



Data Analytics using AI in higher education: A stakeholder's analysis

Research extracted from PHD. In Business Information Systems

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***Scientific Journal for Financial and Commercial Studies and Research
(SJFCSR)***

Faculty of Commerce – Damietta University

Vol.7, No.1, Part 1., January 2026

APA Citation

Mansour, M. M. F.; Hamza, M. and Abd Elaziz, B. A. M. (2026). Data Analytics using AI in higher education: A stakeholder's analysis, ***Scientific Journal for Financial and Commercial Studies and Research, Faculty of Commerce***, Damietta University, 7(1)1, 587-622.

Website: <https://cfdj.journals.ekb.eg/>

Data Analytics using AI in higher education: A stakeholder's analysis

Mostafa Mohamed Mansour; Dr. Meer Hamza and Dr. Rasha Abd Elaziz

Abstract

This study aims to assess the readiness of Egyptian higher education institutions to adopt data analytics through artificial intelligence, with a focus on resource availability. These institutions face unprecedented strategic and operational challenges due to global events such as the COVID-19 pandemic and regional conflicts, including declining enrollment and graduation rates, which threaten institutional sustainability. Data analytics and data mining techniques are promising tools for supporting decision-making and improving operational efficiency. Institutional readiness depends on leadership's ability to embrace and support these technologies.

The study employed a mixed-methods approach, incorporating the Delphi method to gather insights from decision-makers, developing surveys to measure Big Data Readiness Assessment (BDRA), and conducting a quantitative analysis using the DELTTA model, which includes six key components: Data, Enterprise, Leadership, Targets, Technology, and Data Scientists.

The findings indicate that the readiness of Egyptian higher education institutions to adopt data analytics and artificial intelligence is influenced by multiple factors, including the type and size of the institution, available financial resources, and the active involvement and commitment of senior leadership. Furthermore, targeted professional development for staff and data scientists has enhanced institutional capacity to adopt these technologies. The study highlights the importance of artificial intelligence and data mining analytics in supporting decision-making, advancing scientific research, improving student enrollment and retention, and increasing graduation rates. These tools serve as a strategic asset for enhancing resource efficiency and ensuring institutional sustainability in a competitive and digital educational environment.

Keywords: Data Analysis, Artificial Intelligence, and Higher Education.

1. Introduction

The higher education landscape is undergoing rapid transformation, with institutions facing persistent challenges such as declining enrollment, retention difficulties, and lower graduation rates. A survey by the Chronicle of Higher Education reported that more than 40% of U.S. colleges and universities failed to meet enrollment targets in 2016 and 2017, leading to significant tuition revenue losses. Global crises such as the COVID-19 pandemic and regional conflicts have further exacerbated financial instability, with smaller universities losing over half of their anticipated tuition income (Hartle & Leslie, 2021).

To mitigate these pressures, many institutions have sought to attract international students to diversify enrollment. However, this strategy has sometimes led to reduced academic standards, affecting educational quality and institutional reputation (Guszcza et al., 2021).

In this context, data analytics and artificial intelligence (AI) are emerging as strategic solutions to support institutional sustainability. By adopting business-oriented practices and leveraging big-data tools, universities can enhance resource management, decision-making, and long-term adaptability. Evidence suggests that AI-driven analytics enable institutions to address declining enrollment, retention, and graduation rates more effectively (Manyika et al., 2020).

This study aims to assess universities' readiness to utilize big-data analytics as a strategic tool, applying the DELTTA framework, which examines six critical elements: data, enterprise, leadership, targets, technology, and analysts. This model provides insights into how institutional size, financial resources, and governance structures influence adoption, offering a comprehensive approach relevant to diverse university contexts (Mikalef et al., 2018).

2. Importance of Topic

Over the past decades, business information systems have reshaped industries by enhancing efficiency and strategic decision-making. The emergence of big-data analytics has amplified this transformation, enabling organizations to utilize vast datasets for evidence-based decisions. Since 2010, and particularly during the COVID-19 pandemic, higher education institutions in Egypt and globally have faced declining enrollment, retention, and graduation rates, alongside intensified competition and commercialization.

These pressures have made it increasingly difficult for decision-makers to navigate operational and financial challenges, underscoring the urgent need for innovative strategies (UNESCO, 2021; World Bank, 2022).

Artificial intelligence (AI) and data analytics are now recognized as essential tools to address such challenges. Their successful adoption depends on leadership commitment, robust data infrastructures, and investment in evidence-based practices. By leveraging big-data analytics, universities can improve enrollment, retention, and graduation outcomes, while also strengthening their contributions to local economies and the global knowledge ecosystem (Johnson & Smith, 2023; OECD, 2022).

3. Research Questions:

- What are the data analytics (DA) adoption readiness of higher education institutions in Egypt?
- How can educational data mining help solve challenges in higher education institutions?
- What is the effect of data analytics using artificial intelligence on enrollment, retention, and graduation rates of higher education institutions?

