International Journal of Social Science Research
ISSN 2327-5510
2025, Vol. 13, No. 3

# Mediating Function of Organisational Culture in the UAE's Artificial Intelligence Innovation in HRM and Public Organisational Performance

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Received: August 23, 2025 Accepted: Nov. 2, 2025 Published: Nov. 11, 2025
doi:10.5296/ijssr.v13i3.23315 URL: https://doi.org/10.5296/ijssr.v13i3.23315

**Abstract**

Human Resource Management is essential to any organisation. Technological advancements that enhance its functionality continuously drive its evolution. This study focusses on AI innovation in human resource management within government agencies in the UAE. This study analyses the impact of AI HRM innovation characteristics on the performance of public organisations, evaluates the mediating influence of organisational culture, and presents a framework to enhance AI HRM efficacy in UAE public entities. Data were gathered from decision-makers of public organisations in the UAE for this quantitative study. SPSS was utilised for data cleaning and the initial research objective, whereas PLS-SEM was employed to analyse the remaining research objectives. The initial objective indicated that all research variables possess high to very high mean intervals. The examination of the second research objective indicates that all AI innovations in HRM substantially influence organisational performance, with the exception of AI training, which did not achieve significance at the 0.5 level. Aside from AI performance management, which was unaffected by organisational culture, the third research objective demonstrated a notable mediating effect between AI innovation and organisational performance. This study provides insights on AI in Human Resource Management and organisational performance for scholars, researchers, and

practitioners.

**Keywords:** Organisational culture, HRM, aritifical intelligence innovation, organisational performance

## 1. Introduction

In this technological era, the growth of any organization necessitates process optimization and automation, employee skill development, and the concentrated engagement of all stakeholders to achieve a competitive advantage and enhance service delivery (Raisch & Krakowski, 2021). Artificial Intelligence (AI) is an advantageous and extensively utilized technology. It enables a device to discern its environment and make suitable decisions (Almarashda, Baba, Ramli, & Memon, 2022). Human resources departments also have adopted modern AI technologies by employing analytical software to improve process optimization and devise suitable solutions to implement the organization's strategies for performance enhancement (Jatobá, Santos, Gutierriz, Moscon, Fernandes, & Teixeira, 2019). Highlighting the lack in adopting AI technologies by Human Resource Management (HRM) in UAE, Pandya and Al-Jahani (Pandya & Al Janahi, 2021) emphasized that HR professionals and recruitment consultants in UAE should embrace AI to reduce the challenges faced in hiring, administration and operational processes. The UAE's heterogeneous workforce, swift economic expansion, and changing labour regulations, shaped by the nation's reliance on expatriate labour, pose numerous challenges for human resource management (HRM). HR managers face increased pressure to oversee the recruitment of qualified personnel while complying with government regulations (Al Awadhi, & Muslim, 2023). Moreover, it is challenging to to retain top talent in a competitive global market, as well as in addressing elevated employee turnover and compensation to mitigate performance issues in specific industries (Habbal & Al Falasi, 2024).

In response to the current situation and the wave of technology affecting many facets of life, the UAE government created Vision 2030 to develop AI in all fields. The UAE government wants the country to be fully automated by 2031, making it a creative, AI-reliant country (UAE 2031, 2018). To improve government performance efficiency, the policy recommends implementing a variety of AI-centric technological innovations (UAE 2031, 2018). The focus of government to integrate AI in HR to improve organizational performance has a similar impact on human resources management in public organizations. This technology has benefits for assessing worker performance, determining the skills required for the job, and planning hands-on training. There is still a knowledge gap regarding the use of AI in human resource management in the United Arab Emirates, despite strong evidence supporting studies on the adoption of AI technologies in human resources within government organisations. There is still a lack of research on the benefits of implementing AI in human resources within UAE government agencies, as well as its suitability and complexity for these organisations.

A study reveals that empirical research in the United Arab Emirates is limited and narrowly focused, with a dearth of studies examining organisational performance (AlShehhi, AlZaabi, Alnahhal, Sakhrieh, & Tabash, 2021), especially concerning human resource factors. Thus, current study analyses the efficacy of the public sector in the United Arab Emirates concerning artificial intelligence in human resource management. It represents one of the preliminary examinations of the correlation between AI HRM management and performance in public organisations and enterprises in the UAE. The relationship between AI human resource practices and organisational performance is assessed through various identifiers or constructs in the context of the United Arab Emirates.

## 2. Literature Review

### *2.1 Human Resource Management and Organization Performance*

Implicit knowledge produced through intricate social processes is retained within human resources. These instruments are frequently challenging to reproduce because of their ambiguous relationship with organizational performance (Panic, Cvijic, & Petrovic, 2016). Allen, Ericksen and Collins, (2013) assert that the achievement of organizational objectives is directly influenced by the beneficial effects of HRM practices on performance quality, encompassing recruitment and selection, planning, reward management, training and development, empowerment, and quality of work life.

The literature suggests that subjective metrics in certain studies, when compared to quantitative measures like financial and market indicators, have led to HRM performance studies lacking a clear and definitive concept of the organizational performance construct (Anwar & Abdullah, 2021). Thus, a clear theory of organizational performance is required, which can be formulated by HRM practitioners and specialists who rigorously investigate this domain (Baum, 2015).

The proficient and effective utilization of organizational tools and competencies is crucial for improving performance and attaining a competitive edge in both domestic and international markets. To achieve proficiency, the HRM specialist must partner with line managers to develop and implement HRM policies related to selection, training and development, performance assessment, compensation, promotion, benefits, work design, engagement, participation, communication, and job security (Baum, 2015).

Attracting, identifying, and retaining employees with the necessary skills, knowledge, and abilities enhances HRM functions, thereby improving operational productivity and organizational success. The efficacy of HRM operations is determined not only by implementation but also by the degree to which they effectively incorporate fundamental employee attitudes and behaviours (Horwitz, 2015).

Aligning employee performance outcomes with HRM standards through improved productivity and job flexibility can augment organizational efficiency. Consequently, optimising each employee's success and collaborative efforts has likely become the paramount responsibility of HRM across all organizations. This establishes a connection between HRM and operational performance, as the two concepts are inherently linked, with operational success preceding the appropriation process (Shen, 2016).

### *2.2 Human Resource Management and Organization Performance*

The field of computer science known as artificial intelligence (AI) is devoted to enabling computers to simulate human behaviour. Large databases and advanced computing power have made AI technology popular (Almarashda, Baba, Ramli, Memon, & Rahman, 2021). McCarthy (1993) defined AI as "The science and engineering of creating intelligent devices, particularly clever computer programs". Ref Haugeland (1987) defines AI as "the intriguing new endeavour to enable computers to think," with the objective of developing "machines with brains, in the complete and literal sense." In recent decades, the viewpoint on artificial intelligence has largely remained constant, as evidenced by technology-related platforms. Artificial intelligence (AI) aims to emulate human cognitive functions and decision-making, thereby producing actions similar to those executed by humans, with the potential for increased efficiency and rapidity in problem-solving. The notion of artificial intelligence (AI) is founded on the principle that specific technologies can allow computers to replicate human cognitive functions. Artificial intelligence is the technological simulation of human intelligence, primarily utilising computer systems (Uj, 2018). Certain definitions enhance the discourse by equating intelligence exclusively with human intelligence. Table 1 offers a concise overview of the supplied definitions.

