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Moderation Effect of Artificial Intelligent (AI) on the Relationship Between Innovation in Information and Communication Technology (ICT) and Job Performance

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Abstract

Despite significant investments by the Abu Dhabi Police Department in ICT technology, the effectiveness of these applications in enhancing job performance and operational efficiency remains uncertain. This study aims to analyze the influence of ICT adoption attributes on ICT innovation and its impact on job performance, with AI as a moderating factor. A conceptual model was developed from the literature and empirically tested using questionnaire data from 338 Abu Dhabi Police traffic department employees. SmartPLS software was employed for structural equation modelling (SEM) using the partial least squares (PLS) approach, chosen for its effectiveness in theory development. The analysis involved both measurement and structural assessments to ensure model fitness, followed by hypothesis testing and predictive relevance evaluation. The findings indicate that, except for trialability, all attributes for enhancing ICT usage significantly influence ICT innovation adoption. Likewise, all attributes, except for trialability, indirectly impact job performance through ICT innovation adoption. Additionally, AI was found to have a slight negative moderating effect on the relationship between ICT innovation adoption and job performance. This study highlights the critical role of ICT innovation attributes and AI moderation in optimizing job performance and operational efficiency within the police force.

Keywords: Artificial Intelligence, ICT, PLS-SEM, Job Performance

1. Introduction

The Abu Dhabi Police Department has made significant investments in Information and Communication Technology (ICT), yet there is limited empirical research on its impact on employee work performance (Al Darmaki, 2015). This gap raises concerns about ICT's effectiveness in enhancing operational efficiency, communication, and job performance. While prior studies have explored ICT's psychological and behavioural effects, such as knowledge sharing (Hewitt, Walz, & McLeod, 2020) and cognitive impacts (Pitafi, Kanwal, & Khan, 2020), the specific influence of ICT on police work performance remains unclear. Bandura (Bandura, 2001) noted that focusing only on psychological effects overlooks essential work processes. Additionally, ICT's impact on employee-organization relationships and collaboration is underexplored, despite its potential to transform work dynamics (Wang, Liu, & Parker, 2020). Effective communication, a key success factor in any organization, is also influenced by ICT adoption (Ahmed, Memon, & Memon, 2021). This study addresses the gap by examining ICT's influence on individual job performance, particularly within the UAE government sector (Al Darmaki, 2015). Despite growing ICT adoption in the UAE, research on its effects on employee performance and organizational relationships remains limited (Abu Dhabi Police, 2024). Given that employee performance directly impacts operational efficiency, this study is critical to understanding how ICT can optimize government functions (Victoria, 2023). The Abu Dhabi Police have integrated advanced ICT solutions, including data analytics, communication systems, and mobile technology, to enhance law enforcement (Abu Dhabi Police, 2018). However, research on ICT's effectiveness in improving police work performance is insufficient (Al Darmaki, 2015). This lack of empirical data hampers decision-making regarding future investments and resource management (Victoria, 2023). Police performance encompasses various dimensions, such as administrative efficiency, decision-making, and crime prevention, all of which ICT can influence (Victoria, 2023). Identifying the most relevant ICT features for law enforcement is crucial for optimizing job performance in the UAE government sector (Abu Dhabi Police, 2024). Artificial Intelligence (AI) plays a moderating role in maximizing ICT benefits. AI-driven analytics, predictive modelling, and automation enhance ICT's impact on operational efficiency and decision-making. AI's ability to process large data sets in real time strengthens ICT's effectiveness, providing actionable insights (Myeong & Bokhari, 2023; Bokhari & Myeong, 2022; Zeng & Yousaf, 2022; McGrath, 2024; Bansal, 2024). The Abu Dhabi Police leverage ICT to improve security, reduce crime, and establish a systematic and efficient policing framework. The effective utilization of ICT tools is a critical measure of police efficiency (Al Darmaki, 2015). This study aims to bridge the research gap by examining ICT adoption among employees in the Abu Dhabi Police Traffic Department.