4. Research Objective:

- Assess the readiness of Higher Education Institutions (HEIs) in adopting AI-driven data analytics.
- Examine the impact of institutional size, financial capacity, and governance structure on adoption.
- Apply the DELTTA framework (data, enterprise, leadership, targets, technology, and analysts) to evaluate readiness dimensions.
- Provide evidence-based benchmarks to guide HEIs in implementing data analytics effectively.
- Enhance institutional performance, operational efficiency, and stakeholder engagement through data-driven strategies.

5. Research hypotheses:

1. **H1:** There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to gender
2. **H2:** There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions

according to Age

- **H3:** There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to Years of experience
- **H4:** There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to Institutional Position
- **H5:** There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to Capacity of the university
- **H6:** There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to the type of the university.

6. Literature review

Higher education institutions face challenges such as declining enrollment, retention, and graduation, requiring innovative solutions (UNESCO, 2021). Data analytics with artificial intelligence (AI) offers a strategic response, provided institutions build strong leadership, infrastructure, and resources (Wang et al., 2022).

Data mining—through classification, estimation, and visualization—helps predict student outcomes and identify at-risk groups (Luan, 2004). Studies show it can forecast graduation with high accuracy, allowing better resource allocation.

Though still emerging in higher education, AI-driven analytics such as educational data mining (EDM) and learning analytics (LA) have shown strong potential in enhancing decision-making, curriculum design, and student success (Baradwaj & Pal, 2012; Sacin et al., 2009; Ji et al., 2016).

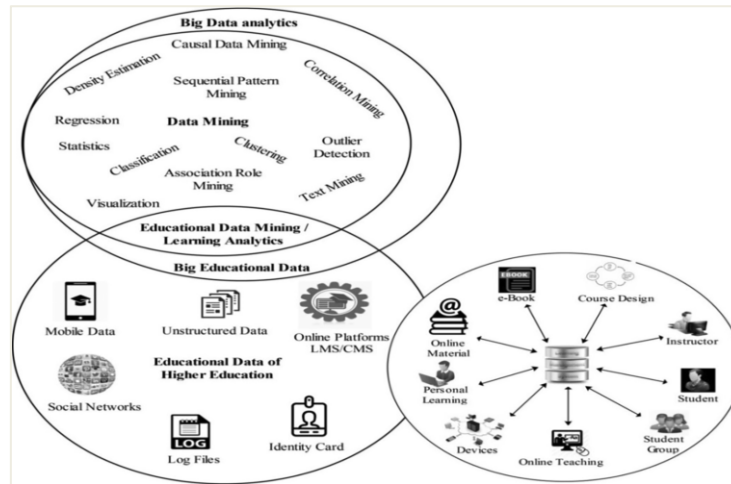


Figure 1: An illustration of data mining (EDM and LA) use in higher education.

Advantages of Data Analytics in Higher Education

- Data analytics enhances student retention by identifying at-risk learners and enabling early interventions, as demonstrated at Georgia State University (Berkner & Chavez, 2019).
- supports personalized learning, with Carnegie Mellon using learning analytics to tailor online courses, improving engagement and completion (Wang et al., 2020).
- analytics improves evidence-based decision-making. UC Berkeley employs dashboards to align academic programs with labor market demands, strengthening adaptability (Liu & Wang, 2021).
- data analytics drives innovation in research, enabling scholars to uncover patterns and correlations across vast datasets, thereby accelerating scientific discoveries across disciplines. (Johnson et al., 2018).

Table 1: Data Analytics in Higher Education example

Metric	Before Analytics	After Analytics	Change
Student Engagement Score	65%	80%	+15%
Course Completion Rate	65%	85%	+15%

Disadvantages of Data Analytics in Higher Education

- Collecting and analyzing sensitive student data raises privacy and ethical risks, with cases such as the University of Michigan showing how predictive models may reinforce systemic biases (Smith & Lee, 2020).
- Algorithms built on incomplete or biased datasets can unintentionally disadvantage minority or low-income students, thereby exacerbating inequalities rather than reducing them (O'Neill, 2016).
- Implementing analytics requires costly infrastructure, skilled personnel, and strong data management; smaller colleges often struggle with delays and overruns due to limited resources (Brown & Patel, 2022).
- Poor data quality, whether outdated or inconsistent, leads to inaccurate insights and ineffective decision-making, highlighting the need for robust governance systems.
- A narrow focus on quantitative indicators risks overlooking qualitative aspects of higher education such as campus culture, student well-being, and faculty satisfaction, resulting in incomplete or unbalanced policies.

Challenges and Limitations

- **Ethical Concerns:** Data analytics in higher education raises privacy and ethical risks, as shown by the University of Michigan which faced scrutiny over biased predictive models, underscoring the need for robust ethical standards and equitable AI applications (Smith & Lee, 2020).
- **Bias:** Algorithms may reproduce systemic inequalities when trained on biased datasets, disadvantaging minority students (O'Neill, 2016).
- **Costs and Infrastructure Challenges:** High implementation costs, ranging from \$50,000 to over \$1 million, create barriers for smaller institutions (Brown & Patel, 2022).

