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Organizational Factors Affecting the Adoption of Artificial Intelligence in the UAE Education Sector with the Mediating Role of Organizational Culture

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Abstract

Studies have consistently demonstrated that organizational factors are the primary drivers of AI adoption in the education sector, significantly influenced by the transformative role of organizational culture. Consequently, this study investigates the organizational factors affecting the adoption of artificial intelligence (AI) in the UAE education sector, with organizational culture acting as a mediator. The investigation was conducted through a relationship model comprising four independent constructs which are management support, organizational resources, management capability, and awareness of AI. Organizational culture serves as the mediator, and the dependent variable is the adoption of AI. The model was rigorously evaluated using SmartPLS software to ensure it met the fitness criteria for both measurement and structural components. The results indicate that the model has a high R^2 value, suggesting effective explanatory power. Specifically, in terms of the strength and significance of relationships, it was found that management support has a significant negative indirect effect on AI adoption through organizational culture, with a path strength of -0.42. Meanwhile, organizational resources showed a small positive indirect effect (path strength of 0.045), which was not statistically significant. Furthermore, both management capability and awareness of AI had significant negative indirect effects, with path strengths of -0.093 and

-0.085, respectively. Regarding mediation effects, organizational culture partially mediated the relationship between management support and AI adoption, as well as between management capability and AI adoption. Additionally, it fully mediated the relationship between awareness of AI and AI adoption. However, organizational culture did not mediate the relationship between organizational resources and AI adoption. The results of this study can assist to improve UAE education sector in adopting AI.

Keywords: Artificial Intelligence Adoption, Organizational Factors, Organizational Culture, Mediation Effects

1. Introduction

Artificial Intelligence (AI) is a beneficial and widely adopted technology. It enables machines to perceive their environment and make context-appropriate decisions (Wang, Chaudhry, & Li, 2016; Huang & Rust, 2018). Incorporating AI into educational institutions holds immense potential, as it can enhance personalization, automate administrative processes, and support data-driven decision-making (Li & Wong, 2023). However, these institutions face several obstacles in adopting AI technologies. One primary challenge is the lack of organizational initiatives and strategic alignment to improve AI adoption (Sai Ambati, Narukonda, Bojja, & Bishop, 2020; Radhakrishnan & Chattopadhyay, 2020).

Additionally, many institutions fail to comprehend the factors that contribute to low AI adoption, which hampers their ability to implement effective AI strategies (Ransbotham, Kiron, Gerbert, & Reeves, 2017; Davenport & Ronanki, 2018). To effectively implement AI technologies, it is crucial for educational institutions to understand the key factors that influence AI adoption among their staff (Alsheibani, Cheung, & Messom, 2018; Awa, Ukoha, & Igwe, 2017). This study aims to investigate these organizational factors within the education sector, particularly from the perspective of employees.

AI adoption must be analysed from an organizational viewpoint, considering aspects such as management support, available resources, management capability, and organizational awareness (Ensslin et al., 2020; Barham, Dabic, Daim, & Shifrer, 2020). Even if an institution decides to adopt AI, successful implementation depends on understanding employees' attitudes toward AI technologies (Davis, 1989; Ajzen, 1991). As the primary users of AI in their daily activities, employees' perspectives are critical to the process.

The UAE government strongly supports the implementation of AI technologies in the education sector, aiming for 100% automation by 2030. However, there remains a gap in the existing literature regarding AI adoption within the UAE's Ministry of Education, the main body managing education nationwide. This study seeks to fill this gap by examining the organizational factors that influence AI adoption in the UAE's education sector, where readiness, technological infrastructure, and leadership support play essential roles (Almarashda et al., 2021).

Moreover, the study explores the impact of organizational culture on AI adoption. It aims to understand how cultural norms, values, and attitudes within educational institutions either facilitate or hinder the acceptance, integration, and effective use of AI technologies (Sharifirad & Ataei, 2012; Scaliza et al., 2022). This understanding is crucial for designing strategies that align organizational culture with technological innovation, ensuring that AI's full potential is realized in improving educational outcomes (Bley, Fredriksen, Skjærvik, & Pappas, 2022; Mutale & El-Gayar, 2024).

Thus, this research aims to provide insights into the factors affecting AI adoption in educational institutions and to develop strategies to enhance AI implementation and utilization in the UAE's education sector. Despite the UAE government's strong support, the level of AI adoption in the education sector remains low, highlighting the need for further investigation in this area (Dwivedi et al., 2021).

2. Formulating Conceptual Framework

2.1 Education Organisational Factors

This section discusses the organizational factors that influence the adoption of Artificial Intelligence (AI) in educational institutions. The discussion encompasses four key factors: management support, organizational resources, management capability, and organizational awareness of AI. These factors were identified based on a review of past literature, which has predominantly focused on user-related factors. However, this research shifts the focus to organizational factors, recognizing that educational institutions play a crucial role in effectively leveraging AI technologies to achieve their educational goals. Additionally, this section addresses organizational culture, which serves as a moderator in this research.

2.1.1 Management Support in Educational Institutions

Management support is essential in any major organizational change within educational institutions as it directs resource allocation, service integration, and strategic alignment. Academics consistently highlight management support as a critical determinant in technology adoption. For instance, Janssen et al. (2020) emphasized that managerial backing significantly influences technology adoption processes, especially in complex institutional environments where decision-making is centralized. Similarly, Ensslin et al. (2020) noted that managers with authority to allocate institutional resources hold greater sway in driving innovation adoption. Barham et al. (2020) further emphasized that managerial support must be consistent and sustained throughout project implementation, as discontinuous or weak support often leads to project failure. This is because managers, particularly at higher levels, play a vital role in designating key individuals to oversee innovation initiatives and committing the necessary financial, technological, and human resources. Conversely, a lack of managerial support can undermine institutional technology projects, leading to ineffective adoption and wasted resources (Khayer, Talukder, Bao, & Hossain, 2020).

