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Influence of Artificial Intelligence on Employee Performance in Sharjah City Municipality

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Abstract

As cities increasingly adopt digital transformation strategies, Artificial Intelligence (AI) is emerging as a pivotal force in reshaping public sector operations and workforce dynamics. This study investigates the influence of AI on employee performance within Sharjah City Municipality (SCM). Employing a quantitative research design, the study aims to establish the structural relationship between AI component usage factors and their impact on employee performance. Data were collected using a structured questionnaire distributed to SCM employees through a purposive convenience sampling method. A total of 233 valid responses were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS software. The analysis confirmed statistically significant and positive relationships between AI components and employee performance. Notably, the standardized beta coefficient of 0.818 indicates a strong influence of AI integration on performance outcomes. These findings provide valuable insights for SCM in enhancing workforce efficiency by promoting AI awareness, delivering targeted training, integrating AI tools into routine operations, and fostering a culture of continuous innovation and upskilling.

Keywords: Natural Language Processing; Machine Learning, Robotic Process Automation, AI-Powered Analytics and Reporting Tools

1. Introduction

In recent years, public sector organizations across the United Arab Emirates (UAE) have undergone rapid digital transformation, with Sharjah City Municipality (SCM) at the forefront of adopting Artificial Intelligence (AI) to improve governance and service delivery. As part of its strategic commitment to enhancing operational efficiency and citizen satisfaction, SCM has integrated various AI components, such as Natural Language Processing (NLP), Machine Learning (ML), Robotic Process Automation (RPA), and AI-powered analytics and reporting tools, into its organizational framework. The primary motivation behind this adoption is to elevate employee performance by automating routine tasks, improving decision-making, supporting real-time performance monitoring, and fostering a culture of innovation and adaptability (Huda et al., 2025; Devi et al., 2025; Lee et al., 2023; Ramachandran et al., 2022).

The implementation of AI technologies in SCM is also intended to align with the UAE government's broader goals of smart governance, agility, and sustainable public sector performance. These technologies empower employees to focus on higher-value responsibilities by automating repetitive tasks (RPA), offering predictive insights (ML), and enhancing communication and accessibility (NLP). This ultimately contributes to improved task efficiency, work quality, adaptability, and job satisfaction (Srinivasan et al., 2021; Pathak et al., 2023; Judijanto et al., 2025). Moreover, AI-powered analytics tools provide immediate and continuous feedback loops, helping both employees and managers make informed decisions and optimize human capital utilization (Mahmood et al., 2025; Hlaing & Nuangjamnong, 2025).

Despite these benefits, the implementation of AI in the public sector, particularly in municipalities like SCM, faces several critical challenges. These include technical integration issues, data privacy concerns, resistance to change among employees, and skill gaps in AI literacy. In many cases, public employees lack the necessary training to use advanced AI tools effectively. This can hinder performance gains and lead to underutilization of technological investments (Sharma, 2025; Ge et al., 2025). Furthermore, there is often a lack of clarity on the strategic alignment between AI capabilities and job functions, which results in fragmented implementation and inconsistent performance outcomes (Yanamala, 2022; Kayusi et al., 2025).

While literature on AI adoption in the private sector is extensive, research on its impact within public sector contexts, especially in Middle Eastern municipalities, remains limited. Specifically, there is a noticeable gap in understanding how individual AI components affect various dimensions of employee performance such as task execution, work accuracy, adaptability to change, and job satisfaction. In addition, few empirical studies investigate the critical success factors required for effective AI deployment in enhancing public workforce performance (Lather et al., 2019; Ye et al., 2021).

To address these gaps, this study aims to examine the structural relationship between key AI components, including NLP, ML, RPA, and AI-powered analytics, and employee performance within Sharjah City Municipality. The proposed model is validated using empirical data collected directly from SCM employees. By establishing this structural relationship, the research provides robust, data-driven insights into how AI adoption influences core aspects of employee performance while also identifying the enablers and barriers that affect implementation success. The findings are expected to inform both theoretical discourse and practical strategies for optimizing workforce effectiveness in public sector organizations.

2. Literature Review

This literature review explores the integration of Artificial Intelligence (AI) components within Sharjah City Municipality (SCM), emphasizing their role in enhancing urban governance and employee performance. Recent advancements in AI technologies, including machine learning, data analytics, and intelligent automation, have been increasingly adopted by municipal bodies to streamline public services and decision-making processes. Sharjah City Municipality has initiated several smart city initiatives that incorporate AI to improve operational efficiency, citizen engagement, and policy responsiveness. The integration of these technologies is also reshaping internal workflows, enabling municipal employees to perform tasks more effectively and with greater precision. The following sub-sections elaborate on key themes and empirical findings related to AI adoption in municipal governance and its implications for organizational performance in the context of SCM.

2.1 Sharjah City Municipality (SCM) and Artificial Intelligence Components

Sharjah City Municipality (SCM) has positioned itself as a proactive and forward-looking institution within the UAE’s evolving urban governance framework. In alignment with national digital transformation goals, SCM is increasingly leveraging Artificial Intelligence (AI) to enhance operational efficiency, environmental sustainability, and the quality of public service delivery. The municipality's embrace of AI reflects a strategic shift toward smart governance and data-driven urban management, which is central to Sharjah's broader vision for sustainable and inclusive development.

One prominent manifestation of this vision is Sharjah Sustainable City, a pioneering urban initiative that integrates AI-powered analytics and digital modelling tools to inform planning and infrastructure decisions. These tools facilitate scenario analysis and priority-setting using methods such as the Analytic Hierarchy Process (AHP), ensuring that environmental objectives, infrastructure efficiency, and resource optimization are aligned with long-term urban sustainability goals (Jung & Awad, 2023).