2. Literature Review

2.1 Innovation in ICT Impact on Job Performance

Various forms of Information and Communication Technology (ICT) innovation significantly impact job performance. Technological innovation involves the adoption of advanced technologies such as artificial intelligence (AI), machine learning, and automation, enhancing productivity and reducing errors. For instance, AI-driven tools improve efficiency in customer service, allowing employees to focus on complex tasks, increasing job satisfaction and performance (Susskind & Susskind, 2022). Process innovation optimizes organizational workflows through reengineering, lean principles, and digital integration. Automating repetitive tasks reduces operational costs and enhances efficiency, enabling employees to engage in strategic and creative work, ultimately improving job performance (van der Duin & Ortt, 2020). Service innovation enhances customer experience by introducing personalized services, improved interaction channels, and new delivery systems. This differentiation boosts customer satisfaction and loyalty, while employees involved in service improvements gain motivation and a sense of achievement (Alnuaimi & Abdulhabib, 2023). Organizational innovation reshapes management practices, structures, and workplace culture to encourage adaptability and innovation. Implementing new management systems, promoting continuous improvement, and fostering employee participation create a dynamic work environment that enhances job satisfaction and performance (Todorovic, Medic, Delic, Zivlak, & Gracanin, 2022). Together, these ICT-driven innovations enhance efficiency, foster creativity, and improve workplace engagement. By integrating these innovations, organizations like the Abu Dhabi Police Traffic Management Office can remain competitive while ensuring employee well-being and productivity.

2.2 AI in ICT Innovation to Enhance Job Performance

The integration of AI technologies in ICT innovation is transforming organizational performance by addressing technical, organizational, social, and human factors. Technical aspects such as stakeholder alignment, technological features, and resolving inconsistencies are crucial for success (Olesen, 2014). Additionally, technological readiness, managerial support, and organizational size play a significant role in the effective deployment of AI solutions like cloud computing (Oliveira, Thomas, & Espadanal, 2014). At the organizational level, factors such as transition costs, team support, workplace culture, and management policies influence AI adoption and performance (Van de Weerd, Mangula, & Brinkkemper, 2016; Maruping & Magni, 2012). Social dynamics, including professional readiness, workplace culture, and regulatory pressures, also shape AI effectiveness. While some social factors can create barriers, professional readiness positively impacts AI implementation (Choudrie & Zamani, 2016). The human factor is critical which is technological expertise and individual capabilities determine the success of AI integration. Without sufficient skills and adaptation, AI technologies may not fully enhance performance (Aggarwal, Kryscynski, Midha, & Singh, 2015; Klaus, Blanton, & Wingreen, 2015; Kummer, Recker, & Bick, 2017). Beyond improving efficiency, AI-driven ICT tools optimize productivity and support decision-making, ultimately enhancing job performance and organizational effectiveness (Grgecic, Holten, & Rosenkranz, 2015).

2.3 Job Performance Through ICT Innovation

ICT has significantly transformed both professional and daily activities, enhancing organizational culture and structure while positively impacting individual performance. Research highlights that ICT-skilled workers boost productivity and performance (Hagsten &

Sabadash, 2014), eliminate trivial tasks (Palvalin, Lönnqvist, & Vuolle, 2013; Seo, Lee, Hur, & Kim, 2012), and reduce techno-stress, thereby improving employee well-being (Tarafdar, Tu, & Ragu-Nathan, 2010). Additionally, ICT adoption enhances profitability, differentiation, and quality, contributing to high-performance work practices (Mihalic, & Buhalis, 2013; Bayo-Moriones, Calleja-Blanco, & Lera-López, 2015). Studies also indicate that ICT positively affects various performance metrics, improving communication, competitiveness, cost reduction, motivation, innovation, work time efficiency, and job satisfaction (Bayo-Moriones, Billon, & Lera-Lopez, 2013; Rezaei, Rezaei, Zare, Akbarzadeh, & Zare, 2014; Elsaadani, 2014). ICT connectivity and self-discipline further enhance productivity (Al-Dabbagh, 2015). ICT proficiency is particularly influential in quality management (Kaluyu, Wambugu, & Oduor, 2015), education (Ahmad, 2012; Ondieki Makori, Odini, & Bernard Ojiambo, 2013), tourism (Polo Pena, Frías Jamilena, & Rodríguez Molina, 2013), and workplace communication (Zhang & Venkatesh, 2013). Furthermore, technological skills are deemed more critical than formal qualifications in ICT-related industries (Yoo, Choi, & Lee, 2014). Demographic factors such as gender and age also influence ICT use, with younger and female employees demonstrating more effective ICT adoption (Hendehjan & Noordin, 2013). However, ICT can pose performance management and quality challenges if not properly implemented (AL-Hannif, Cox, & Almeida, 2014). Overall, ICT innovations substantially impact job performance across multiple sectors by enhancing efficiency, communication, and productivity, although certain challenges require attention.

