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Enhancing Organizational Performance with AI Technologies Through SEM-PLS Analysis in the UAE Ministry of Interior

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Abstract

This study utilizes the SEM-PLS technique in SmartPLS software to conduct a modelling analysis aimed at understanding the impact of various AI dimensions on Organizational Performance (OP) within the Ministry of Interior in the UAE. Data used was collected from 373 employees across different departments, using a simple random sampling technique to ensure representativeness. The analysis involved two main assessments: the measurement model assessment and the structural model assessment, carried out after the PLS Algorithm, bootstrapping, and blindfolding processes. The findings revealed that while Computer Vision (AIC) and Internet of Things (AII) had non-significant effects on OP, with path coefficients of 0.053 and -0.001 respectively, other AI dimensions such as Deep Learning (AID), Machine Learning (AIM), Robotics (AIO), Reinforcement Learning (AIR), and Training (TR) showed significant positive impacts. Their path coefficients were 0.226, 0.245, 0.126, 0.209, and 0.117, respectively. Moreover, the study found that OP significantly influences Satisfaction (OPS), Financial Performance (OPF), Productivity (OPP), and Quality (OPQ), with high path coefficients of 0.886, 0.946, 0.957, and 0.963, respectively. These results were used to establish an empirical framework to guide future implementations and enhancements within the Ministry. This framework offers strategic insights for leveraging AI technologies to improve operational efficiency, public satisfaction, financial sustainability, and service quality within the Ministry of Interior in the UAE.

Keyword: Artificial Intelligence, Organizational Performance, SEM-PLS Analysis

1. Introduction

Organizational performance encompasses both financial and non-financial aspects, including industry acceptance, and is defined by the ability to outperform competition and operate effectively and efficiently (IGI, 2019; Taouab & Issor, 2019; Verboncu & Zalman, 2020). Public sectors in the UAE face significant challenges, with performance issues such as poor communication, project delays, lack of accountability, and inefficiency being prevalent. This has resulted in below-average government performance and declining results in governance-related categories over the past decade (Rahman & Said, 2015; AlJaberi, 2019).

Public companies in the UAE face challenges with performance management and assessment systems, leading to poor goal setting and decision-making (Deloitte, 2016). The Deloitte report and a study by the UAE Ministry of Cabinet Affairs and the Future recommend that these entities adopt performance management systems with precise measures and a results-oriented approach, focusing on specific goals, progress tracking, and data-driven decisions (UAE Government, 2018). This shift can enhance their effectiveness and ability to achieve strategic objectives.

The UAE's government effectiveness and related indicators have declined from 2010 to 2020, impacting public perception and trust (Worldwide Governance Indicators, 2020). A recent survey revealed significant dissatisfaction among UAE citizens with government performance, including the handling of Covid-19 and public services like health and education (Arab Barometer, 2020). This situation underscores the urgency for reforms to improve public sector performance and governance in the Middle East and Northern Africa region.

To effectively implement public administration reform, it is crucial to examine how the system currently operates and identify potential long-term benefits on overall government effectiveness and service delivery. Key aspects to consider include merit-based hiring and promotion decisions, comprehensive training and capacity development programs, integration of advanced technology, and robust staff performance monitoring and management (Rahman & Said, 2015; AlJaberi, 2019). These elements are essential for creating a more efficient and effective public administration, ultimately enhancing service delivery and public trust in government operations.

Several Middle East and Northern Africa (MENA) countries, including the UAE, continue to perform poorly on various governance indicators. According to the V-Dem Institute, public sector recruitment in the MENA region is still heavily influenced by political affiliation and socioeconomic status rather than merit. In 2020, the average scores for socioeconomic status and access to state jobs were 1.6 and 1.8 out of 4, respectively, indicating that many qualified individuals are excluded from public employment opportunities.

The Gulf Cooperation Council (GCC) countries have seen exponential economic growth over the past decade, placing them among the wealthiest nations globally. This growth has allowed countries like the UAE to invest in world-class infrastructure, hotels, cities, and other significant projects. However, this rapid development has led to an extensive reliance on foreign labour, with 85 percent of the UAE's workforce and population consisting of expatriates (Northouse, 2013). This dependence is unsustainable and poses a risk, as disruptions in the international labour market could severely impact the country. Local workers are often unwilling or unable to take on the roles filled by immigrants, leading to a reliance on cheaper and skilled foreign labour (Looney, 2004). The heavy dependence on foreign workers is problematic, especially given the importance of a domestic workforce in achieving long-term sustainable economic growth. In response, the UAE government has implemented the Emiratisation programme, which aims to increase the proportion of native workers in both private and public sectors while reducing reliance on foreign labour. Despite these efforts, challenges persist due to the country's current people management practices.

Organizational performance can be gauged by a company's competitive strategy and its effective utilization of resources to create value and dominate its market. Researchers have identified a range of variables that affect organizational success, including strategic planning, leadership, and a commitment to excellence (Sergio et al., 2017). Recently, academics have highlighted that artificial intelligence (AI) significantly contributes to improving organizational effectiveness (Amer et al., 2019).

AI, a rapidly evolving field that interests societies globally, is expected to play a crucial role in the future, especially within security systems (Zoheir, 2019). It focuses on creating tools that simulate intelligent human behaviour. In the UAE, security services heavily rely on intelligence techniques, and many organizations utilize AI in economics, medicine, engineering, military, and other fields to achieve strategic goals through data processing.

Despite efforts by UAE governmental institutions, particularly the Ministry of Interior, to integrate AI across all activities, various challenges persist. These include issues with system suitability, development of necessary AI technology, and the use of tools and technologies that enhance decision-making, save time, and improve quality (Alhashmi et al., 2019). Such challenges pose threats to organizational success (Mikalef et al., 2021).