Table 1. Definitions of Artificial Intelligence

| Authors | Definition of Artificial Intelligence |
|---|---|
| McCarthy (1993) | Knowledge of producing intelligent technologies, excellent computer databases |
| Haugeland (1987) | An effort to make computers think, leading to make machines with minds |
| Kurzweil (1990) | The art of producing machines for the functions requiring intelligenceto be performed by human |
| Tanimoto (1990) | Study of embracing computational methods for accomplishing tasks which needs intelligence to be performed by humans |
| Simmons and Chappell (1988) | Artificial intelligence symbolizes the behaviour of a machine, which if a human adopts is recognized as intelligent |
| Uj [2018] | Modeling human intelligence administered by machines, mostly computer systems |

According to these definitions, the term "artificial" indicates that the intelligence is not innate or that machines or computer programs, rather than people, are performing the actions or thoughts (Wirth, 2018). Without any additional context, the word "intelligence" appears consistently in all definitions. The lack of a consensus definition of intelligence makes it difficult to define artificial intelligence (Simmons & Chappell, 1988; Wirth, (2018). Fetzer (1990) highlighted that "one of the exciting parts of the study of artificial intelligence (AI) is that the precise nature of its subject matter turns out to be very difficult to define." In essense, artificial intelligence (AI) is a collection of methods and tools that use data to learn, develop, and adjust to shifting conditions, allowing for autonomous problem-solving without constant human assistance.

### *2.3 AI Innovation in HRM*

#### 2.3.1 Artificial Intelligence Planning

Planning is the fundamental step which precede the problem-solving process. The aim of a plan is to formulate a strategy or directive to address a specific problem within a designated configuration space (Tanimoto, 1990). An illustration is the insertion of a contaminated plate into the dishwasher. The task is accomplished upon the proper insertion of the plate into the dishwasher, with the kitchen serving as the operational space. The individual can achieve this by seizing the plate, manoeuvring to the dishwasher, opening it, extracting a tray, locating an available slot, and placing the plate vertically within the tray. This method seems simple at first; however, it is crucial to acknowledge that a machine must evaluate numerous sub-operations, leading to millions of possible strategies to attain the goal, even when only the most fundamental options are considered. The sequence of actions may entail initially opening the dishwasher, proceeding to the table, or manoeuvring around the table in an alternative manner. Furthermore, it may activate another tray or choose an alternative available space, depending on the subject's location within the kitchen. Evaluating all conceivable operations and their alterations substantially amplifies the quantity of possible operation sequences (Russell & Norvig, 1995). Hierarchical methods reduce operational frequency by consolidating distinct phases into a unified macro-operator (Tanimoto, 1990). Although search and planning are interrelated, the latter can be perceived as the execution of the former (Ginsberg, 1994).

Jia, Guo, Li, Li and Chen (2018), propose that human resource management commences with human resource planning. Managers employ artificial intelligence technology as an auxiliary decision-making instrument to improve strategic planning processes. Knowledge discovery and data mining technologies are crucial for aggregating global data and integrating it with existing internal and external datasets. Data compilation facilitates forecasting, evaluating, and modifying the company's future management strategies while understanding the underlying reasons for the current human resources situation. The statistical and modification capabilities of the intelligent decision support system are employed to provide the report with critical information.

2.3.2 Artificial Intelligence Recruitment

The recruitment process is a crucial component of the system, encompassing resume screening, matching qualified candidates to available positions, conducting interviews, and other associated activities. Somen Mondal, CEO of Ideal Corp, a software firm employing AI to automate hiring procedures, recognises the principal benefit of artificial intelligence as its ability to assess candidates and reduce bias autonomously. Artificial intelligence can discern the attributes of proficient employees in particular positions and employ this information to select, evaluate, and rank appropriate candidates. Mondal asserts that the application of artificial intelligence software in recruitment resulted in a 71% decrease in hiring expenses and a threefold enhancement in recruitment efficiency (Jia, Guo, Li, Li, & Chen, 2018).

Initially, resumes and images are identified using optical character recognition (OCR). Thereafter, electronic resumes are subjected to filtering and analysis through big data techniques. Moreover, methods for extracting resumes and textual information are synthesised through statistical analysis, utilising the characteristics of both techniques. The database can be converted into a structured resume in seconds, facilitating the prompt and precise submission of the candidate's resume to the company. The system enables job matching and resume evaluation, specifically for individuals with specialised high-level skills. Artificial intelligence can objectively evaluate candidates in this procedure (Hutson, 2017).

The robot interrogated the candidate during the interview, which was essential to a recruitment framework devised by the company. Based on candidates' responses, the organisation can discern the pertinent issue of aligning postings with the keyword extension matter. If the candidate has experience in data development, the robot will enquire about the operational flow and use the response to identify the suitable database to utilise. Keywords and their corresponding meanings can be gathered to assess the solution. The interviewer may re-examine the video if any issues emerge. Artificial intelligence transforms a 15-minute video interview into 20,000 data points by analysing diction, intonation, and facial expressions. Jia, Guo, Li, Li, & Chen (2018) contend that the method can significantly improve interview efficiency without compromising quality.

Face recognition techniques can be employed during the examination to verify that the candidate matches the identification document, thereby preventing impersonation (Jain & Li, 2011). Natural language processing technology markedly improves the precision and efficiency of recruiters by obviating the need for typing and enabling swift transcription of speech to text. The system may utilise the voice assessment method to identify a suitable interviewer for efficient recruitment. The big data methodology gathers applicant information, evaluates job vacancies, compares interview results, analyses the personality traits, strengths, and weaknesses of employed individuals, and matches appropriate roles through IQ/EQ and personality evaluations. Employees may engage in simultaneous routine evaluations, such as annual assessments. Artificial intelligence aids managers in identifying and allocating new employees with the highest potential for success. Moreover, sophisticated technology aids employees in recognising competent managers, suggesting educational prospects and career paths, and forecasting potential resignations. For individuals pursuing employment changes, it may aid in the rematching of positions.

### 2.3.3 Artificial Intelligence Training

Employees advance in the ongoing development process as a result of internal and external influences. Utilising diverse artificial intelligence technologies, businesses could benefit from cultivating a learning organisation culture that eschews the traditional teaching design model based on conventional gap analysis of the capability model. Human resource managers must perform research to identify employee deficiencies and classify the results using various analytical methods, including surveys, interviews, job observations, evaluations, and job data analysis. It is possible to create artificial intelligence systems for educators. The visual scanning system allows the robot training instructor to monitor each student's daily learning progress, calculate the average attentional value for all students, and utilise data analysis to discern teaching events with differing levels of stimulation. Educators may modify their pedagogical approaches and degrees of leniency based on student feedback. Regular interactions with robots have heightened curiosity in these children (Oshima, Oshima, & Miyake, 2012). Moreover, organisational training can utilise big data analysis to identify employees in need of knowledge acquisition, develop personalised curricula, evaluate and classify staff proficiency via technology, and strategically advance customised courses.

During the training process, learners can benefit from the automated documentation of training data enabled by artificial intelligence technologies. Training managers can effectively evaluate training results and enhance time management by analysing intuitive data that demonstrates the extent and impact of employee learning. Moreover, organisations may utilise a core algorithm, a learning content repository, and speech technology to deliver a rapid and effective educational experience. AI instructors can significantly reduce the costs associated with managing both online and offline education while improving the quality and efficiency of the learning process. AI instructors can proficiently oversee students and enable automated ranking while acting as thorough aides in managing statistical learning data and producing high-quality learning reports. The core tenets of educational design will transform with the incorporation of AI educators. The AI instructor will autonomously finalise the course upon the submission of learning objectives, archives, and key points by staff members. In the era of artificial intelligence, curriculum designers will predominantly employ the "intellectual" framework as a resource to attain essential objectives, such as delineating problem-solving knowledge transfer and specifying learning methodologies (Jia, Guo, Li, Li, & Chen, 2018).

2.3.4 Artificial Intelligence Performance Management

The performance assessment model can be incorporated into the performance management system to gather and analyse data concerning employees' work performance. The intelligent decision support system enables the swift and automated application of particular scientific assessment techniques, including 360-degree performance evaluation methods (Otley, 1999). The evaluation methods are incorporated into the decision support system to improve the precision of employee assessment outcomes.

