Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

The Integration of Artificial Intelligence (AI) Into Decision Support Systems Within Higher Education Institutions

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This study examines the incorporation of artificial intelligence (AI) into decision support systems at higher education institutions in the United Arab Emirates (UAE), using the theoretical framework of the Diffusion of Innovations Theory. This study employs a cross-sectional survey design to examine the significant correlations among system complexity, data quality, organizational readiness, user engagement, technological infrastructure, and the efficacy of decision-making systems utilizing AI in higher education institutions in the UAE. UAE higher education institutions are targeted. A representative sample of institutions is selected via purposive sampling based on size, geography, and academic reputation. To ensure position and department representation, stratified random sampling is used to pick participants within each institution. Structural Equation Modeling (SEM) was used to examine the connections among the investigated variables. Data quality, organizational readiness, user engagement, and technology infrastructure were key factors influencing effective decision-making processes with $\beta = 0.503$; 0.281; 0.193; 0.244 at p-value less than .05, respectively, although system complexity did not reveal a significant association ($\beta = -0.016$, p-value = 0.65). Recommendations suggest focusing on investments in data quality assurance, preparing the organization, increasing user involvement, and improving technology infrastructure. Although limited by geographical focus and a cross-sectional design, this research provides valuable insights for policymakers, educators, and practitioners interested in using AI to enhance educational results and promote innovation in higher education.

Keywords: Artificial Intelligence, Decision Support Systems, Data Quality, Organizational Readiness, User Engagement, Technology Infrastructure.

1. Introduction

Integrating Artificial Intelligence (AI) into Decision Support Systems (DSS) is crucial for making well-informed decisions in higher education institutions in the United Arab Emirates (UAE). The swift advancements in artificial intelligence, as evidenced in fields like healthcare and imaging diagnosis (Tyler & Jacobs, 2020; Suzuki & Chen, 2018), underscore this technology's disruptive capacity in education. Although there have been significant advancements in the application of AI, a persistent problem is the need for more integration of decision support systems, which hampers their effectiveness (Liu et al., 2010). On this note, this present investigation seeks to understand the issues within the framework of higher education in the UAE, where the rapid growth of technology necessitates a detailed assessment of the obstacles to the effective utilization of AI in decision support systems (DSS).

Evidence from previous research endeavors, exemplified by Tyler et al. (2020) and Suzuki and Chen (2018), has produced noteworthy advancements in AI-driven decision support systems. Nevertheless, there remains to be a notable concern regarding the seamless incorporation of these systems (Liu et al., 2010). The ramifications of this issue substantially impact the effectiveness of decision-making processes in higher educational institutions in the UAE. Integrating AI technology into decision support is crucial to enhance operational efficiency and uphold the quality of academic and administrative judgments (S. A. Salloum, Almarzouqi, Aburayya, Shwedeh, Fatin, Ghurabli, Dabbagh, et al., 2024; H. Yas, Aburayya, et al., 2024; H. Yas, Dafri, et al., 2024).

This literature highlights some crucial factors contributing to the persistent challenge of integrating AI-driven decision support systems (DSS). Prior research in other domains has recognized the significance of several factors, including the intricacy of AI systems, concerns about data quality, the need for organizational readiness, and the importance of user engagement (Bonczek et al., 2014; Marakas, 2003; Wen et al., 2008). The selected independent variables (IVs) for investigation include system complexity, data quality, organizational readiness, and user engagement. These variables are closely linked to the overall effectiveness of AI in decision support in the UAE's higher education sector (Shwedeh, Salloum, Aburayya, Fatin, Elbadawi, Ghurabli, Muhammad, et al., 2024; Shwedeh, Salloum, Aburayya, Fatin, Elbadawi, Ghurabli, Murad, et al., 2024; Shwedeh, Salloum, Aburayya, Kaur, et al., 2024). The dependent variable (DV) refers to the comprehensive efficacy of artificial intelligence (AI) in providing decision support (S. A. Salloum, Almarzouqi, Aburayya, Shwedeh, Fatin, Ghurabli, Elbadawi, et al., 2024; Shwedeh, Salloum, Aburayya, Fatin, Elbadawi, Ghurabli, & Dabbagh, 2024; N. Yas, Dafri, et al., 2024).

The chosen independent variables have been confirmed in existing research, highlighting their crucial contribution to decision support performance (Bonczek et al., 2014; Marakas, 2003; Wen et al., 2008). In addition, the study includes a moderating variable called 'Technological Infrastructure' to enhance the effects of the independent variables on the dependent variable (Supriadi et al., 2018). Engaging in a proactive investigation of these inquiries will not only contribute to the progress of our comprehension regarding the obstacles of integrating AI in UAE higher education, but it will also offer significant observations for institutions seeking to use AI's complete capabilities for well-informed decision-making (Alimour et al., 2024; Alkashami, Hussain, et al., 2023; N. Yas, Elyat, et al., 2024).

This study seeks to address a lack of understanding by conducting a detailed assessment of the obstacles to successful integration of artificial intelligence (AI) in decision support systems (DSS) in the higher education sector of the United Arab Emirates (UAE) (S. Salloum, Shwedeh, et al., 2023; Shwedeh, Aburayya, et al., 2023; Shwedeh, Aldabbagh, et al., 2023). The study seeks to promote the adoption of AI in higher education institutions to create a technologically advanced and efficient educational system by answering the following research questions:

i. Does system complexity play a significant role in limiting the effectiveness of AI DSS?

ii. Is there any significant relationship between data quality and the effectiveness of AI DSS?

iii. Does organizational readiness significantly impact the effectiveness of AI DSS?

iv. Is there any significant relationship between user engagement and effective AI DSS?

v. Does technological infrastructure moderate the relationship between system complexity, data quality, organizational readiness, and user engagement on AI DSS?

Advancements and Applications of AI in Decision Support Systems

The rapid development of Artificial Intelligence (AI) has significantly impacted decision support systems in various industries. Sutton et al. (2017) argue that integrating AI in higher education influences the development of quality evaluation models, offering customized insights and individualized learning experiences. Sadowski et al. (2020) emphasize the significant impact of AI in clinical decision support systems, enhancing the accuracy of diagnoses and treatment strategies while acknowledging the need to address data security and bias concerns. Mantelero (2018) highlights the wider societal influence of AI, emphasizing the necessity of ethical frameworks that cover human rights and social consequences. Cao et al. (2021) investigate managers' perspectives toward using AI in decision-making across various industries, whereas Alsheibani et al. (2018) emphasize the significance of organizational preparedness for AI implementation. Buçinca et al. (2021) also explore the cognitive aspects, promoting a well-rounded strategy to avoid excessive dependence on AI. The breakthroughs in AI present unparalleled benefits, but they require cautious management to ensure ethical, transparent, and responsible integration in education, healthcare, and organizations (Shwedeh, 2024; Shwedeh et al., 2020; Shwedeh, Malaka, et al., 2023).