Artificial intelligence (AI) technologies have gained widespread attention due to the availability of robust databases, cloud-based infrastructures, and advanced computing capabilities (Almarashda, Baba, Ramli, Memon, & Rahman, 2021). AI has the potential to transform the educational landscape by enhancing teaching, learning, and administrative practices through automation, predictive analytics, and personalized learning systems (Li & Wong, 2023; Huang & Rust, 2018). Given the central role of managers in technology adoption, AI integration in education requires strong managerial commitment that aligns with institutional goals and innovation strategies (Radhakrishnan & Chattopadhyay, 2020; Barham et al., 2020).

Managers' understanding of AI's strategic value determines their willingness to allocate resources and shape institutional readiness for adoption (Alsheibani, Cheung, & Messom, 2018). When leaders recognize AI as a high-priority innovation, they tend to champion its use, foster a supportive culture, and ensure staff engagement throughout implementation (Govender & Pretorius, 2015; Almarashda et al., 2022). Moreover, managerial awareness of

AI applications and benefits enhances effective integration, particularly when leaders develop both intuitive and technical comprehension of AI's capabilities. Such leadership-driven understanding is essential for achieving successful AI adoption within educational institutions.

Table 1. Management Support factors

Adoption Factors	Description	References
Managerial Understanding of AI	Managers need a comprehensive understanding of AI to effectively employ it within the organisation.	Radhakrishnan & Chattopadhyay (2020); Alsheibani, Cheung, & Messom (2018)
Strategic Alignment	AI applications require managerial backing to align with the firm's strategic goals.	Radhakrishnan & Chattopadhyay (2020); Barham, Dabic, Daim, & Shifrer (2020); Almarashda, Baba, Ramli, Memon, & Rahman (2021)
Active Engagement	Managers tend to be more active and willing to allocate resources if AI applications are prioritized.	Radhakrishnan & Chattopadhyay (2020); Ensslin et al. (2020); Khayer, Talukder, Bao, & Hossain (2020)
Intuitive Grasp of AI	A concrete and intuitive grasp of AI by managers aids in the successful implementation of AI technologies.	Radhakrishnan & Chattopadhyay (2020); Li & Wong (2023); Huang & Rust (2018)

2.1.2 Organisation Resources

Resources refer to the technical capabilities or physical assets required to implement innovations, such as computer hardware, data systems, and networking infrastructure (Almarashda et al., 2021). They also encompass an organization's collective resources that form a scalable and flexible base for adopting emerging technologies like AI (Khayer et al., 2020). In addition to tangible assets, intangible resources such as technical expertise, IT development capabilities, and collaborative mechanisms that are vital for integrating innovative technologies within institutional systems (AlNuaimi et al., 2022; Alshurideh et al., 2023).

Strong resource capacity enhances an institution's ability to overcome technological complexity, enabling AI applications to be implemented efficiently and effectively (Alsheibani et al., 2018; Maroufkhani et al., 2022). When an organization can efficiently integrate AI into its existing infrastructure, it can optimize costs, improve operational efficiency, and accelerate adoption outcomes (Barham et al., 2020; Dubey et al., 2023). Therefore, understanding and managing both tangible and intangible resources is essential for achieving sustainable AI adoption, particularly in education, where resource allocation and institutional readiness determine the success of technological innovation (Alketbi et al., 2023; AlHammadi et al., 2024).

Table 2. Organisational Resources factors

Organisational Resources Factors	**Description**	**References**
Technical Capabilities	Computer hardware, data, and networking required to implement AI technologies	Almarashda et al. (2021); Khayer et al. (2020)
Intangible Assets	Technical knowledge, IT development methods, cooperation methods, and application procedures	AlNuaimi et al. (2022); Alshurideh et al. (2023)
Strong Technical Competency	Reduces integration complexity and enables quick, efficient deployment of AI technologies	Alsheibani et al. (2018); Maroufkhani et al. (2022)
Integration Capability	Speed of integrating new AI technologies into existing IT infrastructure	Barham et al. (2020); Dubey et al. (2023)
Comprehension of AI Technology	Understanding the technology, talents, and resources required to realize the full potential of AI	Alketbi et al. (2023); AlHammadi et al. (2024)

2.1.3 Management Capability

Managerial capability refers to the capacity of educational leaders to influence, motivate, and empower staff to enhance institutional performance and long-term success (Almarashda et al., 2021; Barham et al., 2020). It encompasses decision-making, the development of a strong organizational culture, and the ability to fulfil strategic goals while promoting creativity and innovation within the educational environment (AlNuaimi et al., 2022).

Educational management operates within an increasingly dynamic and technology-driven context. Strong management capability allows institutions to formulate effective strategies, promote collaboration, and optimize the use of available resources. This capacity enables leaders to anticipate technological advancements and integrate them into educational processes to meet institutional objectives (Maroufkhani et al., 2022).

As AI applications expand rapidly across education, the challenge lies not only in introducing AI technology but also in adapting existing organizational culture and work processes to accommodate it (Alshurideh et al., 2023). The success of AI adoption in education heavily depends on the managerial ability to manage change and align staff attitudes with institutional innovation goals (Alsheibani et al., 2018; AlHammadi et al., 2024).

Educational leaders who recognize AI's potential to enhance teaching practices and staff skills can facilitate smoother transitions by rationally allocating resources, hiring technical professionals, and providing comprehensive training programs (Dubey et al., 2023). Effective project management teams, open communication channels, and continuous professional development initiatives can increase employee engagement, reduce resistance, and mitigate challenges associated with AI implementation (Alketbi et al., 2023; Khayer et al., 2020).