The underutilization of AI and insufficient training for organizational staff significantly impact the performance of the UAE's Ministry of Interior (Wamba-Taguimdje et al., 2020; Olan et al., 2022). Additionally, the Ministry faces unique data management issues compared to other UAE organizations, as AI has increasingly complicated data collection and storage processes over time (Allozi et al., 2022).

Ironically, the reluctance to entirely remove humans from the AI decision-making process creates a grey area, complicating accountability. The General Data Protection Regulation (GDPR), for example, has protections against automated decision-making, but these apply only to decisions "based exclusively on automated processing." Consequently, many AI systems incorporating human decision-making might not be considered solely automated, which could affect accountability measures. In the UAE, AI system accountability could independently influence the skilled employee growth objection.

Several studies suggest that training does not mediate the relationship between AI and organizational effectiveness (Allozi et al., 2022). For instance, Para-González et al. (2018)

explored the mediating effects of transformative leadership and organizational performance, while Prentice et al. (2020) examined AI and employee service to engage and retain customers. Despite the UAE Ministry of Interior's (MOI) active adoption of AI to enhance operational efficiency, the mediating role of training in this relationship remains largely unexplored (Almarashdeh, Al-Omoush, & Al-Zu'bi, 2021). This study aims to address this gap by investigating training's mediating effects on the relationship between AI and organizational performance, offering insights for maximizing AI benefits within the MOI.

Although literature emphasizes AI's positive impact on organizational performance across industries, studies on the mediating role of training are scarce (Sinha & Sharma, 2019). Training is crucial for equipping employees with the skills and knowledge to effectively utilize AI technologies. By examining training's mediating effects, this study aims to reveal how AI implementation can enhance organizational performance within the MOI.

2. Literature Review Related to Framework

2.1 Organizational Performance

The Ministry of Interior (MoI) in the United Arab Emirates (UAE) has been at the forefront of leveraging Artificial Intelligence (AI) to enhance its organizational performance. The MoI's strategy for 2023–2026, launched by Lt. Gen. H.H Sheikh Saif bin Zayed Al Nahyan, Deputy Prime Minister and Minister of Interior, outlines a vision to make the UAE the best country in the world in achieving safety and security. The strategy focuses on adopting advanced technology in modern crime prevention, enabling safe road navigation, promoting technology in safety and civil protection, and achieving preparedness in crisis and disaster management (UAE Government, 2024a). Effective leadership is a critical determinant in the success of Total Quality Management (TQM) within the MoI. Leadership sets the culture necessary for TQM to flourish, empowering workers, improving hierarchical culture, and fostering collaboration to reach organizational objectives (UAE Government, 2024b). According to Alnuaimi and Yaakub (2023), leadership practices significantly contribute to the MoI's performance.

The MoI has embraced technology and innovation as key components of its strategy. By integrating advanced technologies in crime prevention and traffic management, the MoI has enhanced its operational efficiency and responsiveness(UAE Government, 2024a). This proactive approach has contributed to a safer and more secure environment for the UAE community. Effective human resource management is another factor contributing to the MoI's performance (Alnuaimi & Yaakub, 2023). The MoI focuses on attracting and empowering the best human talents, providing efficient and effective institutional services, and promoting innovation practices based on flexibility and proactivity (UAE Government, 2024a). This approach ensures that the MoI remains agile and capable of responding to emerging challenges. The MoI's preparedness and readiness in managing crises and disasters are critical to its performance. By adopting modern techniques and technologies in safety and civil protection, the MoI has achieved a high level of preparedness, ensuring a swift and effective response to emergencies (UAE Government, 2024a). The Ministry of Interior UAE has demonstrated a strong commitment to enhancing its organizational performance through strategic vision, effective leadership, technology and innovation, human resource management, and crisis and disaster management. These factors have collectively contributed to the MoI's success in achieving its goals and maintaining the safety and security of the UAE (UAE Government, 2024a).

2.2 AI impacting on Organizational Performance

Artificial Intelligence (AI) has become a transformative force in modern business, driving significant improvements in organizational performance across various industries (Aljuhmani and Neiroukh, 2024). This article explores the positive impacts of AI on organizational performance, supported by recent research and case studies. One of the most notable benefits of AI is its ability to enhance efficiency and productivity. By automating repetitive and mundane tasks, AI allows employees to focus on more strategic and creative activities. This not only increases overall productivity but also reduces the likelihood of human error (Harvard Business School Online, 2024). According to a study by Manyika et al. (2018), AI has the potential to add $3.5 trillion to $5.8 trillion to the global economy by 2030, primarily through productivity gains.

AI significantly improves decision-making processes within organizations. By analyzing large volumes of data and providing actionable insights, AI enables managers to make more informed and timely decisions. This is particularly important in dynamic and competitive environments where quick decision-making can be a critical advantage (Wamba-Taguimdje, et.al., 2020). Research by Neiroukh et al. (2024) highlights that AI capabilities positively affect decision-making speed and quality, leading to enhanced organizational performance. AI fosters a culture of innovation by providing tools that enhance creative processes. Organizations that leverage AI capabilities can develop new products, services, and business models more efficiently. This creative competency is a strategic asset that can lead to competitive advantages in the market. The study by Aljuhmani and Neiroukh (2024) confirms that AI capabilities enhance organizational creativity, which in turn positively impacts performance.