Persistent Challenges in AI Integration in Decision Support Systems

Integrating artificial intelligence (AI) into decision support systems presents challenges, as demonstrated by Liu et al.'s (2010) comprehensive analysis of the obstacles involved (S. Salloum, Shwedeh, et al., 2023; Shwedeh, 2024; Shwedeh, Malaka, et al., 2023). Despite some progress, the integration of AI technologies remains a difficult task. Pedro et al. (2019) and Sambasivan et al. (2021) have recognized problems related to inadequate system integration in higher education, which continue to provide ongoing difficulties. These challenges go beyond simple technical issues and greatly influence the decision-making processes in educational institutions. The research conducted by Sambasivan et al. (2021) unveiled that insufficient incorporation of artificial intelligence (AI) in higher education impedes technological advancement and significantly impacts the efficacy of decision-making processes. This poses a substantial barrier to adequately using the potential of AI in educational settings (Abdallah et al., 2022; Alkashami, Mohammad, et al., 2023; Shwedeh, 2021; Shwedeh et al., 2020).

Dwivedi et al. (2021) and Heavin and Power (2018) present contrasting perspectives on the integration of artificial intelligence (AI), hence expanding the range of the discourse. Dwivedi et al. (2021) highlight the importance of adopting a complete strategy that includes research, practice, and policy, focusing on the complex nature of developing difficulties in AI. In their study, Heavin and Power (2018) highlight the wide range of concerns about implementing AI technology, particularly emphasizing organizational, managerial, and strategic factors. These studies show that the difficulties related to AI integration go beyond technological complexities and involve a complex interaction of organizational, managerial, and strategic elements. Addressing these difficulties is crucial to guarantee the seamless integration of AI in decision support systems across multiple domains (Dahu et al., 2022; Khadragy et al., 2022; Ravikumar et al., 2023).

Factors Contributing to Suboptimal AI Integration

Incorporating Artificial Intelligence (AI) into organizational decision-making processes is complex, including multiple dimensions, and influenced by various factors that can lead to poor outcomes. Clinical decision support systems, which are a subset of artificial intelligence applications, aim to enhance the process of making healthcare decisions. Nevertheless, Sutton et al. (2020) highlight that the smooth integration of AI into clinical practice may face obstacles such as inadequate training data, interoperability challenges, and hesitancy among healthcare staff. In addition, Mantelero (2018) emphasizes the significance of including human rights and social and ethical considerations in incorporating AI. Inadequate AI integration can arise when firms overlook the importance of a comprehensive impact assessment that considers potential biases, privacy concerns, and ethical implications associated with AI systems (Ravikumar et al., 2022; Salameh et al., 2022; Shwedeh et al., 2021; Shwedeh, Adelaja, et al., 2023).

Moreover, organizational characteristics significantly influence the achievement of successful AI integration. The study conducted by Cao et al. (2021) revealed that managers' attitudes and behavioral intentions significantly influenced organizations' decision-making processes concerning the deployment of artificial intelligence (AI) (Aburayya et al., 2023; El Nokiti et al., 2022; Shwedeh, Aburayya, et al., 2022). The reluctance of managers to embrace AI technology can hinder the smooth integration of AI into current processes. In addition, Alsheibani et al. (2018) highlight the importance of corporate-level AI readiness. Inadequate integration may arise when companies do not possess the necessary infrastructure, resources, or a proactive approach to deploy AI technologies effectively. Buçinca et al. (2021) present a cognitive viewpoint, emphasizing the danger of excessive dependence on AI in making decisions. Organizations that do not implement systems that promote a balanced reliance on AI while maintaining critical thinking and human judgment may experience subpar outcomes and fall behind. The inadequate integration of AI can be ascribed to technological, ethical, organizational, and cognitive challenges. This underscores the significance of adopting a thorough and deliberate methodology when leveraging AI to facilitate organizational decision-making (Alkashami, Mohammad, et al., 2023; S. Salloum, Al Marzouqi, et al., 2023; Shwedeh, 2024; Shwedeh, Hami, et al., 2022).

Relationship between System Complexity and Effective Decision Making System using AI

To successfully incorporate artificial intelligence (AI) into decision-making systems, tackling the inherent difficulties related to system complexity is crucial. Bonczek et al. (2014) present a comprehensive analysis of the challenges involved in system integration, focusing on the complex process of integrating AI technologies into pre-existing frameworks. Filip (2008) explores the difficulties linked to decision support and control within the domain of extensive, intricate systems, emphasizing the necessity for advanced AI solutions to navigate intricate operational environments. Contreras and Vehi (2018) contribute to this discussion by examining the challenges of employing artificial intelligence (AI) for decision support in the medical field, specifically focusing on diabetes care. Duan et al. (2019) offer a comprehensive view, outlining the progression and obstacles of artificial intelligence (AI) in decision-making during the era of Big Data (Aboelazm, K. S., & Ramadan, S. A., 2023). Their research goal prioritizes recognizing the complex nature of the difficulties, necessitating holistic strategies to properly incorporate AI into decision-making processes (S. A. Salloum, Almarzouqi, Aburayya, Shwedeh, Fatin, Ghurabli, Dabbagh, et al., 2024; H. Yas, Aburayya, et al., 2024; H. Yas, Dafri, et al., 2024).

Furthermore, Jarrahi (2018) examines the mutually beneficial connection between humans and AI when making organizational decisions. The author highlights the importance of employing flexible solutions to handle the ever-changing intricacies effectively. Shrestha et al. (2019) examine organizational decision-making structures in the era of AI, offering insights into the evolution of organizational frameworks to harness AI capabilities effectively. Cheng et al. (2019) make a valuable contribution by highlighting the importance of user-friendly designs in explaining decision-making algorithms to non-expert stakeholders. They emphasize that a well-designed user interface can ease understanding complex AI-driven decision processes. These studies emphasize the importance of dealing with the complexity of systems to use AI effectively in decision-making systems. They highlight the necessity for sophisticated solutions to navigate complicated operational contexts.