Table 3. Management Capability factors

Management Capability Factors	**Description**	**References**
Influence, Motivation, Empowerment	Managers' ability to influence, motivate, and empower employees to contribute to organizational success	Almarashda et al. (2021); Barham et al. (2020)
Decision-Making	Making effective decisions to build a strong workplace culture and fulfill goals and objectives	AlNuaimi et al. (2022); Maroufkhani et al. (2022)
Adaptation to AI	Adapting organizational culture and processes to integrate AI technologies	Alshurideh et al. (2023); Alsheibani et al. (2018)
Reducing AI Application Difficulty	Recognizing AI's potential to improve professional skills and adjusting staffing and training accordingly	AlHammadi et al. (2024); Dubey et al. (2023); Alketbi et al. (2023); Khayer et al. (2020)

2.1.4 Organisation Awareness of Artificial Intelligence

Technological innovation represents one of the primary pathways to organizational transformation, alongside evolving government policies, economic dynamics, and changes in stakeholder needs and preferences (Almarashda et al., 2021; Dubey et al., 2023). Organizational awareness of emerging technologies such as AI serves as the foundation for transformation by fostering inspiration, proactive adaptation, and readiness for innovation. Awareness is not merely about knowing the existence of a technology; it also involves understanding its potential impact and aligning it with institutional objectives and strategies (Alshurideh et al., 2023).

Drawing on the technology adoption framework, awareness plays a pivotal role in shaping organizational behavior toward technological change. It influences how institutions recognize, evaluate, and prioritize innovations such as AI (AlNuaimi et al., 2022). Organizations that actively cultivate awareness through learning, experimentation, and knowledge-sharing are more likely to integrate AI successfully into their operations (Maroufkhani et al., 2022).

Firms differ in how they search for and process new technological knowledge. A proactive search process, characterized by the systematic exploration and assessment of new ideas that enables institutions to discover AI’s potential for improving productivity, innovation, and strategic competitiveness (Khayer et al., 2020; Alketbi et al., 2023). This process is particularly vital for organizations with a strong external orientation, which continuously monitor technological trends and market opportunities to enhance innovation capacity and maintain competitive advantage (Barham et al., 2020).

Consequently, AI awareness extends beyond cost-saving or automation objectives. It functions as a strategic enabler that enhances adaptability, stimulates innovation, and drives long-term competitiveness (AlHammadi et al., 2024; Dubey et al., 2023). Increasing organizational awareness of AI, therefore, plays a crucial role in promoting effective adoption and ensuring that technology-driven initiatives align with broader institutional goals.

Table 4. Awareness of Artificial Intelligence factors

Awareness Factors	**Description**	**References**
Organisational Transformation	AI awareness serves as the foundation for organisational changes, providing inspiration and initiation	Almarashda et al. (2021); Dubey et al. (2023)
Search Process	Proactive process of seeking, examining, and assessing new AI knowledge and information	Khayer et al. (2020); Alketbi et al. (2023)
Strategic Implications	AI adoption is driven by strategic implications beyond cost-saving and automation	AlHammadi et al. (2024); Dubey et al. (2023)
External Orientation	Firms with an external orientation seek market opportunities by innovating with AI	Barham et al. (2020); Maroufkhani et al. (2022); Alshurideh et al. (2023)

2.2 Education Organisation Culture

Organizational culture significantly impacts an educational institution’s ability to adopt new creative technologies such as artificial intelligence. The cultural values and attitudes within an educational organization play a crucial role in supporting or inhibiting the adoption of new technologies (Al-Maroof et al., 2021). Among the different drivers, Shafie et al. (2022) highlighted learning and information sharing as significant predictors of innovation. According to Shafie et al. (2022), the effects of knowledge sharing on novel technology adoption are positive, and educational institutions that promote knowledge sharing can improve their competitive advantage and operational performance (Al-Kahtani et al., 2023).

Data management, innovation, leadership, and agility all impact the adoption of technology within educational settings. Technology adoption has had a transformative impact across all educational sectors, independent of the style and character of organizational culture.

Furthermore, current AI technology adoption opportunities are intended to be used to enhance educational services and learning outcomes (AlHogail, 2022).

At the organizational level, four dimensions have been identified that impact innovative culture: adaptability, consistency, involvement, and mission. Sharifirad and Ataei (2020) focused on these factors, establishing a relationship between innovation and organizational culture theories. Innovativeness and consistency are essential to establish a mentality or an innovation within an educational institution, directly affecting internal governance processes and developing a creative mindset through consensual support. Innovativeness and consistency encompass an institution's essential beliefs, coordination, agreements, integration, and developing a mindset (Ooi et al., 2021). These factors clarify expectations, foster a sense of identity among staff and students, and enable the resolution of disputes and the reaching of mutual agreements on crucial organizational issues (Hussein et al., 2021).

Other factors identified in the literature that address the adoption of innovation and the aspects of organizational culture that influence innovation adoption decisions include staff perceptions of innovation adoption, the degree and nature of likely organizational changes, employee–employer relationships, workforce capabilities and efficiencies, and the core values and customs adhered to by the institution. Pioneer educational institutions foster innovation adoption in their organizational culture through risk-learning features, anticipating various beneficial outcomes from adoption (Al-Marzouqi et al., 2023). They encourage a culture of risk-taking, experimentation, and learning from errors to produce and embrace change. Consistency among leadership and staff in responding successfully to changes during the stages of innovation adoption demonstrates the competitive traits obtained by an institution in addressing problems (Dubey et al., 2023).

Analyzing organizational culture and innovation models may reveal trends in AI adoption within educational settings. To conclude, organizational culture influences the institution as well as the staff and students' effective usage of artificial intelligence. In other words, creating a conducive organizational culture requires support from the institution so that the tendency to adopt AI technologies becomes higher. Developing an effective culture is a dual responsibility of both the institution and its members, which increases the adoption of AI technologies among staff and students. This makes it suitable for current research as a mediator to examine its role in strengthening the relationship between organizational factors and the adoption of artificial intelligence technologies.

