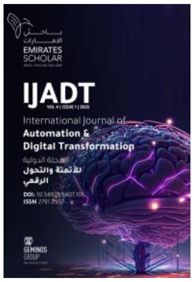


International Journal of Automation and Digital Transformation
Vol 4 Issue 1 (2025)
Pages (4 - 20)

Available at www.emiratesscholar.com

Adoption of Data Analysis Technology and Its Impact on Decision-making Efficiency and Research Output in development in the UAE higher education system

Shafeeq Saidlavi Hyder[1]
shafeeqsali@gmail.com[1]
PhD Student, Banasthali Vidyapith, Rajasthan, India[1]
Senior Business System Analyst, Innovation and Scientific Research Support Department, Ministry of Higher Education and Scientific Research, United Arab Emirates[1]

ARTICLE INFO

Published on 7th of February 2025
Doi:10.54878/9fnx8a79

KEYWORDS

Data Analytics, Data-Driven Decision-making, Student Academic Performance, Institutional Effectiveness, UAE Higher Education

HOW TO CITE

Adoption of Data Analysis Technology and Its Impact on Decision-making Efficiency and Research Output in development in the UAE higher education system. (2025). *International Journal of Automation and Digital Transformation*, *4*(1), 4-20.

ABSTRACT

This research examined the relationship of data analytics to data-driven decision-making with the academic success and the institutional efficacy of higher education students in the United Arab Emirates. The aim was to understand data analytics' impact on student learning, retention, academic results, and institutional efficacy. For quantitative correlational research, stratified random sampling was utilized to solicit responses from 384 educators, administrators, and decision-makers representing all UAE institutions. The results indicate that data analytics improved learning outcomes and increased student retention rates. Data-driven decisions resulted in more efficient institutions. The institution's efficacy further moderates the correlation between data analytics and student academic success. Overall, the results suggest the effectiveness of data analytics in better decision-making and processes within the UAE higher education system, ultimately leading to better educational outcomes and better administration of institutions.

1. Introduction

Roles inside organizations have been transformed entirely by introducing Industry 4.0 and Society 5.0 because of the wide-ranging integration of data analysis technologies, computer networks, and digital applications. HEIs are urged to embrace data-driven approaches to enhance research output, streamline business processes, and make more informed decisions through these innovations(Rodríguez-Abitia & Bribiesca-Correa, 2021). The use of technology has become essential to academic quality and institutional efficiency at UAE HEIs (Chauca et al., 2021). The COVID-19 epidemic pushed HEIs to emphasize sophisticated data analysis tools for operational performance and strategic planning, further speeding up the digital transformation drive (Deja et al., 2021),(Garcez et al., 2022). For higher education in the twenty-first century, scholars concur that digital transformation supported by strong data analytic frameworks is necessary (Valdés et al., 2021). (Rodríguez-Abitia & Bribiesca-Correa, 2021)state that using data analysis technology becomes critical in UAE higher education for efficiency in decision-making, customer happiness, and research output.

Higher education institutions seem reluctant to respond despite technological advancements causing changes in the education sector. Due to a lack of strong leadership and cultural shifts, universities lag behind other industries in digital transformation (Cabero-Almenara et al., 2021). Consequently, All HEIs, or higher learning institutions, must have adequate and thorough internet connections. The university needs leadership and human capital management with sufficient digital capabilities, especially given the Fourth Industrial Revolution's (4IR) rapid technological advancements in robotics, IoT, nanotech, big data, and AI are all parts of this technological landscape. Accordingly, organizational support, change management, and manager and employee engagement are aspects of the leadership dimension for sustainable HEIs' digital transformation (Rodríguez-Abitia & Bribiesca-Correa, 2021). Several research studies stress the importance of digital leadership strategy (Chauca et al., 2021)and top-down university management (Bond et al., 2018) in facilitating digital transformation in higher education.

The primary mission of any HEI is to offer students an excellent education. Funding for many universities is contingent on factors like the number of students enrolled and the quality of their research. Maintaining excellent education at higher education institutions requires ongoing monitoring of activities and management choices (Prasetyo, 2022). Higher Education Institution (HEI) management must make everyday choices to adhere to institutional strategy and fulfil goals. In higher education, trustworthy assistance is essential for making management choices. Increasingly, higher education administration prioritizes accurate and accessible information for fundamental operations and strategic planning (Mukred et al., 2021). Modern universities seek to enhance conventional management methods and address associated difficulties. Recently, HEIs rely more on data gathering, storage, and processing (Şuşnea, 2013). Modern higher education institutions automate their processes with software systems such as information systems for students, systems for managing instruction, systems for tracking employees' performance, and systems for documenting relevant scientific work. In addition, they may tap into other data sets like databases and registrations, which are packed with information, to inform management decisions and improve processes. Data is useless if HEI leaders fail to see its strategic relevance and use it to make informed choices.

With so many systems, it is very challenging for HEI leadership to locate the necessary information for decision-making (Mukred et al., 2021). Human resources participation and manual perusal of continuous data streams are required for data collecting and analysis. Furthermore, the data provided does not reveal the current situation of the HEI and should be reanalyzed whenever the management of the HEI needs the most recent information. As a result, Higher Education leadership is becoming more interested in leveraging data gathered and examined to aid in decision-making (Gagliardi & Turk, 2017),(Swing & Ross, 2016). To support ongoing process optimization, management, and improvement in all significant areas, they are attempting to implement new techniques and solutions for obtaining data from software systems and transforming it into knowledge that can be utilized to guide strategic decisions at all organizational levels (Prasetyo, 2022), (Mora et al., 2017),(Den Heijer, 2012),(Ada & Ghaffarzadeh, 2015).

Investing in suitable technologies that support all management activities is necessary for the latter (Ashour et al., 2022), such as business intelligence (Chairungruang et al., 2022), educational data mining, learning analytics, academic analytics, and semantic and linked-data technologies. Data extraction, analysis, and categorization from various systems may be automatically done using data analysis tools (Karami et al., 2013). By providing graphical summaries of information (charts, tables, and measurement graphs [15]), they enable HEI leadership to monitor and evaluate trends and KPI performance via user-friendly dashboards (Hansoti, 2010)and uncover hidden patterns, trends, or anomalies (Dasgupta et al., 2015) in the data. Consequently, the leadership of HEIs is better able to oversee the organization, assess the results of their projects, decide how best to improve current procedures and gather data for well-informed decision-making (Long & Siemens, 2014),(Patwa et al., 2018). By using these tools, stakeholders in HEIs can gather information on ongoing research and educational processes, track progress over time, and gain insight into nearly every facet of HEI operations, including but not limited to research, cost management, student performance, academic productivity, enrollment patterns, and career development. They can also take action to improve these processes. Managers of HEIs can provide alternative solutions (Bresfelean et al., 2009), reduce the risk and detrimental effects of mistakes (Şuşnea, 2013), increase the validity of management decisions made (Borovyk, 2020), and help achieve sustainable development of HEIs by using software solutions to support the decision-making process. They can also save time, money, and resources by hiring experts to extract pertinent information for decision-making, improve insight, and gain better control over operations. The cost and time required to identify issues, challenges, or roadblocks in higher education systems and make the best judgments are decreased by putting decision-making tools into place and implementing them (Fakeeh, 2015),(Niet et al., 2016),(Acevedo et al., 2018). Time and money spent on finding problems and solutions to differentiate between complexities or barriers of higher education systems are decreased by implementing and using decision-making tools.

