, includes the prominent second-generation variance-based method known as Partial Least Squares Structural Equation Modeling (PLS-SEM). This method proves invaluable in exploring causal relationships among latent constructs in research endeavors. The present study employs PLS-SEM to investigate the role of Artificial Intelligence usage as a mediator in the relationships between innovation factors and organizational performance. The evaluation process of PLS-SEM unfolds in two crucial stages. The initial stage scrutinizes the measurement (outer) model, while the subsequent stage delves into the structural (inner) model, examining the interdependence and interrelationships among the research constructs. Figure 1 illustrates the developed model subsequent to the execution of the PLS Algorithm function in the SmartPLS software utilized in this study.

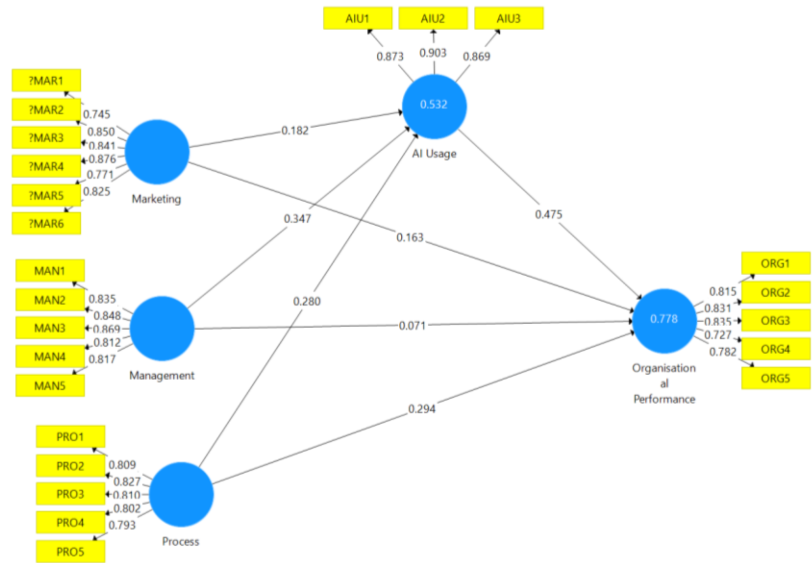

Fig. 1 *The developed model after conducting PLS Algorithm*

3.2 Evaluation of Measurement Component

The evaluation criteria for the measurement component of the model encompass reliability, convergent validity, and discriminant validity. Reliability assessment involves employing measures such as Dillon-Goldstein's or Joreskog's rho to determine the consistency within a block (Vinzi et al., 2010). Following reliability assessment, the validity of the measurement model is thoroughly scrutinized, covering both convergent and discriminant aspects (Hair et al., 2014). Convergent validity is evaluated by analyzing indicators' factor loadings, Construct Reliability, and Average Variance Extracted (AVE), showcasing the model's ability to capture indicator variance and thus confirming its validity (Wong, 2016). Discriminant validity is rigorously examined through criteria such as the Heterotrait-Monotrait (HTMT) ratio and Fornell and Larcker criterion within the outer models..

3.2.1 Convergent Validity [Construct Reliability and Validity]

Measurement models serve a critical function in explaining the variance of observable items to attain convergent validity, which underscores the model's efficacy in accurately predicting or explaining the variability of these variables (Wong, 2016). Convergent validity assesses the extent to which an observable variable is interconnected with other observable variables within the same underlying construct (Hair, Hult, Ringle, & Sarstedt, 2014). Evaluating the variance explanation for observable variables entails scrutinizing the Average Variance Extracted (AVE), items' factor loadings, and their significance level (Lowry & Gaskin, 2014; Memon & Rahman, 2013; Wong, 2016). In ensuring convergent validity, it is essential that factor loadings for observable variables surpass those in alternative models, with a minimum threshold of 0.7 (Hair et al., 2014). Within exploratory research, factor loadings ranging from 0.6 to 0.7 are considered acceptable (Hair, Ringle, & Sarstedt, 2011). Observable variables with factor loadings below 0.4 should be excluded from the measurement model, and items with lower loadings are also recommended for removal to bolster the Average Variance Extracted (AVE) (Hair et al., 2014). Furthermore, factor loadings must attain significance and converge within fewer than 300 iterations (Wong, 2016).