Table 5. Awareness of Artificial Intelligence factors

Organisation Culture Factor	Description	Reference
Learning and sharing	Promotes knowledge sharing, innovation, and performance	Shafie et al. (2022); Al-Kahtani et al. (2023)
Core Dimensions and Agility	Involves adaptability, consistency, involvement, mission, data management, innovation, and leadership	Sharifirad & Ataei (2020); AlHogail (2022); Ooi et al. (2021)
Risk-taking and Leadership	Encourages risk-taking, experimentation, and consistent leadership during innovation adoption	Al-Marzouqi et al. (2023); Dubey et al. (2023)

2.3 AI Adoption in Educational Organisation

Even though many educational institutions comprehend the concepts of artificial intelligence (AI), their chances of implementation remain restricted. In experimental institutions, adoption is often high, but the level of understanding tends to be shallow. Conversely, passive institutions exhibit both poor understanding and limited implementation of AI technologies (Almarashda et al., 2021). Thus, pioneering institutions that those that act as early adopters, demonstrate strong practical understanding of AI principles and considerable acceptance levels among educational organizations.

According to a global survey conducted by the Boston Consulting Group (Ransbotham et al., 2021), major constraints to AI adoption in education relate to execution and ambition. The study found that approximately 80% of institutions, primarily large-scale or multinational educational organizations, supported AI adoption because it offered a competitive advantage, while only 40% had a formal strategy for AI implementation (Khayer et al., 2020). This finding reflects a growing awareness of AI's potential benefits for educational transformation.

Ransbotham et al. (2020) further revealed that early adopters of AI were significantly increasing their investments, widening the adoption gap between pioneering and less adaptive educational institutions. Early adopters tend to organize their operations strategically to maximize AI-driven advantages (AlHogail, 2022). These leaders view AI not merely as a technological tool but as an organizational solution that enhances innovation, efficiency, and competitive edge (Al-Kahtani et al., 2023).

Furthermore, early AI adopters prioritize revenue-generating applications over cost-cutting initiatives. Ransbotham et al. (2020) reported that 72% of pioneering institutions adopted AI primarily to generate new sources of revenue, while 28% aimed to achieve cost reductions. This strategic focus is illustrated by the increasing use of AI-powered systems such as predictive analytics, adaptive learning platforms, and cybersecurity algorithms for data management to enhance operational efficiency and educational service quality (Dubey et al., 2023).

Despite these advancements, challenges remain. Only a small proportion of pioneering institutions that around 20% have achieved effective implementation, integration, and comprehension of AI technologies (Alsheibani et al., 2018). Johnson et al. (2023) noted that while early adopters are making aggressive AI investments, many institutions still struggle with unclear educational objectives, insufficient technical expertise, and limited resource alignment. Nevertheless, the potential of AI to transform pedagogical models, drive institutional innovation, and enhance learning outcomes continues to motivate educational leaders to pursue more comprehensive AI strategies (Li & Wong, 2023).

Therefore, assessing AI adoption readiness and identifying influencing factors are essential steps toward developing a sustainable framework for AI integration in education. Understanding how organizational, managerial, and cultural dynamics interact with technological readiness will guide institutions in overcoming current barriers and maximizing AI's transformative potential.

Table 6. AI Adoption factors

AI Adoption factors	Description	Reference
Adoption Levels	Experimenters, pioneers, and passive institutions	Almarashda et al. (2021)
Support for AI Adoption	80% of institutions supported AI adoption due to competitive advantage	Khayer et al. (2020)
Investment in AI	Early adopters are expanding their AI investment	Ransbotham et al. (2020)
Revenue Generation vs. Cost-Cutting	72% of pioneers supported AI for revenue generation, while 28% for cost savings	Ransbotham et al. (2020)
Challenges in AI Adoption	Unclear educational cases and lack of technical capabilities	Johnson et al. (2023)

3. Conceptual Framework

To develop a comprehensive conceptual framework of organizational factors influencing the adoption of Artificial Intelligence (AI) in the education sector of the United Arab Emirates (UAE), this study integrates three well-established theories: the Theory of Planned Behaviour (TPB), the Technology Acceptance Model (TAM), and the Diffusion of Innovation (DoI) theory. Each of these theories offers unique insights and complements the others to form a robust foundation for understanding AI adoption in educational institutions. The conceptual framework illustrates the relationships among four independent variables which are management support, organizational resources, management capability, and organizational awareness of AI; and one dependent variable, with organizational culture serving as a moderator.

For the first independent variable, management support, TPB is applied to emphasize the role of attitudes, subjective norms, and perceived behavioural control in shaping technology adoption intentions. Management support and commitment significantly influence employees' perceptions of ease of use and readiness to integrate AI technologies (Ajzen, 1991; Al-Maroof et al., 2021). Within educational institutions, supportive management creates a conducive environment that enhances confidence and positive attitudes toward AI integration.

The second independent variable, organizational resources, draws upon TAM to highlight the importance of perceived usefulness and perceived ease of use (Davis, 1989). The availability of financial, technical, and human resources directly affects these perceptions (Venkatesh & Davis, 2000; Khayer et al., 2020). Sufficient resources ensure that AI systems are user-friendly and effectively implemented, thereby enhancing their perceived value and accelerating adoption across educational settings (Almarashda et al., 2021).

The third independent variable, management capability, adopts the Diffusion of Innovation (DoI) theory (Abbas, & Uddin, 2025) to emphasize the role of leadership in facilitating innovation. Effective management capability enables institutions to develop strategies, foster an innovative culture, and communicate the benefits of AI clearly to stakeholders (Dubey et al., 2023; AlHogail, 2022). By enhancing leadership capability, institutions can bridge the gap between technological potential and practical implementation.

The fourth independent variable, organizational awareness of AI, integrates both TAM and TPB theories. According to TAM, awareness of AI's perceived usefulness influences its adoption, while TPB's concept of perceived behavioural control underscores individuals' readiness and confidence to use AI technologies (Ajzen, 1991; Al-Maroof et al., 2021). Awareness initiatives, such as workshops, knowledge-sharing programs, and strategic communication, strengthen institutional readiness and increase the likelihood of successful AI implementation (Shafie et al., 2022).