H_1: System Complexity significantly influences effective decision-making systems using AI

Relationship between Data Quality Concerns and Effective Decision-making Systems Using AI

Given the growing impact of Big Data, the correlation between data quality concerns and the performance of decision-making systems that utilize artificial intelligence (AI) is a crucial part of the current study. Duan, Edwards, and Dwivedi (2019) explore the difficulties presented by the changing environment of Big Data in AI decision-making, recognizing the crucial importance of data quality in guaranteeing the dependability and honesty of decision support systems. Sambasivan et al. (2021) add to this discussion by highlighting the importance of data work and explaining that worries about data quality have far-reaching consequences in high-stakes AI, impacting the entire decision-making process. Janssen et al. (2020) emphasize the significance of data governance in structuring data for reliable AI. They highlight that issues about data quality directly affect the dependability and credibility of AI-driven decision support systems. These studies collectively assert that data quality is not merely a worry but a fundamental requirement for the efficient operation of AI in decision-making processes.

Furthermore, Shrestha et al. (2019) offer valuable insights into organizational decision-making structures in the era of artificial intelligence. They explain that concerns about data quality are widespread within organizations, and these issues significantly impact the overall efficacy of adopting AI. McGilvray's (2021) research highlights the necessary steps for successfully carrying out data quality initiatives, emphasizing the importance of high-quality data in establishing confidence and credibility in decision-making processes powered by information (Aboelazm, K. S., & Afandy, A., 2019). The combination of information from these sources provides a strong justification for the substantial correlation between concerns about the quality of data and the efficiency of AI decision-making systems. To fully leverage the capabilities of AI technologies, it is crucial to prioritize resolving data quality issues. This involves establishing decision support systems based on dependable, precise, and credible data.

H_2: Data Quality significantly contributes to the effectiveness of decision-making systems using AI

Relationship between Organizational Readiness and Effective Decision-Making System using AI

The current study focuses on the essential problem of the relationship between organizational readiness and the effectiveness of AI-based decision-making systems. Marakas (2003) establishes the foundation by highlighting its significance in incorporating technological advancement. Alami et al. (2021) expand upon this groundwork in the healthcare field, illustrating how organizational readiness significantly influences the successful integration of AI, modifying decision-making procedures and enhancing overall system efficiency (Shwedeh, Salloum, Aburayya, Fatin, Elbadawi, Ghurabli, Muhammad, et al., 2024; Shwedeh, Salloum, Aburayya, Fatin, Elbadawi, Ghurabli, Murad, et al., 2024; Shwedeh, Salloum, Aburayya, Kaur, et al., 2024). This stance aligns with the findings of Pumplun, Tauchert, and Heidt (2019), who examined the organizational framework for AI and determined that a well-prepared organizational structure is crucial for maximizing the effectiveness of AI technology. The research conducted by Jöhnk, Weißert, and Wyrtki (2021) highlights the significance of organizational readiness factors in implementing AI technology, contributing to a more comprehensive comprehension of the subject (Aboelazm, K. S., & Ramadan, S. A., 2023).

Najdawi (2020) highlights the importance of evaluating firms' preparedness in the UAE for artificial intelligence (AI) and creating a direct relationship between readiness levels and the successful integration of AI. In addition, Cao et al. (2021) examine the perspectives and intentions of managers on the use of AI in decision-making, uncovering behavioral traits influenced by the organization's preparedness. Alsheibani, Cheung, and Messom (2018) thoroughly evaluated the level of readiness for artificial intelligence (AI) at the firm level. They highlighted the importance of organizational readiness and explained how it contributes to the overall adoption of AI. The findings of these studies collectively support the argument that the effectiveness of AI in decision-making systems is closely connected to organizational readiness. This highlights the significance of having a detailed understanding of readiness factors to guide strategic decision-making and maximize the use of AI in modern organizational settings.

H_3: There is a significant relationship between organizational readiness and effective decision-making systems using AI

Relationship between User Engagement and Acceptance and Effective Decision Making System using AI

Marakas (2003) emphasizes the significant correlation between user engagement and the acceptability and effectiveness of decision-making systems utilizing artificial intelligence (AI). The study by Bader and Kaiser (2019) emphasizes the significance of the user interface in promoting human participation and enhancing acceptance and engagement with decision-support systems driven by artificial intelligence. In their study, Wen et al. (2008) contribute to this ongoing discourse by highlighting the importance of user engagement in decision-support systems. They argue that having an active user base is crucial for effectively utilizing AI technology in decision-making procedures .

In addition, Prentice, Weaven, and Wong (2020) examine the correlation between the quality of AI performance and consumer engagement, highlighting the moderating influence of AI preference. Shrestha, Ben-Menahem, and Von Krogh (2019) examine the decision-making patterns inside organizations in the era of AI. They provide a valuable understanding of the intricate connections between user involvement and the acceptability of AI in organizational settings. In addition, Cao et al. (2021) examine managers' attitudes and behavioral intentions toward AI, offering crucial insights into the human aspects of adopting and engaging with AI. Buçinca, Malaya, and Gajos (2021) propose the use of cognitive forcing functions as a means to prevent excessive reliance on AI. They emphasize the need for a cautious and balanced approach to enhance user engagement without fostering excessive dependence. These studies provide a comprehensive rationale for the crucial correlation between user involvement, acceptance, and the effectiveness of AI-driven decision-making systems in contemporary business environments.

The amalgamation of findings from Marakas (2003), Bader and Kaiser (2019), Wen et al. (2008), Prentice et al. (2020), Shrestha et al. (2019), Cao et al. (2021), and Buçinca et al. (2021) substantiate the contention that user engagement and acceptance play pivotal roles in determining the triumphant assimilation of artificial intelligence in decision-making systems. Firms are motivated to prioritize projects that enhance user engagement, leading to a positive user experience and maximizing the advantages of AI-driven decision support systems (Khudhair, H. Y., Jusoh, A., Nor, K. M., & Mardani, A., 2021).

H_4: There is a significant relationship between user engagement and effective decision-making systems using AI

Moderating the Role of Technological Infrastructure on the Relationships between the Selected Variables and Effective Decision Making Using AI

The influence of technological infrastructure on the connections between specific factors and the efficiency of decision-making with artificial intelligence (AI) is an essential aspect of current discussions in organizations. Marakas (2003) establishes the fundamental principles for comprehending complex interactions, highlighting the crucial significance of technological infrastructure in managing the integration and influence of AI technologies. Supriadi et al. (2018) elaborate on this point, emphasizing the importance of robust technological infrastructure in optimizing the potential advantages of AI applications. Benzidia et al. (2021) argue that technical infrastructure regulates the influence of big data analytics and AI in the context of green supply chains and hospital environmental performance. Mohtaramzadeh, Ramayah, and Jun-Hwa (2018) and Suseno et al. (2022) emphasize the significance of technological infrastructure in influencing the adoption of B2B e-commerce and AI among human resource managers, respectively.