At the beginning of the year, each department within the organization may formulate its business objectives. The system can assess individual performance objectives, departmental manager ratings, personal evaluations, peer assessments, customer feedback, access control punch card records, resignation statistics, and other extensive analyses and evaluations. Artificial intelligence can aid decision-makers in evaluating the performance of each indicator, suggesting improvements for suboptimal indicators, creating and executing effective new indicators, and advising on upgrade strategies. Trend projection can provide a foundation for setting future performance goals (Jia, Guo, Li, Li, & Chen, 2018).

2.3.5 Artificial Intelligence Compensation Management

Compensation management, commonly known as salary management, is a dynamic process that establishes, allocates, and modifies employee compensation levels, structures, components, and strategies in accordance with business development plans (Henderson, 2003). The implementation of AI could enhance the fairness of compensation management. The BP neural network is a supervised artificial intelligence framework based on principles from biology, neuroscience, psychology, and statistics. It can create a standard computational model, incorporate multiple neural network nodes, and emulate the human brain's nervous system (Richard & Lippmann, 1991). Artificial intelligence systems can enable the development of an intelligent decision support system to create an equitable compensation evaluation framework using big data.

2.3.6 Organizational Culture

Jones (2009) asserts that an organization's culture consists of a collection of values and customs that influence interactions among its members and with external parties. Organizational culture denotes a group's collective methodology for confronting internal and external challenges, which is subsequently imparted to new members as a pragmatic framework for understanding, contemplation, and emotional involvement with these challenges. Robbins (Robbins & Judge, 2012) characterizes organizational culture as a compilation of shared meanings among members that differentiates these enterprises from others. Ref Amrutha & Geetha (2020) contend that organizational culture is a recognisable process initiated by the founders, employee training, and senior management of the organization. It experiences socialisation and conforms to particular standards over time. The wider environment will recognize, support, and execute the culture that best aligns with the business goals. Management is encouraged to leverage organizational culture to foster rational initiatives and effective idea generation. Neither the guiding nor constraining principles have been established to improve these behaviours. Workers assert authority over themselves and each other in response to their challenges. Thus, the principal duty of directors is to cultivate and define an organization's culture to improve its performance.

*2.4 Development of Conceptual Model*

Limited research has examined how AI advancements affect UAE organisation performance, particularly through organisational culture. This contrasts with extensive research on AI's global impact on organisational performance. Most AI in human resource management research comes from Western countries with different cultural norms and organisational practices than the UAE. The UAE's cultural and legal landscape presents AI implementation opportunities and challenges. A thorough analysis of how artificial intelligence technology interacts with the UAE's culturally diverse workforce is lacking.

HRM practices are thought to be influenced by organisational culture, but their role as a mediator between AI and organisational performance is unknown. The organisational culture affects employees' perceptions and use of AI tools, determining their effectiveness. Since local and expatriate UAE workers have very different cultural values and expectations, more research is needed to determine how organisational culture mediates the relationship between AI advancements and performance. Thus, addressing this understudied research area can help to understand how AI developments affect UAE organisational performance.

Therefore, this study examines how innovative artificial intelligence features in human resource management affect UAE government agency performance. The investigation requires independent and dependent variables to measure effects. Based on a review of prior research, this study identified five independent variables of AI in human resource

International Journal of Social Science Research
ISSN 2327-5510
2025, Vol. 13, No. 3

management. These include AI planning, hiring, training, performance, and compensation management. Organisational culture mediates organisational performance. To clarify the research trajectory, a conceptual model showing the relationships and directions of the research variables is developed as in Figure 1. The conceptual model shows direct and mediator effects of independent variables and devices research hypotheses

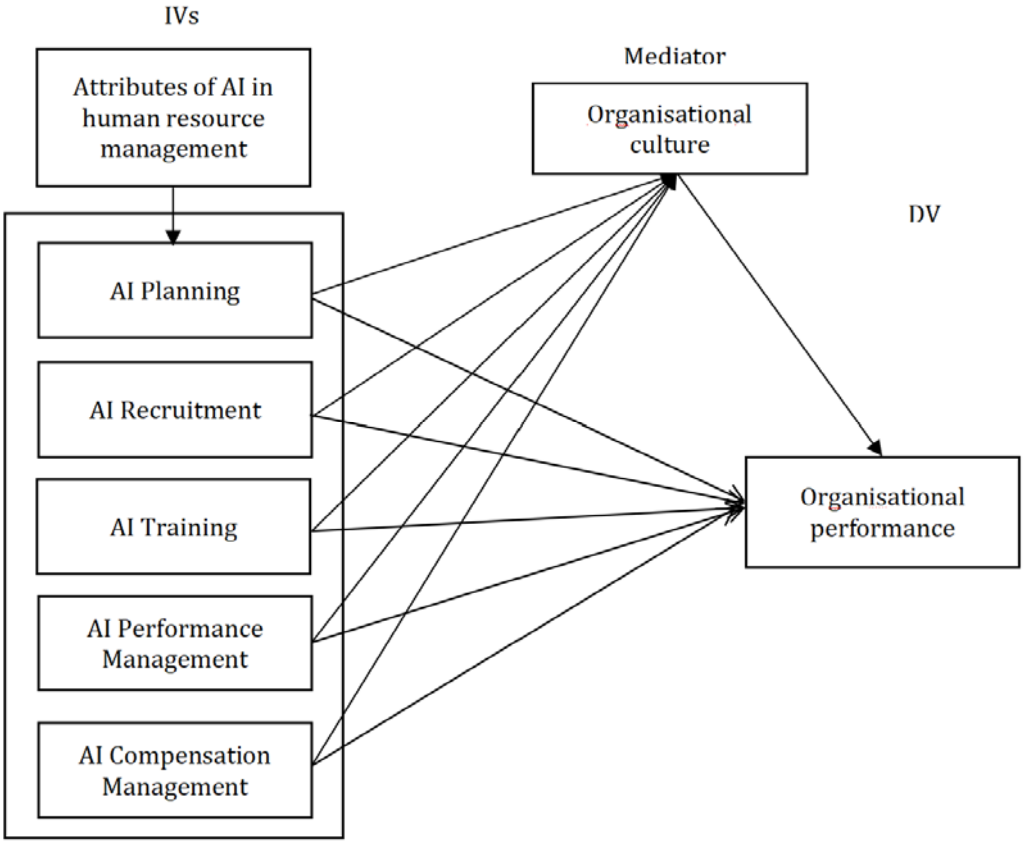


Figure 1. Conceptual Model

Based on Figure A1, the following hypotheses will be investigated in line with the research objectives:

$H_1$: Artificial Intelligence planning has a positive effect on the performance of government organisations.

$H_2$: Artificial Intelligence recruitment has a positive effect on the performance of government organisations.

$H_3$: Artificial Intelligence training has a positive effect on the performance of government organisations.

$H_4$: Artificial Intelligence performance management has a positive effect on the performance of government organisations.

$H_5$: Artificial Intelligence compensation management has a positive effect on the performance of government organisations.

$H_6$: Organisational culture significantly mediates the relationship between Artificial Intelligence planning and the performance of government organisations.

$H_7$: Organisational culture significantly mediates the relationship between Artificial Intelligence recruitment and the performance of government organisations.

$H_8$: Organisational culture significantly mediates the relationship between Artificial Intelligence training and the performance of government organisations.

$H_9$: Organisational culture significantly mediates the relationship between Artificial Intelligence performance management and the performance of government organisations.

$H_{10}$: Organisational culture significantly mediates the relationship between Artificial Intelligence compensation management and the performance of government organisations

The attributes representing the variables in conceptual model are presented in Table 2.