3. Conceptual Model

This study aims to examine how various traits of Information and Communication Technology (ICT) innovation impact the job performance of Abu Dhabi Police traffic management employees, with Artificial Intelligence (AI) acting as a moderator. The literature review conducted previously provided a foundation for creating the research conceptual model. The conceptual model, derived from prior theories and models, visually represents the research outcomes and illustrates the relationships among various research factors. It defines both direct and indirect relationships between the identified variables, with arrows indicating the proposed hypotheses of the study. Figure 1 provides a visual illustration of the conceptual model underpinning this research.

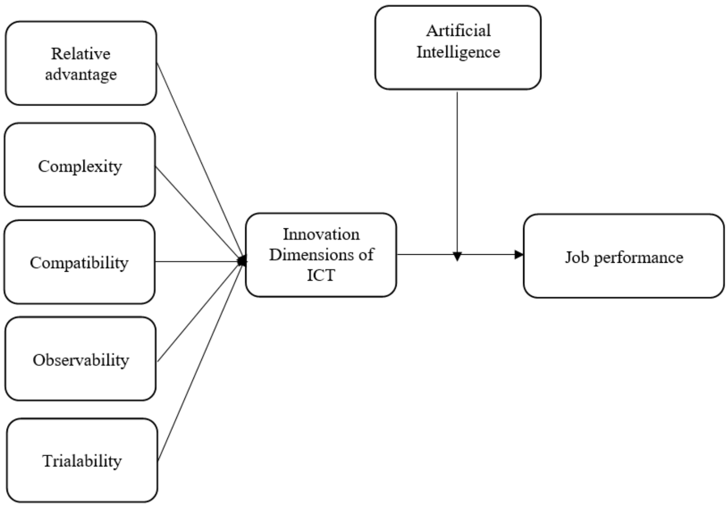

Figure 1. Conceptual Model

Figure 1 presents the conceptual model, which incorporates five traits designed to enhance ICT usage, the intermediary construct of ICT innovation adoption, AI as a moderator, and job performance as the dependent construct. The model is grounded in the Theory of Breakthrough Diffusion (Rogers, 2010), which includes these five traits to improve ICT utilization. Following the principles of the Technology Acceptance Model (TAM), these traits influence the adoption rate of ICT innovation, which in turn impacts employees' job performance. Additionally, AI is introduced as a moderating factor in the relationship between ICT innovation adoption and job performance, providing insights into its potential influence.

4. Modelling Analysis

The model illustrated in Figure 2 incorporates five traits that enhance ICT usage, which influence the adoption rate of ICT innovation, subsequently impacting employees' job performance. Additionally, AI application is integrated as a moderator in the relationship between the adoption rate of ICT innovation and job performance.