SCM has also applied AI in the development and monitoring of urban public spaces, particularly within culturally significant areas such as the Heart of Sharjah. Using a mixed-method analytical approach that combines sensor data with citizen feedback, municipal planners are now equipped to assess real-time usability, safety, and inclusivity of public spaces. This AI-supported approach, as highlighted by Karakus and Hasan (2023), strengthens SCM’s ability to design human-centred environments and fosters more responsive and adaptive governance models.

As municipalities across the Gulf region transition from oil-reliant economies to innovation-driven societies, AI has become a fundamental enabler of this transformation. Assi (2020) underscores the shifting role of local governments in shaping post-oil urban futures through the adoption of smart technologies. Within this context, SCM's AI integration mirrors national and regional trends, reinforcing the municipality's role in shaping a knowledge-based urban ecosystem.

AI technologies are also reshaping Sharjah's property and land use management practices. Alyafei (2019) notes that AI-enabled data analytics are transforming property valuation, zoning, and land development decisions. By predicting market trends and modeling development impacts, these tools enable more strategic land resource allocation, ensuring greater alignment between urban growth and sustainability objectives.

A key example of AI-driven innovation in Sharjah is the Bee'ah AI City Vision, a flagship project that demonstrates how intelligent systems can enhance urban services. AI is deployed in areas such as automated waste management, smart utility control, and building management systems, supporting a comprehensive smart city ecosystem. Sultan and Sultan (2025) highlight Bee'ah's role as a model of technology-enabled governance and its alignment with national efforts to deliver efficient, transparent, and citizen-centric services.

Finally, the broader AI readiness of the UAE has created enabling conditions for municipalities like Sharjah to implement next-generation solutions, including predictive maintenance systems, smart mobility infrastructure, and intelligent service delivery platforms. Alsheroa and Iyer (2025) emphasize that strong leadership support, sustained investment in digital infrastructure, and inter-agency collaboration have empowered SCM to actively participate in the AI-driven transformation of the public sector across the Emirates.

Sharjah City Municipality's adoption of AI components reflects a comprehensive approach to smart urban governance. By embedding AI across key areas of planning, infrastructure, service delivery, and citizen engagement, SCM is not only responding to local and national imperatives but is also contributing to the global discourse on sustainable and intelligent urban development.

2.2 Artificial Intelligence Components

In the context of this study, the artificial intelligence (AI) components examined include Natural Language Processing (NLP), Machine Learning (ML) Algorithms, Robotic Process Automation (RPA), and AI-Powered Analytics and Reporting Tools. These technologies are considered key enablers that can support and enhance the operational performance of Sharjah City Municipality. The following subsections provide a detailed explanation of each AI component and its relevance to improving organizational efficiency, decision-making, and employee performance within the municipal context.

2.2.1 Natural Language Processing (NLP) for Employee Performance

Natural Language Processing (NLP), a fundamental domain of artificial intelligence (AI), plays a pivotal role in enhancing employee performance and overall organizational efficiency by enabling systems to interpret, analyse, and generate human language. In modern workplace environments, NLP has become instrumental in automating routine administrative and customer-facing tasks through intelligent interfaces such as chatbots and virtual assistants. These tools help minimize manual workload and free employees to focus on strategic, high-value activities (Lee et al., 2023).

One of the significant benefits of NLP in the organizational context is its ability to streamline internal communication. Real-time messaging platforms embedded with NLP features can extract summaries from long conversations, translate multilingual inputs, and highlight key information, thereby fostering more effective collaboration across teams (Srinivasan et al., 2021). Such technologies are particularly valuable in global organizations where linguistic diversity can present barriers to seamless communication.

Moreover, NLP facilitates personalized learning and professional development by adapting training materials to individual learning styles and performance data. This enables a more targeted approach to upskilling employees, increasing engagement and retention. In addition, NLP-driven sentiment analysis and data mining can help managers make informed decisions by processing vast amounts of unstructured text data from sources like customer feedback, emails, and market reports (Ye et al., 2021).

Another important contribution of NLP is its role in promoting workplace inclusivity. Features like speech-to-text and text-to-speech provide essential support for employees with disabilities, ensuring more equitable access to communication and information (Lapata & Keller, 2004). These inclusivity features not only comply with accessibility standards but also contribute to a more diverse and empowered workforce.

The integration of NLP in workplace systems not only enhances individual employee performance through automation and personalized support but also strengthens organizational decision-making, communication, and inclusivity. As NLP models continue to evolve in accuracy and multilingual capabilities, their impact on employee productivity is expected to grow significantly across sectors (Srinivasan et al., 2021; Ye et al., 2021).

2.2.2 Machine Learning (ML) for Employee Performance

Machine Learning (ML), a critical branch of artificial intelligence, significantly enhances employee performance by enabling data-driven automation, continuous learning, and real-time decision-making. In organizational contexts, ML algorithms process vast datasets to generate predictive insights, empowering employees to make more informed decisions. For example, in sales and customer service environments, ML models can analyse historical trends to forecast customer behaviour, helping employees to proactively address client needs and improve satisfaction (Pathak et al., 2023).

ML also boosts productivity by automating repetitive and time-consuming tasks such as data entry, report generation, and basic administrative decisions. This not only reduces operational inefficiencies but also allows employees to redirect their efforts toward strategic, creative, and high-impact responsibilities, which fosters greater job satisfaction and engagement (Ramachandran et al., 2022).