The Average Variance Extracted (AVE) signifies the average of the squared loadings of the observable variables within the measurement model, indicating the model's commonality (Hair et al., 2014). AVE values for the measurement models are advised to exceed 0.5 (Hair et al., 2014; Hair et al., 2011; Lowry & Gaskin, 2014; V. E. Vinzi et al., 2010; Wong, 2016), indicating that at least 50 percent of the variance of the outer model is explicated by the observable variables (Memon & Rahman, 2013).

Composite reliability pertains to the extent of consistency and stability demonstrated by a scale in generating measures over time, particularly concerning reflective items within the measurement model (Lowry & Gaskin, 2014). It denotes the degree to which a measurement scale is free from random error and measures the uniformity of responses across constructs (Pallant, 2011; Creswell, 2014). Although Cronbach's alpha is commonly utilized to assess reliability,

However, in PLS-SEM the assessment of convergent validity is through construct reliability and validity where construct reliability pertains to the consistency and stability of measurements, while construct validity focuses on the accuracy and appropriateness of measurements in representing the underlying theoretical construct. Both are crucial for ensuring that research instruments yield meaningful and reliable results (Hair et al., 2011; Memon & Rahman, 2013; Wong, 2016). In the context of PLS-SEM, a composite reliability of at least 0.7 is recommended for a measurement model to be considered reliable (Wong, 2013). Nonetheless, a threshold of 0.6 is also deemed acceptable, especially for emerging scales (Chin, 1998; Hair et al., 2011; Bagozzi & Yi, 1988). Thus, the generated construct reliability and validity values for this study is as in table 7.

Table 7 *Construct reliability and validity of the measurement models*

Construct	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
AI Usage	0.857	0.857	0.913	0.778
Management	0.892	0.893	0.921	0.699
Marketing	0.901	0.905	0.924	0.671
Organisational Performance	0.858	0.864	0.898	0.638
Process	0.867	0.868	0.904	0.653

Table 7 presents reliability and validity statistics for five constructs: AI Usage, Management, Marketing, Organisational Performance, and Process. It was found that Cronbach's Alpha which measures internal consistency having higher values indicating greater consistency among the items measuring each construct. While, Rho_A is another measure of internal consistency, with values similar to Cronbach's Alpha also having high consistency. For composite reliability, it assesses the reliability of a construct by considering both the factor loadings and measurement errors. It was found that it has higher values which indicate greater reliability. Finally, AVE represents the amount of variance captured by the construct relative to measurement error. It was found that it has higher values indicate that a larger proportion of the variance is explained by the construct itself rather than measurement error.

3.2.2 Discriminant Validity

Discriminant validity serves as a crucial measure to determine how distinct measurement models are from other research constructs, thereby evaluating their uniqueness within the structural model (Memon & Rahman, 2013). Traditionally, two main criteria have been utilized for this assessment: the Fornell and Larcker criterion, and the Cross-loading criterion. However, a more recent addition, the Heterotrait-Monotrait (HTMT) criterion, has garnered both theoretical and empirical support. This criterion calculates the average heterotrait-heteromethod correlations relative to monotrait-heteromethod correlations (Henseler et al., 2015). Typically, discriminant validity is established when the HTMT ratio with other measurements falls below 0.85, or, with a more lenient threshold, below 0.9 (Henseler et al., 2015). Fornell and Larcker's (1981) criterion suggests that the square root of the Average Variance Extracted (AVE) of each measurement model should exceed its correlation with any other model in the structural model. Additionally, according to the cross-loading criterion proposed by Chin (1998), items should load more substantially on their underlying constructs than on other constructs. Thus, for this study presents two discriminant validity assessment criteria were employed to affirm the distinctiveness of each measurement model, as detailed in Tables 8 and 9.