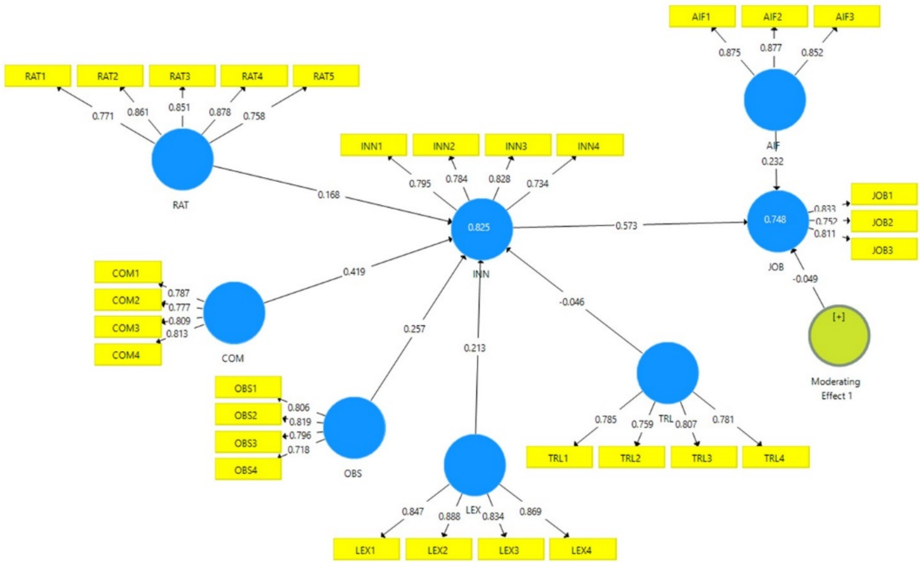

Figure 2. Final Model

Figure 2 presents a structural equation model (SEM) that examines the relationships between latent variables and their observed indicators. Innovation (INN) acts as an intermediary construct, influenced by five factors: Relative Advantage (RAT) (path strength = 0.168), Compatibility (COM) (path strength = 0.419), Observability (OBS) (path strength = 0.257), Complexity (LEX) (path strength = 0.213), and Trialability (TRL) (path strength = 0.213). These factors collectively contribute to ICT innovation adoption. INN significantly impacts Job Performance (JOB), with a path strength of 0.573. Additionally, Artificial Intelligence (AIF) moderates the INN-JOB relationship, with a moderating effect of 0.232, suggesting an interaction between constructs.

4.1 Assessment of the Measurement Model

Assessment of the measurement model involves evaluating construct reliability and validity (CRV) as well as discriminant validity. Parameters such as Composite Reliability (CR), Average Variance Extracted (AVE), Cronbach's Alpha, rho_A, and Discriminant Validity (Fornell-Larcker) are assessed (Fornell, & Larcker, 1981; Nunnally & Bernstein, 1994; Dijkstra & Henseler, 2015; Hair, Risher, Sarstedt, & Ringle, 2019).

4.1.1 Construct Reliability and Validity (CRV)

Construct reliability assesses the consistency of indicators in measuring a construct, ensuring they reliably reflect the same concept. Construct validity confirms that these indicators accurately measure the intended construct (Hair, Risher, Sarstedt, & Ringle, 2019; Rahman, Memon, Abdullah, & Azis, 2013). The generated Composite Reliability (CR) and Validity (CRV) values for the study model are presented in Table 1.

Table 1. Construct reliability and validity results

Constructs	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AIF	0.837	0.902	0.754
COM	0.808	0.874	0.634
INN	0.793	0.866	0.617
JOB	0.718	0.841	0.639
LEX	0.882	0.919	0.74
OBS	0.792	0.866	0.618
RAT	0.882	0.914	0.681
TRL	0.79	0.864	0.613

Table 1 shows that all constructs exhibit strong reliability, with Cronbach's Alpha values exceeding 0.7, indicating good internal consistency. The CR values surpass the 0.7 threshold, confirming measurement reliability (Hair, Risher, Sarstedt, & Ringle, 2019). Additionally, AVE values exceed 0.5, establishing convergent validity (Fornell, & Larcker, 1981). These results affirm that the measurement models for each construct are both reliable and valid.

4.1.2 Discriminant Validity (DV)

Discriminant validity ensures that each construct in a model is distinct from the others, indicating that the constructs measure unique aspects of the model (Hair, Risher, Sarstedt, & Ringle, 2019; Memon & Rahman, 2013). It is assessed using methods like the Fornell-Larcker criterion, which compares the square root of the AVE to the correlations between constructs (Fornell, & Larcker, 1981; Zainun, Roslan, & Memon, 2014). High discriminant validity signifies that construct are not only reliable but also validly distinct from each other (Henseler, Ringle, & Sarstedt, 2015). The generated results of the model discriminant validity are as Table 2.