In the realm of employee development, ML enables personalized learning pathways by analysing individual performance metrics and identifying skill gaps. Based on these insights, it can recommend tailored training modules aligned with each employee's developmental needs, thereby enhancing workforce capability and motivation (Yanamala, 2022). Such adaptive learning systems also encourage continuous improvement and promote a culture of self-directed growth.

Another transformative aspect of ML is its ability to facilitate real-time performance monitoring. ML tools can track employee activity and provide instant feedback, enabling more dynamic performance evaluations and supporting managers in delivering timely and targeted guidance. This fosters a feedback-rich environment that supports employee growth and accountability (Lather et al., 2019).

Furthermore, in complex organizational scenarios, ML supports high-stakes decision-making by uncovering patterns within large and diverse data streams. For instance, it can detect anomalies in financial transactions to prevent fraud or analyse HR data to identify trends in employee turnover, enabling proactive retention strategies (Ramachandran et al., 2022).

Machine Learning plays a multifaceted role in enhancing employee performance by enabling predictive analytics, automating tasks, supporting personalized development, and facilitating data-informed management. Its integration into organizational workflows leads to higher productivity, more agile decision-making, and overall operational excellence (Pathak et al., 2023; Yanamala, 2022).

2.2.3 Robotic Process Automation (RPA) for Employee Performance

Robotic Process Automation (RPA) is a transformative AI-driven technology designed to automate repetitive, rule-based digital tasks by simulating human interactions with computer systems. In contemporary organizational settings, RPA significantly enhances employee performance by taking over mundane tasks such as data entry, invoice processing, and routine report generation. This allows employees to redirect their focus toward more strategic, analytical, and value-added responsibilities, thereby improving engagement, creativity, and job satisfaction (Huda et al., 2025).

One of RPA's most prominent benefits is its ability to boost operational efficiency. RPA bots perform tasks at greater speed and with higher accuracy than manual methods, minimizing human errors and ensuring process consistency. This is especially beneficial in data-intensive roles such as finance, procurement, and administrative operations, where precision and efficiency are crucial (Judijanto et al., 2025). By automating these processes, organizations can reduce processing time and enhance service delivery without increasing headcount.

From a regulatory standpoint, RPA also supports compliance and governance by strictly following predefined rules and generating comprehensive logs of all actions performed. This auditability is critical in industries such as healthcare and financial services, where accountability, data security, and adherence to regulations are non-negotiable (Sharma, 2025). Employees, in turn, benefit from a reduction in compliance-related burdens and risks. Furthermore, RPA contributes to workforce satisfaction by removing repetitive and monotonous duties, enabling staff to engage in more stimulating work that promotes skill enhancement, innovation, and professional growth. This shift not only improves morale but also supports employee retention and development initiatives (Ge et al., 2025).

RPA's scalability makes it an even more valuable asset. During peak periods or high-demand cycles, RPA bots can seamlessly manage increased workloads without requiring additional staff, thereby maintaining productivity and service continuity. Moreover, when integrated with other AI technologies such as machine learning (ML) and natural language processing (NLP), RPA can move beyond simple task execution. These integrations allow RPA bots to handle unstructured data, adapt based on historical patterns, and execute more complex decision-making processes, expanding their utility across various departments (Huda et al., 2025).

Thus, RPA enhances employee performance not by replacing human effort but by complementing it, automating low-value tasks, increasing process accuracy, supporting compliance, and enabling staff to focus on higher-level contributions. This not only elevates individual productivity but also drives long-term organizational growth and competitiveness (Judijanto et al., 2025; Sharma, 2025).

2.2.4 AI-Powered Analytics and Reporting Tools for Employee Performance

AI-powered analytics and reporting tools are fundamentally reshaping how organizations leverage data to enhance employee performance and operational excellence. These tools utilize advanced machine learning algorithms to process large volumes of structured and unstructured data, generating real-time, actionable insights that facilitate informed decision-making and continuous improvement across all levels of the organization (Devi et al., 2025).

A major benefit of AI-powered analytics is real-time performance monitoring, which provides employees with instant feedback on their tasks and behaviors. This continuous feedback loop fosters a performance-driven culture, encouraging employees to make timely adjustments and improve efficiency. Managers, in turn, can utilize dashboards and visual reports to track team productivity, benchmark performance metrics, and identify high-performing individuals or units, which enhances team motivation and organizational effectiveness (Mahmood et al., 2025).

Beyond monitoring, these tools also support strategic planning through predictive analytics. By analyzing historical and current data patterns, AI systems can forecast trends, such as customer behavior, project bottlenecks, or employee attrition. For example, HR departments can proactively identify turnover risks and implement retention strategies, while sales teams can anticipate client needs, thereby increasing responsiveness and competitiveness (Hlaing & Nuangjamnong, 2025).

Furthermore, AI-driven analytics enhance personalized learning and talent development. By evaluating individual performance data, these tools can detect specific skill gaps and recommend customized training programs. This targeted approach not only boosts employee capabilities but also aligns talent development with organizational goals, fostering a more competent and future-ready workforce (Kayusi et al., 2025).

In terms of resource optimization, AI-powered reporting tools help organizations identify which departments, teams, or projects are excelling and which require intervention. Managers can then allocate resources more effectively, ensuring support is directed to where it is most needed. This data-informed resource allocation improves operational alignment and contributes to higher performance outcomes (Devi et al., 2025).

Additionally, these tools promote transparency and accountability by offering accessible, detailed, and objective performance reports. Employees gain clarity on expectations and outcomes, which cultivates a culture of trust, ownership, and continuous growth. When employees understand how their contributions impact organizational success, they are more likely to stay engaged and take initiative (Mahmood et al., 2025).