Table 2: Estimated costs and challenges by institution type

Institution Type	Estimated Cost (\$)	Major Challenges
Small college	50,000–150,000	Infrastructure, skilled HR
Large university	500,000–1,000,000	Data integration, maintenance

Case Study Analysis:

- **Case 1 – Georgia State University:** GSU implemented predictive analytics to track student performance and provide early interventions. This approach increased retention by 22% and improved graduation rates, particularly for underrepresented students.
- **Case 2 – Carnegie Mellon University:** Carnegie Mellon used learning analytics in online courses to tailor content to individual needs, resulting in higher engagement, satisfaction, and course completion rates.
- **Case 3 – University of California, Berkeley:** UC Berkeley integrated analytics into strategic planning, using dashboards to align programs with labor market demands, optimize resource use, and foster a data-driven culture.
- **Case 4 – University of Michigan:** Michigan faced criticism for predictive admissions models that embedded racial and socioeconomic bias, highlighting the importance of transparency, fairness, and ethical safeguards in analytics.
- **Case 5 – Small Liberal Arts College:** A small college attempted to adopt analytics but encountered high costs (\$50,000–\$150,000), delays, and data quality issues, illustrating the financial and logistical challenges smaller institutions face.

Data analytics holds immense potential to transform higher education by enhancing student success, personalizing learning, and informing strategic decisions. However, its adoption also involves significant challenges, including privacy concerns, bias, high costs, and data quality issues. Therefore, institutions must carefully weigh these pros and cons, implementing data analytics responsibly and ethically to maximize benefits while minimizing harm. As higher education continues to evolve in the digital age, the prudent use of data analytics will be essential in shaping equitable and effective educational environments.

A Five-Year Analysis of Enrollment, Retention, and Graduation Rates in Higher Education Institutions

Over the past five years, higher education institutions worldwide have faced challenges and opportunities shaped by technological advances, demographic shifts, and the COVID-19 pandemic. Enrollment, retention, and graduation rates remain critical indicators of access, student success, and institutional quality (UNESCO, 2022).

Global Trends (2018–2023)

1. **Enrollment:** Global tertiary enrollment rose from 35% in 2018 to 39% in 2022. Developed countries such as Canada and Australia maintained high participation (~80%), while Africa and Asia showed rapid growth but remained below global averages. (UNESCO, 2022)
2. **Retention:** Average first-year retention in OECD countries improved from 78% in 2018 to 81% in 2022, supported by academic services, financial aid, and predictive analytics for early interventions. (OECD, 2021).
3. **Graduation:** Graduation rates reached an average of 58% in 2022, with South Korea and Canada exceeding 70%, while Latin America and Africa often fell below 50%. COVID-19 disrupted timelines but accelerated online and hybrid learning adoption, reshaping completion patterns (OECD, 2022).

Egyptian Higher Education: A Five-Year Perspective (2018–2023)

1. **Enrollment:** University enrollment in Egypt increased from 2.8 million in 2018 to 3.2 million in 2022—a 14% growth (Egyptian Ministry of Higher Education, 2022). Female participation rose slightly (43% → 45%), and international students reached 55,000, mostly from neighboring Arab countries. Cairo University expanded from 300,000 to 340,000 students, while Ain Shams grew from 250,000 to 290,000, supported by digital initiatives. The American University in Cairo maintained ~9,000 students but leveraged advanced analytics to sustain high graduation rates above 70%.
2. **Retention** National retention rates remain between 75–80%, shaped by financial and academic challenges. Digital learning platforms and early warning systems improved outcomes; Cairo University, for example, reported a 3% increase in retention after adopting predictive tools (Cairo University Annual Report, 2022).
3. **Graduation:** Graduation rates rose from 50% in 2018 to 55% in 2022, with the government aiming for 60% by 2025 under the Higher Education Reform Program (Egyptian Ministry of Higher Education, 2022). Reforms focus on curriculum modernization and stronger research capacity.

- 4. Continuing Innovations** Egyptian universities are increasingly integrating data analytics and AI for student support, resource management, and research. Sustained investments in digital infrastructure, faculty training.

Higher education, both globally and in Egypt, has shown remarkable resilience and adaptability, navigating evolving demands through strategic integration of data analytics and AI. These technologies hold immense potential to enhance institutional efficiency, student outcomes, and long-term sustainability. However, realizing these benefits fully requires proactive solutions for data quality, ethical considerations, and resource management, ensuring that innovations translate into equitable and impactful advancements.

Financial Instability of Higher Education Institutions: Causes, Consequences, and Future Outlook.

Higher Education: Challenges, Opportunities, and the Egyptian Context

Higher education institutions (HEIs) play a critical role in societal progress, fostering innovation and driving economic growth. Yet, both globally and in Egypt, these institutions confront significant challenges that jeopardize their sustainability and effectiveness. This section examines the root causes of financial instability in higher education, the unique dynamics of Egypt's higher education sector, and the strategic opportunities for future development.