AI offers several ways to reduce operational costs. By optimizing supply chain management, improving resource allocation, and reducing waste, organizations can achieve significant cost savings. Additionally, AI-driven predictive maintenance can prevent costly equipment failures and downtime. AI improves customer experience by enabling personalized interactions and faster response times. Through AI-powered chatbots and customer service tools, organizations can provide 24/7 support and tailored solutions to their clients. This leads to higher customer satisfaction and loyalty, which are crucial for long-term success (Harvard Business School Online, 2024). The integration of AI into organizational processes has a profound positive impact on performance. By enhancing efficiency, improving decision-making, fostering innovation, reducing costs, and enhancing customer experience, AI serves as a powerful tool for achieving sustainable business growth. As organizations continue to adopt AI technologies, it is essential to invest in training and development to fully realize these benefits (Neiroukh, et.al., 2024).

2.3 Effective AI Training for Organizational Performance

The integration of Artificial Intelligence (AI) into organizational processes has become a game-changer for enhancing performance and productivity. However, the successful implementation of AI technologies hinges on effective training programs that equip employees with the necessary skills and knowledge. Training is a critical component in bridging the AI skills gap within organizations. As AI technologies evolve, employees need to be up-to-date with the latest advancements and applications (Alnuaimi, & Yaakub, 2023). According to New Horizons (2024), targeted training programs can address skills gaps at every level of the organization, from technical understanding to strategic application. This ensures that employees are well-prepared to harness the full potential of AI technologies. One of the key benefits of AI in training is the ability to create personalized learning pathways. AI-powered training solutions can tailor the learning experience to the unique preferences and goals of each employee, addressing specific skill gaps and career development aspirations. This personalized approach not only enhances employee engagement but also leads to better learning outcomes and improved performance (New Horizons, 2024).

AI can provide consistent, actionable feedback that aids in immediate performance calibration. Unlike traditional annual reviews, AI-driven feedback mechanisms allow employees to make instant course corrections, fostering a culture of continuous improvement. This real-time feedback is instrumental in enhancing employee performance and organizational efficiency. AI's ability to forecast employee performance trends is another significant advantage. By analysing historical and current data, AI models can predict potential improvements or identify areas susceptible to underperformance. These insights are crucial for resource allocation and strategic planning, enabling organizations to proactively address performance issues and optimize their workforce (SHRM, 2024). While the benefits of AI training are substantial, there are also challenges that organizations must navigate. Data privacy and ethics are significant concerns, particularly regarding employee privacy. Organizations must be transparent about the data they collect, how it is analysed, and the implications for their employees. Additionally, fostering a supportive learning environment and encouraging employee engagement are essential for the successful adoption of AI technologies (Alnuaimi, & Yaakub, 2023; SHRM, 2024). The training is a vital component in effectively utilizing AI technologies for organizational performance. By creating personalized learning pathways, providing real-time feedback, and leveraging predictive analytics, organizations can enhance employee performance and drive overall efficiency. However, addressing challenges such as data privacy and fostering a supportive learning environment is crucial for successful AI adoption (SHRM, 2024).

2.4 Formulation of Conceptual Model

The conceptual framework model of this study integrates various AI dimensions and training to influence Satisfaction (OPS), Financial Performance (OPF), Productivity (OPP), and Quality (OPQ) through Organizational Performance (OP). The independent constructs encompass Computer Vision (AIC), Deep Learning (AID), Internet of Things (AII), Machine Learning (AIM), Natural Language Processing (AIN), Robotics (AIO), Reinforcement

Learning (AIR), and Training (TR) (Goodfellow, Bengio, & Courville, 2016; LeCun, Bengio, & Hinton, 2015; Russell & Norvig, 2016). Serving as the intermediary construct, Organizational Performance (OP) bridges the relationship between the independent variables (AI dimensions and training) and the dependent variables (Satisfaction, Financial Performance, Productivity, and Quality).

This conceptual framework is grounded in causal relationship theory, positing that advancements in AI dimensions causally influence organizational performance, which in turn affects the dependent constructs. By applying causal relationship theory, the model suggests that improvements in AI capabilities lead to enhanced organizational outcomes through both direct and mediated effects (Baron & Kenny, 1986). Moreover, the Technology-Organization-Environment (TOE) Framework offers a theoretical basis for understanding the adoption and impact of AI technologies within the organization (Tornatzky & Fleischer, 1990). According to the TOE Framework, technological factors (such as AI dimensions), organizational factors (like employee training and empowerment), and environmental factors (including market demands and competitive pressures) interact to influence the implementation and effectiveness of AI initiatives. Through combining causal relationship theory with the TOE Framework, the model demonstrates that AI dimensions directly impact Organizational Performance (OP), which then influences Satisfaction (OPS), Financial Performance (OPF), Productivity (OPP), and Quality (OPQ). The interaction of these factors provides a deeper understanding of the intricate causal dynamics that underlie AI implementation and its effects on various aspects of organizational performance. By explicitly mapping out the causal paths and relationships, the study offers robust evidence on how AI dimensions and employee training work synergistically to drive Organizational Performance (OP). This approach highlights not only the direct effects of AI technologies but also the extended impact on satisfaction, financial performance, productivity, and quality through organizational performance.

In essence, this conceptual framework as Figure 1 leverages causal relationship theory and the TOE Framework to dissect and comprehend the mechanisms through which AI influences performance. By examining both the direct and indirect causal pathways, the study provides a comprehensive view of how AI dimensions, coupled with employee training, create a dynamic interplay that ultimately enhances organizational outcomes. This deeper engagement with these theories ensures that the study's findings are grounded in a rigorous understanding of the cause-and-effect relationships that drive organizational success.