Furthermore, the studies conducted by Saeidi et al. (2019), Nisar et al. (2021), Chatterjee et al. (2022), Prentice et al. (2020), and Kautish and Khare (2022) collectively emphasize the importance of technological infrastructure as a moderator in various organizational contexts. These contexts include enterprise risk management, significant data decision-making capabilities, and customer engagement. These studies emphasize that the moderating role of technology infrastructure significantly influences the performance of decision-making systems that use AI in different organizational areas.

Overall, the combination of insights from Marakas (2003), Supriadi et al. (2018), Benzidia et al. (2021), Mohtaramzadeh et al. (2018), Suseno et al. (2022), Saeidi et al. (2019), Nisar et al. (2021), Chatterjee et al. (2022), Prentice et al. (2020), and Kautish and Khare (2022) strengthens the argument that technological infrastructure plays a crucial moderating role in shaping the effectiveness of decision-making systems that utilize AI. As businesses aim to use AI technologies fully, it is essential to prioritize the development and upkeep of a robust technological infrastructure. This infrastructure plays a significant role in shaping the complex connections between AI and other organizational activities.

Importance in the UAE Higher Education Landscape

Recent academic analyses demonstrate the importance of introducing artificial intelligence (AI) into decision-making systems in the UAE's higher education industry. Qasim et al. (2022) underline the significance of incorporating emerging technologies and artificial intelligence (AI) into undergraduate accounting curricula, proposing a paradigm shift in educational delivery. Mustapha et al. (2023) highlight the potential for data-driven insights in higher education by integrating Big Data analytics with mobile applications. In their comprehensive assessment of generative AI in educational settings, Bahroun et al. (2023) underline AI's revolutionary potential in redefining education techniques. Kamalov et al. (2023) make a scholarly contribution to this discussion by depicting a new era of AI and suggesting a long-term and complex education reform. Integrating artificial intelligence (AI) into decision-making systems in higher education in the UAE is consistent with the global trend toward innovative and technology-oriented educational techniques. This integration ensures that students benefit from a dynamic and responsive learning environment (Khudhair, H. Y., Jusoh, A., Mardani, A., Nor, K. M., & Streimikiene, D., 2019).

2. Research Framework

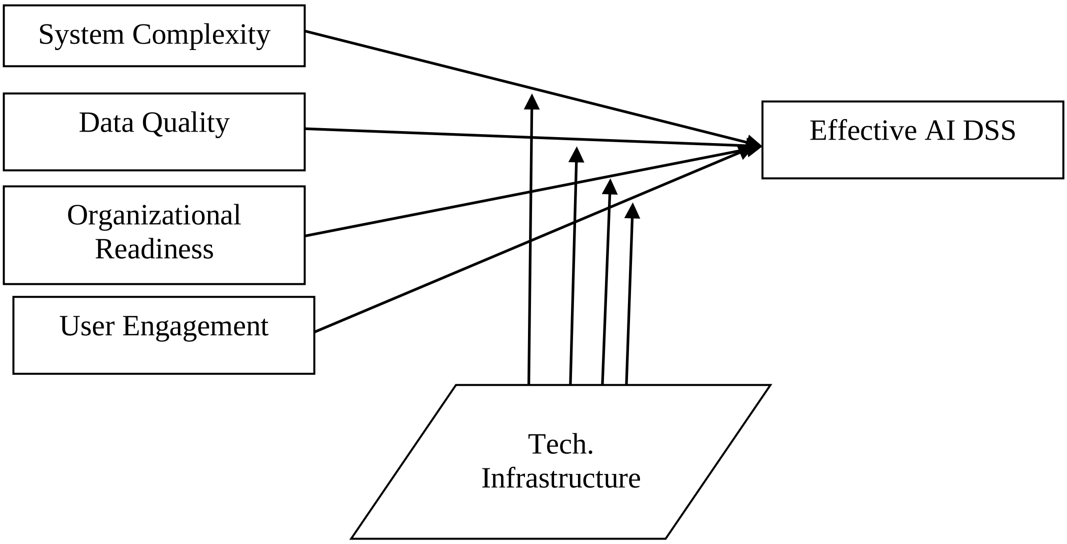

Figure 1: Research Framework

Theoretical Underpinning: Diffusion of Innovations Theory

The Diffusion of Innovations Theory provides the theoretical foundation for comprehending the incorporation of artificial intelligence (AI) into decision support systems in higher education. This idea, coined by Everett Rogers, elucidates how innovations, such as AI in this context, disseminate and become embraced within a social system as time progresses. Goss (1979) and Orr (2003) examine the ramifications and intricacies of disseminating innovations, offering fundamental perspectives on the societal effects of embracing novel technologies.

Studies by Musmann (1982) and Wejnert (2002) analyze the spread of new ideas in libraries and suggest a theoretical framework for incorporating diffusion models. Greenhalgh et al. (2004) expand upon this hypothesis by undertaking a comprehensive analysis of innovations spread in service organizations, providing helpful suggestions for successful implementation. Implementing this idea in integrating AI into decision support systems in higher education requires tackling obstacles associated with the rate at which it is adopted and diffused, as Ain et al. (2019) examined in the context of adopting business intelligence systems. In this study, Clohessy and Acton (2019) discuss how organizational factors impact the adoption of blockchain technology, focusing on the perspective of innovation theory. They emphasize the importance of comprehending the dynamics of adoption.

Moreover, Greenhalgh et al. (2008) comprehensively analyze the spread of new ideas and practices in healthcare organizations, highlighting the significance of considering the intricate organizational environment during the adoption process. Amron et al. (2019) investigate the elements that affect the acceptability of cloud computing, offering valuable insights into the aspects that determine the adoption of innovation. By incorporating AI into decision support systems in higher education, organizations can utilize the Diffusion of Innovations Theory to comprehend the factors that impact adoption, overcome challenges associated with the diffusion rate, and improve organizational preparedness and user involvement. This will ultimately facilitate a more seamless integration process.

3. Methodology

This study employs a cross-sectional survey design to examine the significant correlations among system complexity, data quality, organizational readiness, user engagement, technological infrastructure, and the efficacy of decision-making systems utilizing artificial intelligence (AI) in higher education institutions in the UAE.

Sample Strategy: UAE higher education institutions are targeted. A representative sample of institutions is selected via purposive sampling based on size, geography, and academic reputation. To ensure position and department representation, stratified random sampling is used to pick participants within each institution.

Data Collection: Selected individuals complete self-administered internet surveys. Based on the research objectives and theoretical framework, the survey instrument measures data quality, organizational readiness, user engagement, technology infrastructure, and decision-making efficacy using validated scales. Demographic questions concerning roles, tenure, and experience are contained in the survey.