Implementing new educational policies will be significantly aided by the unified program that will help those in charge of making decisions about schooling in coming up with prompt and appropriate responses. It takes time and often does not go well to implement analytical tools to help managerial decision-making. Using such technologies presents HEIs with several technical obstacles and issues about privacy and the moral and responsible use of data (Webber & Zheng, 2020). Large datasets also don't always translate into superior choices. The implementation process often includes six stages: planning, business analysis, design, construction, deployment, and justification (Webber & Zheng, 2020). This process requires a detailed analysis of the current procedures, including the choice of suitable data for processing, the choice of data extraction and visualization tools, the establishment of data warehouses, the integration of relevant data sources, etc. (Chairungruang et al., 2022),(Yulianto& Kasahara, 2018). Besides addressing the privacy and security concerns, HEI leaders also need to think about whether they can better use the data analytics and methods or how they can utilize available data in making decisions, which leads to the integrative process of analytical tools into the HEI structure of decision-making, with resource allocations and institutional strategic planning based on its ever-increasing importance for progress The institution's objective. Implementing a data-based decision-making culture in the HEI requires trained personnel and data management systems, data integration technologies, reporting, analysis, and visualization tools.

To enhance academic performance for sustainable development, this study focuses on the critical data-driven decision-making tools universities need. This focuses on how educational data mining techniques greatly aid students in reaching their potential. There could be a paradigm shift with these tools. Then, the decision-making process moves more toward data-driven models. So, HEIs are eased off of needing to make such conventional decisions. This adjustment ensures that HEIs remain responsive to new educational environments while promoting academic results and improvements and being consistent with the more significant imperatives of institutional expansion and innovation. In this regard, our research further examines how the installation of data analysis tools - especially within the UAE's academic institutions - affects decision-making efficiency and output in research work.

1.1 Objective

- The goal is to examine how higher education institutions in the UAE can make better decisions after implementing data analysis technologies.
- In higher education institutions in the UAE, we want to measure how user happiness affects the

efficiency of decision-making after the introduction of data analysis technologies.

- We want to find out how educational policies affect the connection between data analysis technologies and the effectiveness of decision-making in higher education institutions in the UAE.

2. Literature review and Hypothesis development

2.1 Impact of Data Analysis Technology on Decision-making Efficiency in UAE Higher Education Institutions

Analytics in Higher education may be a crucial problem in the future. It encompasses all initiatives for improved education, including research, assistance distribution, massive record management, and control. Because of the many benefits of extensive information analytics, there are excellent prospects for higher education to be investigated and evaluated for improved competitive performance (Sutrisno et al., 2020). Each institution may employ significant statistics generation to get information about their students. Using enormous data records, executing data series, cleaning, processing, and storing basic instructional facts at colleges and universities is feasible. We may then mine and evaluate this information to produce technical reports within charts using statistical assessment and model construction (Hwang, 2019).

Much attention has been paid to using data analytics to inform educational decisions. Data analytics will enable academic institutions to improve curricula, student performance, and resource distribution. (Gaftandzhieva et al., 2023).Institutions may use learning analytics and educational data mining methods to find trends and insights that help them make better decisions (Pelletier et al., 2022). In higher education, data analytics technologies are beneficial. According to (Gaftandzhieva et al., 2023), they can help institutions monitor and predict student performance so that interventions can promptly be made for students on the danger list. Additionally, these technologies offer fact-based information on student demographics, enrolment trends, and student performance, which can contribute to strategic planning and policymaking(Gaftandzhieva et al., 2023),(Swargiary, 2024). So, based on the above studies, we can develop our hypothesis as follows:

H1: Using data analysis tools has a favourable and substantial impact on decision-making efficiency in UAE higher education institutions.

2.2 Impact of User Satisfaction on Decision-making Efficiency in Data Analysis Technology Adoption

For data analysis technologies to be adopted and used in higher education institutions, user happiness is critical. Teaching, learning, and administrative procedures have been profoundly changed by the incorporation of technologies like electronic classrooms, smart classrooms, digital data warehouses, electronic libraries, and shared e-learning materials (Aldunate Vera & Nussbaum, 2021),(Fuadah & Kalsum, 2021). Universities that prioritize user happiness by addressing system usability, accessibility, and dependability make effective data-driven decision-making possible. Users are likely to interact closely with data analysis systems, give reliable data inputs, and apply insights for strategic decision-making when they are happy with the platforms and tools offered (Abrahams, 2010).

It shows that service quality is among the crucial determining factors for user satisfaction, based on cybersecurity features, teachers' proficiencies, data correctness, the use of specialized technology, and administrative and technical support, as reported by (Akhtar, 2023). Good service quality persuades stakeholders to be engaged with the institutional decision-making processes by creating trust and confidence in data analysis systems (Pham et al., 2021). Research shows stronger correlations exist between higher institutional efficiency levels and better decision outcomes with further system utilization and increased user satisfaction (Kuo et al., 2009).

User satisfaction levels and better performance of technology tools used to make decisions are significantly linked to continuous assessment of experience and perception (Kuo et al., 2009). Suppose such an organization is proactive enough to solve problems for the customer and, subsequently, improve the delivery of its services. In that case, it becomes well-prepared to employ data analysis technologies to support its operations and strategic decision-making. Ultimately, user satisfaction is a bridge connecting technology adoption to the success of decision-making, urging higher education institutions to prioritize user-centric strategies in efforts toward achieving sustainable digital transformation. So, based on the above studies, we can develop our hypothesis as:

User satisfaction impacts decision-making efficiency favorably and substantially during the adoption of inside data analysis technology.

2.3 The Moderating Role of Educational Policies in the Relationship Between Data Analysis Technology Adoption and Decision-making Efficiency

The relationship between educational and higher education institutions, particularly in the UAE, has been using data analysis technology, suggesting that policies are moderating in improving decision-making efficiency. As administrative and policy frameworks drive technological innovations in education (Ball, 2020), it can be observed that improvement in educational policies leads to effective and efficient uptake of data analysis technologies. A strong policy environment, described by the strategic integration of data management guidelines, can significantly determine the process's course and adoption outcomes (Yueh & Chiang, 2020). Data policies and regulation frameworks are among the recent ways data handling and protection have been managed. Their impact on the processes of data analysis technology uptake cannot be understated. Clear, detailed policies ensure that data handling is ethical and legal and that there is responsible data practice and support for the safe collection, storage, and sharing of student data in a manner that protects individual privacy rights (Cheryl et al., 2021)(Dwivedi et al., 2021). In this context, educational policies enhance transparency and accountability, increasing stakeholder trust and effective, data-driven decision-making processes.