Table 2. Attributes Measuring the Model

| Item Code | Items' Description |
|---|---|
| **AI Planning** | |
| AIPLAN1 | In my organization, we use artificial intelligence techniques to solve issues. |
| AIPLAN2 | In my organization, we employ artificial intelligence technology as a supportive decision-making mechanism to carry out more extensive strategic planning. |
| AIPLAN3 | My organization uses artificial intelligence to get data for better planning for the organization work. |
| AIPLAN4 | My organization uses artificial intelligence to assess its current performance and plan for improvement. |
| AIPLAN5 | In my organization, we use artificial intelligence to adapt the company's future management. |
| **AI Recruitment** | |
| AIRECRUIT1 | In my organization, we use artificial intelligence technologies to review the CVs of the applicants. |
| AIRECRUIT2 | In my organization, we use artificial intelligence to match relevant vacancies with applicants' qualifications and skills. |
| AIRECRUIT3 | My organization uses artificial intelligence to assess the applicants' application documents. |
| AIRECRUIT4 | My organization uses artificial intelligence to assess job interviews. |
| AIRECRUIT5 | My organization uses artificial intelligence technologies to get statistical data on employees' performance. |
| **AI Training** | |
| AITRAIN1 | My organisation uses artificial intelligence technologies to suggest professional training courses. |
| AITRAIN2 | My organisation uses artificial intelligence technologies to assess the employees' training needs. |
| AITRAIN3 | My organisation uses artificial intelligence technologies to identify work gaps to overcome them by training. |
| AITRAIN4 | My organisation uses big data analysis to extract the employees who need to learn from a wide |

| | |
|---|---|
| | knowledge base. |
| AITRAIN5 | My organisation uses artificial intelligence technologies to identify the staff level and intelligently promote tailor-made courses. |
| **AI Performance Management** | |
| AIPFRM1 | My organisation uses a performance assessment model in the system to gather information about workers' work performance. |
| AIPFRM2 | My organisation uses performance assessment technologies to analyse the data on employees' work performance. |
| AIPFRM3 | My organisation uses artificial intelligence technologies to support the decisions regarding the assessment of the employees' performance. |
| AIPFRM4 | My organisation uses artificial intelligence technologies to assess the performance of each department. |
| AIPFRM5 | My organisation uses artificial intelligence technologies to assess the key performance indicators. |
| **AI Compensation Management** | |
| AICOMMGT1 | My organisation uses artificial intelligence technologies to establish the compensation of the employees. |
| AICOMMGT2 | In my organisation, artificial intelligence technologies are used to modify the compensations to be given to the employees |
| AICOMMGT3 | My organisation uses artificial intelligence technologies to design the compensation strategies of the organisation. |
| AICOMMGT4 | My organisation uses artificial intelligence technologies to assess the compensation decisions at the organisation. |
| AICOMMGT5 | In my organisation, artificial intelligence technologies are used to evaluate the fairness of compensation of the employees. |
| **Organizational Culture** | |
| ORGCUL1 | Employees in my organisation have a positive attitude towards using artificial intelligence technologies. |
| ORGCUL2 | In my organisation, employees support each other in using current technologies at work. |
| ORGCUL3 | Employees in my organisation learn from each other. |
| ORGCUL4 | Employees in my organisation work collaboratively. |
| ORGCUL5 | In my organisation, employees share ideas to enhance work performance. |
| **Organizational Performance** | |
| ORGPFRM1 | My organisation focuses on work efficiency. |
| ORGPFRM2 | My organisation there is constantly increasing productivity. |
| ORGPFRM3 | There is work flexibility in my organisation. |
| ORGPFRM4 | My organisation pays attention to individual's work to enhance the organisational performance. |
| ORGPFRM5 | My organisation focuses on goal achievement. |
| ORGPFRM6 | In my organisation, every employee is supported to enhance the overall effective performance of the organisation. |

## 3. Research Methodology

A conceptual model was built based on the literature to achieve the research objective. This study mostly employed the quantitative method. Quantitative methods are utilised to collect, analyse, and quantify statistical data from a large sample to ascertain the correlations among different variables (Diamond, Mostashari, & Shirky, 2009). This metric was utilised to assess hypotheses derived from initial literature to achieve the research objectives. A quantitative methodology yields statistical proof for the association between two constructs (Saunders, Lewis, & Thornhill, 2009; Klassen, Creswell, Clark, Smith, & Meissner, 2012). Klassen, Creswell, Clark, Smith, and Meissner (2012) contend that statistical evidence demonstrates the extent and direction of the relationship between constructs by validating or assessing a hypothesis in conjunction with a theory. The quantitative paradigm methodology relies on quantitative measurement and the examination of causal interactions among variables (Krishna, Lazarus, & Dhaka, 2013). Quantitative analysis can measure specific traits in a large representative sample and generalise the results to the entire population using traditional data collection techniques (Creswell, 2013).

This exploratory study aims to uncover the IT advancements that influence the performance of government enterprises in the UAE. The quantitative approach is a research methodology utilised to analyse these study variables. This method is particularly successful for analysing UAE government agencies, and the researcher employed a quantitative methodology to allow participants to express their opinions at their own pace. In light of these factors, together with the fundamental nature and aim of the research, the researcher selected a quantitative methodology. This entails administering a questionnaire survey to employees of government entities in the UAE. The quantitative approach is beneficial as it enables the collection of data from a large sample size and allows for the utilisation of advanced statistical methods, including Structural Equation Modelling (SEM) and Partial Least Squares (PLS), to investigate theoretical relationships among variables.

## 4. Results and Discussion

### *4.1 Survey Response*

The data collection process for this study involved the use of a questionnaire for data collection. A total of 387 practitioners participated in the data collection process of the study. Web-based tools and software applications were utilized to distribute the questionnaire. The survey conducted in this study garnered responses from 387 individuals within the target group, with 379 responses considered valid and utilized for analysis in this investigation which represent 97.9% of the surveys. The questionnaire's response rate is detailed in Table 3.

Table 3. Response Rate

| Questionnaires | Frequency | Percentage |
|---|---|---|
| Returned | 387 | 100% |
| Useable/Valid | 379 | 97.9% |
| Unusable/Invalid | 8 | 2.1% |

Demographic Information of the Respondents

The section on demographic information details the attributes of the respondents participated in the study. The characteristics of the participants of this study, such as age, years of experience, and educational qualifications, are presented in Table 4.

Table 4. Participant's Demographic Information

| Characteristic | Frequency | Percentage % |
|---|---|---|
| Gender | | |
| 20 years old and less | 18 | 4.75 |
| 21 to 30 years old | 92 | 24.27 |
| 31 to 40 years old | 98 | 25.85 |
| 41 to 50 years old | 82 | 21.63 |
| 51 to 60 years old | 55 | 14.51 |
| 61 years old and above | 34 | 8.97 |
| Total | 379 | 100 |
| Gender | | |
| Male | 267 | 70.45 |
| Female | 112 | 29.55 |
| Total | 379 | 100 |
| Work experience | | |
| 1 to 5 | 28 | 7.39 |
| 6 to 10 | 112 | 29.55 |
| 11 to 15 | 108 | 28.50 |
| 16 to 20 | 89 | 23.48 |
| 21 and above | 42 | 11.09 |
| Total | 379 | 100 |

The age breakdown presented in Table 4 indicates that the largest group of participants falls within the 21 to 30-year-old range, followed by those aged 31 to 40. The smallest group comprises participants aged 20 years and younger. Additionally, the number of males appears to be twice that of females. The distribution of experience years shows that most individuals fall within the 6 to 10 range, followed by those with 11 to 15 years, while the least number have 1 to 5 years of experience.

*4.2 Assessment of Measurement Model*

The evaluation of PLS-SEM involves two stages: measurement model and the structural model calculation (Memon, Rahman, Aziz, & Abdullah, 2013). Before examining the structural model, it is crucial to ensure that the measurement models meet specific quality criteria. The assessment of the measurement model aims to verify the consistency and validity of manifest variables (Memon & Rahman, 2014). Initially, this process involves evaluating the reliability of measurement models, as well as their convergent and discriminant validity, as noted by Rahman, Memon, Abdullah, & Azis (2013). The subsequent phase establishes the legitimacy of the measurement model which is confirmed through convergent and discriminant validity (Hair, Hult, Ringle, & Sarstedt, 2014). Convergent validity assessment involved factor loadings; calculating the Average Variance Extracted (AVE). The data supports the efficacy of measurement models for variance indicators (Wong, 2016). Discriminant validity in measurement models is evaluated using the Fornell and Larcker criterion and cross-loading of outer models. The following section will delve into the analysis of these evaluations. The evaluation of the measurement model is depicted in Figure 2.