The AI-powered analytics and reporting tools significantly elevate employee performance by enabling real-time feedback, strategic foresight, personalized development, and data-driven decision-making. These tools not only empower individual employees but also support broader organizational agility, alignment, and sustainable growth (Hlaing & Nuangjamnong, 2025; Kayusi et al., 2025).

2.3 Artificial Intelligence Components Affecting Employee Performance

As public sector organizations embrace digital transformation, the integration of Artificial Intelligence (AI) technologies has emerged as a pivotal driver of employee performance and service excellence. In the context of Sharjah City Municipality, understanding the specific effects of core AI components namely Natural Language Processing (NLP), Machine Learning (ML), Robotic Process Automation (RPA), and AI-powered analytics and reporting tools on various dimensions of employee performance is essential. This study focuses on four key dimensions: task performance, work quality, adaptability, and job satisfaction.

Task performance, which involves the effective execution of core duties, can be significantly enhanced through AI applications. RPA technologies automate rule-based, repetitive tasks such as data entry and reporting, enabling employees to concentrate on more strategic, creative, and high-impact responsibilities (Huda et al., 2025; Sharma, 2025). NLP-based tools such as chatbots and real-time summarization platforms further streamline routine communication and administrative tasks, enhancing task focus and reducing cognitive load (Lee et al., 2023; Srinivasan et al., 2021). Similarly, AI-powered analytics provide real-time feedback and task-specific insights, supporting employees in achieving performance targets more efficiently (Mahmood et al., 2025; Hlaing & Nuangjamnong, 2025).

Work quality, defined by the accuracy, consistency, and reliability of output, also benefits from AI-enhanced systems. ML models improve decision accuracy through predictive analytics, supporting high-quality outcomes in areas like sales forecasting and risk detection (Pathak et al., 2023; Yanamala, 2022). RPA minimizes human error by consistently executing repetitive processes with high precision, which is especially valuable in sectors that demand compliance and accuracy (Judijanto et al., 2025; Ge et al., 2025). NLP tools also contribute to quality enhancement by interpreting and generating human language with increasing contextual relevance, as seen in multilingual and sentiment analysis applications (Ye et al., 2021; Lapata & Keller, 2004).

Adaptability, or the ability to respond effectively to changes in technology and work processes, is increasingly crucial in AI-integrated workplaces. As AI tools evolve and reshape traditional workflows, employees must continuously upskill and adapt. ML supports this transition by offering personalized learning and development pathways based on performance data and identified skill gaps (Ramachandran et al., 2022; Lather et al., 2019). Additionally, NLP-facilitated communication platforms help employees interact seamlessly across languages and departments, further enhancing their ability to integrate into dynamic environments (Srinivasan et al., 2021).

Job satisfaction is heavily influenced by the perceived value, ease, and support that AI systems bring to the workplace. When AI tools are seen as intuitive and supportive, employees are more likely to report reduced stress, improved work-life balance, and higher motivation (Hlaing & Nuangjamnong, 2025). RPA plays a particularly influential role by eliminating monotonous work, allowing employees to engage in more meaningful tasks (Ge et al., 2025). AI-powered analytics promote transparency and accountability, offering clear visibility into performance expectations and outcomes, which reinforces employee confidence and trust in the organization (Devi et al., 2025; Kayusi et al., 2025).

Hence, AI technologies through NLP, ML, RPA, and advanced analytics are reshaping employee performance by streamlining operations, enhancing precision, facilitating adaptation, and enriching employee experience. These tools not only optimize task efficiency and work quality but also contribute to a more engaged, adaptable, and satisfied workforce. In the context of Sharjah City Municipality, where digital transformation is increasingly prioritized, understanding and leveraging these impacts is vital for sustainable public sector performance and workforce development.

3. Data Collection

To assess the influence of key Artificial Intelligence (AI) components on employee performance within Sharjah City Municipality (SCM), this study examined the relationship between AI components as independent variables and employee performance as the dependent variable. The AI components investigated comprised four core dimensions: Natural Language Processing (NLP), Machine Learning (ML) algorithms, Robotic Process Automation (RPA), and AI-powered analytics and reporting tools. Each of these dimensions was operationalized through a set of specific factors to capture the breadth of AI technologies in the organizational context. Natural Language Processing (NLP) was measured through elements such as language comprehension, automated communication, virtual assistance, and document processing, reflecting its role in enhancing human-computer interaction and communication efficiency. Machine Learning (ML) was represented by predictive analytics, pattern recognition, decision support, and real-time performance tracking, highlighting its analytical and adaptive capabilities for informed decision-making. Robotic Process Automation (RPA) focused on task automation, reduction of manual errors, workflow efficiency, and process standardization, illustrating its contribution to operational streamlining. Finally, AI-powered analytics and reporting tools were assessed through real-time data analysis, performance monitoring, forecasting, and strategic decision-making support, emphasizing their value in transforming data into actionable insights for organizational performance.

The dependent variable, employee performance, was measured across four key dimensions that reflect both behavioural and attitudinal aspects of workplace effectiveness. Task performance captured employees' efficiency in completing tasks, meeting deadlines, and achieving work targets, serving as a direct indicator of productivity. Work quality was assessed through the accuracy, consistency, and reliability of work outputs, highlighting the standard and dependability of employee contributions. Adaptability measured the ability of employees to adjust to new technologies, embrace change, and effectively learn new tools, which is especially critical in AI-driven environments. Lastly, job satisfaction encompassed motivation, personal fulfilment, and overall satisfaction with the AI-supported work context, offering insight into employees' emotional and psychological engagement with their roles.