Supportive policies inside schools have been associated with more effective operations and better compliance with the Data Protection Act (Horani et al., 2023)(Akram et al., 2019). Robust data policies will likely require institutions to adopt data analysis technology better to enhance their decision-making ability. This helps bridge the gap between technological adoption and decision-making efficiency. Indeed, educational policies help the necessary infrastructure and training programs to support technological adoption and strengthen the relationship between adopting data technologies and decision-making efficiency (Mossberger, 2003). However, although literature reveals the importance of data policies, it also points to the fact that their influence is not always homogeneous throughout the institutions.

In some cases, even when there are complete frameworks, there are issues of lack of awareness, inadequate resources, or insufficient training that hinder the smooth implementation of policies (Mossberger, 2003)(Khadragy et al., 2022). Hence, the success of education policies in controlling the link between data technology adoption and decision-making efficiency depends not only on the quality of the policies but also on the implementation and institutional preparedness(Hazra et al., 2021). So, based on the above studies, we can develop our hypothesis as follows:

H3: Educational Policies moderate the connection between decision-making and data analysis technologies. Efficiency in UAE higher education institutions makes the effect more potent when supportive policies are in place.

2.4 Literature gap

This study aims to fill a knowledge vacuum about the effect of data analysis technologies on the decision-making efficiency of UAE higher education institutions. Despite the rise of research on technology use in various sectors, little is known about how technology influences educational decision-making in the UAE. Less research has focused on the impact of user happiness on the decision-making capabilities of data-driven technologies, especially in the UAE's higher education sector. The effect of enabling policies on the connection between data analysis technologies and decision-making efficiency is another underexplored subject.

3. Materials and Methods

3.1 Research Design

This quantitative correlational study spanned universities in the UAE and focused on data analysis technology utilization, user happiness, instructional techniques, and decision-making efficiency. Our objective was to explore the relationship between technology adoption for data analysis and decision-making efficiency, focusing on the effects of user happiness and instructional interventions on the relationship. Data were collected through a systematic survey conducted by decision-making education institutions to derive answers about what factors would influence the decision-making process.

The selected variables, based on prior research, form the essence of this study. The Data Analysis Technology Adoption variable, comprising five items, is taken from (Emon, 2023), which measures the extent to which organizations adopt data analysis technologies, including predictive analytics, machine learning, and artificial intelligence tools. User Satisfaction, measured using a 5-item scale from (Vaezi et al., 2016), includes items related to the user's perceived value, overall satisfaction, ease of use, and experience with data analysis systems. The Educational Policies variable, consisting of 7 items, has been adapted from (Ghimire & Edwards, 2024), which assesses the impact of government policies and institutional regulations on integrating data analysis in education. Lastly, the DDecisionmakingEfficiency variable, comprising six items, was adopted from (Hsieh et al., 2020) to measure the effectiveness of decision-making processes in educational institutions, focusing on data-driven decisions, speed, and accuracy in achieving desired outcomes.

Variable	Number of Items	Source of Adoption
Data Analysis Technology Adoption	5	Emon, 2023
User Satisfaction	5	Vaezi et al., 2016
Educational Policies	5	Ghimire & Edwards, 2024
DDecisionmakingEfficiency	5	Hsieh et al., 2020

3.2 Conceptual Model

The study considered three primary parameters: DDecisionmakingEfficiency, User Satisfaction, Data Analysis Technology Adoption, and Educational Policies as the moderator. The conceptual model explores how user happiness and the adoption of data analysis technologies directly influence decision-making effectiveness. Assuming that accommodating policies will increase the impact of data uptake on decision-making efficiency, it also examines how educational policies affect these connections. Figure 1 delineated the proposed links and anticipated impacts among these factors.

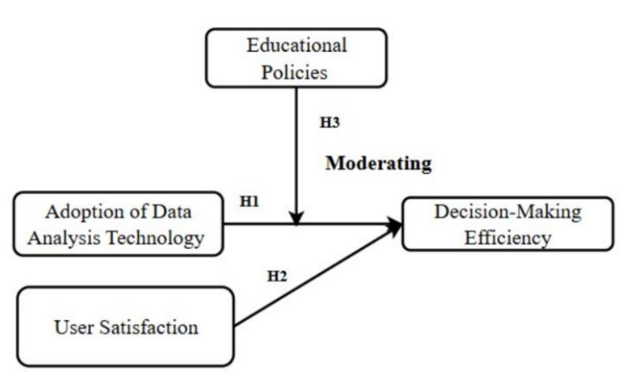


Figure 1 Conceptual model

Description of the Study Area

The primary subjects of the research were administrators, faculty, and decision-makers in the UAE's higher education system. The research institutes used various data analysis approaches to make their assessments. The impact of data analysis tools and instructional strategies on respondents was better understood due to the diversity of their positions, experiences, and levels of technical literacy.

Sampling

Three hundred eighty-four participants were surveyed from various universities in the United Arab Emirates (UAE) using a stratified random sampling technique. Stratification ensured that the sample adequately represented a few kinds of respondents: academic administrators, professors, and decision-making staff. The categorization was based on aspects such as institution type-whether public or private-academic position-administrators, professors, or support staff-and experience with data analysis technologies. This methodology guaranteed a varied sample, enhancing the data's representativeness.

Data Collection Tools and Techniques

Higher education institutions in the UAE were surveyed using a standardized questionnaire to gather data on data analysis technology uptake, user satisfaction, and decision-making efficiency. A survey instrument containing Likert-scale items to measure each variable - adoption of data analysis technology, frequency of use and technology types adopted and perceived ease of use; user satisfaction with system usability, training quality, and support services; decision through speed, accuracy, and effectiveness; and educational policies, their supportiveness and effects on how healthy judgments are made and how widely used the technology is. Members of the academic staff, administrative personnel, and decision-makers from the participating universities in the UAE took part. The chosen participants will gain first-hand experience with data analysis tools. Structural equation modelling was employed to examine the acquired data, with AMOS utilized to evaluate the connection between components. SEM enabled the testing of direct, indirect, and moderating effects, explaining how adopting data analysis technology, user satisfaction, and educational policies influence decision-making efficiency.

Measures

This research used many validated scales to assess the relevant components. Using a 5-point Likert scale, where one indicates "strongly disagree", and 5 indicates "strongly agree," the **Data Analysis Technology Adoption** Scale evaluated the extent to which the company has integrated data analytic tools. The survey consisted of five items scored on a 5-point Likert scale, **User Satisfaction** Scale, measuring user satisfaction with data analysis tools based on performance, usability, and reliability. The **DDecisionmakingEfficiency** Scale used five questions on a Likert-scale measuring tool for data analysis and was believed to influence decision-making processes based on speed, accuracy, and effectiveness in ddecisionmaking The **Educational Policies** Scale had five questions, and each was graded to evaluate the severity of the strength of perceived institutional policies about the deployment of data analysis technologies, such as clarity, support, and enforcement. These scales were modified and verified from earlier research and thus guaranteed the validity and reliability of the measurements.