Table 8 *Discriminant validity using HTMT ratio criterion*

Construct	AI Usage	Management	Marketing	Organisational Performance	Process
AI Usage					
Management	0.779				
Marketing	0.711	0.829			
Organisational Performance	0.943	0.827	0.803		
Process	0.75	0.812	0.75	0.88	

Using the HTMT criterion, Table 8 reports the discriminant validity results. The highest HTMT ratio, 0.943 between Organisational Performance and AI Usage, but still remains below the liberal threshold of 1.0 (Henseler et al., 2015). All other HTMT ratios fall below the recommended conservative maximum of 0.969 (Henseler et al., 2015). Consequently, the measurement models meet the discriminant validity requirement based on the HTMT criterion.

Table 9 *Discriminant validity using Fornell and Larcker criterion*

Constructs	AI Usage	Management	Marketing	Organisational Performance	Process
AI Usage	0.882				
Management	0.683	0.836			
Marketing	0.625	0.744	0.819		
Organisational Performance	0.799	0.727	0.708	0.816	
Process	0.649	0.715	0.662	0.761	0.808

Table 9 presents the assessment of discriminant validity using the Fornell and Larcker criterion. The diagonally italicized and bolded values signify the square roots of the Average Variance Extracted (AVE) for each measurement model, while the values below the diagonal depict the correlations between the measurement models. The findings reveal that none of the measurement models show correlations surpassing the square root of their AVE with any other measurement model. Therefore, the measurement models have effectively met the discriminant validity criteria according to the Fornell and Larcker criterion.

3.3 Evaluation of Structural Model

The second phase of PLS-SEM evaluation involves scrutinizing the structural (inner) model, responsible for establishing the cause-and-effect relationships between the measurement models to address research questions and test hypotheses (Hair et al., 2014). This model seeks to predict endogenous constructs by exploring the relationships between these constructs and the exogenous ones (Hair et al., 2014). The assessment of the structural model encompasses various criteria, such as examining path coefficients and their significance through a bootstrapping procedure, evaluating the coefficients of determination (R2) for endogenous constructs, assessing the model's predictive relevance using cross-validated redundancy (Q2) (Arshad, Goh, & Rasli, 2014; Hair et al., 2011; Lowry & Gaskin, 2014; Memon & Rahman, 2013; Vinzi et al., 2010; Wong, 2016).

3.3.1 Path coefficients evaluation

Path coefficients quantify the strength of relationships between constructs in the structural model, where values closer to 1 indicate a robust positive relationship (Hair et al., 2014). The significance of the paths is assessed using p-values or t-statistics obtained through bootstrapping (Kock, 2014). The path coefficients, along with their significance levels, offer insights into the internal quality of the model (Hair et al., 2011). To ensure the inner model's quality, it is imperative that path coefficients be statistically significant (Wong, 2016). The path coefficients for this study are outlined in Table 10.

Table 10 *Path coefficients*

Path or relationship	Path coefficient	T values	P Values	Remarks
AI Usage -> Organisational Performance	0.475	8.075	0	Significant
Management -> AI Usage	0.347	2.97	0.003	Significant
Management -> Organisational Performance	0.071	1.197	0.232	Not significant
Marketing -> AI Usage	0.182	1.841	0.066	Not significant
Marketing -> Organisational Performance	0.163	2.741	0.006	Significant
Process -> AI Usage	0.28	2.911	0.004	Significant
Process -> Organisational Performance	0.294	5.714	0	Significant

Table 10 illustrates path coefficient for seven direct relationships. However, two of the relationships are not significant which the path coefficients are not considered. Out of the five significant paths, the path/relationship of AI Usage -> Organisational Performance is having the highest strength/coefficient

3.3.2 Coefficient of Determination (R2) Assessment

The structural model's effectiveness can be gauged through R^2, which measures how well the model elucidates the variance. R^2, also known as the coefficient of determination, signifies the collective impact of exogenous constructs on predicting or elucidating the variance of the endogenous construct within the structural model. A higher R^2 value denotes a superior model quality in terms of variance explanation, whereas a lower value suggests diminished quality (Hair et al., 2014; Hair et al., 2011; Memon & Rahman, 2013; Wong, 2016).