Data were collected through a structured questionnaire administered to selected employees of SCM using a purposive convenience sampling method. The questionnaire was designed to measure perceptions regarding the influence of AI components on various aspects of employee performance. AI-related constructs and their respective measurement items are detailed in Table 1, while employee performance dimensions and indicators are outlined in Table 2. Respondents indicated their agreement using a five-point Likert scale ranging from "strongly disagree" to "strongly agree."

A total of 233 completed questionnaires were received and validated for analysis. The collected data, treated as ordinal-level responses, were used to model and examine the structural relationships between the independent and dependent variables. This analysis was conducted using SmartPLS software, applying Partial Least Squares Structural Equation Modelling (PLS-SEM) to evaluate the hypothesized relationships within the conceptual framework.

Table 1. AI Component factors and questions

Constructs	Code	Factor	Question
Natural Language Processing (NLP)	NLP1	Language comprehension	Do you agree that NLP tools help you understand and process language more effectively?
	NLP2	Automation of communication	Do you agree that NLP enables automated and efficient communication in your work?
	NLP3	Virtual assistance	Do you agree that virtual assistants enhance your productivity at work?
	NLP4	Document processing	Do you agree that NLP improves the speed and accuracy of processing documents?
Machine Learning (ML) Algorithms	ML1	Predictive analytics	Do you agree that ML tools help you anticipate trends or outcomes in your tasks?
	ML2	Pattern recognition	Do you agree that ML improves your ability to identify patterns in data?
	ML3	Decision support	Do you agree that ML systems assist you in making better work-related decisions?
	ML4	Real-time performance tracking	Do you agree that ML tools enable real-time tracking of your performance?
Robotic Process Automation (RPA)	RPA1	Task automation	Do you agree that RPA reduces the time you spend on repetitive tasks?
	RPA2	Reduction of manual errors	Do you agree that RPA minimizes manual errors in your work?
	RPA3	Workflow efficiency	Do you agree that RPA enhances the efficiency of your workflow?
	RPA4	Process standardization	Do you agree that RPA ensures consistent and standardized task processes?
AI-Powered Analytics & Reporting Tools	AR1	Real-time data analysis	Do you agree that AI analytics tools help you analyse data in real time?
	AR2	Performance monitoring	Do you agree that AI tools help you monitor your performance continuously?
	AR3	Forecasting	Do you agree that AI tools improve your ability to forecast work outcomes?
	AR4	Strategic decision-making support	Do you agree that AI reporting tools support strategic decision-making in your role?

Table 2. Employee Performance factors and questions

Constructs	Code	Factor	Question
Task Performance	TP1	Ability to complete tasks efficiently	Do you agree that you are able to complete your tasks efficiently?
	TP2	Meeting deadlines	Do you agree that you consistently meet your work deadlines?
	TP3	Achieving set work targets	Do you agree that you regularly achieve your assigned work targets?
Work Quality	WQ1	Accuracy of outputs	Do you agree that the work you produce is accurate and error-free?
	WQ2	Reliability of work	Do you agree that your work output is reliable and dependable?
	WQ3	Consistency in performance	Do you agree that your job performance is consistent over time?
Adaptability	AD1	Ability to adjust to new technologies	Do you agree that you can easily adapt to using new technologies?
	AD2	Willingness to accept change	Do you agree that you are open to changes in the workplace environment?
	AD3	Learning and using new tools effectively	Do you agree that you are effective at learning and using new digital tools?
Job Satisfaction	JS1	Motivation at work	Do you agree that you feel motivated to perform well in your job?
	JS2	Sense of accomplishment	Do you agree that you feel a sense of accomplishment from your work?
	JS3	Overall satisfaction with AI-supported work	Do you agree that you are satisfied with your work environment when supported by AI tools?

4. Modelling Analysis

The structural framework proposed in this study was empirically validated using quantitative data collected from a sample of 233 employees from Sharjah City Municipality (SCM). These respondents were purposefully selected to reflect a diverse range of public service roles, leadership experiences, and exposure to innovation practices within the municipality. To analyse the data, Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed using SmartPLS 4 software. This approach was chosen for its suitability in evaluating complex models, particularly those involving higher-order constructs. PLS-SEM is widely recognized in exploratory and theory-building research due to its flexibility in handling non-normal data distributions, smaller sample sizes, and its ability to model latent variables effectively, making it especially appropriate for studies within public sector and social science contexts. The modelling process was carried out in two main stages, as described in the following sub-sections.

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4.1 Measurement Component Assessment

Following the execution of the PLS Algorithm procedure, the resulting measurement model is illustrated in Figure 1. The assessment of the measurement component focuses on evaluating construct reliability, convergent validity, and discriminant validity. Construct reliability and validity are assessed using indicators such as Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE), and, Discriminant validity, using the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT).