Global Challenges in Higher Education

Higher education institutions worldwide face financial pressures due to declining public funding, demographic shifts, rising costs, and the impact of COVID-19. Reduced government support has pushed institutions to rely more on tuition fees, while the pandemic cut international student enrollments and revenues. These pressures have led to program cuts, staff reductions, and in some cases bankruptcy, underscoring the urgency of sustainable funding models (Heller, 2018).

The Higher Education Landscape in Egypt

Egypt's higher education system enrolls over three million students across public, private, and international universities. Despite reforms aimed at aligning with global standards, challenges persist, including outdated curricula, limited research capacity, funding shortages, and brain drain. These issues weaken institutional quality and global competitiveness (El Mahdy, 2020).

Ongoing reforms, particularly the Higher Education Reform Program (2014–2024), aim to modernize curricula, improve accreditation, and expand institutional capacity. Opportunities include fostering international collaborations, adopting digital learning technologies, and investing in research areas tied to national priorities such as renewable energy and water resources (Ministry of Higher Education and Scientific Research, 2023).

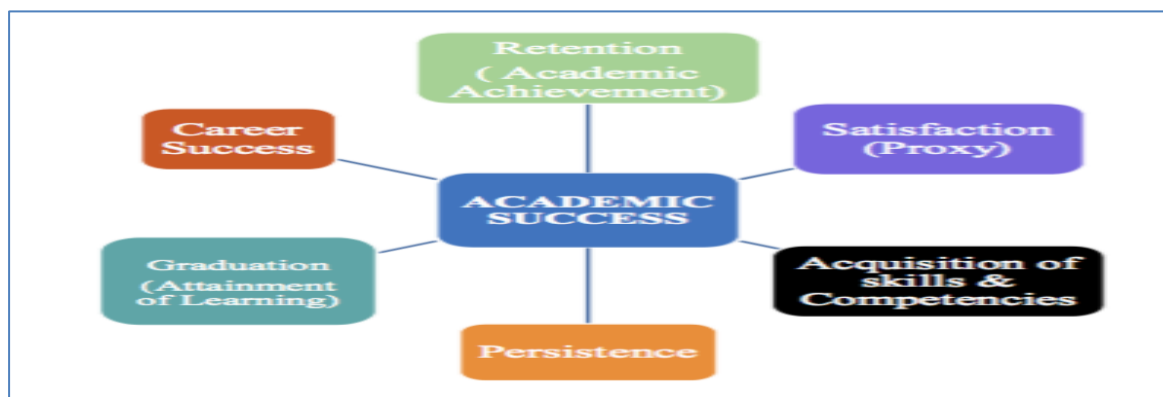


Figure 2: Revised Conceptual Model of Academic Success (York, Gibson, & Rankin)

Responsible Artificial Intelligence (AI)

Artificial Intelligence (AI) has become a transformative technology with the potential to significantly impact various sectors, including education, healthcare, finance, and industry. While AI offers numerous benefits such as automation, efficiency, and personalized experiences, it also raises critical ethical, social, and legal challenges. Responsible AI (RAI) emphasizes the importance of developing and deploying AI systems in ways that are transparent, fair, accountable, and aligned with human values.

Principles of Responsible AI

Responsible AI emphasizes transparency, fairness, privacy, and safety. Transparent and explainable systems foster accountability and trust. Fairness requires eliminating biases that might result in discrimination, while privacy safeguards data rights. Robust and safe systems ensure reliability across diverse contexts (Floridi et al., 2018).

Challenges in Implementing Responsible AI

Despite its potential, RAI faces obstacles. Biased training data can reinforce inequalities, as shown in facial recognition tools underperforming on minority groups. Complex models like deep learning often lack explainability, reducing accountability in critical applications such as healthcare or criminal justice (Buolamwini & Gebru, 2018).

The Role of Policy and Ethics.

Effective implementation requires strong regulatory frameworks and ethical oversight. The EU's proposed AI Act illustrates efforts to prioritize human rights and societal well-being. Ethical AI development also involves stakeholder collaboration and adoption of frameworks such as FATE (Fairness, Accountability, Transparency, and Ethics), which guide institutions toward inclusive and responsible AI practices (European Commission, 2021).

7. Methodology

This study adopts a mixed-method approach, combining qualitative and quantitative techniques. The Delphi method was first used to gather expert insights from executives at selected higher education institutions. These findings informed the design of a quantitative, cross-sectional survey guided by the DELTTA framework (Data, Enterprise, Leadership, Targets, Technology, Analysts).

7.1 Study population

The study population includes senior leaders and decision-makers in Egyptian HEIs—such as presidents, vice presidents, deans, registrars, and data managers—who are directly involved in strategic planning and technology adoption. To ensure representativeness, both public and private universities were included, reflecting the diversity of the higher education sector.