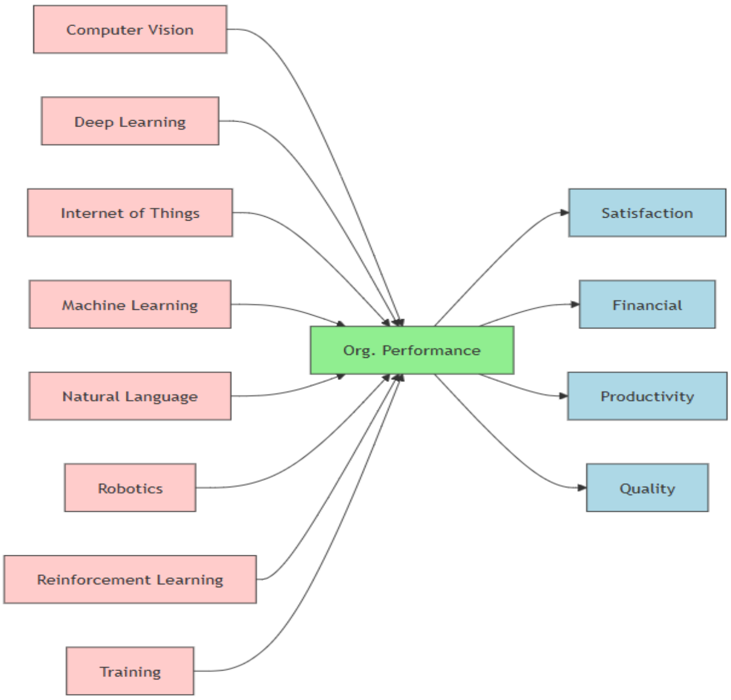

Figure 1. Conceptual framework

3. Modelling of the Conceptual Framework

To validate the conceptual framework, this study conducted a modelling analysis using the SEM-PLS technique in SmartPLS software. Data for this modelling was collected from 373 employees across various departments within the Ministry of Interior in the UAE. These departments include the General Directorate of Residency and Foreigners Affairs, the Federal Traffic Council, the Federal Authority for Identity and Citizenship, the Federal Law Execution Department, the Directorate General of Punitive and Correctional Institutions, the Federal Intelligence Agency, and the Directorate General of Naturalization, Residency, and Ports. The survey utilized a simple random sampling technique to ensure a representative sample. The modelling analysis involved two key assessments which are the measurement model assessment and the structural model assessment. These assessments were performed after completing three critical processes that are the PLS Algorithm, bootstrapping, and blindfolding. This approach ensured a thorough evaluation of the model's reliability, validity, and predictive relevance.

The measurement model assessment evaluates the reliability and validity of the constructs using key criteria. Indicator reliability is measured by the loadings of each indicator on its associated construct, with a threshold of greater than 0.70 (Hair et al., 2014). Internal consistency reliability is assessed using Composite Reliability (CR) and Cronbach’s Alpha, both of which should be greater than 0.70 (Nunnally & Bernstein, 1994). Convergent validity is evaluated through the Average Variance Extracted (AVE), which should exceed 0.50 (Fornell & Larcker, 1981). Discriminant validity is assessed using the Fornell-Larcker

Criterion, where the square root of AVE for each construct should be greater than the correlation with any other construct (Fornell & Larcker, 1981), and the Heterotrait-Monotrait Ratio (HTMT), which should be below 0.90 (Henseler, Ringle, & Sarstedt, 2015).

The structural model assessment evaluates the relationships between constructs using key criteria. The significance of path coefficients is assessed with a typical threshold of a t-value greater than 1.96, indicating significance at the 0.05 level (Hair et al., 2014). Coefficient of Determination (R^2) values indicate the amount of variance explained by the independent variables, with values of 0.75, 0.50, and 0.25 considered substantial, moderate, and weak, respectively (Hair et al., 2014). Effect size (f^2) measures the impact of an independent variable on a dependent variable, with values of 0.02, 0.15, and 0.35 representing small, medium, and large effects, respectively (Cohen, 1988). Predictive relevance (Q^2) values greater than zero indicate the model has predictive relevance (Geisser, 1974; Stone, 1974). Model fit is assessed with the Standardized Root Mean Square Residual (SRMR) value, which should be below 0.08 to indicate a good fit (Hu & Bentler, 1999).

By fulfilling these criteria, the study ensures that the model is robust and capable of providing reliable and valid results. The use of the PLS Algorithm, bootstrapping, and blindfolding processes further enhances the rigor of the analysis, ensuring confidence in the findings related to the impact of AI dimensions and training on organizational performance.

3.1 Reliability and Convergent Validity of the Measurement Models

In Partial Least Squares Structural Equation Modelling (PLS-SEM), composite reliability is often considered the most reliable measure. Hair et al. (2014) highlight two primary reasons for its preference. First, composite reliability does not assume equal loadings for all indicators, which is a limitation of Cronbach's alpha. Instead, it aligns with the PLS-SEM algorithm that treats indicators according to their respective reliabilities during estimation. Second, composite reliability overcomes Cronbach's alpha's sensitivity to the number of items in a scale, which can lead to the underestimation of internal consistency reliability (Hair et al., 2014; Memon & Rahman, 2013).

Additionally, other reliability measures such as Cronbach's alpha and rho_A are used to provide a comprehensive check on reliability. A measurement model is considered reliable if Cronbach's alpha, composite reliability, and rho_A values are at least 0.7, though 0.6 is acceptable for newly developed scales (Nunnally, 1978; DeVellis, 2003; Wong, 2013; Hair et al., 2011). Convergent validity in reflective measurement models evaluates their ability to explain the variance in their indicators. This validity is defined by Hair et al. (2014) as the degree to which an indicator correlates with other indicators of the same construct. Assessment of convergent validity involves examining item factor loadings and their significance, the Average Variance Extracted (AVE), and the number of iterations required for model convergence (Jeo F Hair et al., 2014; Joe F Hair et al., 2011).