The research instrument was derived from validated sources identified throughout the literature review. The questionnaire comprises items derived from the findings of Duan et al. (2019), Filip (2008), Cheng et al. (2019), Jarrahi (2018) and Sambasivan et al. (2021), acknowledging the inherent complexities of integrating AI into decision support systems. In total, seven (7) questionnaire items were developed. The developed items are:

1. Integrating AI technology into existing frameworks impedes higher education decision-making.

2. Adequate decision support and administration require addressing the complexity of complex systems in academic settings.

3. A study on integrating AI for decision help in healthcare and diabetes management in education emphasizes the need for improved ways to address difficult situations.

4. Our institution focuses on creating comprehensive solutions for AI decision-making in the Big Data era, recognizing the complexity of the challenges.

5. Flexible solutions must accommodate ever-changing complexities for a successful partnership between AI and humans in corporate decision-making.

6. To fully utilize AI, our institution must comprehend organizational decision-making frameworks in the AI era.

7. Emphasizing the need for simple designs in presenting complicated decision-making algorithms to non-expert stakeholders highlights the complexity of AI-powered processes.

The questions used to assess data quality are derived from Dwivedi (2019), Janssen et al. (2020), McGilvray (2021) and Shrestha et al. (2019), and they encompass a wide range of attributes related to data quality in decision-making powered by artificial intelligence. Like system complexities, seven items were developed in this regard, extending to respondents' perception of data quality as a professional, consequences, data quality initiatives and issues. The adapted items are:

1. We must prioritize data quality in our organization's decision-making processes to ensure the decision support system's reliability and integrity.

2. Data quality issues must be addressed to ensure the reliability and trustworthiness of AI-driven decision support systems in education.

3. I believe that data governance and data integrity affect the dependability and credibility of AI-powered decision support systems.

4. Data quality issues in high-stakes AI impair our higher education institution's decision-making process.

5. Analyzing and improving our organization's AI preparedness requires evaluating data quality issues to ensure seamless AI integration into decision-making.

6. Understanding the relationship between AI performance, customer involvement, and AI preference improves our decision-making.

7. Data quality must be addressed to maximize AI technology's potential. Decision support systems based on reliable, accurate, and trustworthy data are our educational goal.

References to organizational readiness are derived from studies like Alsheibani et al. (2018), Cao et al. (2021), Najdawi (2020) and Shrestha et al. (2019), which examine the preparedness of higher education institutions for implementing artificial intelligence. The adapted items are given below:

1. Our organization has the competencies to incorporate artificial intelligence (AI) into its decision-making processes.

2. In my view, the impact of organizational structure on the effectiveness of AI-driven decision-making processes is significant.

3. Organizational readiness plays a crucial role in adjusting decision-making processes and improving system efficacy through the integration of AI, based on my personal experience.

4. I believe the elements related to the organization's readiness are essential for optimizing the efficiency of AI technology at our institution.

5. We must assess our organization's readiness in the United Arab Emirates to ensure the smooth incorporation of artificial intelligence into decision-making procedures.

6. The degree of organizational readiness significantly impacts managers' decision-making behavior, influenced by their attitudes and intentions.

7. From my perspective, the level of preparedness of higher education institutions to handle artificial intelligence is a crucial determinant of the total incorporation of AI into the education industry.

Additionally, items measuring users' engagement were adopted from the studies that include Bader and Kaiser (2019), Buçinca, Malaya, and Gajos (2021), Shrestha, Ben-Menahem, and Von Krogh (2019), and Wen et al. (2008). Also, a seven items were developed in this regard.

Furthermore, the user engagement metrics are derived from the insights emphasized by McGilvray (2021) and Shrestha et al. (2019), which encompass user-focused factors in the deployment of artificial intelligence.

1. Our institution's technology dramatically affects AI-based decision-making systems.

2. I believe smooth technology infrastructure integration is essential for leveraging AI in decision-making.

3. I think AI-driven decision support systems depend on the efficiency and endurance of our technology infrastructure.

4. In my experience, technical infrastructure significantly affects AI decision-making.

5. A solid, contemporary technological foundation is needed to check AI's decision-making effectiveness.

6. Technology infrastructure is essential for regulating and maintaining AI-driven decision support system reliability.

7. we must invest in and upgrade our technical infrastructure to maximize AI's impact on decision-making processes.

The questionnaire also assesses the moderating impact of technological infrastructure by incorporating literature-based items and examining the role of technology in influencing the outcomes of AI integration. The sources for this include the studies of Buçinca et al. (2021), Cao et al. (2021), Mantelero (2018), and Sutton et al. (2020). Six items were developed in this regard.

Measuring Decision-Making Systems Using AI

1. Organizational issues and the attitudes and actions of managers impact the integration of AI decision-making.

2. Understanding our educational institution's decision support system concerns requires a detailed evaluation of AI integration issues.

3. I believe that the challenges of integrating the higher education system impede technological advancement and the process of making informed decisions.

4. To integrate AI into our organization's decision-making process, we must conduct a complete impact assessment that examines biases, privacy, and ethics.

5. The absence of artificial intelligence in higher education hinders technological advancement, causing our university to face challenges.

6. AI integration issues, including organizational, managerial, and strategic interactions, go beyond technology.

7. It is imperative to conduct research, implement solutions, and adopt appropriate policies to address the complex issues surrounding the integration of AI in educational decision-support systems.

8. Our AI strategy for higher education should prioritize human rights and actively tackle social and ethical concerns.

4. Findings and Discussion

Before testing the proposed hypotheses, we assess the convergent and discriminant validity model to confirm the measurement model. With this, we access the item loadings, meaning each item's loadings should be greater than 0.4. (Shrestha, 2021). This condition is presented in Figure 2 and Table 1. Also, Average Variance Extracted (dos Santos & Cirillo, 2023) and composite reliability were used in assessing the constructed model. According to the postulations by Ghadi, Alwi, Bakar and Talib (2012) and Ramayah et al. (2017), the AVE value should be greater than five (5), and the CR value for each construct should be greater than 0.7. Evidence from Fig 2 and Table 1 shows that these conditions were satisfied.