While there are no universally defined benchmarks for an acceptable R^2 level, researchers propose various recommendations that can differ across disciplines. As a general guideline, a value of 0.25 is considered weak, 0.50 is seen as moderate, and 0.75 is deemed substantial (Hair et al., 2014; Wong, 2016). However, Hair et al. (2014) argued that in the field of consumer behaviour, an R^2 value of 0.2 is considered high. These benchmarks were applied to evaluate the R^2 levels in this study, and the R^2 values of the final model are presented in Table 11

Table 11 *R^2 values of the model*

Endogenous constructs	R Square values
AI Usage	0.532
Organisational Performance	0.778

Table 11 showcases the coefficient of determination (R^2) values for the structural model in this research, revealing the proportion of variance in the endogenous construct explained by the exogenous constructs. Both the endogenous constructs which are AI Usage; Organisational Performance are having R^2 values of 0.532 and 0.778 respectively. With a general guideline considering an R^2 value, the research's R^2 values are deemed moderate and highly substantial respectively.

3.3.3 Predictive Relevance (Construct Cross Validated Redundancy)

Accuracy is a general term reflecting how well a model's predictions match actual outcomes, typically calculated as the ratio of correctly predicted instances to the total. While accuracy gauges correctness on the training data, predictive relevance focuses on the model's ability to generalize effectively to new data. Predictive relevance assesses a model's ability to make accurate predictions on new, unseen data, often measured using criteria like the Stone-Geisser Q^2 in PLS-SEM (Hair et al., 2014). The Stone-Geisser indicator or redundancy of cross validity (Q^2) criteria recommend that the conceptual model be able to predict the latent structure. In SEM, the measured Q^2 value must be greater than zero for a particular endogenous latent structure (Tenenhaus, et.al., 2005). The result of Q2 values for this study model are as in table 12 which generated Construct Cross validated redundancy values using the PLS-SEM blindfolding approach

Table 12 *Construct Cross validated redundancy values*

Constructs	SSO	SSE	Q^2 (=1-SSE/SSO)
AI Usage	1194	708.358	0.407
Management	1990	1990	
Marketing	2388	2388	
Organisational Performance	1990	1031.186	0.482
Process	1990	1990	

Table 12 shows the cross validated redundancy score for the endogenous variable (AI Usage = 0.407) was greater than zero which implies the existence of predictive significance of the path model. While, the mediation model, the cross-redundancy score for the endogenous variable (Organisational Performance = 0.482) was greater than zero suggesting the presence of predictive relevance of the path model. Thus, it can be concluded that the study model has achieved predictive relevance to make accurate predictions (Ulfig, 2019).

3.4 Determine the Path Significant Level

In PLS analysis, bootstrapping is a statistical method used for hypothesis testing. It works by repeatedly sampling data from the observed dataset, creating multiple simulated samples. This helps estimate the variability of a statistic and provides more reliable confidence intervals. Bootstrapping allows researchers to assess the distribution of test statistics and calculate confidence intervals without strict assumptions about the population. It is especially valuable for small sample sizes or non-normally distributed data, improving the reliability of statistical inferences when traditional assumptions may not apply (Hair et al., 2014; Ulfig, 2019). Figure 2 show the model after conducting bootstrapping process in SmartPLS software.