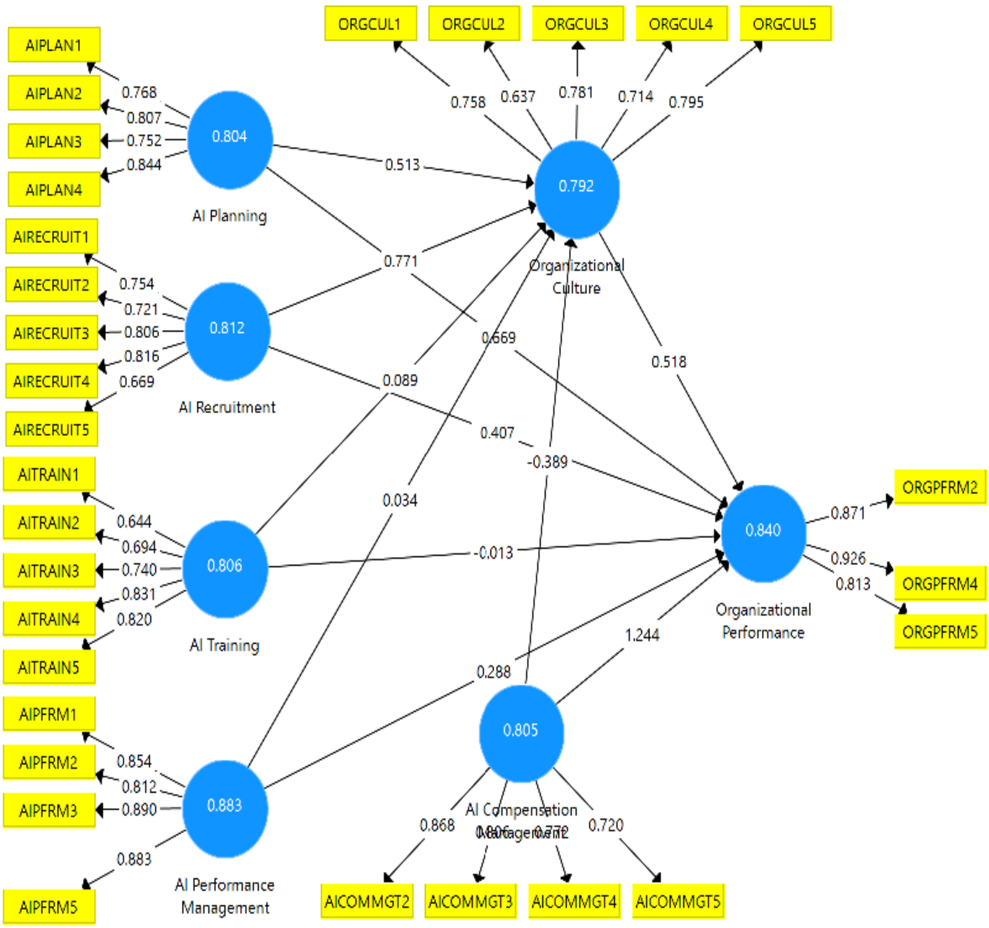


Figure 2. Measurement Model

### 4.2.1 Convergent Validity

Consistency and stability in measurements over time define reliability of measurement models (Hair et al. 2014). The reliability is the consistency of measurement scale (Pallant, 2011; Creswell, 2014) which evaluated with Cronbach's alpha (Memon, Memon, Soomro, Memon, & Khan, 2023) and composite reliability (Wong, 2016; Hair, Ringle, & Sarstedt, 2011). The model is deemed reliable when its composite reliability value reaches or exceeds 0.7 (Almansoori, Rahman, Memon, & Nasaruddin, 2021; Rahman, Al Ameri, Memon, Al-Emad, & Alhammadi, 2022). Some researchers consider 0.6 value is acceptable to confirm composite reliability (Hair, Ringle, & Sarstedt, 2011; Wong, 2013; Chin, 1998; Bagozzi & Yi, 1988). Khahro, Memon, Memon, Arsal and Ali (2021) state that latent variables should explain at least 50% of the variance in an observed variable, meaning the AVE should be 0.5 or higher. Table 5 illustrates the reliability of the measuring models.

Table 5 presents loading, Alpha, CR and AVE values obtained for the model run with SmartPLS for defining the convergent validity. The loading value shows the strength of the link between the construct and representative measurable variables. Loading value 0.7 or above are reported as high whereas the value in b/w 0.4 and 0.7 are considered moderate (Hair, Hult, Ringle, & Sarstedt, 2017). Memon (2013) cites that loadings below 0.4 may be considered weak. It's worth noting that there is no unanimously accepted threshold for outer loadings. Caution should be exercised when applying the thresholds, considering that the applicability of these may vary subject to the specific research framework and measurement instrument used.

Table 5. Measurement Mode's Reliability

| Items | Loading | Alpha | C. R. | AVE |
|---|---|---|---|---|
| AICOMMGT2 | 0.868 | 0.805 | 0.871 | 0.63 |
| AICOMMGT3 | 0.806 | | | |
| AICOMMGT4 | 0.772 | | | |
| AICOMMGT5 | 0.72 | | | |
| AIPFRM1 | 0.854 | 0.883 | 0.919 | 0.74 |
| AIPFRM2 | 0.812 | | | |
| AIPFRM3 | 0.89 | | | |
| AIPFRM5 | 0.883 | | | |
| AIPLAN1 | 0.768 | 0.804 | 0.872 | 0.63 |
| AIPLAN2 | 0.807 | | | |
| AIPLAN3 | 0.752 | | | |
| AIPLAN4 | 0.844 | | | |
| AIRECRUIT1 | 0.754 | 0.812 | 0.868 | 0.57 |
| AIRECRUIT2 | 0.721 | | | |
| AIRECRUIT3 | 0.806 | | | |
| AIRECRUIT4 | 0.816 | | | |
| AIRECRUIT5 | 0.669 | | | |
| AITRAIN1 | 0.644 | 0.812 | 0.868 | 0.57 |
| AITRAIN2 | 0.694 | | | |
| AITRAIN3 | 0.74 | | | |
| AITRAIN4 | 0.831 | | | |
| AITRAIN5 | 0.82 | | | |
| ORGCUL1 | 0.758 | 0.792 | 0.857 | 0.547 |
| ORGCUL2 | 0.637 | | | |
| ORGCUL3 | 0.781 | | | |
| ORGCUL4 | 0.714 | | | |
| ORGCUL5 | 0.795 | | | |
| ORGPFRM2 | 0.871 | 0.84 | 0.904 | 0.759 |
| ORGPFRM4 | 0.926 | | | |
| ORGPFRM5 | 0.813 | | | |
| AICOMMGT2 | 0.868 | 0.805 | 0.871 | 0.63 |
| AICOMMGT3 | 0.806 | | | |
| AICOMMGT4 | 0.772 | | | |
| AICOMMGT5 | 0.72 | | | |
| AIPFRM1 | 0.854 | 0.883 | 0.919 | 0.74 |
| AIPFRM2 | 0.812 | | | |
| AIPFRM3 | 0.89 | | | |
| AIPFRM5 | 0.883 | | | |

In PLS-SEM analysis, evaluating outer loadings alongside other metrics like convergent validity, discriminant validity, and composite reliability is crucial for assessing the measurement model's overall quality and dependability. The study's items demonstrate factor loadings of 0.6 or higher, which is deemed suitable for analysis given that other convergent validity assessments, including Cronbach's Alpha, Composite Reliability, and AVE, are confirmed for all variables. Consequently, the analysis excludes items AIPLAN5, AIPERFORM4, AICOMPMG1, ORGPERF1, ORGPERFORM3, and ORGPERFORM6 due to their loadings falling below 0.6.