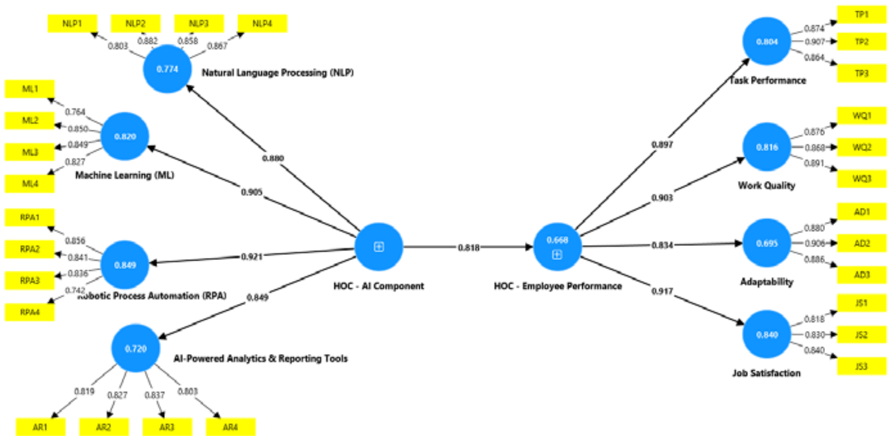

Figure 1. After PLS Algorithm procedure

Table 3. Construct reliability and validity

Constructs	**Cronbach's alpha**	**Average variance extracted (AVE)**
AI-Powered Analytics & Reporting Tools	0.839	0.675
Adaptability	0.870	0.794
HOC - AI Component	0.944	0.544
HOC - Employee Performance	0.938	0.596
Job Satisfaction	0.773	0.688
Machine Learning (ML)	0.841	0.678
Natural Language Processing (NLP)	0.875	0.727
Robotic Process Automation (RPA)	0.836	0.672
Task Performance	0.857	0.778
Work Quality	0.852	0.771

Table 3 shows that all constructs meet the recommended thresholds for internal consistency and convergent validity. Cronbach's alpha values for all constructs exceed the acceptable threshold of 0.70, indicating strong internal reliability. The composite constructs which are AI Components and Employee Performance, also demonstrate high reliability with alpha values of 0.944 and 0.938, respectively. Additionally, the Average Variance Extracted (AVE) values for all constructs are above the minimum acceptable level of 0.50, confirming adequate convergent validity. These results indicate that the measurement model is both reliable and valid for further structural analysis.

Table 4. Fornell Larcker criterion

	AI-Powered Analytics & Reporting Tools	Adaptability	HOC – AI Component	HOC – Employee Performance	Job Satisfaction	Machine Learning (ML)	Natural Language Processing (NLP)	Robotic Process Automation (RPA)	Task Performance	Work Quality
AI-Powered Analytics & Reporting Tools	0.822									
Adaptability	0.631	0.891								
HOC – AI Component	0.749	0.680	0.787							
HOC – Employee Performance	0.746	0.834	0.818	0.772						
Job Satisfaction	0.683	0.752	0.726	0.817	0.829					
Machine Learning (ML)	0.650	0.585	0.805	0.711	0.629	0.823				
Natural Language Processing (NLP)	0.615	0.616	0.880	0.695	0.594	0.780	0.853			
Robotic Process Automation (RPA)	0.771	0.587	0.921	0.757	0.679	0.785	0.720	0.820		
Task Performance	0.622	0.615	0.723	0.897	0.744	0.652	0.606	0.691	0.882	
Work Quality	0.711	0.609	0.770	0.903	0.773	0.657	0.648	0.726	0.811	0.878

Table 4 presents the results of the Fornell-Larcker criterion to assess discriminant validity. Where the square root of the AVE (shown on the diagonal) is greater than the correlations between constructs (off-diagonal values). In this study, all constructs meet this requirement. For example, the square root of AVE for Adaptability is 0.891, which is higher than its correlations with other constructs such as AI-Powered Analytics & Reporting Tools (0.631) and HOC – AI Component (0.680). Similarly, Robotic Process Automation (RPA) has a diagonal value of 0.820, exceeding its correlations with other constructs. These results indicate that discriminant validity is established, confirming that each construct in the model is empirically distinct from the others.

Table 5. Heterotrait-Monotrait ratio (HTMT)

	AI-Powered Analytics & Reporting Tools	Adaptability	HOC - AI Component	HOC - Employee Performance	Job Satisfaction	Machine Learning (ML)	Natural Language Processing (NLP)	Robotic Process Automation (RPA)	Task Performance	Work Quality
AI-Powered Analytics & Reporting Tools										
Adaptability	0.737									
HOC - AI Component	0.858	0.752								
HOC - Employee Performance	0.841	0.829	0.870							
Job Satisfaction	0.849	0.816	0.852	0.876						
Machine Learning (ML)	0.773	0.684	0.884	0.801	0.779					
Natural Language Processing (NLP)	0.717	0.707	0.866	0.767	0.723	0.807				
Robotic Process Automation (RPA)	0.823	0.690	0.836	0.855	0.847	0.835	0.841			
Task Performance	0.734	0.712	0.805	0.896	0.809	0.769	0.700	0.818		
Work Quality	0.841	0.706	0.859	0.896	0.850	0.777	0.749	0.860	0.849	

Table 5 presents the Heterotrait-Monotrait (HTMT) ratios, which provide a more rigorous assessment of discriminant validity compared to the Fornell-Larcker criterion. HTMT is widely regarded as a robust method for identifying potential overlap between constructs. A threshold of 0.90 is commonly accepted, with more conservative evaluations applying a stricter cutoff of 0.85. In this study, the majority of HTMT values fall below the 0.90 threshold, indicating that the constructs are empirically distinct. These results confirm that discriminant validity is sufficiently established across all constructs in the measurement model.

4.2 Structural Component Assessment

The structural component of the model was assessed through multiple evaluation techniques following the PLS Algorithm and Bootstrapping procedures. The R-square (R^2) and F-square (f^2) values were first examined to evaluate the explanatory power and effect size of the independent variables on the dependent constructs. These indicators help determine how well the AI components account for variance in employee performance. Next, path coefficient analysis was conducted using the Bootstrapping procedure, which provided insights into the significance and strength of the relationships between constructs within the hypothesized model. Finally, predictive relevance (Q^2) was evaluated using the Blindfolding procedure, which tests the model's ability to predict the observed values of the endogenous constructs.