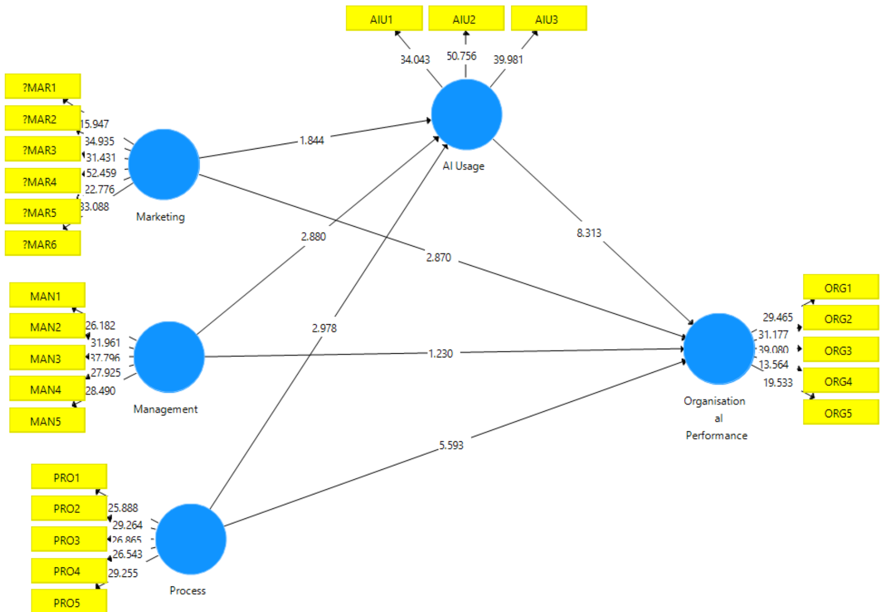

Fig. 2 *Structural model after bootstrapping*

After the bootstrapping process, the generated results of the hypothesis are as in Table 13. Through an examination of the path coefficients and their significance, then it can assess whether the data aligns with the hypothesized relationships between constructs, providing essential insights for drawing meaningful conclusions and advancing theoretical understanding in the field.

Table 13 *Result of direct and indirect hypothesis testing*

Hypothesis	Direct or indirect relationship	Path coefficient	T value	P Value	Significant
	Direct [IV - DV]				
H1	Process -> Organisational Performance	0.294	5.741	0	**Yes**
H2	Management -> Organisational Performance	0.071	1.307	0.192	**No**

H3	Marketing -> Organisational Performance	0.163	2.731	0.007	**Yes**
	Direct [IV – M]				
H4	Process -> AI Usage	0.28	2.75	0.006	**Yes**
H5	Management -> AI Usage [IV TO M]	0.347	3	0.003	**Yes**
H6	Marketing -> AI Usage	0.182	1.859	0.064	**No**
	Direct [M – DV]				
H7	AI Usage -> Organisational Performance	0.475	8.194	0	**Yes**
	Indirect [IV-M-DV]				
H8	Process -> AI Usage -> Organisational Performance	0.133	2.576	0.01	**Yes**
H9	Management -> AI Usage -> Organisational Performance	0.165	2.742	0.006	**Yes**
H10	Marketing -> AI Usage -> Organisational Performance	0.086	1.869	0.062	**No**

IV- independent variables; DV-dependent variable; M-mediator

4. Mediation Effect

According to Ghasemy et al. (2020), mediation effects manifest in various forms: full, partial, and no mediations. Full mediation occurs when the direct relationship is not significant, but the indirect relationship is. In contrast, partial mediation occurs when both the direct and indirect relationships are significant. Lastly, no mediation is observed when the direct relationship is significant, but the indirect relationship is not, or when both the direct and indirect relationships are not significant. The decision of mediation effects for this study involves the direct and indirect relationship between the IV to Mediator and IV to DV because Mediator to DV is significant as described in the above table 14.