7.2 Study sample

Sample size calculation is based on the desired level of precision and statistical power. This calculation considered the total number of members in the university, estimated standard deviation and confidence interval.

$$\text{Unlimited population: } n = \frac{z^2 \times \hat{p}(1-\hat{p})}{\epsilon^2}$$

$$\text{Finite population: } n' = \frac{n}{1 + \frac{z^2 \times \hat{p}(1-\hat{p})}{\epsilon^2 N}}$$

n = sample size

z = critical value = 1.960 with the selected confidence level of 95%

N = population size

P = sample proportion (number of people in a sample with a certain trait or characteristic), ranging from 50 to 70%

Then the estimated sample size = 384

The study sample is determined using stratified random sampling with proportional allocation, reflecting the actual distribution of students across public and private universities. According to the latest CAPMAS bulletin, public university students represent approximately 81.5% of the total, while private university students constitute about 18.5%. This stratification ensures that the sample accurately mirrors the population structure and enhances the representativeness of the study finding

Table 3: Summary Table for sample

University Type	Population	Relative Weight	Sample Size (n=384)
Private	24,892	18.50%	71
Public	109,475	81.50%	313
Total	134,367	100%	384

Source: CAPMAS bulletin

7.3 Analysis of the demographic variables

The demographic analysis demonstrates a broad and diverse participant pool. Males constituted 63% and females 37% of the respondents, with a wide age distribution (20% under 30, 17% above 50). The years of experience are also varied, with a third of participants having 5-10 years of experience, and representation across both academic (68%) and administrative (32%) roles. Institutional size was dominated by large universities (>30,000 capacity, 74%), and the distribution between public (82%) and private (18%) matches both the sample and the population weighting. Such diversity ensures comprehensive coverage of perspectives regarding AI adoption and institutional readiness, thereby strengthening the validity and reliability of the study findings.

7.4 Data Collection

Primary data were collected through structured surveys and interviews with academic and administrative leaders, including program directors, department heads, registrars, and data warehouse administrators. The instrument was based on Davenport's (2014) DELTTA framework, which evaluates institutional readiness across six elements: Data, Enterprise, Leadership, Targets, Technology, and Analysts. Minor demographic items were added to capture respondents' positions and institutional characteristics.

7.5 Survey Administration

The survey consisted of 30 readiness questions, each measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), in addition to demographic questions. Invitations were distributed through targeted institutional email lists to ensure responses from eligible participants.

7.6 Reliability and Validity

Instrument reliability was tested using Cronbach's alpha. A pilot study with 30 respondents confirmed internal consistency, and the adapted DELTTA framework has been validated in previous studies (Quinn, 2016; Brynjolfsson & McAfee, 2013). These steps ensured that the survey tool was both reliable and valid for assessing big-data readiness in Egyptian HEIs.

7.7 Validity test

1- Validity test for Data

Table 4: Coefficient of correlation between the degrees of each statement of Data

Statements	Pearson	Sig.
Our institution provides us with access to very large, unstructured, or fast- moving data for analysis.	.847**	0.000
Our institution integrates data from multiple internal sources into a data warehouse for efficient access.	.900**	0.000
Our Institution integrates external data with internal to facilitate high-value analysis of our business environment.	.897**	0.000
Our institution maintains consistent definitions and standards across the data used for analysis.	.921**	0.000
Users and decision makers within our institution trust the quality of our data.	.861**	0.000

The table 4 shows that the correlation coefficients between each statement of the first dimension (Data), where the value of the correlation coefficient are between (0.847 – 0.921) which is a positive correlation, the Sig value of each statement is less than 0.05 and thus considered to be honest and intended to measure.

2- Validity test for Enterprise**Table 5: Coefficient of correlation between the degrees of each statement of Enterprise**

Statements	Pearson	Sig.
Our institution employs a combination of AI generated big data and traditional analytics approaches to achieve our organizational goals.	.767**	0.000
Our institutions' management ensures that business units and functions collaborate to determine data and analytics priorities for the organization.	.899**	0.000
Our institutional structure allows our data scientists and analytical professionals to enable learning and capabilities sharing across the organization.	.855**	0.000
Our big data and analytics initiatives and infrastructure receive adequate funding and other resources to build the capabilities we need.	.859**	0.000
As an enterprise, we collaborate with partners, customers, and other members of our ecosystem to share data content, insights, and applications.	.823**	0.000

The table 5 shows that the correlation coefficients between each statement of the second dimension (Enterprise), where the value of the correlation coefficient are between (0.823 – 0.899) which is a positive correlation, the Sig value of each statement is less than 0.05 and thus considered to be honest and intended to measure.