The results of the convergent validity and reliability check for the first run of the PLS model are crucial for establishing the robustness and efficacy of the measurement model (Wong, 2016). These evaluations ensure that the model accurately captures the underlying constructs it is intended to measure and that the relationships between indicators and constructs are reliable and valid.

Table 1. Results of reliability and convergent validity

Constructs	Code	Factor Loadings	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Computer Vision	AIC	0.869	0.938	0.938	0.953	0.802
Deep Learning	AID	0.902	0.881	0.882	0.920	0.744
Internet Things	AII	0.935	0.919	0.947	0.940	0.758
Machine Learning	AIM	0.936	0.959	0.959	0.968	0.859
Natural Language	AIN	0.906	0.947	0.947	0.960	0.826
Robotics	AIRO	0.876	0.908	0.908	0.935	0.783
Reinforcement Learning	AIR	0.888	0.940	0.941	0.954	0.806
Organisational Performance	OP	0.731	0.974	0.975	0.976	0.670
Satisfaction	OPS	0.791	0.894	0.897	0.922	0.704
Financial	OPF	0.855	0.943	0.944	0.956	0.813
Productivity	OPP	0.826	0.892	0.896	0.921	0.700
Quality	OPQ	0.902	0.944	rho_A	0.957	0.817
Training	TR	0.887	0.974	0.938	0.977	0.810

Table 1 shows that all constructs exhibit high reliability and validity in the PLS-SEM model. Most constructs have factor loadings above 0.85 and composite reliability values above 0.9, indicating strong internal consistency. Cronbach's alpha and rho_A values are generally above 0.7, confirming the reliability. The Average Variance Extracted (AVE) for all constructs is also high, supporting good convergent validity. These metrics confirm the robustness and effectiveness of the measurement model.

3.2 Discriminant Validity

Discriminant validity measures the distinctiveness of measurement models from other research constructs. It evaluates how unique a particular measurement model is within the structural model (Memon & Rahman, 2013). Traditionally, discriminant validity has been assessed using the Fornell-Larcker criterion and the cross-loading criterion. Recently, the Heterotrait-Monotrait (HTMT) criterion has gained theoretical and empirical support for assessing discriminant validity (Henseler, Ringle, & Sarstedt, 2015).

The HTMT ratio is the average of the heterotrait-hetero method correlations (correlations of indicators across different constructs) relative to the monotrait-hetero method correlations (correlations of indicators within the same construct) (Henseler et al., 2015). Discriminant validity is achieved if the HTMT ratio is less than 0.85, or more liberally, less than 0.9 (Henseler et al., 2015).

The Fornell-Larcker criterion requires the square root of the Average Variance Extracted

(AVE) of each measurement model to be greater than its correlation with any other model in the structural model. In other words, the square root of the AVE of each outer model should be higher than its correlation with any other construct (Hair et al., 2014). This research used these discriminant validity assessment criteria to establish the distinctiveness of each measurement model, as presented in Tables 2 and 3.

Table 2. Heterotrait-Monotrait (HTMT)

	AIC	AID	AII	AIM	AIN	AIRO	AIR	OP	OPS	OPF	OPP	OPQ	TR
AIC													
AID	0.752												
AII	0.149	0.077											
AIM	0.689	0.799	0.035										
AIN	0.745	0.798	0.053	0.845									
AIRO	0.613	0.596	0.108	0.664	0.728								
AIR	0.708	0.809	0.068	0.731	0.822	0.614							
OP	0.745	0.865	0.073	0.842	0.842	0.697	0.825						
OPC	0.761	0.807	0.045	0.846	0.814	0.611	0.817	0.858					
OPF	0.698	0.791	0.105	0.777	0.818	0.696	0.762	0.883	0.813				
OPP	0.740	0.873	0.046	0.852	0.826	0.692	0.831	0.821	0.857	0.826			
OPQ	0.685	0.785	0.080	0.785	0.797	0.692	0.782	0.801	0.835	0.883	0.879		
TR	0.772	0.812	0.111	0.797	0.851	0.608	0.762	0.813	0.773	0.774	0.814	0.784	

Table 2 shows the assessment of discriminant validity using HTMT criterion. The result shows that the highest HTMT ratio value of 0.883 is between OPF and OP which is less than the maximum liberal value of 0.9 (Henseler et al., 2015). The HTMT between AIM and AII have value of 0.035 is also below the maximum liberal value of 0.9. The remaining HTMT ratios are below the recommended maximum conservative value of 0.9 (Henseler et al., 2015). Thus, the measurement models achieve discriminant validity through HTMT criterion.

According to Fornell and Larcker (1981), items should share more variance with their underlying construct than with other constructs. This means that the square root of the Average Variance Extracted (AVE) for each measurement model should be greater than its correlation with any other construct in the structural model (Hair et al., 2014).