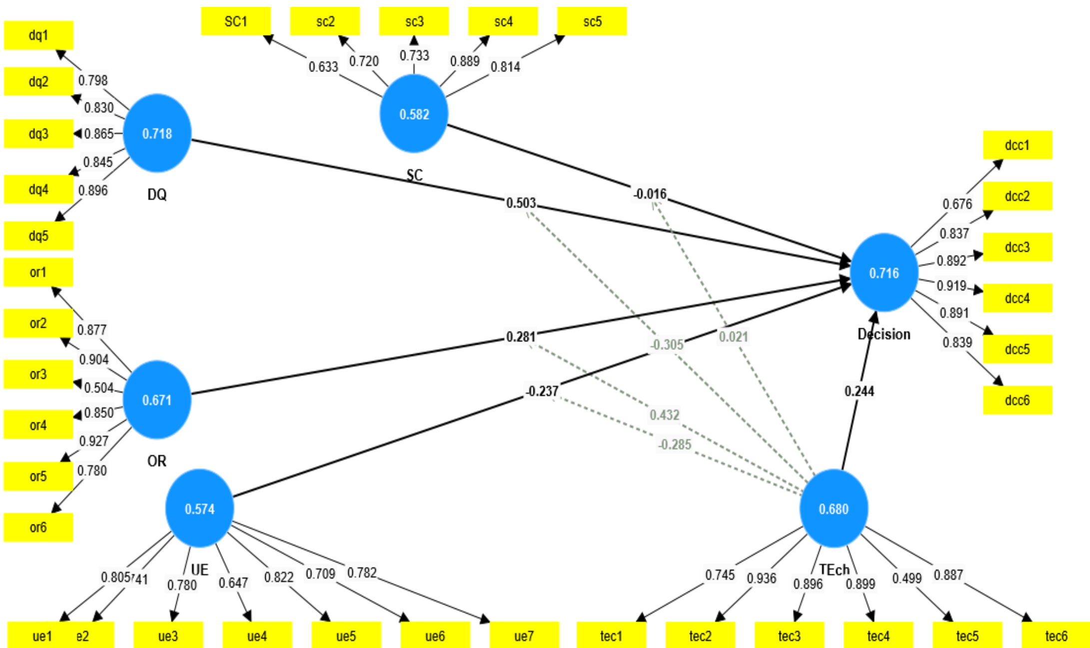

Figure 2. Measurement Model Assessment

Table 1 Construct and Discriminant Validity

Construct	Item	Item Loadings	CR	AVE	Discriminant Validity
Decision	dcc1	0.676	0.938	0.716	Yes
	dcc2	0.837			
	dcc3	0.892			
	dcc4	0.919			
	dcc5	0.891			

	dcc6	0.839			
System Complexity	sc1	0.633	0.873	0.582	Yes
	sc2	0.72			
	sc3	0.733			
	sc4	0.889			
	sc5	0.814			
Data Quality	dq1	0.798	0.927	0.718	Yes
	dq2	0.83			
	dq3	0.865			
	dq4	0.845			
	dq5	0.896			
Organization Readiness	or1	0.877	0.922	0.671	Yes
	or2	0.904			
	or3	0.504			
	or4	0.85			
	or5	0.927			
	or6	0.78			
Users' Experience	ue1	0.805	0.904	0.574	Yes
	ue2	0.741			
	ue3	0.78			
	ue4	0.647			
	ue5	0.822			
	ue6	0.709			
	ue7	0.782			
Technology	tec1	0.745	0.925	0.68	Yes
	tec2	0.936			
	tec3	0.896			
	tec4	0.899			
	tec5	0.499			
	tec6	0.887			

Moreover, we assess the model's discriminant validity using Heterotrait Monotrait (HTMT) correlations. According to Hensler et al. (2015), the model is discriminant valid when the HTMT correlation is less than 0.9. Insight to Table 2 shows that the HTMT values between the constructs are less than 0.9. Given this, it is acknowledged that discriminant validity is achieved. Meanwhile, other studies access data discriminant validity using the Fornel Larcker Criterion. However, Henseler, Ringle and Sarstedt's (2015) argument claims that the Fornel Larcker parameter lacks practical inference. Given this, we did not employ such a parameter in this investigation.

Table 2 HTMT Correlations

	DQ	Decision	OR	SC	Tech	UE	Tech x UE	Tech x OR	Tech x DQ
Decision	0.778								
OR	0.875	0.848							
SC	0.151	0.19	0.316						
Tech	0.839	0.842	0.651	0.255					
UE	0.745	0.664	0.822	0.149	0.888				

TEch x UE	0.386	0.473	0.43	0.065	0.488	0.644			
Tech x OR	0.418	0.364	0.418	0.079	0.333	0.483	0.821		
Tech x DQ	0.206	0.405	0.395	0.089	0.329	0.421	0.706	0.782	
TEch x SC	0.12	0.047	0.038	0.028	0.096	0.082	0.128	0.209	0.026

Additionally, we assess the presence of multicollinearity in the data using the Variance Inflated Factor (VIF). As proposed by Paul (2006) and Lavery, Acharya, Sivo and Xu (2019), a statistical model is said to have multicollinearity issues if the VIF value is greater than five (5). As presented in Table 4 and Table 5, the VIF value for the items and constructs is below 5. Considering this, we believe the data set is free from multicollinearity issues. Thus, we examine the significant relationship between the investigated constructs.

Table 3 Item Vif

	VIF
SC1	1.636
dcc1	1.628
dcc2	2.53
dcc3	3.607
dcc4	0.864
dcc5	3.764
dcc6	2.467
dq1	2.488
dq2	2.308
dq3	3.533
dq4	2.297
dq5	3.463
or1	3.019
or2	2.209
or3	1.213
or4	2.624
or5	2.108
or6	1.963
sc2	1.402
sc3	2.071
sc4	1.858
sc5	2.096
tec1	1.877
tec2	5.807
tec3	4.258
tec4	4.308
tec5	1.312

tec6	3.541
ue1	2.47
ue2	2.812
ue3	2.054
ue4	2.411
ue5	2.654
ue6	1.832
ue7	2.745
Tech x OR	1
Tech x UE	1
TEch x DQ	1
Tech x SC	1

Table 4 Construct Vif

	Decision
DQ	3.829
OR	2.455
SC	1.187
TEch	3.794
UE	3.811
Tech x UE	0.683
Tech x OR	1.863
TEch x DQ	3.505
Tech x SC	1.115