3- Validity test for Leaders**Table 6: Coefficient of correlation between the degrees of each statement of Leaders**

Statements	Pearson	Sig.
Senior executives and leadership in our institution regularly consider the opportunities that AI generated data analytics can bring to our organization.	.842**	0.000
Senior executives in our institution challenge business unit and functional leaders to incorporate AI and data analytics into their decision-making and business processes.	.866**	0.000
Senior executives in our organization utilize AI and data analytics to guide both strategic and tactical decisions.	.793**	0.000
Non-executive level managers in our organization utilize AI and data analytics to guide their decisions.	.738**	0.000
Our process for prioritizing and deploying our data assets (data, people, software and hardware) is directed and reviewed by senior management.	.849**	0.000

The table 6 shows that the correlation coefficients between each statement of the third dimension (Leaders), where the value of the correlation coefficient are between (0.738 – 0.866) which is a positive correlation, the Sig value of each statement is less than 0.05 and thus considered to be honest and intended to measure.

4- Validity test for Targets

Table 7: Coefficient of correlation between the degrees of each statement of Targets

Statements	Pearson	Sig.
Senior executives in our institution regularly consider the opportunities that AI and data analytics can bring to our organization in terms of reaching targets.	.909**	0.000
Senior executives in our institution challenge business unit and functional leaders to incorporate AI and data analytics into their decision-making and business processes in terms of reaching targets.	.888**	0.000
Senior executives in our institution utilize AI and data analytics to guide both strategic and tactical decisions in terms of reaching targets.	.829**	0.000
Non-executive level managers in our institution utilize AI and data analytics to guide their targeted decisions.	.778**	0.000
Our process for prioritizing and deploying our data assets (data, people, software and hardware) in terms of reaching targets is directed and reviewed by senior management.	.843**	0.000

The table 7 shows that the correlation coefficients between each statement of the fourth dimension (Targets), where the value of the correlation coefficient are between (0.778 – 0.909) which is a positive correlation, the Sig value of each statement is less than 0.05 and thus considered to be honest and intended to measure.

5- Validity test for Technology**Table 8: Coefficient of correlation between the degrees of each statement of Technology**

Statements	Pearson	Sig.
Senior executives in our institution regularly consider the opportunities that AI and data analytics technology can bring to our organization.	.879**	0.000
Senior executives in our institution challenge business unit and functional leaders to incorporate AI and data analytics technology into their decision-making and business processes.	.876**	0.000
Senior executives in our institution utilize AI and data analytics technology to guide both strategic and tactical decisions.	.869**	0.000
Non-executive level managers in our organization utilize AI and data analytics technology to guide their decisions.	.855**	0.000
Our process for prioritizing and deploying our data assets (data, people, software and hardware) in terms of technology is directed and reviewed by senior management.	.864**	0.000

The table 8 shows that the correlation coefficients between each statement of the fifth dimension (Technology), where the value of the correlation coefficient are between (0.855 – 0.879) which is a positive correlation, the Sig value of each statement is less than 0.05 and thus considered to be honest and intended to measure.

6- Validity test for Analysts**Table 9: Coefficient of correlation between the degrees of each statement of Analysts**

Statements	Pearson	Sig.
We have a sufficient number of capable data scientists and analytics professionals to achieve our analytical objectives.	.796**	0.000
Our data scientists and analytics professionals act as trusted consultants to our senior executives on key decisions and data-driven innovation in general.	.850**	0.000
Our data scientists and analytical professionals understand the industry disciplines and processes to which AI and data analytics are being applied.	.863**	0.000
Our data scientists operate effectively in teams to address AI and data analytics projects.	.855**	0.000
Our institution has programs (either internal or in partnership with external organizations) to develop data science and analytical skills in our human capital.	.706**	0.000

The table 9 shows that the correlation coefficients between each statement of the fifth dimension (Analysts), where the value of the correlation coefficient are between (0.706 – 0.863) which is a positive correlation, the Sig value of each statement is less than 0.05 and thus considered to be honest and intended to measure.

7.8 Reliability test

Table 10: Cronbach's Alpha Coefficient for the main and subdimensions

The dimension	Cronbach's Alpha	No. of Statements
Data	0.930	5
Enterprise	0.897	5
Leaders	0.877	5
Targets	0.904	5
Technology	0.918	5
Analysts	0.862	5
Big-Data Readiness	0.972	30

The results presented in Table 10 indicate that all six dimensions of the Big-Data Readiness instrument possess extremely high internal consistencies. More specifically, Cronbach's alpha scores of the subdimensions ranged from 0.862 (Analysts) to 0.930 (Data), while the whole scale achieved a Cronbach's alpha of 0.972. These findings indicate that each dimension is consistently measuring its respective construct and that the items of each dimension are extremely highly correlated. The extremely high total scale value shows that the instrument as a whole is extremely reliable to use in measuring Big-Data Readiness in higher education.

7.9 Statistical methods.

Data were analyzed using SPSS (v.26). Descriptive statistics (means, standard deviations, frequencies, percentages) were applied to profile respondents and assess readiness levels. Inferential statistics included independent t-tests to compare public and private universities and ANOVA to evaluate differences across demographic groups. Correlation analysis was used to test validity, while Cronbach's alpha assessed reliability.