Table 2. Discriminant validity results using Fornell & Larcker

Constructs	AIF	COM	INN	JOB	LEX	OBS	RAT	TRL
AIF	0.868							
COM	0.668	0.796						
INN	0.745	0.852	0.786					
JOB	0.747	0.791	0.841	0.799				
LEX	0.762	0.729	0.796	0.806	0.86			
OBS	0.693	0.763	0.819	0.786	0.783	0.786		
RAT	0.588	0.707	0.739	0.667	0.644	0.678	0.825	
TRL	0.636	0.804	0.782	0.753	0.696	0.819	0.792	0.783

Table 2 that all constructs meet this criterion, indicating good discriminant validity. For example, the construct AIF has a square root of AVE of 0.868, which is higher than its correlations with other constructs such as COM (0.668) and INN (0.745). Similarly, the construct INN has a square root of AVE of 0.786, which is higher than its correlations with other constructs, including COM (0.852) and JOB (0.841). This pattern is consistent across all constructs, confirming that each construct is distinct and validly measures what it is intended to measure (Fornell, & Larcker, 1981; Hair, Risher, Sarstedt, & Ringle, 2019).

4.2 Assessment of the Structural Model

The assessment criteria of the structural component involve several parameters and processes such as Path Coefficients, Explanatory Power (R^2), Variance Inflation Factor (VIF), Effect Size of Predictor Variables (f^2), Predictive Power (Q^2), model fit, and hypothesis testing for significant relationships (Hair, Risher, Sarstedt, & Ringle, 2019; Ramayah, Cheah, Chuah, Ting, & Memon, 2018).

4.2.1 Path Coefficients and Significance Level

Path coefficients in Partial Least Squares (PLS) Structural Equation Modelling indicate the strength and direction of the relationships between latent variables (Hair, Risher, Sarstedt, & Ringle, 2019; Memon, Memon, Soomro, Memon, & Khan, 2023). These coefficients are assessed for significance through bootstrapping, where high path coefficients suggest stronger, more impactful relationships (Sarstedt, Henseler, & Hair, 2021). The interpretation of path coefficients helps in understanding the causal connections within the model, guiding theoretical and practical implications (Hair, Henseler, Ringle, & Sarstedt, 2022).

Table 3. Path coefficient of the model

Direct relationship	**Path strength**	**P Values**	**Significant**
AIF -> JOB	0.232	0.000	Significant
COM -> INN	0.419	0.000	Significant
INN -> JOB	0.573	0.000	Significant
LEX -> INN	0.213	0.000	Significant
OBS -> INN	0.257	0.000	Significant
RAT -> INN	0.168	0.001	Significant
TRL -> INN	-0.046	0.500	Not Significant
Indirect Relationship			
COM -> INN -> JOB	0.240	0.000	Significant
LEX -> INN -> JOB	0.122	0.001	Significant
RAT -> INN -> JOB	0.096	0.001	Significant
TRL -> INN -> JOB	-0.027	0.510	Not Significant
OBS -> INN -> JOB	0.148	0.001	Significant

Table 3 presents the path coefficients, significance, and strength of direct and indirect relationships in the model. All direct relationships, including AIF → JOB (0.232), COM →

INN (0.419), INN → JOB (0.573), LEX → INN (0.213), OBS → INN (0.257), and RAT → INN (0.168), are significant, except for TRL → INN (-0.046). Similarly, indirect relationships such as COM → INN → JOB (0.240), LEX → INN → JOB (0.122), RAT → INN → JOB (0.096), and OBS → INN → JOB (0.148) are significant, while TRL → INN → JOB (-0.027) is not. These findings emphasize the strong impact of multiple constructs on job performance through innovation, with INN → JOB exhibiting the highest path strength

4.2.2 Quality of the Model Through R Square Value

R-square values, or the coefficient of determination, assess the proportion of variance in the dependent variable explained by the independent variables in the model. Higher R-square values indicate a better model fit, with values closer to 1.0 signifying stronger explanatory power (Hair, Risher, Sarstedt, & Ringle, 2019). The R-square values generated for the model are presented in Table 4.

Table 4. R square values of the model

Construct	R Square
INN	0.825
JOB	0.748

Table 4 presents the R-square values for the model's constructs, highlighting its explanatory power. The R-square value for the dependent construct INN is 0.825, meaning 82.5% of its variance is explained by the independent variables. Similarly, the moderator construct JOB has an R-square value of 0.748, indicating that 74.8% of its variance is explained by the model (Hair, Risher, Sarstedt, & Ringle, 2019).