Table 3. Fornell and Larcker

	AI	**AID**	**AII**	**AIM**	**AIN**	**AIRO**	**AIR**	**OP**	**OPS**	**OPF**	**OPP**	**OPQ**	**TR**
AIC	*0.896*												
AID	0.683	*0.863*											
AII	0.138	0.066	*0.871*										
AIM	0.654	0.735	0.026	*0.927*									
AIN	0.703	0.729	0.046	0.806	*0.909*								
AIRO	0.566	0.533	0.099	0.620	0.675	*0.885*							
AIR	0.665	0.737	0.063	0.695	0.776	0.567	*0.898*						
OP	0.709	0.798	0.068	0.811	0.807	0.657	0.788	*0.818*					
OPC	0.696	0.805	0.032	0.783	0.748	0.550	0.750	0.886	*0.839*				
OPF	0.657	0.721	0.101	0.739	0.772	0.645	0.717	0.946	0.747	*0.902*			
OPP	0.676	0.772	0.039	0.787	0.757	0.623	0.761	0.957	0.850	0.852	*0.837*		
OPQ	0.645	0.715	0.076	0.747	0.754	0.641	0.737	0.963	0.767	0.929	0.901	*0.904*	
TR	0.739	0.751	0.105	0.770	0.818	0.571	0.730	0.792	0.721	0.742	0.760	0.752	*0.900*

The assessment of discriminant validity using Fornell and Larcker criterion is presented in Table 3. The diagonally italicised values are the square roots of the AVEs of the measurement models. The values beneath the diagonal are correlations between the measurement models. The result shows that none of the measurement models has correlation with any other measurement model more than the square root of its AVE. Therefore, the measurement models achieved the required discriminant validity based on Fornell and Larcker criterion

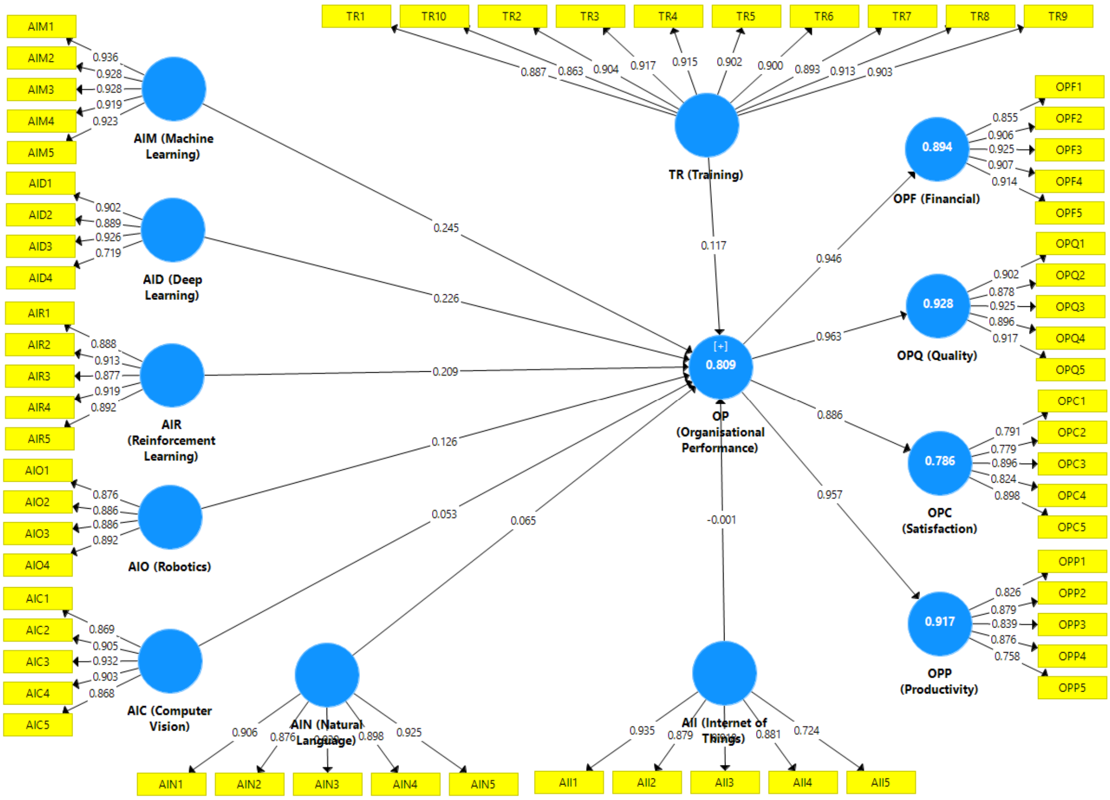

Figure 2. PLS Model

3.3 Path Relationship Analysis

Path relationship analysis is essential for understanding the connections and causal effects between variables in a model. Following hypothesis testing using the bootstrapping process in the software, the resulting path coefficients, which reflect the strength of the relationships, along with their significance based on T-statistics values (Hair et al., 2014; Kock, 2014), are detailed in Table 4.

Table 4. Results of path relationship

Path Relationship	Path Coefficient	T Statistics > 1.96	Remark
AIC (Computer Vision) -> OP (Org. Performance)	0.053	1.280	Not Significant
AID (Deep Learning) -> OP (Org. Performance)	0.226	4.221	Significant
AII (Internet of Things) -> OP (Org. Performance)	-0.001	0.053	Not Significant
AIM (Machine Learning) -> OP (Org. Performance)	0.245	4.442	Significant
AIN (Natural Language) -> OP (Org. Performance)	0.065	0.872	Not Significant
AIO (Robotics) -> OP (Org. Performance)	0.126	2.827	Significant
AIR (Reinforcement Learning) -> OP (Org. Performance)	0.209	3.756	Significant
TR (Training) -> OP (Org. Performance)	0.117	2.187	Significant
OP (Org. Performance) -> OPS (Satisfaction)	0.886	68.619	Significant
OP (Org. Performance) -> OPF (Financial)	0.946	151.417	Significant
OP (Org. Performance) -> OPP (Productivity)	0.957	152.075	Significant
OP (Org. Performance) -> OPQ (Quality)	0.963	237.125	Significant

Table 4 summarizes the path relationships, path coefficients, T-statistics, and their significance for various AI dimensions and organizational performance metrics within the Ministry of Interior in the UAE. Specifically, it shows that Computer Vision and Internet of Things did not significantly affect Organizational Performance (OP), as indicated by their low path coefficients of 0.053 and -0.001, and T-statistics below the threshold of 1.96. In contrast, Deep Learning, Machine Learning, Robotics, Reinforcement Learning, and Training exhibited significant positive impacts on OP. The path coefficients for these relationships were 0.226, 0.245, 0.126, 0.209, and 0.117, respectively, with T-statistics well above 1.96, marking them as significant. On the other hand, Natural Language did not have a significant impact on OP, as its path coefficient was 0.065 and its T-statistic was below 1.96.