8. The results.

8.1 Descriptive Statistics for the scale.

The results indicate that the sampled educational institutions have good data management capabilities, with an overall mean of 3.91 reflecting a positive assessment. The main strengths are data quality and user confidence in it, while maintaining consistent data definitions and standards requires slight improvement. The institutions also demonstrate good efficiency in integrating internal and external data to support analysis, the results indicate that the sampled educational institutions are generally enterprise-ready for big-data analytics, with an overall mean of 3.88 reflecting a positive assessment. Key strengths include the use of AI alongside traditional analytics and collaboration with external partners, while funding and resources for big-data projects may require slight improvement.

The results show that institutional leadership is generally engaged with AI-driven data analytics, with an overall mean of 3.87. Key strengths include executives promoting analytics use (3.97) and considering AI opportunities (3.90), while direct involvement in prioritizing data assets (3.79) could be slightly enhanced.

Also show that institutions generally use AI and data analytics to support organizational targets (mean = 3.78). Executive-level use of analytics for decision-making is strong (3.85), while application by non-executive managers is lower (3.65), indicating leadership plays the main role in aligning analytics with goals, it shows that institutions generally have good technological readiness for AI and data analytics, with an overall mean of 3.84. Executive awareness and use of technology in decision-making are strong (3.91 and 3.90), while senior management involvement in prioritizing and leveraging data assets (3.76) is slightly lower, indicating a potential area for improvement,

Also, institutions are generally well-prepared in terms of data science and analytics personnel, with an overall mean of 3.84. The strongest area (3.97) is effective teamwork among data scientists on AI and analytics projects, while the adequacy of personnel to meet objectives is also high (3.89). The lowest-rated area (3.61) is the availability of programs to develop analytics skills, suggesting that skill development could be improved.

For the open questions, Overall, the responses overwhelmingly support big data adoption, citing its transformative potential for educational quality, operational efficiency, and institutional competitiveness. Only a negligible minority expressed reservations, and these were primarily related to implementation challenges rather than the principle of adoption itself.

8.2 Testing the hypotheses

The research has some important hypotheses as follows:

- The first Hypothesis: There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to gender
- The second Hypothesis: There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to Age
- The third Hypothesis: There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to Years of experience
- The fourth Hypothesis: There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to Institutional Position
- The fifth Hypothesis: There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to Capacity of the university
- The sixth Hypothesis: There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to the type of the university

8.2.1 Testing the first hypothesis

The first Hypothesis: There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to gender.

Table 11: Shows the results of the first Hypothesis

Gender	Gender	N	Mean	Std. Deviation	t	P.Value
Data	Male	241	3.95	0.804	1.210	0.227
	Female	143	3.85	0.887		
Enterprise	Male	241	3.92	0.686	1.422	0.156
	Female	143	3.81	0.758		
Leaders	Male	241	3.91	0.626	1.588	0.113
	Female	143	3.80	0.727		
Targets	Male	241	3.80	0.629	0.776	0.438
	Female	143	3.75	0.722		
Technology	Male	241	3.86	0.636	0.574	0.567
	Female	143	3.81	0.800		
Analysts	Male	241	3.90	0.722	2.000	0.461
	Female	143	3.74	0.795		
Big-Data Readiness	Male	241	3.89	0.595	1.440	0.151
	Female	143	3.79	0.702		

The results of the independent sample t-tests for the first hypothesis indicate that, across all dimensions of big-data readiness (Data, Enterprise, Leaders, Targets, Technology, Analysts, and the overall Big-Data Readiness score), male respondents have greater mean scores than female respondents. Apart from these differences, they are not statistically significant for every dimension, Overall, gender has no significant influence on big-data readiness or its subdimensions in institutions of higher education, as for all other dimensions and readiness score overall, gender differences are not significant, as p.value are greater than 0.05.

8.2.2 Testing the second hypothesis

The second Hypothesis: There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to Age.

Table 12: Shows the results of the second Hypothesis

		N	Mean	Std. Deviation	F	Sig.
Data	Less than 30 years	78	3.97	0.749	4.475	0.004
	From 30 to 40 years	135	4.09	0.640		
	From 41 to 50 years	107	3.79	1.006		
	Above 50 years	64	3.69	0.921		
Enterprise	Less than 30 years	78	3.89	0.623	5.112	0.002
	From 30 to 40 years	135	4.05	0.560		
	From 41 to 50 years	107	3.78	0.875		
	Above 50 years	64	3.69	0.746		
Leaders	Less than 30 years	78	3.91	0.563	4.887	0.002
	From 30 to 40 years	135	4.01	0.530		
	From 41 to 50 years	107	3.77	0.804		
	Above 50 years	64	3.67	0.729		
Targets	Less than 30 years	78	3.82	0.563	3.336	0.020
	From 30 to 40 years	135	3.90	0.571		
	From 41 to 50 years	107	3.71	0.769		
	Above 50 years	64	3.62	0.739		
Technology	Less than 30 years	78	3.90	0.679	3.167	0.024
	From 30 to 40 years	135	3.95	0.610		
	From 41 to 50 years	107	3.75	0.752		
	Above 50 years	64	3.68	0.777		
Analysts	Less than 30 years	78	3.92	0.648	5.642	0.001
	From 30 to 40 years	135	4.01	0.626		
	From 41 to 50 years	107	3.72	0.863		
	Above 50 years	64	3.61	0.836		
Big-Data Readiness	Less than 30 years	78	3.90	0.540	5.672	0.001
	From 30 to 40 years	135	4.00	0.487		
	From 41 to 50 years	107	3.75	0.772		
	Above 50 years	64	3.66	0.709		