4.2.2 Discriminant Validity

Discriminant validity evaluates the distinctiveness of measurement constructs from other constructs under examination. Ref Memon and Rahman, (2013) examined the dissimilarities between a specific measurement model and alternative models within the structural framework with Fornell and Larker criterion and the Cross-loading criterion. According to Fornell and Larcker (1981), the principle for discriminant validity requires that the square root of the AVE for each constructs should exceed its correlation with it self than with any other construct. Consequently, it is expected that the square root of the AVE for each outer model will be greater than its correlation with any other construct (Hair, Hult, Ringle, & Sarstedt, 2014). Table 6 illustrates the results of discriminant validity.

Table 6. Fornell Laker's Test

| | AI Comp. | AI Per Man | AI Plan | AI Recruit | AI Traini | Org. Cult. | Org. Perf. |
|---|---|---|---|---|---|---|---|
| AI Compens | 0.993 | | | | | | |
| AI Perf Mag | 0.78 | 0.86 | | | | | |
| AI Planning | 0.733 | 0.713 | 0.893 | | | | |
| AI Recruit | 0.692 | 0.618 | 0.67 | 0.855 | | | |
| AI Training | 0.721 | 0.756 | 0.752 | 0.739 | 0.889 | | |
| Org Culture | 0.724 | 0.641 | 0.759 | 0.733 | 0.752 | 0.839 | |
| Org Perform | 0.727 | 0.753 | 0.707 | 0.657 | 0.712 | 0.705 | 0.871 |

The cross-loading test can be used to further validate discriminant validity (Chin, 1998). To meet discriminant validity standards, it is crucial that items show stronger loadings on their intended constructs compared to other constructs (Hair, Hult, Ringle, & Sarstedt, 2014; Wong, 2016). Table 7 presents the findings from the discriminant validity assessment.

Table 7. Cross-Loading Assessment

| | AI Comp. | AI Per Man | AI Plan | AI Recrui | AI Traini | Org. Cult. | Org. Perf. |
|---|---|---|---|---|---|---|---|
| AICOMMGT2 | **0.868** | 0.766 | 0.682 | 0.659 | 0.772 | 0.657 | 0.726 |
| AICOMMGT3 | **0.806** | 0.565 | 0.768 | 0.481 | 0.597 | 0.552 | 0.613 |
| AICOMMGT4 | **0.872** | 0.591 | 0.707 | 0.526 | 0.667 | 0.517 | 0.57 |
| AICOMMGT5 | **0.82** | 0.525 | 0.752 | 0.518 | 0.555 | 0.558 | 0.555 |
| AIPFRM1 | 0.618 | **0.854** | 0.493 | 0.465 | 0.573 | 0.453 | 0.714 |
| AIPFRM2 | 0.592 | **0.812** | 0.566 | 0.552 | 0.573 | 0.524 | 0.589 |
| AIPFRM3 | 0.704 | **0.89** | 0.698 | 0.543 | 0.689 | 0.58 | 0.723 |
| AIPFRM5 | 0.75 | **0.883** | 0.675 | 0.564 | 0.742 | 0.629 | 0.671 |
| AIPLAN1 | 0.706 | 0.565 | **0.868** | 0.481 | 0.597 | 0.552 | 0.713 |
| AIPLAN2 | 0.772 | 0.591 | **0.807** | 0.526 | 0.667 | 0.517 | 0.57 |
| AIPLAN3 | 0.72 | 0.525 | **0.852** | 0.518 | 0.555 | 0.558 | 0.555 |
| AIPLAN4 | 0.664 | 0.579 | **0.844** | 0.599 | 0.574 | 0.758 | 0.593 |
| AIRECRUIT1 | 0.525 | 0.463 | 0.468 | **0.854** | 0.665 | 0.781 | 0.623 |
| AIRECRUIT2 | 0.508 | 0.45 | 0.502 | **0.821** | 0.456 | 0.714 | 0.431 |
| AIRECRUIT3 | 0.561 | 0.479 | 0.585 | **0.806** | 0.588 | 0.795 | 0.528 |
| AIRECRUIT4 | 0.6 | 0.546 | 0.576 | **0.816** | 0.634 | 0.673 | 0.495 |
| AIRECRUIT5 | 0.389 | 0.386 | 0.37 | **0.869** | 0.392 | 0.492 | 0.348 |
| AITRAIN1 | 0.491 | 0.482 | 0.417 | 0.317 | **0.844** | 0.293 | 0.505 |
| AITRAIN2 | 0.406 | 0.398 | 0.315 | 0.455 | **0.894** | 0.445 | 0.467 |
| AITRAIN3 | 0.743 | 0.634 | 0.7 | 0.581 | **0.874** | 0.563 | 0.692 |
| AITRAIN4 | 0.645 | 0.618 | 0.644 | 0.734 | **0.831** | 0.744 | 0.621 |
| AITRAIN5 | 0.718 | 0.651 | 0.642 | 0.587 | **0.82** | 0.655 | 0.712 |
| ORGCUL1 | 0.664 | 0.579 | 0.744 | 0.599 | 0.574 | **0.858** | 0.593 |
| ORGCUL2 | 0.386 | 0.385 | 0.357 | 0.554 | 0.476 | **0.837** | 0.402 |
| ORGCUL3 | 0.525 | 0.463 | 0.468 | 0.754 | 0.665 | **0.881** | 0.623 |
| ORGCUL4 | 0.508 | 0.45 | 0.502 | 0.721 | 0.456 | **0.814** | 0.431 |
| ORGCUL5 | 0.561 | 0.479 | 0.585 | 0.606 | 0.588 | **0.895** | 0.528 |
| ORGPFRM2 | 0.75 | 0.883 | 0.675 | 0.564 | 0.742 | 0.629 | **0.871** |
| ORGPFRM4 | 0.768 | 0.766 | 0.682 | 0.659 | 0.772 | 0.657 | **0.926** |
| ORGPFRM5 | 0.706 | 0.565 | 0.768 | 0.481 | 0.597 | 0.552 | **0.813** |

The results shown in Table 7 indicate that each component analyzed in this study demonstrates a greater level of cross-loading on its construct relative to the other variables. This indicates that the present investigation demonstrates discriminant validity.

*4.3 Assessment of Structural Model*

The second stage of evaluating Partial Least Squares Structural Equation Modelling (PLS-SEM) involves examining the structural (inner) model. According to Hair, Hult, Ringle and Sarstedt (2014), this model illustrates the causal links between measurement models.

These connections are designed to address research questions and test hypotheses. The primary objective of this assessment is to gauge the model's predictive capacity for endogenous constructs and accurately determine its overall quality. Path coefficients and their significance are evaluated using bootstrapping. Additionally, the analysis includes the coefficients of determination ($R^2$) for the endogenous construct, Cohen's $f^2$ to measure effect sizes of the exogenous measurement model, cross-validated redundancy ($Q^2$) to assess predictive relevance, and the model's overall goodness of fit (GoF). The initial structural model is shown in Figure 2, while Figure 3 presents the final version.