4.2.3 Effect Size of Predictor Variables (f square)

The effect size of predictor variables in a PLS model is evaluated during the structural assessment, measuring each predictor's impact on the dependent variable and the strength of their relationships. In SmartPLS, f-square values quantify this effect size by indicating the unique variance each predictor explains in the dependent variable. Standard benchmarks for interpretation classify f-square values as 0.02 (small effect), 0.15 (medium effect), and 0.35 (large effect), aiding in assessing the practical significance of the model’s predictors (Hair, Henseler, Ringle, & Sarstedt, 2022).

Table 5. Generated f square values

All constructs	Intermediary construct	Dependent construct
	INN	JOB
AIF	-not connected-	0.087
COM	0.289	-not connected-
INN	-not connected-	0.463
LEX	0.087	-not connected-
Moderating Effect 1	-not connected-	0.030
OBS	0.090	-not connected-
RAT	0.056	-not connected-
TRL	0.002	-not connected-

The construct INN shows in Table 5 the most significant effect size with a f-square value of 0.463, indicating a strong impact (Hair, Henseler, Ringle, & Sarstedt, 2022). COM follows with a value of 0.289, suggesting a moderate effect size. Other constructs like AIF and LEX have smaller yet notable effects with values of 0.087 each. Moderating Effect 1 and OBS show smaller effect sizes, with values of 0.03 and 0.09 respectively, while RAT and TRL have the smallest effect sizes at 0.056 and 0.002, indicating minimal impact (Ramayah, Cheah, Chuah, Ting, & Memon, 2018).

4.2.4 Model Fit of the Model

The model fit results from SmartPLS include key measures such as the Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), and Goodness of Fit Index (GFI), which assess how well the model fits the data. Lower values indicate a better fit, with SRMR values below 0.08 considered acceptable and NFI values closer to 1 signifying a well-fitting model (Hair, Henseler, Ringle, & Sarstedt, 2022). Additionally, the Chi-square (χ^2) test and Root Mean Square Error of Approximation (RMSEA) further validate the model's fit (Hair, Risher, Sarstedt, & Ringle, 2019).

Table 6. Results of model fit

Items	Saturated Model	Estimated Model
SRMR	0.074	0.079
d_ULS	2.719	3.064
d_G	1.362	1.415
Chi-Square	2914.129	2926.165
NFI	0.705	0.704

Table 6 presents the model fit results, comparing the Saturated Model and the Estimated Model. The Standardized Root Mean Square Residual (SRMR) values are 0.074 and 0.079, respectively, both within the acceptable threshold of 0.08, indicating a good model fit (Hair, Henseler, Ringle, & Sarstedt, 2022). The Normed Fit Index (NFI) values are 0.705 and 0.704, suggesting an acceptable fit with potential for improvement. Additional metrics, including d_ULS and d_G, assess model discrepancy and fit. The Chi-square values of 2914.129 for the Saturated Model and 2926.165 for the Estimated Model further confirm the model's overall good fit (Ramayah, Cheah, Chuah, Ting, & Memon, 2018).

4.2.5 Predictive Relevance (Q^2)

Blindfolding is a technique in SmartPLS used to assess a model's predictive relevance by systematically removing indicators and comparing predictive accuracy (Hair, Henseler, Ringle, & Sarstedt, 2022). This method evaluates each indicator's impact on the model's overall predictive power. However, it has been replaced by the PLSPredict procedure in SmartPLS for assessing predictive relevance. The assessment relies on two key outputs: Construct Cross-Validated Redundancy and Construct Cross-Validated Communality (Hair, Henseler, Ringle, & Sarstedt, 2022).

4.2.5.1 Construct Cross Validated Redundancy

Construct cross-validated redundancy, also known as Q^2, measures the predictive relevance of a model by assessing how well it predicts omitted data points indicator (Hair, Henseler, Ringle, & Sarstedt, 2022). The results of Construct cross-validated redundancy generated through blinding folding are as in Table 7.