Furthermore, the analysis revealed that OP has a significant influence on Satisfaction, Financial Performance, Productivity, and Quality. The path coefficients for these relationships were notably high, with values of 0.886, 0.946, 0.957, and 0.963, respectively. The T-statistics for these paths were exceptionally high, demonstrating strong direct effects. Overall, this detailed analysis highlights which AI dimensions are most impactful for enhancing organizational performance and associated outcomes within the Ministry, providing valuable insights for strategic decision-making and improving operational processes.

3.4 Quality of the Model by R^2

The quality of a model is often represented by the R square (R^2) value. This value indicates the proportion of variance in the dependent variable that is accounted for by the independent variables. In essence, it measures how well the independent variables explain the changes in the dependent variable. High R^2 values suggest that the model possesses strong explanatory power and effectively captures the variance in the dependent constructs (Hair et al., 2017; Henseler et al., 2015).

Table 5. R^2 value of the model

Endogenous construct	R Square
OP (Organisational Performance)	0.809
OPC (Satisfaction)	0.786
OPF (Financial)	0.894
OPP (Productivity)	0.917
OPQ (Quality)	0.928

Table 5 provides the R^2 values for several endogenous constructs within the model, illustrating the proportion of variance in each dependent variable that is explained by the independent variables. These R^2 values serve as a measure of the model's explanatory power. Organizational Performance (OP) acts as an intermediary construct in the model. With an R^2 value of 0.809, the model accounts for 80.9% of the variance in OP. This suggests that the independent variables have a strong influence on OP, which in turn explains its effectiveness as an intermediary construct.

Satisfaction (OPC), Financial Performance (OPF), Productivity (OPP), and Quality (OPQ) are all dependent constructs whose explanatory power is derived from OP. The R^2 value for Satisfaction (OPC) is 0.786, indicating that 78.6% of its variance is explained by the model. This highlights a robust relationship where OP effectively mediates the influence of the independent variables on Satisfaction. For Financial Performance (OPF), the model explains 89.4% of its variance, as shown by the high R^2 value of 0.894, reflecting a very strong explanatory capacity. Similarly, Productivity (OPP) has an R^2 value of 0.917, meaning that 91.7% of the variance in Productivity is accounted for by the model. This demonstrates excellent explanatory power regarding productivity outcomes.

Finally, Quality (OPQ) has the highest R^2 value at 0.928, indicating that 92.8% of its variance is explained by the model. This underscores the model's strong capability to capture the factors influencing Quality, with OP serving as an effective intermediary construct that helps explain these relationships. Overall, these high R^2 values across different constructs confirm that the model is highly effective in explaining the variance in the dependent constructs, supporting the robustness and validity of the proposed relationships.

3.5 Predictive Relevance (Q^2) Assessment

The predictive relevance of a structural model is assessed using cross-validated redundancy. This is evaluated through Stone-Geisser's predictive relevance (Q^2), which tests whether the data points of all indicators in the outer model of endogenous constructs are predicted accurately (Wong, 2016). This approach employs a sample re-use technique that omits part of the data matrix, estimates the model parameters, and predicts the omitted part using those estimates (Hair et al., 2011; Hair et al., 2014). For a model to have effective predictive relevance, the cross-validated redundancy (Q^2) value must be a positive integer above 0 (Chin, 1998). Based on this premise, the structural model of the study was evaluated to determine its cross-validated redundancy (Q^2) using the blindfolding procedure with the aid of SmartPLS3 software (Ringle, Wende, & Becker, 2015). The results of the blindfolding procedure are presented in Table 6.

Table 6. Cross-validated redundancy (Predictive relevance, Q^2)

	SSO	SSE	Q^2 (=1-SSE/SSO)
AI (Artificial Intelligence)	12408.000	12408.000	
AIC (Computer Vision)	1880.000	836.350	
AID (Deep Learning)	1504.000	703.976	
AII (Internet of Things)	1880.000	1865.673	
AIM (Machine Learning)	1880.000	616.967	
AIN (Natural Language)	1880.000	570.131	
AIO (Robotics)	1504.000	846.557	
AIR (Reinforcement Learning)	1880.000	737.765	
OP (Organisational Performance)	7520.000	3541.196	0.529
OPC (Satisfaction)	1880.000	850.383	0.548
OPF (Financial)	1880.000	521.528	0.723
OPP (Productivity)	1880.000	681.088	0.638
OPQ (Quality)	1880.000	464.168	0.753
TR (Training)	3760.000	1526.102	0.594

Table 6 presents the cross-validated redundancy (Q^2) values, which indicate the predictive relevance of various constructs within the model. The table includes the Sum of Squares of Observations (SSO), Sum of Squares of Prediction Errors (SSE), and the calculated Q^2 value for each construct. A positive Q^2 value above 0 suggests that the model has predictive relevance. It is important to note that Q^2 values for cross-validated redundancy only appear for the endogenous constructs. Therefore, the Q^2 values for Organizational Performance (0.529), Satisfaction (0.548), Financial Performance (0.723), Productivity (0.638), Quality

(0.753), and Training (0.594) indicate strong predictive relevance, confirming the model's capability to predict these constructs effectively. On the other hand, constructs without a Q^2 value listed (such as AI) or with SSO equal to SSE do not show predictive relevance. Thus, the high Q^2 values demonstrate that the model possesses substantial predictive relevance for the key dependent constructs, thereby validating the robustness and efficacy of the structural model.