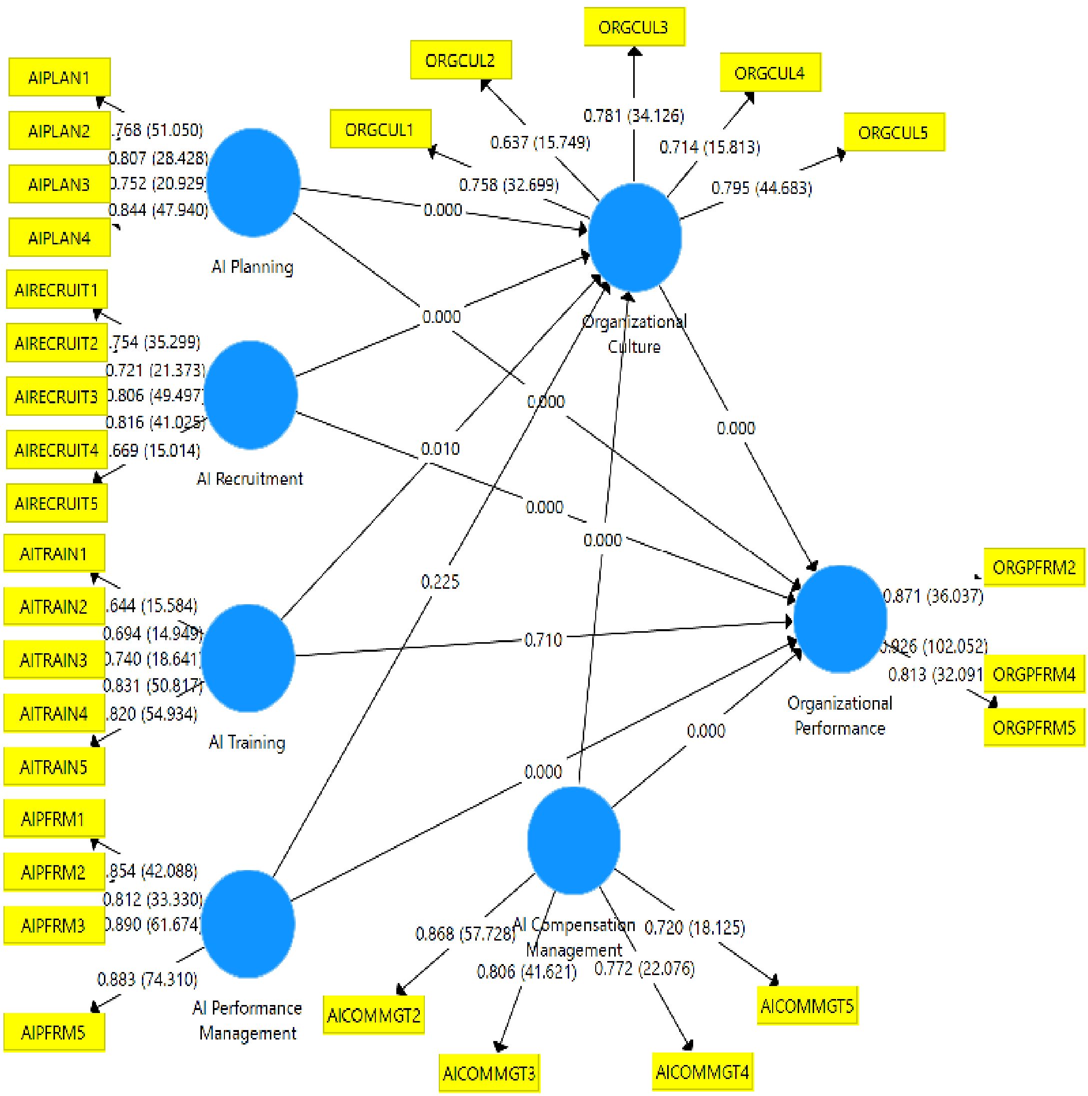


Figure 3. Final structural Model

The structural model and relevant data are presented in Figure 3. Within this model, the strength of relationships between constructs is quantified using path coefficients. These coefficients serve as indicators of relationship intensity, with values approaching 1 signifying a strong positive connection. To determine the significance of each path, t-statistics are employed through the bootstrapping method, as outlined by Kock (2014). According to Hair, Ringle and Sarstedt (2011), the model's internal consistency is reflected in both the path coefficients and their corresponding significance levels. For the inner model to be considered valid, it is crucial that the path coefficients show significance (Wong, 2016). The study's hypotheses are evaluated using the data obtained from the structural model (Hair, Hult, Ringle, & Sarstedt, 2014; Wong, 2016). The initial structural model is shown in Figure 2, while the final version is depicted in Figure 3.

#### 4.3.1 Path Coefficient Evaluation

PLS-SEM is a robust model for studying the causal links between exogenous and endogenous constructs which are normally presented as hypotheses. These links can be ascertained by examining the path coefficient values (Hair, Hult, Ringle, & Sarstedt, 2014). Path coefficients enumerated the strength of relationships between the variables where the value closer to 1 defines a strong positive correlation. Ref Kock (2014) highlighted that t-statistic considering bootstrapping is used for path evaluation. Ref Hair, Ringle, & Sarstedt (2011) demonstrated that internal consistency of the model is affirmed with strength of path coefficient value. Structural data for the model shown in Figure 3 is assessed for evaluating the hypothesis defined in conceptual model.

The conceptual model revealed a total of 10 hypotheses, including five assessing the direct effect of AI human resource management innovation attributes on organizational performance, and five explaining the indirect effect by evaluating organizational culture's mediating role. Based on Figure 3 and considering the path coefficient, the results of the hypotheses are presented in Table 8.

Table 8. Hypothesis Testing

| | Original Sample (O) | T Statistics (\|O/STDEV\|) | P Values | Remark |
|---|---|---|---|---|
| AI Compensation Management -> Organizational Performance | 1.244 | 27.107 | 0.000 | Supported |
| AI Performance Management -> Organizational Performance | 0.288 | 13.834 | 0.000 | Supported |
| AI Planning -> Organizational Performance | 0.669 | 13.611 | 0.000 | Supported |
| AI Recruitment -> Organizational Performance | 0.407 | 10.202 | 0.000 | Supported |
| AI Training -> Organizational Performance | 0.013 | 0.359 | 0.72 | Not supported |

Based on Table 8, it can be seen that for:

$H_1$: Artificial Intelligence planning has a positive effect on the performance of government organisations. The result shows that the p-value is 0.000, which is significant at 0.05. Hence, this hypothesis is supported.

$H_2$: Artificial Intelligence recruitment has a positive effect on the performance of government organisations. The result shows that the p-value is 0.000, which is significant at 0.05. Hence, this hypothesis is supported.

$H_3$: Artificial Intelligence training has a positive effect on the performance of government organisations. The result shows that the p-value is 0.000, which is significant at 0.05. Hence, this hypothesis is supported.

$H_4$: Artificial Intelligence performance management has a positive effect of the performance of government organisations. The result shows that the p-value is 0.000, which is significant at 0.05. Hence, this hypothesis is supported.

$H_5$: Artificial Intelligence compensation management has a positive effect of the performance of government organisations. The result shows that the p-value is 0.720, which is not significant at 0.05. Hence, this hypothesis is not supported.

Similarly, the indirect effect was tested through the following hypotheses of the moderator e-learning self-efficacy as presented in Table 9.

Table 9. Indirect Effect Relationship

| | Original Sample (O) | T Statistics (\|O/STDEV\|) | P Values |
|---|---|---|---|
| AI Recruitment -> Organizational Culture -> Organizational Performance | 0.399 | 11.002 | 0.000 |
| AI Planning -> Organizational Culture -> Organizational Performance | 0.266 | 7.951 | 0.000 |
| AI Compensation Management -> Organizational Culture -> Organizational Performance | 0.201 | 6.219 | 0.000 |
| AI Performance Management -> Organizational Culture -> Organizational Performance | 0.018 | 1.231 | 0.219 |
| AI Training -> Organizational Culture -> Organizational Performance | 0.046 | 2.426 | 0.016 |

From Table 9, it can be seen that for:

H6: Organisational culture significantly mediates the relationship between Artificial Intelligence planning and the performance of government organisations. The result shows that the p-value is 0.000, significant at 0.05. Hence, this hypothesis is supported.

H7: Organisational culture significantly mediates the relationship between Artificial Intelligence recruitment and the performance of government organisations. The result shows that the p-value is 0.000, which is significant at 0.05. Hence, this hypothesis is supported.

H8: Organisational culture significantly mediates the relationship between Artificial Intelligence training and the performance of government organisations. The result shows that the p-value is 0.000, which is significant at 0.05. Hence, this hypothesis is supported.