Table 7. Construct cross-validated redundancy

Constructs	**SSO**	**SSE**	**Q^2 (=1-SSE/SSO)**
AIF	1194	1194	
COM	1592	1592	
INN	1592	808.097	0.492
JOB	1194	645.549	0.459
LEX	1592	1592	
Moderating Effect 1	398	398	
OBS	1592	1592	
RAT	1990	1990	
TRL	1592	1592	

Table 7 shows that endogenous constructs of INN and JOB exhibit Q^2 values of 0.492 and 0.459, respectively, indicating moderate predictive relevance (Hair, Henseler, Ringle, & Sarstedt, 2022). The Moderating Effect construct has the highest Q^2 value at 0.549, suggesting strong predictive relevance. These results highlight the model's moderate to strong predictive capabilities, emphasizing the significance of INN, JOB, and the Moderating Effect within the framework (Ramayah, Cheah, Chuah, Ting, & Memon, 2018).

4.2.5.2 Construct Cross Validated Communality

Construct cross-validated communality measures the proportion of variance in a construct explained by its indicators, providing insight into the construct's predictive relevance (Hair, Henseler, Ringle, & Sarstedt, 2022). The results of the construct cross-validated communality for the model are shown in Table 8.

Table 8. Construct cross-validated communality

Construct	SSO	SSE	Q^2 (=1-SSE/SSO)
AIF	1194	616.268	0.484
COM	1592	980.778	0.384
INN	1592	1020.442	0.359
JOB	1194	855.098	0.284
LEX	1592	711.364	0.553
Moderating Effect 1	398		1
OBS	1592	1019.587	0.360
RAT	1990	958.306	0.518
TRL	1592	1031.553	0.352

Table 8 presents the results of construct cross-validated communality, which evaluates the proportion of variance explained by each construct's indicators. The constructs analysed include AIF, COM, INN, JOB, LEX, Moderating Effect, OBS, RAT, and TRL. The Q^2 values, calculated as (1 - SSE/SSO), indicate the predictive relevance of each construct. The findings reveal that LEX has the highest Q^2 value at 0.553, meaning over 55% of its variance is explained by its indicators, demonstrating strong predictive relevance. RAT also exhibits significant predictive relevance with a Q^2 value of 0.518. AIF follows with a Q^2 value of 0.484, while OBS has a moderate predictive relevance at 0.36. Conversely, JOB has the lowest Q^2 value at 0.284, indicating lower predictive relevance. The Moderating Effect construct has a Q^2 value of 1, which is expected due to its role as a moderator variable. Other constructs, including COM (0.384), INN (0.359), and TRL (0.352), show moderate to lower predictive relevance (Ramayah, Cheah, Chuah, Ting, & Memon, 2018).

4.2.6 Hypothesis Testing

Following the assessment of the model at both measurement and structural levels, hypothesis testing was conducted using the bootstrapping function in SmartPLS. This non-parametric procedure estimates the sampling distribution by repeatedly resampling with replacement from the original data, allowing for the statistical significance testing of path coefficients and other PLS-SEM results (Hair, Henseler, Ringle, & Sarstedt, 2022).

4.2.6.1 Direct Relationships

Table 9 provides a comprehensive overview of the direct path strengths and p-values for each of these relationships, illustrating their statistical significance and impact within the model.

Table 9. Direct relationship hypothesis testing results

Direct relationship	Path strength	T Statistics (|O/STDEV|)	P Values
AIF -> JOB	0.232	3.504	0.000
COM -> INN	0.419	7.421	0.000
INN -> JOB	0.573	8.445	0.000
LEX -> INN	0.213	3.897	0.000
Moderating Effect 1 -> JOB	-0.049	2.339	0.020
OBS -> INN	0.257	4.073	0.000
RAT -> INN	0.168	3.340	0.001
TRL -> INN	-0.046	0.676	0.500

Table 9 presents the results of direct relationship hypothesis testing, including path strengths and corresponding p-values. The findings indicate that AI factors (AIF) significantly influence job performance (JOB), with a path strength of 0.232 and a p-value of 0.000. Similarly, Compatibility (COM) positively impacts Innovation (INN), with a path strength of 0.419 and a p-value of 0.000. The strongest relationship is observed between Innovation (INN) and Job Performance (JOB), with a path strength of 0.573 and a p-value of 0.000, underscoring the critical role of innovation in job performance. Other significant relationships include the positive impact of Complexity (LEX) on Innovation (INN) (path strength = 0.213, p-value = 0.000), Observability (OBS) on Innovation (INN) (path strength = 0.257, p-value = 0.000), and Relative Advantage (RAT) on Innovation (INN) (path strength = 0.168, p-value = 0.001). However, the relationship between Trialability (TRL) and Innovation (INN) is not significant, with a path strength of -0.046 and a p-value of 0.500. Additionally, the moderating effect of AIF on JOB is significant but negative, with a path strength of -0.049 and a p-value of 0.011. These results emphasize the importance of various constructs in shaping job performance and innovation, with most relationships being significant and positively contributing to the model. Regarding the conceptual model hypothesis, it was found Compatibility, Complexity, Relative Advantage, and Observability are directly significant, whereas Trialability is not.