Result:

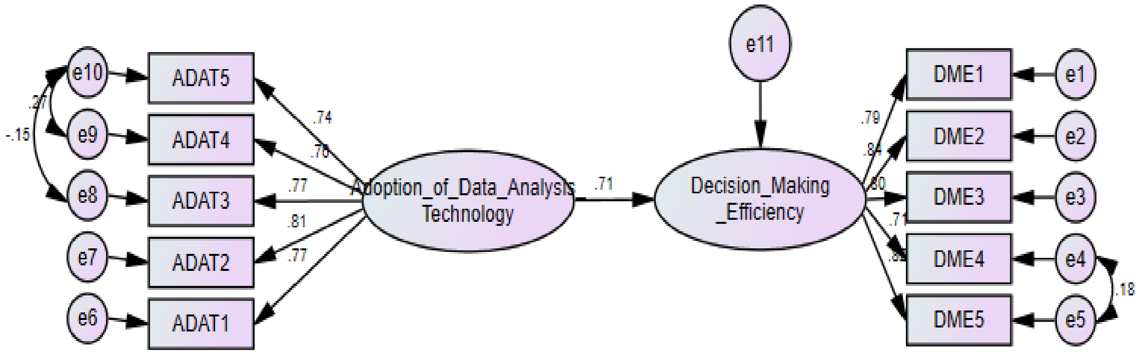
Table 1 Demographic variables

		Frequency	Percent
AGE	18-24 years	172	44.8
	25-34 years	90	23.4
	35-44 years	62	16.1
	45-54 years	53	13.8
	55+ years	7	1.8
	Total	384	100.0
GENDER	Male	211	54.9
	Female	173	45.1
	Total	384	100.0
EDUCATION	High School or Equivalent	80	20.8
	Associate Degree	147	38.3
	Bachelor’s Degree	113	29.4
	Master’s Degree	23	6.0
	Doctorate or Higher	21	5.5
	Total	384	100.0
Employee Status	Full-time	144	37.5
	Part-time	25	6.5
	Self-employed	38	9.9
	Unemployed	98	25.5
	Retired	79	20.6
	Total	384	100.0

With 384 participants, the study sample is representative of the population in terms of age, gender, level of education, and occupation. By age group, the most common responses fall into the following categories: 18–24 years old (44.8%), 25–34 years old (23.4%), 35–44 years old (16.1%), 45–54 years old (13.8%), and 55 and up (1.8%). Regarding **gender**, males constitute a slightly higher proportion (54.9%) than females (45.1%). Educational qualifications show that the largest group holds an **Associate Degree** (38.3%), followed by a **Bachelor’s Degree** (29.4%), **High School or Equivalent** (20.8%), **Master’s Degree** (6.0%), and **Doctorate or Higher** (5.5%). In terms of **employee status**, the sample comprises **Full-time employees** (37.5%), **Unemployed individuals** (25.5%), **Retired persons** (20.6%), **Self-employed individuals** (9.9%), and **Part-time workers** (6.5%). These distributions give a thorough synopsis of the study's demographics of participants.

Proposed Hypothesis:

1. Adopting Data Analysis Technology has a positive and significant effect on DDecisionmakingEfficiency in UAE higher education institutions."



X'Table1 Regression Weights: (Group number 1 - Default model)

Path			Estimate	S.E.	C.R.	P
Decision Making Efficiency	<---	Adoption of Data Analysis Technology	.709	.056	11.711	***
DME1	<---	Decision Making Efficiency	.789			
DME2	<---	Decision Making Efficiency	.836	.059	17.648	***
DME3	<---	Decision Making Efficiency	.801	.060	16.754	***
DME4	<---	Decision Making Efficiency	.709	.059	14.252	***
DME5	<---	Decision Making Efficiency	.825	.058	17.259	***
ADAT1	<---	Adoption of Data Analysis Technology	.772			
ADAT2	<---	Adoption of Data Analysis Technology	.811	.053	16.266	***
ADAT3	<---	Adoption of Data Analysis Technology	.775	.058	15.251	***
ADAT4	<---	Adoption of Data Analysis Technology	.764	.057	15.016	***
ADAT5	<---	Adoption of Data Analysis Technology	.740	.063	14.125	***

The interdependence between sensing capacities and economic performance is illustrated in the table by a hypothetical structural equation model. In this model, the adoption of data analysis technologies is the independent variable, with decision-making efficiency as the dependent variable. The study discovered a strong positive relationship (β=.709, P<0.05) between utilizing data analysis tools and the effectiveness of decision-making.

There is a favorable correlation (standardized coefficient = 0.709) between the use of data analysis technology and decision-making efficiency. Significant relationships are indicated by large correlation coefficient values (C.R. values). The components are statistically significant (p-values > 0.05), as shown in Table 7, suggesting a good match between the model and the data. There was a positive and statistically significant correlation between sensing capabilities and economic performance, as shown by seven fit indices that evaluated the model fit.

Table 3 Model fit summary

Variable	**Value**
Chi-square value(χ^2)	56.611
Degrees of freedom (df)	31
CMIN/DF	1.826
P value	0.003
GFI	0970
RFI	0964
NFI	0.975
IFI	0.989
CFI	0.989
RMR	0.037
RMSEA	0.046

The sample data showed promising results with values over 0.90 for all fitting metrics ($\chi2$ = 56.611, NFI = 0.975, IFI = 0.989, GFI = 0.970, RFI = 0.964, and CFI = 0.989). Likewise, RMR and RMSEA are less than the 0.080 cutoff, coming in at 0.037 and 0.046, respectively. The model agreed with the data, with RMSEA=0.046, RMR=0.037, GFI=0.970, and CFI=.989.

2. User Satisfaction positively and significantly affects decision-making efficiency in data analysis technology adoption.

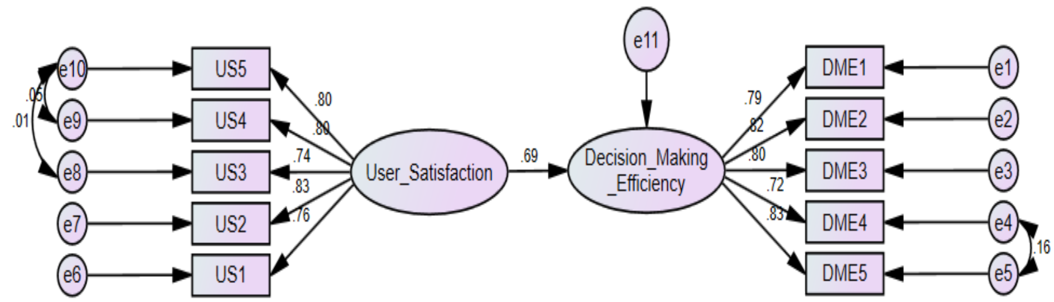


Table 4 Regression Weights: (Group number 1 - Default model)

Path			Estimate	S.E.	C.R.	P
Decision Making Efficiency	<---	User Satisfaction	.688	.062	11.437	***
DME1	<---	Decision Making Efficiency	.793			
DME2	<---	Decision Making Efficiency	.823	.058	17.410	***
DME3	<---	Decision Making Efficiency	.803	.059	16.910	***
DME4	<---	Decision Making Efficiency	.716	.058	14.459	***
DME5	<---	Decision Making Efficiency	.831	.058	17.484	***
US1	<---	User Satisfaction	.764			
US2	<---		.830	.064	16.689	***
US3	<---	User Satisfaction	.743	.066	14.516	***
US4	<---	User Satisfaction	.801	.064	15.737	***
US5	<---	User Satisfaction	.805	.066	15.534	***

User Satisfaction and Decision-Making Efficiency are interrelated, as shown in the hypothetical structural equation model in the table. The model's dependent variable is the efficacy of decision-making, while the independent variable is the level of user satisfaction. User satisfaction and decision-making efficiency were shown to have a strong positive association (β=.688, $P<0.05$) in the research.