The dependent variable, AI adoption, represents the extent to which AI technologies are integrated and utilized within educational institutions. It functions as the outcome variable, shaped by the independent constructs and moderated by organizational culture. The moderating variable, organizational culture, is conceptualized based on the DoI and TPB frameworks. TPB highlights the influence of peer norms and leadership behaviour, while DoI emphasizes aligning innovations with existing cultural values and practices (Rogers, 2003; Sharifirad & Ataei, 2020). A supportive organizational culture encourages experimentation, knowledge sharing, and openness to change, all of which are vital for successful AI integration.

Through integrating TPB, TAM, and DoI, this study provides a holistic conceptual framework that captures the multidimensional nature of AI adoption within UAE educational institutions. This combined theoretical approach allows for a comprehensive understanding of how management support, resource availability, leadership capability, and organizational awareness that mediated by organizational culture, collectively influence the adoption and sustainability of AI technologies in the education sector.

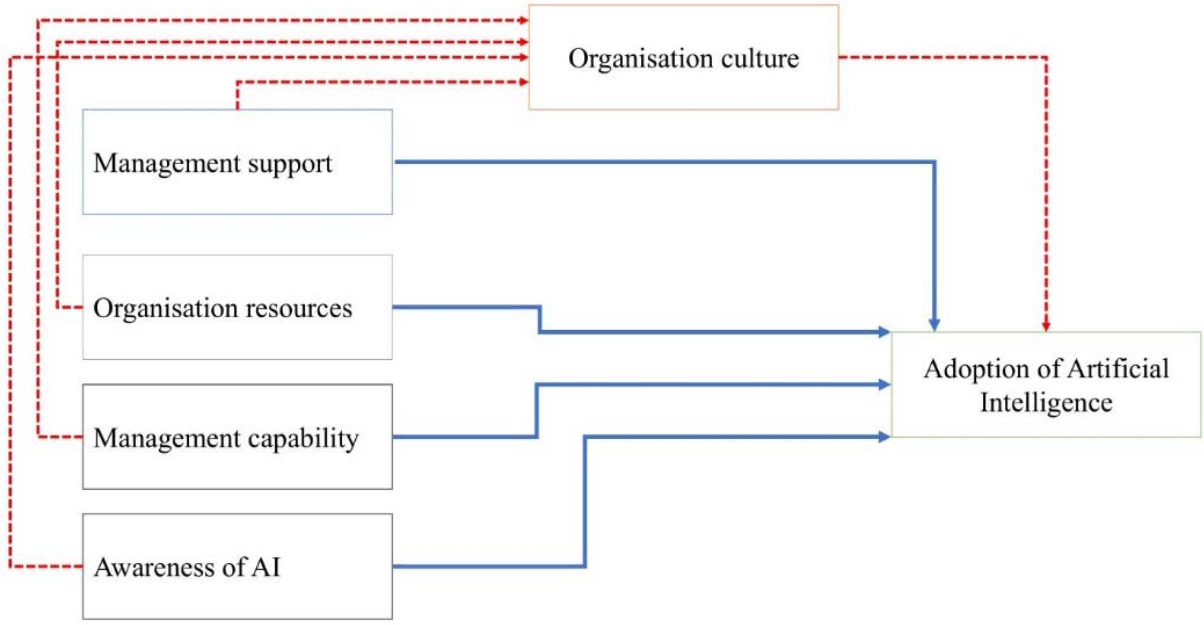

Figure 1. Conceptual framework

4. Modelling of Conceptual Framework

The modelling process began with the conceptual framework being structured using SmartPLS software. This program was selected because it applies structural equation modelling (SEM) through the partial least squares (PLS) approach. Since this study proposes a new model, the use of PLS-SEM aligns with the recommendation of Hair et al. (2021), who emphasized that this analytical method is more suitable for theory development rather than theory confirmation.

Data for the model were collected through a questionnaire survey administered to employees of educational institutions in Abu Dhabi, including both teaching and administrative staff. A total of 379 participants were surveyed to gain insights into the organizational factors influencing AI adoption. The study employed simple random sampling to ensure representativeness within the UAE's education sector (Creswell & Creswell, 2018).

The modelling analysis followed several essential steps. First, the measurement model was assessed to establish the constructs' reliability and validity (Hair et al., 2021; Henseler, Ringle, & Sarstedt, 2015). This step involved evaluating internal consistency, convergent validity, and discriminant validity to ensure that all constructs accurately represented their corresponding latent variables. Second, the structural model was examined to test the hypothesized direct and indirect relationships between variables (Sarstedt et al., 2020). Finally, goodness-of-fit indices were reviewed to confirm the overall adequacy and predictive relevance of the model (Chin, 1998).

This comprehensive analytical approach provided a robust framework for understanding how various organizational factors influence the adoption of AI in the UAE's education sector.

Within this model, direct relationships represent the immediate effects of organizational factors on AI adoption, while indirect relationships capture the mediating role of organizational culture in enhancing or moderating these effects (Hair et al., 2021; Ali et al., 2023).