4.2.6.2 Indirect Relationships

The detailed results of the hypothesis testing for these indirect relationships are presented in Table 10.

Table 10. Indirect relationships results

Indirect Relationship	Path Strength	T Statistics (|O/STDEV|)	P Values
COM -> INN -> JOB	0.240	5.455	0.000
LEX -> INN -> JOB	0.122	3.354	0.001
RAT -> INN -> JOB	0.096	3.202	0.001
TRL -> INN -> JOB	-0.027	0.659	0.510
OBS -> INN -> JOB	0.148	3.493	0.001

Table 10 presents the indirect relationships between constructs, detailing path strength values and corresponding p-values. The results indicate that the relationship between COM and JOB through INN is significant, with a path strength of 0.240 and a p-value of 0.000, reflecting a strong positive indirect effect. Likewise, LEX and JOB through INN show a significant positive indirect effect, with a path strength of 0.122 and a p-value of 0.001. The relationship between RAT and JOB through INN is also significant, with a path strength of 0.096 and a p-value of 0.001. Conversely, the relationship between TRL and JOB through INN is not significant, as evidenced by a path strength of -0.027 and a p-value of 0.510, which exceeds the significance threshold. Finally, OBS and JOB through INN exhibit a significant positive indirect effect, with a path strength of 0.148 and a p-value of 0.001. These findings confirm that all indirect relationships, except for TRL to JOB through INN, play a crucial role in influencing job performance through innovation. Regarding the conceptual model hypothesis, it was found that Compatibility, Complexity, Relative Advantage, and Observability are indirectly significant in influencing job performance through ICT innovation adoption, while Trialability is not significant.

4.2.7 Determine the Moderation Effects

Moderation effects can be classified into positive, negative, or no moderation, depending on whether the moderator enhances, weakens, or does not significantly alter the relationship between the independent and dependent variables. This study found that the AIF construct negatively moderates the relationship between innovation (INN) and job performance (JOB), with a path strength of -0.049 and a p-value of 0.020, indicating a slight negative effect [refer to Table 9]. These findings underscore the significance of various constructs in shaping job performance and innovation, with most relationships contributing positively to the model. Consequently, the AIF construct falls under negative moderation as it weakens the INN-JOB relationship. For instance, in the Abu Dhabi Police Traffic Department, the adoption of an AI-driven communication tool initially enhances innovation and job performance (Hair, Henseler, Ringle, & Sarstedt, 2022). However, the complexity of the AI tool moderates this relationship negatively, as employees may struggle to adapt, slightly reducing the expected performance gains. Despite this, innovation remains a significant factor in job performance, albeit with a minor negative moderation effect from AI technology (Frazier, Tix, & Barron, 2004). Regarding the conceptual model hypothesis (H3), which proposed that Artificial Intelligence positively moderates the relationship between innovation adoption in ICT and employees' job performance, the findings indicate a slight negative moderating effect, contradicting the initial assumption.

5. Conclusion

The study aimed to examine the moderating effect of artificial intelligence (AI) on the relationship between innovation in information and communication technology (ICT) and job performance. Utilizing SmartPLS 3 and the partial least squares (PLS) structural equation modelling (SEM) approach, two key assessments were conducted: the measurement model assessment and the structural model assessment. These assessments confirmed the model's reliability, validity, and overall fit, validating the conceptual framework in achieving the study's objectives. The predictive relevance analysis indicated that the constructs exhibited moderate to lower predictive relevance. In hypothesis testing, only one direct and one indirect relationship were found to be non-significant. The findings highlight the robustness of the model in analysing AI's moderating effect on ICT innovation and job performance within the Ministry. This study offers strategic insights into leveraging AI technologies to enhance job performance through innovative ICT solutions.

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