H9: Organisational culture significantly mediates the relationship between Artificial Intelligence performance management and the performance of government organisations. The result shows that the p-value is 0.219, which is not significant at 0.05. Hence, this hypothesis is not supported.

H10: Organisational culture significantly mediates the relationship between Artificial Intelligence compensation management and the performance of government organisations. The result shows that the p-value is 0.016, which is significant at 0.05. Hence, this hypothesis is supported.

4.3.2 Coefficient of Determination ($R^2$) Assessment

Effectiveness of the structural model can be studies with $R^2$. $R^2$ explains the explanatory power of the model and variability of the endogenous variable. Ref Hair, Hult, Ringle, & Sarstedt (2014); Wong (2016) consider 0.25, 0.50 and 0.75 threshold values and are defined as low, moderate, and high respectively in explaining power of the model. For the developed model, $R^2$ value was obtained with SmartPLS as in Table 10.

Table 10. $R^2$ Assessment

| | R Square | R Square Adjusted |
|---|---|---|
| **Organizational Culture** | 0.917 | 0.916 |
| **Organizational Performance** | 0.947 | 0.946 |

The values of $R^2$ as seen in Table 10 are higher than the threshold value , thus it can be said that the model has substantial explaining power.

4.3.3 Effect Size ($F^2$) Evaluation

The influence of external structures on individuals cannot be adequately assessed through an exclusive focus on $R^2$. The route coefficients and $R^2$ values elucidate the distinct influence of each path within the structural model. However, they do not provide details on the relative contributions of each exogenous construct to $R^2$. $R^2$ offers a thorough assessment of the overall influence of all external factors on variance prediction. The effect size ($f^2$) quantifies the individual impact of each external construct on $R^2$, as described by Hair, Ringle, & Sarstedt (2011). Chin (1998) proposed an effect size that quantifies the impact of exogenous factors on endogenous constructs through the evaluation of changes in the R-squared value. The effect size of each construct in the structural model is assessed using Cohen's $f^2$. This study's methodology consists of extracting a specific construct from the model and subsequently evaluating its outcomes (Hair, Hult, Ringle, & Sarstedt, 2014).

Effect Sizes: $$f^2 = \frac{R^2 incl - R^2 excl}{1 - R^2 incl} \quad (1)$$

Where:

$f^2$ = effect sizes

$R^2$ incl = $R^2$ inclusive ($R^2$ with a particular construct included in the model)

$R^2$ excl = $R^2$ excluded ($R^2$ with a particular construct excluded from the model)

1= Constant

Cohen (2013) described that for $f^2$ values as 0.02, 0.15 and 0.35 can be considered as small, medium and large effect size. The effects suze values obtained for the developed model are presented in Table 11.

Table 11. Effect Size ($F^2$)

| Constructs | Organisational Culture | Organizational Performance |
|---|---|---|
| AI Compensation Management | 0.162 | 2.232 |
| AI Performance Management | 0.005 | 0.542 |
| AI Planning | 0.403 | 0.762 |
| AI Recruitment | 3.023 | 0.327 |
| AI Training | 0.024 | 0.001 |
| Organizational Culture | | 0.419 |

Table 11 presents the proportional contribution of each external component to the $R^2$. The values presented in the table exceed 0.02, indicating that the endogenous constructions attained the requisite $F^2$ values, except for the $F^2$ associated with AI training, which did not exhibit a significant effect on organisational learning. Additionally, regarding the mediating effect of organisational culture, it is important to highlight that the $F^2$ value is notably high, with the exception of AI Compensation Management. The findings of $F^2$ corroborate the research outcomes, affirming the validity of the structural model proposed in the study.

4.3.4 Predictive Relevance ($Q^2$) Assessment

This research examines the predictive implication of the structural model using cross-validated redundancy (CVR) analysis. Wong (2016) suggested to evaluate the predictive capability of the data with Stone-Geisser's predictive relevance ($Q^2$). The current study employs a data reuse approach, which involves excluding a few data sets to re-estimate the model's fitness parameters. These parameters were used to confirm the predictive capability of the remaining data (Hair, Hult, Ringle, & Sarstedt, 2014; Hair, Ringle, & Sarstedt, 2011). Chin (1998) highlighted that for a good predictive relevance of the model, cross-validity redundancy ($Q^2$) should be more than zero i.e. positive number.

For the developed model, $Q^2$ values were estimated using blindfolding technique (Ringle, Wende, & Becker, 2015) and the obtained values are depicted in Table 12.

Table 12. Predictive Relevance using CVR

| | SSO | SSE | $Q^2$ (=1-SSE/SSO) |
|---|---|---|---|
| AI Compensation Management | 1516 | 1516 | |
| AI Performance Management | 1516 | 1516 | |
| AI Planning | 1516 | 1516 | |
| AI Recruitment | 1895 | 1895 | |
| AI Training | 1895 | 1895 | |
| Organizational Culture | 1895 | 962.85 | 0.492 |
| Organizational Performance | 1137 | 331.758 | 0.708 |

Table 12 presents the cross-validated redundancy of the model. The results illustrate that the constructs have positive $Q^2$ values which confirm the predictive relevance of the developed model.

4.3.5 Goodness-of-Fit (GoF) Assessment

Vinzi, Chin, Henseler, & Wang (2010) pointed that PLS-SEM lacks in goodness of fit measures when compared to covariance-based SEM. To address this, Tenenhaus, Amato, & Esposito (2004) proposed the "GoF" index for PLS-SEM. It depends on $R^2$ and geometric mean of AVE as described in equation:

$$GoF = \sqrt{\overline{AVE} \; X \; \overline{R^2}} \tag{2}$$

The GoF value evaluates model's overall predictivity and confirms the performance of the model at measurement and structural level (Memon & Rahman, 2013). Structural performance is considered in terms of R2 while AVE represent the quality of measurement mode. The value of GoF is described small, medium or large with threshold values of 0.1, 0.25 and 0.36 as suggested by (Akter, D'Ambra, & Ray, 2011). GoF value for the developed model is as:

$$GoF = \sqrt{0.774 \; x \; 0.946}$$

$$GoF = \sqrt{0.7312}$$

$$GoF = 0.8553$$

Above value of GoF i.e. 0.8553 represent that the developed model has high degree of GoF and thus the model is substantial is describing the assessed parameters.

## 5. Conclusion

The research assessed the mediating influence of organisational culture on the relationship between the innovative characteristics of AI human resource management and the performance of public organisations in the UAE. This was achieved by structural equation modelling, utilising data collected via a structured questionnaire survey. This study demonstrated that the incorporation of artificial intelligence (AI) in human resource (HR) planning markedly improves organisational performance by improving efficiency and implementing strategic workforce management. Artificial intelligence technologies can optimise recruiting processes, facilitating the rapid discovery of qualified individuals and minimising the duration required to fill vacancies. The utilisation of extensive datasets in HR planning facilitates the forecasting of talent requirements using predictive analytics, hence supporting succession planning and skill enhancement (Jia, Guo, Li, Li, & Chen, 2018). Integrating artificial intelligence (AI) into performance management systems fosters a workforce that is adaptable and flexible, connecting individual contributions with organisational objectives. Consequently, this synergy leads to a holistic improvement in organisational performance (Vrontis, Christofi, Pereira, Tarba, Makrides, & Trichina, 2022). The examination of the mediating role of organisational culture in the association between AI innovation attributes and organisational performance in the UAE revealed a substantial mediating effect of organisational culture, except for AI performance management, which was not significantly mediated by organisational culture. This highlights the critical significance of organisational culture in shaping the connection between AI innovation attributes in HRM and organisational performance, emphasising the necessity for a synergistic relationship between technological advancement and cultural integration to optimise the advantages of AI-enhanced HR practices. The findings of this study provide decision-makers and practitioners with a comprehensive understanding of how creative features might facilitate the adoption of AI in Human Resource Management (HRM) in the United Arab Emirates (UAE).

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