With a standard coefficient of 0.688, the route connecting User Satisfaction and Decision-Making Efficiency demonstrates a positive association. Significant relationships are indicated by large correlation coefficient values (C.R. values). The components are statistically significant (p-values > 0.05), as shown in Table 7, suggesting a good match between the model and the data. There was a positive and statistically significant correlation between sensing capabilities and economic performance, as shown by seven fit indices that evaluated the model fit.

Table 2 Model fit summary

Variable	Value
Chi-square value(χ^2)	43.050
Degrees of freedom (df)	31
CMIN/DF	1.389
P value	0.074
GFI	0.977
RFI	0.973
NFI	0.982
IFI	0.995
CFI	0.995
RMR	0.018
RMSEA	0.032

The quality of fit was satisfactory in terms of representing the sample data (χ2 = 43.050), with the Normalized Fit Index (NFI) equal to 0.982, the Incremental Fit Index (IFI) equal to 0.995, the Goodness of Fit (GFI) equal to 0.977, the Relative Fit Index (RFI) equal to 0.973, and the Comparative Fit Index (CFI) equal to 0.995, which is significantly higher than the value of 0.90. Similarly, the values of RMR (Root Mean Square Residuals) = 0.018 and RMSEA (Root mean square error of approximation) = 0.032 are lower than the crucial threshold of 0.080. An excellent match was found for the submitted model, as evidenced by the RMSEA value of 0.032, the RMR value of 0.018, the GFI value of 0.977, and the CFI value of.995.

3.Educational Policies moderate the relationship between the Adoption of Data Analysis Technology and Decision-Making Efficiency in UAE higher education institutions.

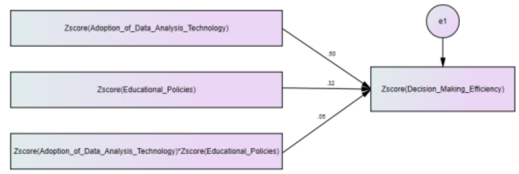


Table 6 Regression Weights: (Group number 1 - Default model)

path			Estimate	S.E.	C.R.	P
Zscore(Decision Making Efficiency)	<---	Zscore(Adoption of Data Analysis Technology)	.460	.038	12.251	***
Zscore(Decision Making Efficiency)	<---	Zscore(Educational Policies)	.295	.038	7.866	***
Zscore(Decision Making Efficiency)	<---	Zscore(Adoption of Data Analysis Technology)* Zscore(Educational Policies)	.015	.012	1.200	.230

Table 31 reports the SEM used to test the relationship between Zscore (Adoption of Data Analysis Technology) and Zscore (Decision Making Efficiency), with Zscore (Educational Policies) as the moderator. This model is used to test the interaction between the two dimensions. An all-inclusive analysis can make available all the key streams for analysis. Also, it considers measurement errors directly and feedback inside the model.

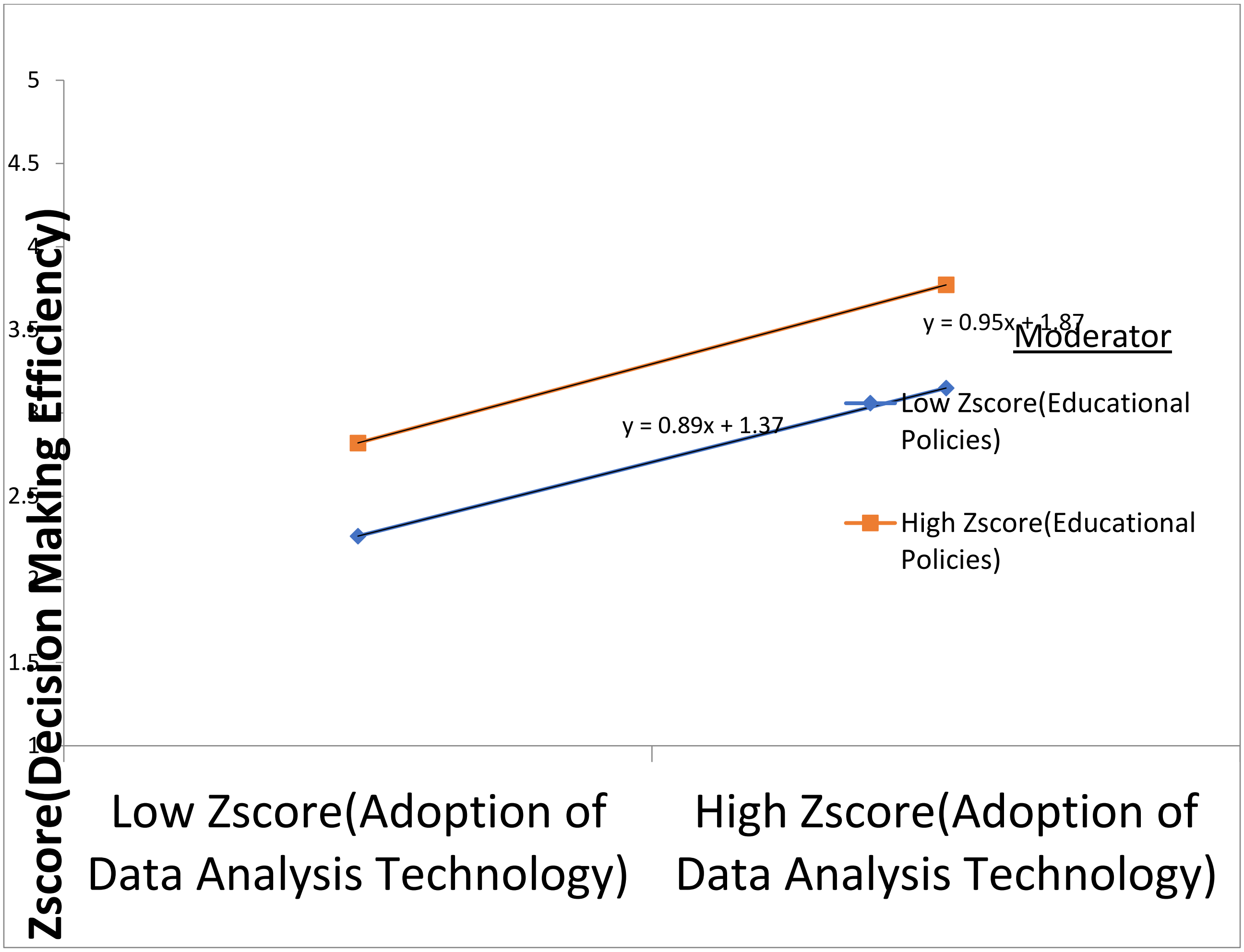
The hypothesis that was generated from the route analysis is that there is a positive and significant correlation between the Zscore (Adoption of Data Analysis Technology) and the Zscore (Decision Making Efficiency) (β=0.460, P<0.05). This is what the path analysis points to. It has been found that the Zscore (Educational Policies) has a correlation that is positive and statistically significant with the Zscore (Decision Making Efficiency) (β=.295, P<0.05).