Structural Model Assessment

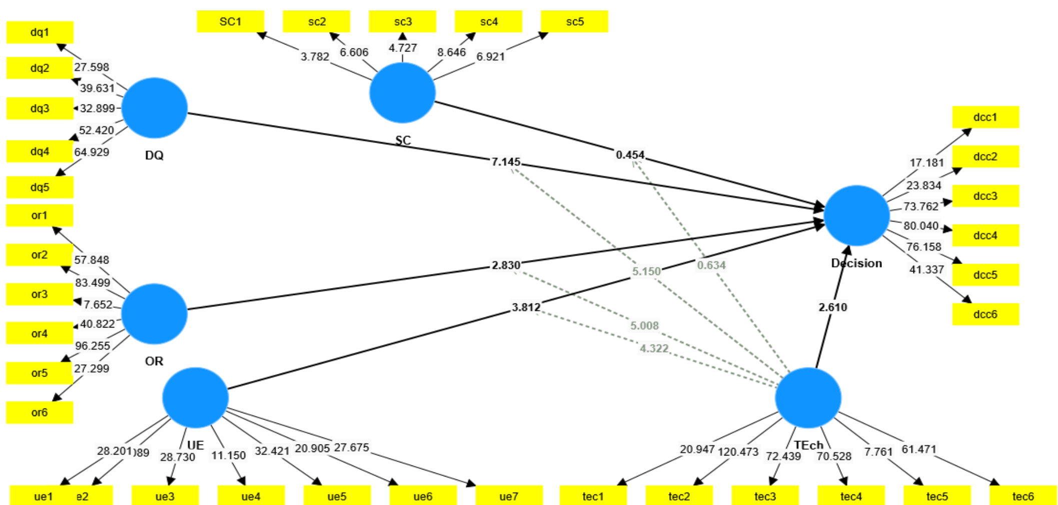

Figure 3. Structural Model Assessment

Table 5. Hypothesis Testing

Relationship	β	STDEV	T stat	P values	Verdict
SC -> Decision	-0.016	0.035	0.454	0.65	Not Accepted
DQ -> Decision	0.503	0.07	7.145	0	Accepted
OR -> Decision	0.281	0.099	2.83	0.005	Accepted
UE -> Decision	-0.237	0.062	3.812	0	Accepted
Tech -> Decision	0.244	0.094	2.61	0.009	Accepted
Tech x SC -> Decision	0.021	0.033	0.634	0.526	Not Accepted
Tech x DQ -> Decision	-0.305	0.059	5.15	0	Accepted
Tech x OR -> Decision	0.432	0.086	5.008	0	Accepted
Tech x UE -> Decision	-0.285	0.066	4.322	0	Accepted

Using SEM to analyze the relationship between the investigated variables, we found system complexity (SC) to have a negative insignificant relationship with effective decision-making process using AI among higher education institutions in the UAE having insignificant having (SC) ($\beta = -0.016$, p-value = 0.65, ($p > 0.05$)); hence, H_1 was not accepted. Data quality (DQ) was found to have a significant influence on effective decision-making using AI among higher educational institutions in the UAE having (DQ) ($\beta = 0.503$, p-value = 0.000, ($p < 0.05$)); therefore, H_2 was accepted. Organizational readiness (OR) in this investigation has a significant relationship with effective decision-making using AI amongst higher education institutions in the UAE having (OR) ($\beta = 0.281$, p-value = 0.000, ($p < 0.05$)); hence, H_3 was accepted. Also, users' engagement has a significant influence on the effective decision-making process, having (UE) $\beta = 0.193$, p-value = 0.000, ($p < 0.05$)). Even though this relationship is negative, nevertheless, a significant relationship exists. Hence, H_4 was accepted. Technology infrastructure (tech) was found to have a significant relationship with effective decision making having (tech) $\beta = 0.244$, p-value = 0.000, ($p < 0.05$)). Therefore, the fifth hypothesis (H_5) was accepted.

Similarly, the moderating role of technology infrastructure on the relationship between the independent variables was examined. It was observed that the moderating role of technology infrastructure on system complexity (Tech x SC) -> DSS having ($\beta = 0.021$, p-value = 0.000, ($p > 0.05$)). Hence, the sixth hypothesis (H_6) was not accepted. The moderating influence of technology infrastructure on data quality (Tech x DQ -> DSS) having ($\beta = -0.305$, p-value = 0.000, ($p < 0.05$)). Despite the negative relationship, the relationship is significant; hence, H_7 was accepted. The moderating role of technology infrastructure and organizational readiness on effective decision-making process using AI produce a significant moderating effect having (Tech x OR -> Decision) ($\beta = 0.432$, p-value = 0.000, ($p < 0.05$)); hence, H8 was accepted. The moderating effect of technology and users' engagement on effective decision-making using AI among higher education institutions (Tech x UE -> Decision) having ($\beta = -0.285$, p-value = 0.000, ($p < 0.05$)); although the observed relationship was negative, nevertheless, the relationship was significant; given this, H_9 was accepted.

The analysis result shows that the investigated variables, namely system complexity, data quality, organizational readiness, user engagement and technology infrastructure, explain 74.40% variance in effective AI decision-making in higher education institutions among higher education institutions in the UAE having r^2 equals 0.744.

Table 6. Variance Explained

	R-square	R-square adjusted
Decision	0.744	0.734

Table 7. Effect Size (f^2)

	f^2	Decision
DQ	0.258	Large
OR	0.056	Low
SC	0.001	Low
Tech	0.04	Low
UE	0.058	Low
Tech x UE	0.081	Low
Tech x OR	0.118	Low
Tech x DQ	0.104	Low
Tech x SC	0.001	Low

We employ Cohen's (1988) effect sizes where f2 of 0.02, 0.15, and 0.35 relate to low, medium and significant effects to determine which factors have more influence on decision-making using AI. Our findings reveal that data quality has approximately more than the medium effect on decision making, followed by the relationship between the moderating impact of tech and OR; tech x DQ and Tech x UE having 0.258, 0.111, 0.104 and 0.81 having lower effects while others have lesser than lower (minute) effects.

5. Discussions of Findings

This research reveals insights into how artificial intelligence (AI) is integrated into decision-making processes in higher education institutions in the UAE. Using Structural Equation Modeling (SEM) to analyze the connections between variables revealed numerous significant findings with implications for theory and practice.

System complexity (SC) was found to have a minimal and insignificant correlation with successful decision-making processes using AI, as reported by Paul (2006) and Marakas (2003). Although not statistically significant, this discovery indicates that increased system complexity may not hinder good decision-making. Further investigation into the intricacies of system complexity and its interaction with decision-making could offer a more profound understanding of this connection (Khudhair, H. Y., Jusoh, A., Mardani, A., & Nor, K. M., 2019).

Data quality (DQ) has been identified as a critical factor that significantly impacts the efficiency of decision-making processes (Bonczek et al., 2014; Nisar et al., 2021). Emphasizing the need for top-notch data inputs in AI-based decision support systems in educational environments. Organizations must prioritize data governance and quality assurance to utilize AI in decision-making fully.