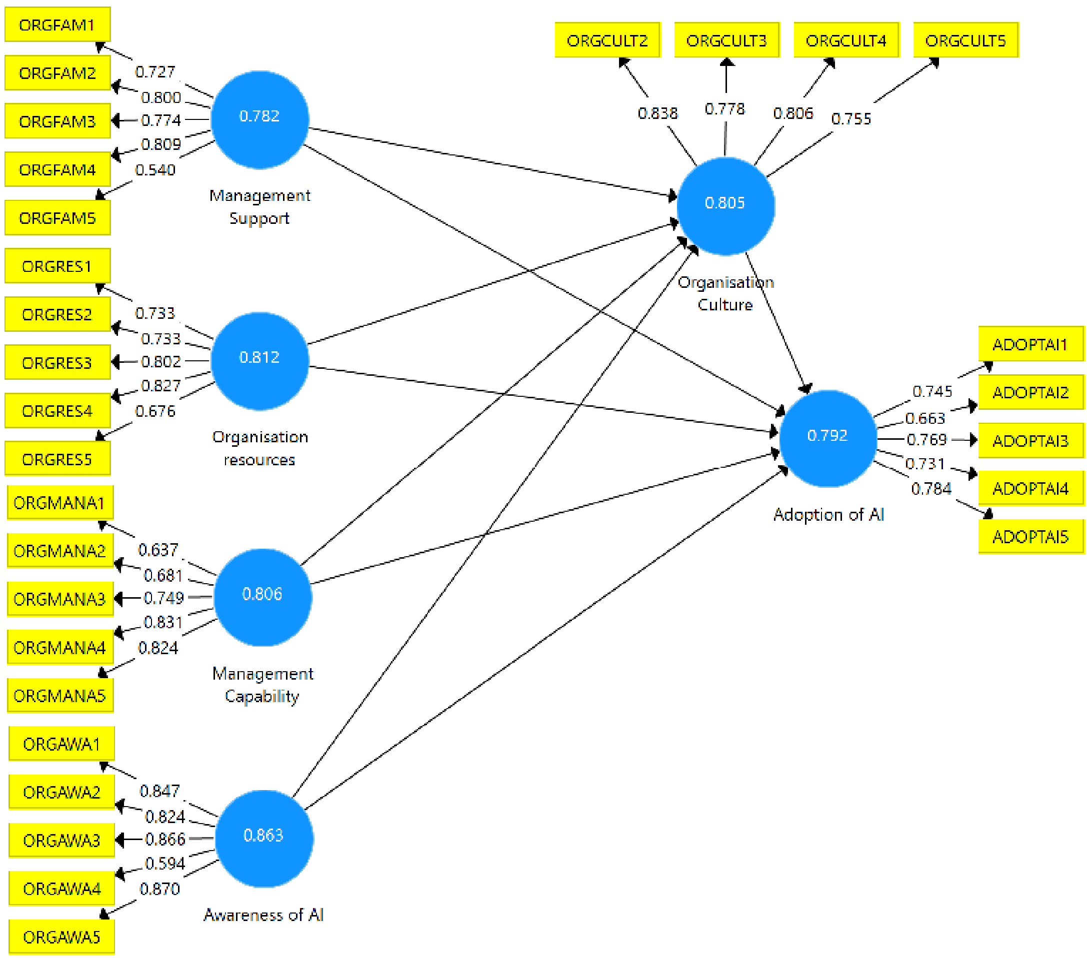

Figure 2. Conceptual framework

The evaluation analysis of the measurement and structural model was conducted using three main processes in the SmartPLS software. The PLS Algorithm was used to assess the measurement component, Bootstrapping was used for structural evaluation, and Blindfolding was applied to evaluate the model’s predictive relevance. All these assessments confirmed that both the measurement and structural components met the fitness criteria. However, this paper focuses only on the results related to hypothesis testing to highlight the path causal relationships of direct and indirect effects, as well as the mediation effect of organizational culture.

4.1 Construct Validity and Reliability

Construct reliability was assessed using several established metrics, including Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) (Hair et al., 2021). The Cronbach's alpha values ranged from 0.732 to 0.951, indicating strong internal consistency across all constructs, as they exceeded the recommended threshold of 0.70. Similarly, the composite reliability scores ranged from 0.792 to 0.902, confirming the constructs' reliability. The AVE values ranged between 0.516 and 0.683, surpassing the minimum acceptable value of 0.50, which indicates satisfactory convergent validity (Fornell & Larcker, 1981; Henseler, Ringle, & Sarstedt, 2015).

Table 7. Construct validity and reliability

Constructs	**Cronbach's Alpha**	**Composite Reliability**	**Average Variance Extracted (AVE)**
Adoption of AI	0.792	0.858	0.547
Awareness of AI	0.863	0.902	0.651
Management Capability	0.806	0.863	0.56
Management Support	0.782	0.853	0.543
Organisation Culture	0.805	0.873	0.632
Organisation resources	0.812	0.869	0.572

Table 7 presents the reliability and validity evaluation of the constructs associated with AI adoption in the UAE education sector, including Adoption of AI, Awareness of AI, Management Capability, Management Support, Organizational Culture, and Organizational Resources. The key indicators used in this assessment were Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) (Hair et al., 2021). High scores across these measures reflect strong internal consistency and convergent validity for the constructs, confirming the robustness of the measurement model.

4.2 Discriminant Validity

Discriminant validity assesses the distinctiveness of each construct in comparison with other constructs within the structural model. It ensures that a given construct measures a unique concept rather than overlapping with others (Hair et al., 2021). Traditionally, the Fornell and Larcker criterion has been the most widely used method for assessing discriminant validity. According to Fornell and Larcker (1981), the square root of the average variance extracted (AVE) for each construct should exceed the correlations between that construct and any other construct in the model, thereby confirming discriminant validity.

Table 8. Fornell Laker's test

	Adoption of AI	Awareness of AI	Management Capability	Management Support	Organisation Culture	Organisation resources
Adoption of AI	**0.780**					
Awareness of AI	0.644	**0.807**				
Management Capability	0.751	0.781	**0.848**			
Management Support	0.718	0.707	0.787	**0.837**		
Organisation Culture	0.717	0.766	0.722	0.737	**0.895**	
Organisation resources	0.728	0.649	0.738	0.726	0.691	**0.796**

The square root of the average variance extracted (AVE) for each construct should exceed its correlation with any other construct, as recommended by Fornell and Larcker (1981) and supported by Hair et al. (2021). This criterion was satisfied in the Fornell and Larcker test conducted in the present study. Table 8 presents the results of the discriminant validity assessment, confirming that the criterion for discriminant validity was successfully achieved.