Table 14 *Decision of mediation effect*

Relationship	Direct Hypothesis	Result	Indirect Hypothesis	Result	Mediation effect
Process/AI Usage/Organisational Performance	H1	significant	H8	Significant	Partial
Management/AI Usage/Organisational Performance	H2	Not Significant	H9	Significant	Full
Marketing/AI Usage/Organisational Performance	H3	Significant	H10	Not Significant	No

Based on table 14, the process innovation has attained partial mediation, the management innovation attained full mediation and marketing has no mediation effect on the AI usage

5. The Established Framework

Based on the hypothesis testing results of direct relationship, the framework of Artificial Intelligence Usage as a mediator on the direct relationship between Innovation factors and organisational performance is as figure 3

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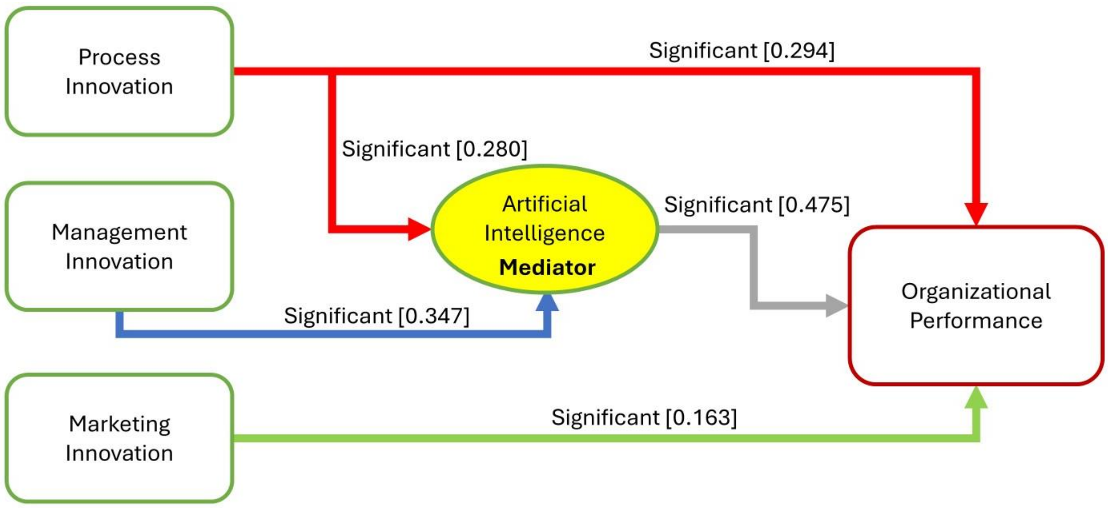

Fig. 3 *Framework of direct relationship between constructs*

Figure 3 illustrates the established framework in which process innovation has a direct connection with artificial intelligence usage (mediator) and organisational performance (dependent construct). For process innovation, it has direct relationship with both the artificial intelligence and, also organisational performance. while for management innovation, it has only direct relationship to the mediator but not to the dependent construct. This is vice versa with the marketing innovation which has direct relationship with dependent construct but not with the mediator. Finally, the mediator has direct relationship with the dependent construct. The following is the framework for the indirect relationship between the construct as in figure 4.