Moderation testing:

In moderation research, Zscore, an acronym for "Adoption of Data Study Technology, " is considered an independent variable. However, it is regarded as a dependent variable if the Zscore stands for "Decision Making Efficiency". On the contrary, Zscore (Educational Policies) is considered a moderator variable. It is understood that both are interdependent with respect for each other. Standardized scores of the variables are used as a basis for using the programme when creating interaction terms in SPSS to calculate the findings. This is done to ensure that the program is used correctly. These interaction terms are found by using the basis of the scores of the variables to carry out an analysis.

Table 3 Regression Weights: (Group number 1 - Default model)

path			Estimate	S.E.	C.R.	P
Zscore(Decision Making Efficiency)	<---	Zscore(Adoption of Data Analysis Technology)* Zscore(Educational Policies)	.015	.012	1.200	.230



As moderators, we tried to study the variable Zscore, which is an acronym for Education Policies. Results of the study show that the moderator term between Zscore (Implementation of Data Analysis Technology), and Zscore (Education Policy) has a significant as well as positive effect over Zscore (Decision-Making Efficiency) ($\beta = 0.015$, $P > .05$). This finding is supported by the fact that the interaction term has a substantial and favorable effect on Zscore. According to the findings of our inquiry, there is no statistical evidence to support the hypothesis that Zscore (Educational Policies) has a moderating influence on the distribution of our data. This is the conclusion that we have reached.

Discussion:

According to the research results, the assertion that the exploitation of data analysis technologies has a substantial and beneficial influence on the efficacy of decision-making is supported by the study's findings, which support higher education institutions headquartered in the United Arab Emirates. This highlights how essential cutting-edge technology tools are for accelerating decision-making processes and providing stakeholders with the ability to make decisions in a timely way that are built on solid information. The fact that this is the case demonstrates how essential these tools are. There is a connection between the use of data analysis technology by businesses and a rise in the overall efficiency of these companies. This is because these technologies offer insights in real-time, improved forecasting, and superior resource allocation. This is the reason why this is the case. The findings of research that emphasize the revolutionary potential of data-driven decision-making in the field of education are congruent with this conclusion, which is consistent with the findings of other studies that also highlight the revolutionary potential of data-driven decision-making Based on the research, it was found that the level of satisfaction users have in their use of data analysis technology also determines the effectiveness with which that technology is used in making decisions. It does not matter what kind of technology is being deployed; it is always so. Users are more likely to engage with data analysis tools and take full advantage of their utility if they find these tools easy to use, trustworthy, and efficient in satisfying their requirements. This increases the probability that users will engage with these tools. The users have a higher probability of satisfying their criteria; that is why. In introducing technology to the classroom, this relationship, being relevant to the situation, emphasizes the need to consider the user experience. Due to the provision of comprehensive training, the continued improvement of the system, and the simultaneous supply of help to users, there is a possibility of elevating satisfaction levels and improving decision-making. Based on the research project's findings, the educative policies moderate the relationship between decision-making efficiency and data analysis technology utilization. This is reflected by the fact that the aim of the study was successfully achieved.

The result is that policies that encourage the employment of technology serve as a catalyst, thereby boosting the capability of the technology to aid the decision-making process characterized by intelligence. This is the result of this. It has been proven that there is a connection between policies that promote digital transformation, provide funds for technological advancements, foster a culture of creativity, and increase the benefits that data analysis tools provide. Limits that are not obvious or constrained may make it more difficult for them to be accepted and implemented. This is the other side of the coin. Therefore, the findings highlight that policymakers must craft and implement frameworks that make it easier for higher education institutions to make choices with technological considerations in mind. This is evidenced by the fact that the frameworks are implemented.

Conclusion:

This was a study that aimed to find how the utilization of data analysis technology influenced the effectiveness of decision-making procedures within higher learning establishments in the United Arab Emirates. Generally speaking, this research focused on the United Arab Emirates as the region of interest. In particular, the findings yield significant proof and reveal the importance of having tools regarding data analytics in its potential capability to improve the procedure related to decision-making and permit a decision in a fashion more rapid, efficient, and with fuller knowledge. Therefore, These technologies were implemented in the strategic and operational frameworks of these educational institutions of higher learning to upgrade their research outputs, improve their operational efficiency, and increase their academic performance. The objectives were achieved in this regard. According to the study's findings, users' satisfaction was acknowledged as a critical factor that significantly contributes to effectively utilizing data analysis technologies.

Indeed, this was demonstrated. Users were more likely to engage actively with the technology and resources supplied to them when they were satisfied with the technology and resources that were provided to them. Regardless of whether the users were from the academic community, staff, or administrators, this was always the case. The decision-making processes were subjected to this activity so that they could successfully accomplish their intended goals. For educational institutions to make the most of the influence that data analysis tools had, it was essential for them to place the highest significance on tools that were not only user-friendly but also readily available and trustworthy throughout the process. In addition, the research provided a better understanding of the moderating influence that educational policies had on the phenomenon being investigated. It was essential to build instructional programs that were useful and robust enough to ensure that the employment of data analysis tools would result in good decision-making.

This was the only way to ensure that the program would be successful. The availability of significant and well-defined standards that guide the management of data and moral conduct has exponentially increased the link between technology exploitation and the efficiency of judgments. That has resulted in a significant improvement concerning the efficacy of decisions. The findings of this study must add to the already increasing literature on the transformation of higher education towards being more digital, especially in the United Arab Emirates. Also, the study furnished essential insights that might be used to improve the digital infrastructure of higher education institutions and their decision-making capabilities. This move was made in an educational environment that is becoming increasingly data-driven to assure the continuing survival of higher education institutions over the long term and ensure that they continue to be relevant.

The core of research to be focused on in the years ahead must be the practice of these concepts and the difficulties and hurdles the institutions of higher education have while trying to embrace these technologies. This study was carried out with the primary aim of exploring the moderating effect of educational policies while analyzing the impacts of technology adoption in data analysis and user satisfaction upon the effectiveness of decision-making in higher education institutions based within the United Arab Emirates. Therefore, the population of concern in this research included only higher learning institutions. To support the conceptions, the findings provide a large amount of evidence that may be considered as evidence. To get things started, the findings show that using data analysis technologies positively and significantly impacts decision-making effectiveness.