The combination of these assessments supports the robustness and predictive power of the structural model.

4.2.1 R-square (R^2)

The R-square (R^2) value indicates the proportion of variance in an endogenous construct that is explained by its predictor variables, serving as a key indicator of model strength and relevance. Higher R^2 values suggest that the model has strong explanatory power, meaning the independent constructs effectively predict outcomes.

Table 6. R-square values

Endogenous construct	**R-square**
HOC - Employee Performance	0.668

Table 6 presents the R-square value for the endogenous construct, HOC – Employee Performance, which is reported as 0.668. This indicates that approximately 66.8% of the variance in employee performance is explained by the exogenous constructs included in the model. According to Chin (1998), an R^2 value of 0.67 or higher is considered substantial, suggesting that the model has a strong explanatory power for predicting employee performance.

4.2.2 F-square (f^2)

The f-square (f^2) value is a key metric in PLS-SEM used to assess the effect size of an exogenous construct on an endogenous construct. It quantifies how much a specific predictor contributes to explaining the variance of a dependent variable, offering insight into which relationships are most influential in the structural model (Hair et al., 2019; Sarstedt et al., 2020). According to established thresholds, f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effect sizes, respectively (Cohen, 1988; Hair et al., 2017). Higher f^2 values suggest stronger contributions of a particular construct to the model's explanatory power, helping to prioritize which variables are most impactful for practical and theoretical considerations.

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Table 7. f-square values

	AI-Powered Analytics & Reporting Tools	Adaptability	HOC – Employee Performance	Job Satisfaction	Machine Learning (ML)	Natural Language Processing (NLP)	Robotic Process Automation (RPA)	Task Performance	Work Quality
HOC – AI Component	2.578		2.016		4.551	3.417	5.617		
HOC – Employee Performance		2.282		5.253				4.110	4.436

Table 7 displays that the HOC – AI Component demonstrates large effect sizes on several variables: Natural Language Processing (5.617), Task Performance (4.551), Robotic Process Automation (3.417), Job Satisfaction (2.016), and AI-Powered Analytics & Reporting Tools (2.578). These values suggest that AI components play a significant role in influencing both job-related technologies and satisfaction outcomes. Similarly, HOC – Employee Performance shows strong effects on Work Quality (4.436), Task Performance (4.110), and particularly on Job Satisfaction (5.253) and Adaptability (2.282). This indicates that employee performance significantly influences critical outcomes related to workplace adaptability and output quality.

4.2.3 Path Analysis

Path analysis was conducted following the bootstrapping procedure to assess the significance and strength of the hypothesized relationships between constructs in the structural model as in Figure 2. This process generated key outputs, including the path coefficients (β values), which indicate the strength and direction of the relationships, and the p-values, which determine the statistical significance of each path.

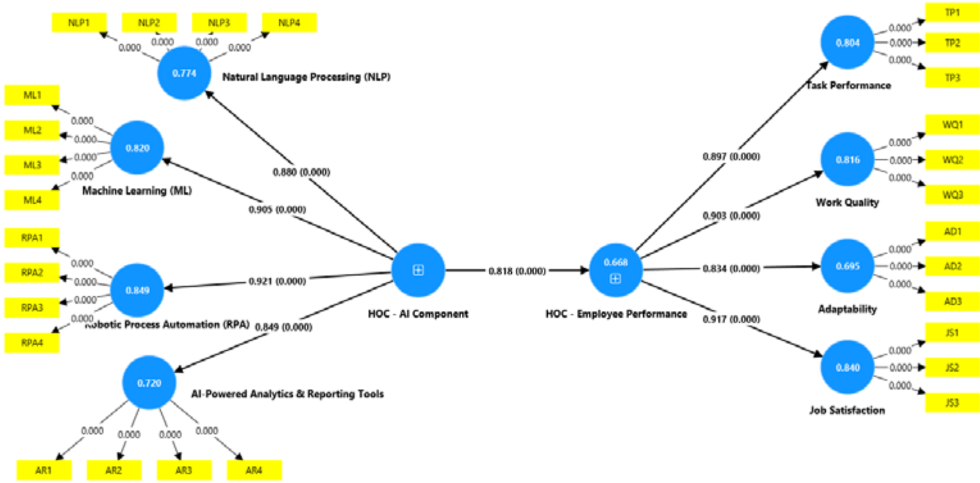

Figure 2. After Bootstrapping procedure

The results provided in Table 8 demonstrate the hypothesis testing of the paths in the model.

Table 8. Results of hypothesis testing

	Path strength	T statistics	P values
HOC - AI Component -> AI-Powered Analytics & Reporting Tools	0.849	30.678	0.000
HOC - AI Component -> HOC - Employee Performance	**0.818**	**23.441**	**0.000**
HOC - AI Component -> Machine Learning (ML)	0.905	55.363	0.000
HOC - AI Component -> Natural Language Processing (NLP)	0.880	40.963	0.000
HOC - AI Component -> Robotic Process Automation (RPA)	0.921	66.673	0.000
HOC - Employee Performance -> Adaptability	0.834	24.246	0.000
HOC - Employee Performance -> Job Satisfaction	0.917	53.039	0.000
HOC - Employee Performance -> Task Performance	0.897	48.673	0.000
HOC - Employee Performance -> Work Quality	0.903	56.218	0.000

Table 8 presents the results of the hypothesis testing through path analysis, indicating the strength and significance of relationships between the higher-order constructs (HOC) and their respective lower-order constructs. All path coefficients are statistically significant at $p < 0.001$, as evidenced by high T-statistics and p-values of 0.000. The HOC – AI Component shows strong positive effects on its associated dimensions, with path coefficients ranging from 0.849 to 0.921, confirming robust relationships with AI-Powered Analytics, Machine Learning, NLP, and RPA. Similarly, the HOC – Employee Performance construct demonstrates strong and significant associations with its underlying dimensions, including Adaptability ($\beta = 0.834$), Job Satisfaction ($\beta = 0.917$), Task Performance ($\beta = 0.897$), and Work Quality ($\beta = 0.903$).