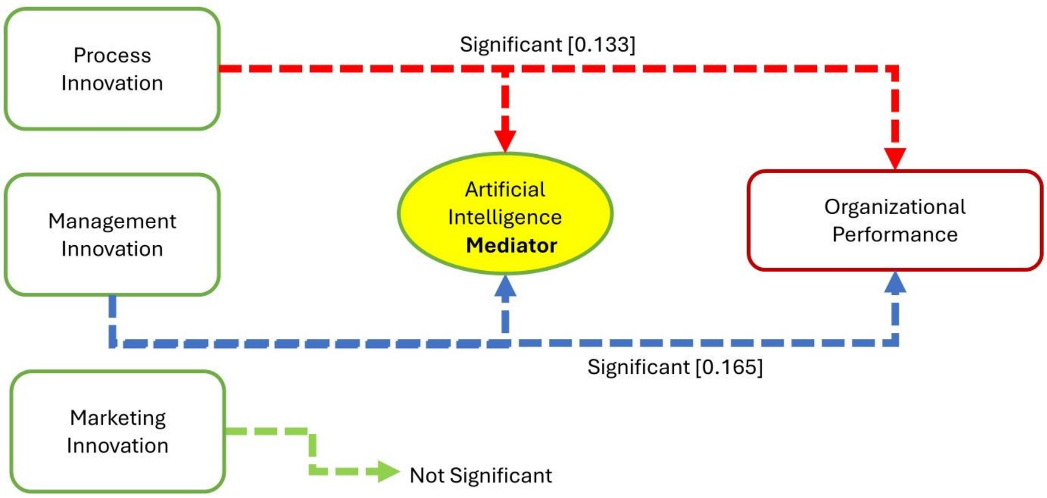

Fig. 4 *Framework of indirect relationship between constructs*

For indirect relationship between the constructs as figure 4, process innovation and management innovation constructs have attained significant relationship through the mediator to the dependent construct. Unfortunately, marketing innovation does not attain significant relationship. The following is the framework for the mediation effects between the construct as in figure 5.

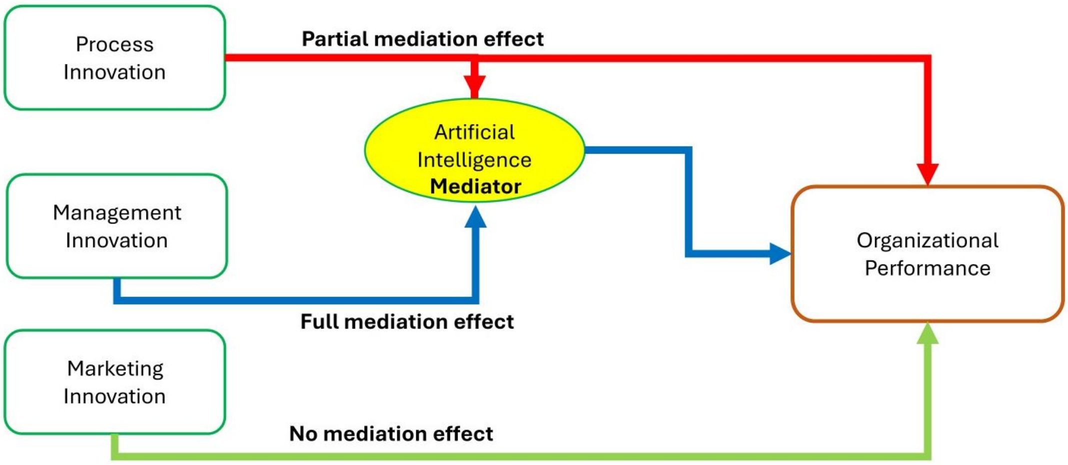

Fig. 5 *Framework of the mediation effect between constructs*

Based on the framework of the mediation effect of artificial intelligence usage on the relationship between innovation factors and organisational performance is as figure 5, it was found that process innovation has attained partial mediation, management innovation attained full mediation and finally, marketing innovation with no mediation effect.

6. Conclusion

This article introduces a study focused on crafting a framework to understand the mediating role of Artificial Intelligence (AI) Usage in the relationship between innovation factors and organizational performance. The framework encompasses three clusters of innovation factors—marketing, management, and process—treated as independent constructs, with organizational performance as the dependent construct, and AI usage as the mediator. Before constructing the framework, a Partial Least Squares Structural Equation Modeling (PLS-SEM) mediation model was built using SmartPLS software, leveraging data gathered from a questionnaire survey involving 129 employees of ADNOC, selected through convenient random sampling. The model underwent thorough assessment of both its inner and outer components until meeting predefined fitness criteria. Subsequently, a bootstrapping procedure was employed for hypothesis testing to ascertain the significance level of each relationship path, thereby determining the mediation effects. The framework emerged from the results of these hypothesis tests. It is envisioned that this framework will support ADNOC employees in integrating innovation factors with AI usage to enhance organizational performance.

Acknowledgement

The authors would like to thank Universiti Tun Hussein Onn Malaysia, Malaysia for supporting this study.

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

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