4. Empirical Framework

The empirical framework is essentially the conceptual framework that has been validated using data in a rigorous statistical manner. This involves gathering relevant data, employing appropriate statistical methods, and analysing the data to confirm the relationships and hypotheses proposed in the conceptual framework. The empirical validation provides robust evidence and confidence in the theoretical constructs, ensuring that the findings are both reliable and valid. This rigorous process transforms theoretical models into practical insights that can be applied to real-world situations, enhancing their relevance and utility (Hair et al., 2014; Nunnally & Bernstein, 1994). In the context of this study, the results from the modelling analysis presented in the earlier section are used to establish the empirical framework as shown in Figure 3.

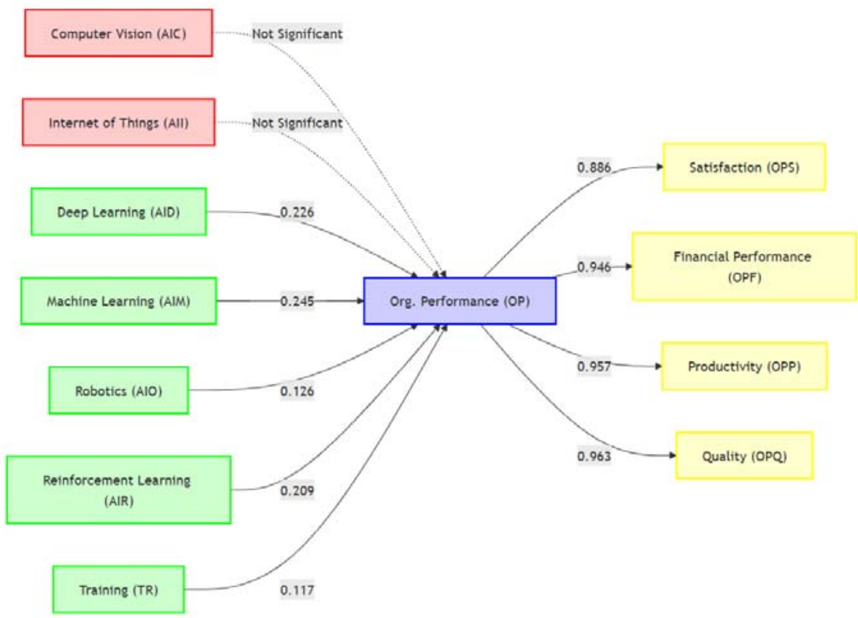

Figure 3. Empirical Framework

The framework illustrated in Figure 3 demonstrates that key elements such as Deep Learning, Machine Learning, Robotics, and Reinforcement Learning can significantly enhance various aspects of the Ministry of Interior's functions in the UAE. For example, Deep Learning, with a path coefficient of 0.226, and Machine Learning, with a path coefficient of 0.245, can be employed to improve decision-making processes in areas such as crime analysis and traffic management. Similarly, Reinforcement Learning, with a path coefficient of 0.209, could be used to optimize resource allocation or enhance surveillance systems, while Robotics, with a path coefficient of 0.126, can support automation in emergency response, patrolling, and border security operations.

Furthermore, the incorporation of Training, with a path coefficient of 0.117, ensures that staff are equipped with the necessary skills to effectively utilize these technologies, fostering a culture of innovation and continuous improvement. However, it is important to note that Computer Vision and Internet of Things were not found to have a significant relationship with Organizational Performance (OP) as hypothesized. This shortfall may be due to several factors, such as the collected data not being strong enough to establish a significant relationship or implementation challenges.

Ultimately, the primary goal of improving Organizational Performance (OP) ties directly to the Ministry’s key performance indicators, such as operational efficiency, public satisfaction, financial sustainability, and service quality. By leveraging these AI dimensions, the Ministry can significantly enhance its operations and services. For instance, even though the Internet of Things (IoT) did not show a significant impact in this study, it can still be used to enable real-time monitoring of public spaces, enhancing situational awareness and safety…

5. Conclusion

In summary, this study applied the SEM-PLS technique using SmartPLS software to investigate the influence of various AI dimensions on Organizational Performance (OP) within the Ministry of Interior in the UAE. Data was gathered from 373 employees across different departments, ensuring a representative sample through simple random sampling. The analysis comprised two main assessments: measurement model assessment and structural model assessment, following the implementation of the PLS Algorithm, bootstrapping, and blindfolding processes. The results indicated that Computer Vision and Internet of Things did not significantly impact OP. In contrast, Deep Learning, Machine Learning, Robotics, Reinforcement Learning, and Training were shown to positively and significantly affect OP. Moreover, the study revealed that OP has a significant influence on Satisfaction, Financial Performance, Productivity, and Quality. These insights were instrumental in developing an empirical framework to guide future strategies and improvements within the Ministry. This framework provides valuable strategic guidance for the Ministry to harness AI technologies effectively, aiming to enhance operational efficiency, public satisfaction, financial sustainability, and service quality within the UAE's Ministry of Interior.

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