4.3 Coefficient of Determination R^2

R^2, a key quality metric in structural equation modelling, measures the proportion of variance in the endogenous construct explained by exogenous constructs within the structural model. Often referred to as the coefficient of determination, it represents the explanatory or predictive power of the model (Hair et al., 2021). The higher the variance explained or predicted by the model, the greater its quality and robustness (Chin, 1998; Gefen et al., 2000; Henseler et al., 2009). Although there is no universally agreed-upon threshold for acceptable R^2 values, several scholars have proposed benchmarks that vary by research discipline. For example, Hair et al. (2021) and Henseler et al. (2009) suggested that R^2 values of 0.25, 0.50, and 0.75 can be interpreted as weak, moderate, and substantial, respectively.

Table 9. R^2 values of endogenous constructs

Endogenous constructs	**R Square**
Adoption of AI – **Dependent construct**	0.936
Organisation Culture - **Mediator**	0.908

Table 9 presents the R^2 values for two endogenous constructs which are Adoption of AI and Organizational Culture. The R^2 value indicates the proportion of variance in the dependent variable that can be explained by the independent variables in the model. For the dependent construct, Adoption of AI, the R^2 value is 0.936, meaning that 93.6% of the variance in AI adoption can be explained by the model. This high R^2 value suggests that the model is highly effective in predicting the factors influencing the adoption of AI. For the mediator construct, Organizational Culture, the R^2 value is 0.908, indicating that 90.8% of the variance in organizational culture can be explained by the model. This also signifies strong explanatory power, suggesting that the model effectively captures the factors impacting organizational culture. Both constructs exhibit high R^2 values, demonstrating the model's robustness and its capability to explain a significant portion of the variance in these dependent variables.

4.4 Path Causal Relationship

Based on Figure 2, the model demonstrates both direct and indirect causal relationships. After conducting hypothesis testing, it provides the strength and significance level of each path. The results of the hypothesis testing are presented in Tables 10 and 11.

Table 10. Direct effect relationship

Direct relationship	**Path strength**	**P Values**	**Remark**
Management Support -> Adoption of AI	0.756	0.000	Significant
Organisation resources -> Adoption of AI	0.68	0.000	Significant
Management Capability -> Adoption of AI	0.097	0.001	Significant
Awareness of AI -> Adoption of AI	0.017	0.536	**Not Significant**

Table 10 illustrates the direct effects of various factors on AI adoption. Management support and organizational resources have a strong positive impact on AI adoption, with path strength values of 0.756 and 0.68, respectively, both highly significant (P values = 0.000). Management capability also shows a statistically significant, though smaller, effect on AI adoption (path strength = 0.097, P Value = 0.001). In contrast, awareness of AI has a minimal and non-significant effect (path strength = 0.017, P Value = 0.536). These results underscore the importance of management support and resources in driving AI adoption.

Table 11. Indirect effect relationship

Indirect relationship	**Path strength**	**P Values [<0.05]**	**Remark**
Management Support -> Organisation Culture -> Adoption of AI	-0.42	0.000	Significant
Organisation resources -> Organisation Culture -> Adoption of AI	0.045	0.079	**Not Significant**
Management Capability -> Organisation Culture -> Adoption of AI	-0.093	0.000	Significant
Awareness of AI -> Organisation Culture -> Adoption of AI	-0.085	0.000	Significant

Table 11 outlines the indirect effects of various factors on AI adoption through organizational culture. Management support has a significant negative indirect effect on AI adoption via organizational culture, with a path strength of -0.42 (P Value = 0.000). Organization resources show a small positive indirect effect (path strength of 0.045, P Value = 0.079), which is not statistically significant. Management capability and awareness of AI both have significant negative indirect effects, with path strengths of -0.093 and -0.085 respectively (both P Values = 0.000). These findings emphasize the crucial role of organizational culture in mediating the impact of different factors on AI adoption.

4.5 Determination of Mediation Effect of Organisation Culture

Determining mediation effects involves assessing the significance of both direct and indirect relationships between variables. According to Baron and Kenny (1986), this process includes demonstrating that the independent variable significantly affects the mediator and that the mediator significantly affects the dependent variable while controlling for the independent variable. More recent approaches, such as the bootstrapping method proposed by Preacher and Hayes (2008), test the significance of indirect effects by resampling, offering a robust technique for analyzing mediation through the estimation of confidence intervals for the indirect paths.

Mediation effects can be classified into three categories: no effect, partial effect, and full effect. A no effect occurs when the mediator does not significantly influence the relationship between the independent and dependent variables. A partial effect exists when the mediator partially transmits the relationship, with both direct and indirect effects being significant. A full effect occurs when the mediator completely explains the relationship, rendering the direct relationship non-significant. These classifications are valuable for understanding the mechanisms through which various organizational factors interact and influence outcomes (Baron & Kenny, 1986; Preacher & Hayes, 2008).

Table 12. Determine the mediation effect

Indirect relationship	**Remark**	**Direct relationship**	**Remark**	**Mediation effect**
Management Support -> Organisation Culture -> Adoption of AI	Significant	Management Support -> Adoption of AI	Significant	Partial effect
Organisation resources -> Organisation Culture -> Adoption of AI	**Not Significant**	Organisation resources -> Adoption of AI	Significant	No effect
Management Capability -> Organisation Culture -> Adoption of AI	Significant	Management Capability -> Adoption of AI	Significant	Partial effect
Awareness of AI -> Organisation Culture -> Adoption of AI	Significant	Awareness of AI -> Adoption of AI	**Not Significant**	Full effect

Table 12 presents the mediation analysis results showing the relationships between organizational factors and AI adoption, as well as the mediating role of organizational culture. Management support exhibits both significant direct and indirect effects on AI adoption, indicating partial mediation. Organizational resources show a significant direct effect but no significant indirect effect, suggesting no mediation. Management capability displays significant direct and indirect effects, resulting in partial mediation. Conversely, awareness of AI demonstrates a significant indirect effect but no significant direct effect, indicating full mediation through organizational culture.