Among all the structural paths tested in the model, the relationship between HOC – AI

Component and HOC – Employee Performance emerges as a dominant and highly significant path, with a path coefficient (β) of 0.818, a T-statistic of 23.441, and a p-value of 0.000. This result indicates a very strong and statistically significant positive effect, suggesting that the integration and effective utilization of AI components within Sharjah City Municipality (SCM) have a substantial influence on overall employee performance. The strength of this relationship demonstrates that AI technologies when combined as a holistic, higher-order construct, play a critical role in shaping employee outcomes, including adaptability, task performance, job satisfaction, and work quality. This dominant path also reinforces the central hypothesis of the study: that AI is not only a technological asset but a strategic driver of workforce productivity and transformation in public sector settings. Given its high beta value and statistical power, this relationship can be interpreted as the core linkage in the model, underscoring the need for SCM and similar institutions to prioritize AI adoption, integration, and capacity-building initiatives to unlock performance gains across departments.

4.2.4 Predictive Relevance

The predictive relevance of the structural model was assessed using the blindfolding procedure, which evaluates the model's ability to predict the data points of endogenous constructs. This technique produced two key indicators: Cross-Validated Communality (CCVC) and Cross-Validated Redundancy (CCVR), as reported in Tables 7 and 8, respectively. Values greater than zero for CCVC and CCVR indicate that the model has acceptable predictive relevance. The results from both tables confirm that the model possesses sufficient predictive capability, reinforcing the validity of its structural relationships and its utility for forecasting outcomes related to employee performance in the context of AI integration.

Table 9. CCVR

	SSO	SSE	Q^2 (=1-SSE/SSO)
AI-Powered Analytics & Reporting Tools	1592.000	825.776	0.481
Adaptability	1194.000	547.164	0.542
HOC - AI Component	6368.000	6368.000	0.000
HOC - Employee Performance	4776.000	2911.249	0.390
Job Satisfaction	1194.000	513.374	0.570
Machine Learning (ML)	1592.000	714.511	0.551
Natural Language Processing (NLP)	1592.000	707.065	0.556
Robotic Process Automation (RPA)	1592.000	696.086	0.563
Task Performance	1194.000	451.669	0.622
Work Quality	1194.000	449.143	0.624

Table 9 indicates that all endogenous constructs which are Work Quality ($Q^2 = 0.624$), Task Performance ($Q^2 = 0.622$), and Job Satisfaction ($Q^2 = 0.570$) show substantial predictive relevance. The HOC – AI Component, as an exogenous construct, has a Q^2 value of 0.000, which is expected since it is not predicted by other variables in the model. Overall, these results confirm that the structural model demonstrates strong predictive capability for employee performance outcomes across multiple dimensions.

Table 10. CCVM

	SSO	SSE	Q^2 (=1-SSE/SSO)
AI-Powered Analytics & Reporting Tools	1592.000	872.982	0.452
Adaptability	1194.000	532.855	0.554
HOC - AI Component	6368.000	3320.852	0.479
HOC - Employee Performance	4776.000	2283.825	0.522
Job Satisfaction	1194.000	755.077	0.368
Machine Learning (ML)	1592.000	863.425	0.458
Natural Language Processing (NLP)	1592.000	738.527	0.536
Robotic Process Automation (RPA)	1592.000	879.478	0.448
Task Performance	1194.000	563.660	0.528
Work Quality	1194.000	579.424	0.515

Table 10 indicates that all constructs exhibit positive Q^2 values, confirming strong indicator-level predictive power across the model. Notably, Adaptability ($Q^2 = 0.554$), HOC – Employee Performance ($Q^2 = 0.522$), and Task Performance ($Q^2 = 0.528$) show relatively high predictive relevance. Even constructs such as HOC – AI Component ($Q^2 = 0.479$) and NLP ($Q^2 = 0.536$) demonstrate moderate to strong prediction quality. These results validate the model's capacity to reliably estimate the performance of individual indicators associated with each latent construct.

5. Conclusion

This study investigated the influence of key Artificial Intelligence (AI) components on employee performance in Sharjah City Municipality (SCM). It focused on four main AI components: Natural Language Processing (NLP), Machine Learning (ML) algorithms, Robotic Process Automation (RPA), and AI-powered analytics and reporting tools. The study examined how these components affect various aspects of employee performance, including task execution, work quality, adaptability, and job satisfaction by analyzing the structural relationship between AI usage and performance outcomes.

Data were collected from 233 SCM employees across different departments through a structured questionnaire using a purposive sampling method. Analysis using Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS revealed a statistically significant and strong positive relationship between AI integration and employee performance, with a standardized beta coefficient of 0.818. The findings highlight the important role of AI in improving employee performance in the public sector. Effective AI implementation enhances operational efficiency, supports employee adaptability, and increases job satisfaction. This study provides empirical support for strategies that encourage AI integration, continuous training, and the development of a digitally empowered and future-ready workforce within SCM and similar organizations.

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