We will begin our discussion with this particular topic. The statistical research revealed a strong connection (β =.709, $P < 0.05$), which states that the ability of the institutions to make successful judgments becomes greatly enhanced when they apply current data analysis approaches. This conclusion can be derived from the results of the inquiry. As an illustration of how the utilization of technology to gather information to make decisions in higher education has the potential to be transformative, this serves as an interesting example.

In the second place, the research findings indicate how crucial it is to emphasize the relevance of user satisfaction to bring about an increase in the effectiveness of decision-making The based evidence allows demonstrating the presence of a sound, positive relationship between the levels of user satisfaction and the adequacy of technology in meeting its purpose; $\beta = 0.688$, $P <0.05$. It has become possible to establish the presence of a direct influence by the degree of satisfaction with the operational efficiency of technology. When considering these findings, it is abundantly clear that implementing technical solutions using user-centred methodologies is most important. This is because such technical solutions must meet stakeholders' requirements and expectations.

The findings prove that educational policies moderate the link between the effectiveness of decision-making and data analysis tools. In conclusion, the findings confirm this hypothesis. Through the interaction between educational policies and the utilization of technology, there is a favorable and substantial influence on the efficiency of decision-making ($\beta = 0.015$, $P < 0.05$). The effectiveness of decision-making is significantly influenced by this interaction, which has a strong impact. In light of the facts presented here, it appears that legislation that supports incorporating technology into decision-making processes can potentially increase the benefits associated with doing so. When deciding these results, it is feasible to conclude that the institutional policy environment is more significant than other factors. This is because other moderating factors, such as values and motivation, lack statistical evidence to support their assertions. This is the reason why this is the case. The findings, in conclusion, shed light on the importance of deploying data analysis tools and assuring users' satisfaction to increase the efficacy of decision-making processes at educational institutions of higher learning. This is because the findings shed light on the necessity of deploying these tools.

Furthermore, the moderating effects of favorable educational policies highlight the significance of lawmakers establishing an environment that is welcoming and supports the effective utilization of technology in the decision-making process. Politicians must establish such an atmosphere for several reasons, and this is one of them. When it comes to guiding policies intended to improve the effectiveness of institutions that are a part of the higher education sector in the United Arab Emirates, these insights are of the utmost importance.

References

Abrahams, D. A. (2010). Technology adoption in higher education: A framework for identifying and prioritizingprioritizing issues and barriers to adoption of instructional technology. *Journal of Applied Research in Higher Education*, *2*(2), 34–49.

Acevedo, Y. V. N., Marín, C. E. M., Garcia, P. A. G., & Crespo, R. G. (2018). A proposal for a decision support system with learning analytics. *2018 IEEE Global Engineering Education Conference (EDUCON)*, 161–168.

Ada, Ş., & Ghaffarzadeh, M. (2015). Decision-making is based on a management information system and a decision-support system. *European Researcher*, *4*, 260–269.

Akhtar, Z. (2023). Deepfakes Generation and Detection: A Short Survey. *Journal of Imaging*, *9*(1). https://doi.org/10.3390/jimaging9010018

Akram, A., Fu, C., Li, Y., Javed, M. Y., Lin, R., Jiang, Y., & Tang, Y. (2019). Predicting students' academic procrastination in blended learning courses using homework submission data. *Ieee Access*, *7*, 102487–102498.

Aldunate Vera, R., & Nussbaum, M. (2021). *Teacher adoption of technology*.

Ashour, G., Al-Dubai, A., Romdhani, I., & Alghazzawi, D. (2022). Ontology-Based Linked Data to Support DDecisionmakingwithin Universities. *Mathematics*, *10*(17), 3148.

Ball, S. J. (2020). Journal of Education Policy–1985–2020. In *Journal of Education Policy* (Vol. 35, Issue 1, pp. 1–2). Taylor & Francis.

Bond, M., Marín, V. I., Dolch, C., Bedenlier, S., & Zawacki-Richter, O. (2018). Digital transformation in German higher education: student and teacher perceptions and digital media usage. *International Journal of Educational Technology in Higher Education*, *15*(1), 1–20.

Borovyk, M. (2020). Підвищення якості прийняття управлінських рішень за рахунок використання інтелектуальної рекомендаційної системи. *Scientific Notes of Ostroh Academy National University," Economics" Series*, *18 (46)*, 26–30.

Bresfelean, V. P., Ghisoiu, N., Lacurezeanu, R., & Sitar-Taut, D.-A. (2009). Towards the development of decision support in academic environments. *Proceedings of the ITI 2009 31st International Conference on Information Technology Interfaces*, 343–348.

Cabero-Almenara, J., Guillén-Gámez, F. D., Ruiz-Palmero, J., & Palacios-Rodríguez, A. (2021). Digital competence of higher education professors according to DigCompEdu. Statistical research methods with ANOVA between fields of knowledge in different age ranges. *Education and Information Technologies*, *26*(4), 4691–4708.

Chairungruang, S., Khampuong, P., Rodcharoen, P., Leelitthum, C., & Eak-ieamvudtanakul, P. (2022). Business Intelligence for Data-Driven DDecisionmakingin in Vocational Education. *International Journal of Educational Communications and Technology*, *2*(2), 61–69.

Chauca, M., Phun, Y., Curro, O., Chauca, C., Yallico, R., & Quispe, V. (2021). Disruptive innovation in active activity-based learning methodologies through digital transformation. *International Journal of Information and Education Technology*, *11*(4), 200–204.

Cheryl, B.-K., Ng, B.-K., & Wong, C.-Y. (2021). Governing the progress of internet-of-things: ambivalence in the quest of technology exploitation and user rights protection. *Technology in Society*, *64*, 101463.

Dasgupta, A., Poco, J., Wei, Y., Cook, R., Bertini, E., & Silva, C. T. (2015). Bridging theory with practice: An exploratory study of visualization use and design for climate model comparison. *IEEE Transactions on Visualization and Computer Graphics*, *21*(9), 996–1014.

Deja, M., Rak, D., & Bell, B. (2021). Digital transformation readiness: perspectives on academia and library outcomes in information literacy. *The Journal of Academic Librarianship*, *47*(5), 102403.

Den Heijer, A. (2012). *Managing the university campus: Exploring models for the future and supporting today's decisions*.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., & Eirug, A. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994.

Emon, M. M. H. (2023). Insights Into Technology Adoption: A Systematic Review of Framework, Variables and Items. *INFORMATION MANAGEMENT AND COMPUTER SCIENCE*, *6*, 55–61. https://doi.org/10.26480/imcs.02.2023.55.61

Fakeeh, K. (2015). Decision Support System (DSS) in Higher Education System. *International Journal of Applied Information System (IJAIS)*, *9*(2).

Fuadah, L. L., & Kalsum, U. (2021). The impact of corporate social responsibility on firm value: The role of tax aggressiveness in Indonesia. *The Impact of Corporate Social Responsibility on Firm Value: The Role of Tax Aggressiveness in Indonesia*, *8*(3), 1–8.