The findings of this study align with prior research underscoring the importance of organizational culture in driving AI adoption. For example, Bley et al. (2023) found a strong positive relationship between organizational culture, AI capabilities, and organizational performance. Similarly, Mutale and El-Gayar (2023) emphasized that organizational culture plays a critical role in shaping AI adoption and performance outcomes. The results of the present study extend these insights, highlighting that while management support and organizational resources are vital enablers of AI adoption, awareness of AI alone is insufficient without a supportive organizational culture.

5. Empirical Framework of the Study

Saunders, Lewis, and Thornhill (2019) explained that an empirical framework is developed after a theoretical or conceptual framework has been validated through empirical evidence. This framework relies on data collected from observations, surveys, experiments, or other empirical methods, focusing on testing hypotheses and exploring relationships proposed in the conceptual model based on real-world evidence. Figure 3 illustrates the empirical framework of this study, which is derived from the hypothesis testing results presented earlier.

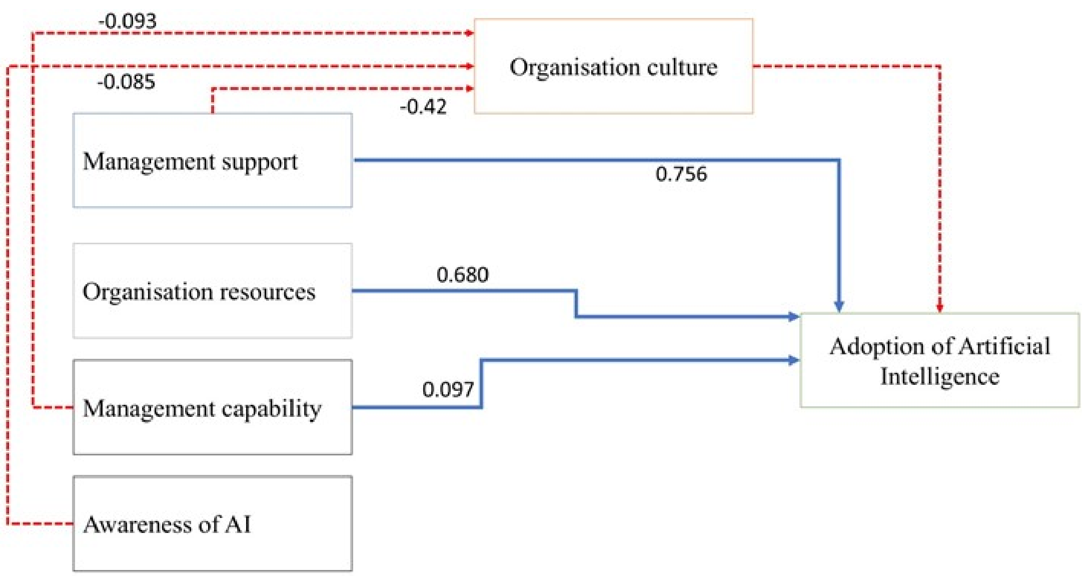

Figure 3. Empirical framework

The empirical framework in Figure 3 highlights the significant relationships among organizational factors influencing AI adoption. Direct relationships are represented in blue, while indirect relationships are shown in red, emphasizing the mediating role of organizational culture. The analysis indicates that, among direct relationships, only awareness of AI does not have a significant relationship with AI adoption. For indirect relationships, only organizational resources show no significant effect. In terms of path strength, management support demonstrates the strongest direct influence on AI adoption ($\beta = 0.756$). For indirect paths, all coefficients are negative, suggesting inverse relationships, with management support showing the highest indirect path strength ($\beta = -0.42$).

This empirical framework provides a comprehensive understanding of the complex interactions between organizational factors and AI adoption. By highlighting both direct and indirect effects, it underscores the critical role of management support and organizational culture as mediators. These insights assist institutions in identifying strategic intervention areas to enhance AI adoption readiness, decision-making, and implementation effectiveness.

Comparatively, previous research has emphasized similar patterns. For instance, Al Nuaimi et al. (2023) found that management support is essential for successful AI implementation, as it ensures strategic alignment and resource allocation. Likewise, Al-Maroof et al. (2022) and Mutale and El-Gayar (2023) identified organizational culture as a key mediator promoting innovation and acceptance of AI technologies. Furthermore, Chen et al. (2022) argued that employee awareness alone is insufficient without adequate managerial and resource backing, consistent with the current findings that awareness of AI shows no direct effect on adoption. Additionally, Ahmed and Brohi (2021) highlighted that while organizational resources such as infrastructure and funding are important, their impact may be overshadowed by leadership commitment and cultural adaptability.

Overall, the current framework extends prior studies by revealing that while direct relationships between organizational factors and AI adoption are generally positive, indirect relationships mediated by culture may manifest inverse effects. This nuanced perspective enriches the understanding of organizational dynamics in AI adoption and offers valuable implications for developing effective AI strategies in educational institutions.

6. Conclusion

The study investigated the organizational factors affecting the adoption of artificial intelligence (AI) in the UAE education sector, with organizational culture acting as a mediator. The research utilized a relationship model comprising four independent constructs of organizational factors which are management support, organizational resources, management capability, and awareness of AI. Organizational culture served as the mediator, and the dependent variable was the adoption of AI. The model was rigorously evaluated using SmartPLS software to ensure it met the fitness criteria for both measurement and structural components. The results indicated that the model has a high R^2 value, suggesting effective explanatory power. In terms of strength and significance of relationships, it was found that management support has a significant negative indirect effect on AI adoption through organizational culture, with a path strength of -0.42. Organizational resources showed a small positive indirect effect (path strength of 0.045), which was not statistically significant. Both management capability and awareness of AI had significant negative indirect effects, with path strengths of -0.093 and -0.085, respectively. Regarding mediation effects, organizational culture partially mediated the relationship between management support and AI adoption, as well as between management capability and AI adoption. It fully mediated the relationship between awareness of AI and AI adoption. However, organizational culture did not mediate the relationship between organizational resources and AI adoption. In conclusion, the findings underscore the pivotal role of organizational culture in mediating the adoption of AI, highlighting the need for targeted strategies to enhance organizational support and capabilities.

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