Organizational readiness (OR) was discovered to have a considerable influence on successful decision-making processes, according to Alami et al. (2021) and Jöhnk et al. (2021). This emphasizes the need for organizations to be ready and open to incorporating AI integration projects. Institutions must prioritize developing a culture that welcomes technological progress and encourages preparedness for AI implementation. Users' engagement (UE) had a notable impact on decision-making efficacy, even if there was a negative correlation (Benzidia et al., 2021; Prentice et al., 2020). User engagement is essential but does not necessarily directly lead to great results. Strategies should be developed to increase user engagement in line with organizational objectives and decision-making goals.

Furthermore, the study highlighted that having a solid technology infrastructure is crucial for making effective decisions, underscoring the necessity of reliable technological frameworks to facilitate AI-driven operations (Bader & Kaiser, 2019; Saeidi et al., 2019). Investing in digital infrastructure enables smooth integration and enhances decision-making capabilities (Khudhair, H. Y., & Mardani, A., 2021).

The study investigated how technology infrastructure influences the connection between independent variables. Some moderating effects were noted on data quality and organizational readiness, as discussed by Pumplun et al. (2019) and Shrestha et al. (2019). However, the interaction between technology infrastructure and system complexity did not moderate substantially. The results highlight the complex relationship between technology infrastructure and other factors affecting decision-making efficiency, indicating more research is needed.

6. Theoretical Implications

Our research results are consistent with the theoretical foundations of diffusion theory, providing valuable insights into the implementation and effects of AI-driven decision support systems in higher education institutions in the UAE. System complexity (SC) did not significantly correlate with successful decision-making processes. However, variables like data quality (DQ), organizational readiness (OR), users' engagement (UE), and technology infrastructure (Tech) were identified as essential factors. Addressing organizational factors, developing a culture of readiness, and investing in firm technological foundations are crucial for seamlessly integrating AI into decision support systems. Studying moderating effects reveals the complex relationship between technology infrastructure and essential factors, emphasizing the detailed nature of AI adoption procedures. Institutions can utilize diffusion theory to leverage the revolutionary potential of AI for improving decision-making processes and increasing educational practices and outcomes in the UAE and beyond.

The research findings have theoretical implications based on the Diffusion of Innovations Theory, providing valuable insights for academia and practical applications. Our study highlights the significance of comprehending the complex nature of technology adoption in higher education environments. Our research enhances comprehension of the elements affecting artificial intelligence (AI) incorporation into decision support systems, contributing to a better understanding of innovation dissemination in educational settings.

The essential connections between critical criteria like data quality, organizational readiness, user engagement, and technology infrastructure emphasize the crucial significance of these elements in supporting efficient decision-making processes. Institutions can utilize these findings to create customized strategies to improve organizational readiness, encourage user participation, and enhance technological infrastructure for AI-based decision support systems.

Examining moderating effects highlights the significance of considering how technology infrastructure interacts with other factors to influence decision-making effectiveness. A deep knowledge allows companies to pinpoint chances for intervention and optimization, ultimately enhancing the integration and application of AI technology in educational decision-making processes.

The theoretical implications of our research underscore the necessity of a comprehensive strategy for technology adoption, considering organizational, technological, and human variables. By adopting these insights, higher education institutions may effectively negotiate the complexity of AI integration, improve decision-making capacities, and ultimately achieve positive educational results in the digital age.

7. Practical Implications

The study found some crucial factors affecting UAE higher education institutions' AI decision-making. Educational leaders and administrators can learn from the study's findings on variable-decision relationships. Our research shows that data quality is essential for AI decision-making. Data quality is strongly correlated with decision-making effectiveness, emphasizing the need for institutions to maintain data quality. Robust data governance frameworks can increase AI-driven decision support system reliability and efficacy by ensuring data accuracy and trustworthiness.

Furthermore, this investigation reveals that organizational readiness is vital to AI adoption and integration. Leadership support, resource allocation, and staff abilities are crucial to AI integration since institutions with more vital organizational preparedness make better decisions. By addressing organizational readiness concerns, institutions can speed up the implementation of AI decision assistance.

Our study emphasizes user interaction and training to maximize the benefits of AI-powered decision-help systems. User involvement greatly influences decision-making, emphasizing end-users importance in AI adoption despite a negative relationship. Institutions may help staff use AI technology and make educated decisions through targeted training, capacity-building, and active engagement.

Our analysis shows that higher education institutions need continual IT infrastructure investment for AI applications. Hardware, software, and network infrastructure are crucial to AI-based decision support systems, as institutions with robust technology infrastructure make better decisions. Institutions should prioritize technology infrastructure upgrades and maintenance to ensure AI stability, scalability, and security to improve decision-making.

We offer practical advice for higher education institutions using AI to improve decision-making. Data quality assurance, organizational preparation, user engagement and training, and technology infrastructure investment can help institutions fully leverage AI technologies. This will assist them to attain success and fulfill their aim of excellent education and research.

Our research findings provide many recommendations to enhance the incorporation of artificial intelligence (AI) into decision support systems at higher education institutions in the UAE. Institutions should focus on investing in data quality assurance procedures to guarantee the dependability and significance of data inputs for decision-making processes driven by AI. This involves establishing strong data governance structures, conducting data validation procedures, and providing training programs to improve data literacy among stakeholders. Creating a culture of organizational readiness is crucial for adequately implementing AI adoption programs. Institutions should allocate resources to projects that foster innovation, open communication, and collaboration while offering support to allow smooth integration processes.

8. Limitations

Our study provides essential insights into incorporating AI into decision support systems in higher education, but it is crucial to recognize numerous limitations. The generalizability of our findings may be limited because we focused on higher education institutions in the UAE. Future research should focus on replicating the study in various geographical regions and educational settings to confirm the strength of the results. The study’s cross-sectional design restricts our capacity to determine causal correlations between variables. Conducting longitudinal studies to monitor the implementation and effects of AI-based decision support systems over time would offer more definitive proof of causation, enabling a more profound comprehension of the mechanisms at play in accepting technology in educational environments.

9. Conclusions

Our study explores the incorporation of artificial intelligence (AI) into decision support systems at higher education institutions in the UAE, based on the Diffusion of Innovations Theory. System complexity did not significantly impact data quality, organizational readiness, user engagement, and technology infrastructure, which are crucial elements influencing effective decision-making processes. Institutions should focus on investing in data quality assurance, promoting organizational readiness, improving user engagement, and enhancing technical infrastructure to support AI-driven decision support systems effectively. Although limited by geographical focus and a cross-sectional design, our findings provide valuable insights for policymakers, educators, and practitioners interested in utilizing AI to enhance educational outcomes and promote innovation in higher education.

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