Gaftandzhieva, S., Doneva, R., Hussain, S., Talukder, A., Chetia, G., & Gohain, N. (2023). QUALITY OF BLENDED LEARNING COURSES: STUDENTS'PERSPECTIVE. *Mathematics & Informatics*, *66*(6).

Gagliardi, J. S., & Turk, J. M. (2017). *The data-enabled executive: Using analytics for student success and sustainability*.

Garcez, A., Silva, R., & Franco, M. (2022). Digital transformation shaping structural pillars for academic entrepreneurship: A framework proposal and research agenda. *Education and Information Technologies*, *27*(1), 1159–1182.

Ghimire, A., & Edwards, J. (2024). From guidelines to governance: A study of AI policies in education. *International Conference on Artificial Intelligence in Education*, 299–307.

Hansoti, B. (2010). *Business intelligence dashboard in decision making*.

Hazra, A., Adhikari, M., Amgoth, T., & Srirama, S. N. (2021). A comprehensive survey on interoperability for IIoT: Taxonomy, standards, and future directions. *ACM Computing Surveys (CSUR)*, *55*(1), 1–35.

Horani, O. M., Al-Adwan, A. S., Yaseen, H., Hmoud, H., Al-Rahmi, W. M., & Alkhalifah, A. (2023). The critical determinants impacting artificial intelligence adoption at the organizational organizational level. *Information Development*, 02666669231166889.

Hsieh, C.-J., Fifić, M., & Yang, C.-T. (2020). A new measure of group ddecisionmakingefficiency. *Cognitive Research: Principles and Implications*, *5*(1), 45. https://doi.org/10.1186/s41235-020-00244-3

Hwang, Y. (2019). Adoption of big data in higher education for better institutional effectiveness. *American Journal of Creative Education*, *2*(1), 31–44.

Karami, M., Safdari, R., & Rahimi, A. (2013). Effective radiology dashboards: key research findings. *Radiol Manage*, *35*(2), 42–45.

Khadragy, S., Elshaeer, M., Mouzaek, T., Shammass, D., Shwedeh, F., Aburayya, A., Jasri, A., & Aljasmi, S. (2022). Predicting diabetes in United Arab Emirates healthcare: artificial intelligence and data mining case study. *South Eastern European Journal of Public Health*.

Kuo, Y.-F., Wu, C.-M., & Deng, W.-J. (2009). The relationships among service quality, perceived value, customer satisfaction, and post-purchase intention in mobile value-added services. *Computers in Human Behavior*, *25*(4), 887–896.

Long, P., & Siemens, G. (2014). Penetrating the fog: analytics in learning and education. *Italian Journal of Educational Technology*, *22*(3), 132–137.

Mora, M., Wang, F., Gómez, J. M., Rainsinghani, M. S., & Shevchenko, V. S. T. (2017). DDecisionmakingsupport systems in quality management of higher education institutions: A selective review. *International Journal of Decision Support System Technology (IJDSST)*, *9*(2), 56–79.

Mossberger, K. (2003). *Virtual inequality: Beyond the digital divide*. Georgetown University Press.

Mukred, M., Yusof, Z. M., Mokhtar, U. A., Sadiq, A. S., Hawash, B., & Ahmed, W. A. (2021). Improving the decision-making process in higher learning institutions via electronic records management system adoption. *KSII Transactions on Internet and Information Systems (TIIS)*, *15*(1), 90–113.

Niet, Y. V., Díaz, V. G., & Montenegro, C. E. (2016). Academic decision-making model for higher education institutions using learning analytics. *2016 4th International Symposium on Computational and Business Intelligence (ISCBI)*, 27–32.

Patwa, N., Seetharaman, A., Sreekumar, K., & Phani, S. (2018). Learning Analytics: Enhancing the Quality of Higher Education. Res J Econ 2: 2. *Of*, *7*, 2.

Pelletier, K., Mccormack, M., Reeves, J., Robert, J., Arbino, N., Dickson-Deane, C., Guevara, C., Koster, L., Sanchez-Mendiola, M., & Bessette, L. S. (2022). *2022 Educause horizon report teaching and learning edition*. EDUC22.

Pham, L., Williamson, S., & Berry, R. (2021). Student perceptions of e-learning service quality, e-satisfaction, and e-loyalty. In *Research Anthology on Preparing School Administrators to Lead Quality Education Programs* (pp. 806–830). IGI Global.

Prasetyo, D. (2022). Decision Support System to Determine Higher Education Resource Needs Using Accreditation Assessment Standards. *International Journal of Engineering Technology and Natural Sciences*, *4*(2), 175–184.

Rodríguez-Abitia, G., & Bribiesca-Correa, G. (2021). Assessing digital transformation in universities. *Future Internet*, *13*(2), 52.

Şuşnea, E. (2013). Improving decision-making process in universities: A conceptual model of intelligent decision support system. *Procedia-Social and Behavioral Sciences*, *76*, 795–800.

Sutrisno, E., Oh, H., Vasan, A. S. S., Pecht, M., Aseeri, M., Banasser, G., Baduhduh, O., Baksh, S., Ghalibi, N., Rodinadze, S., Zarbazoia, K., Montanucci, G., Peconi, A., Su, Y., Lin, Y. Y.-F. Y., Lai, C., Baskara, R., Sari, M. N., Shatri, Z. G., … Liu, X. H. X. (2020). Design of half-mode substrate integrated cavity-inspired dual-band antenna. *IEEE Access*, *2*(1), 1–6. https://doi.org/10.1007/978-3-031-09835-2_16

Swargiary, K. (2024). The Impact of Data Analytics on Educational Decision-Making: A Mixed-Methods Study in Bengaluru Higher Education Institutions. *Available at SSRN 4897517*.

Swing, R. L., & Ross, L. E. (2016). A new vision for institutional research. *Change: The Magazine of Higher Learning*, *48*(2), 6–13.

Vaezi, R., Mills, A., Chin, W., & Zafar, H. (2016). User Satisfaction Research in Information Systems: Historical Roots and Approaches. *Communications of the Association for Information Systems*, *38*, 501–532. https://doi.org/10.17705/1CAIS.03827

Valdés, K. N., y Alpera, S. Q., & Cerdá Suárez, L. M. (2021). An institutional perspective for evaluating digital transformation in higher education: Insights from the Chilean case. *Sustainability*, *13*(17), 9850.

Webber, K. L., & Zheng, H. Y. (2020). Data analytics and the imperatives for data-informed decision making in higher education. *Big Data on Campus: Data Analytics and Decision Making in Higher Education*, 3–29.

Yueh, H., & Chiang, F. (2020). AI and robotics in reshaping the dynamics of learning. *British Journal of Educational Technology*, *51*(5).

Yulianto, A. A., & Kasahara, Y. (2018). Implementation of business intelligence with improved data-driven decision-making approach. *2018 7th International Congress on Advanced Applied Informatics (IIAI-AAI)*, 966–967.