Table 12 shows the results. Significant differences ($p < 0.05$) were found across all DELTTA dimensions. The 30–40 age group consistently demonstrated the highest readiness (Means ≈ 4.0), while respondents over 50 years showed the lowest scores, age significantly affects big-data readiness, with younger leaders (especially 30–40 years) showing higher preparedness than older groups.

8.2.3 Testing the third hypothesis

The third Hypothesis: There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to Years of experience.

Table 13: Shows the results of the third Hypothesis

		N	Mean	Std. Deviation	F	Sig.
Data	Less than 5 years	76	4.08	0.736	5.128	0.002
	From 5 to 10 years	125	4.06	0.543		
	From 11 to 15 years	107	3.75	0.995		
	Above 15 years	76	3.74	1.003		
Enterprise	Less than 5 years	76	3.97	0.658	6.265	0.000
	From 5 to 10 years	125	4.05	0.527		
	From 11 to 15 years	107	3.68	0.779		
	Above 15 years	76	3.79	0.858		
Leaders	Less than 5 years	76	3.96	0.558	3.429	0.017
	From 5 to 10 years	125	3.96	0.545		
	From 11 to 15 years	107	3.70	0.770		
	Above 15 years	76	3.86	0.753		
Targets	Less than 5 years	76	3.85	0.589	2.197	0.088
	From 5 to 10 years	125	3.83	0.592		
	From 11 to 15 years	107	3.64	0.741		
	Above 15 years	76	3.83	0.720		
Technology	Less than 5 years	76	3.92	0.620	2.957	0.032
	From 5 to 10 years	125	3.90	0.622		
	From 11 to 15 years	107	3.67	0.766		
	Above 15 years	76	3.91	0.770		
Analysts	Less than 5 years	76	3.90	0.650	3.665	0.013
	From 5 to 10 years	125	3.94	0.651		
	From 11 to 15 years	107	3.64	0.834		
	Above 15 years	76	3.91	0.840		
Big-Data Readiness	Less than 5 years	76	3.95	0.530	4.381	0.005
	From 5 to 10 years	125	3.96	0.485		
	From 11 to 15 years	107	3.68	0.735		
	Above 15 years	76	3.84	0.759		

Table 13 shows the results. Significant differences were found across most DELTTA dimensions ($p < 0.05$), except for Targets. Respondents with less than 10 years of experience reported the highest readiness levels (Means ≈ 3.95 – 4.06), while those with 11–15 years of experience showed the lowest, years of experience influence readiness, with early-career professionals (<10 years) reporting greater preparedness than more experienced staff.

8.2.4 Testing the fourth hypothesis

The fourth Hypothesis: There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to Institutional Position

Table 14: Shows the results of the fourth Hypothesis

Institutional Position		N	Mean	Std. Deviation	t	P.Value
Data	Academic	260	3.70	0.908	7.799	0.000
	Administrative	124	4.36	0.379		
Enterprise	Academic	260	3.68	0.758	8.858	0.000
	Administrative	124	4.31	0.332		
Leaders	Academic	260	3.68	0.698	8.971	0.000
	Administrative	124	4.27	0.341		
Targets	Academic	260	3.57	0.680	10.204	0.000
	Administrative	124	4.23	0.329		
Technology	Academic	260	3.65	0.755	8.313	0.000
	Administrative	124	4.24	0.304		
Analysts	Academic	260	3.62	0.792	9.411	0.000
	Administrative	124	4.31	0.334		
Big-Data Readiness	Academic	260	3.65	0.664	10.355	0.000
	Administrative	124	4.29	0.248		

Table 14 shows the results. Statistically significant differences ($p < 0.001$) were found across all DELTTA dimensions. Administrative staff consistently scored higher (Means ≈ 4.2 – 4.3) than academic staff (Means ≈ 3.6 – 3.7), Institutional role strongly affects readiness, with administrative leaders perceiving significantly higher readiness than academic staff.

8.2.5 Testing the fifth hypothesis

The fifth Hypothesis: There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to Capacity of the university

Table 15: Shows the results of the fifth Hypothesis

		N	Mean	Std. Deviation	F	Sig.
Data	less than 10000	45	3.91	0.478	2.098	0.124
	From 10000 to 30000	56	3.71	1.114		
	More than 30000	283	3.96	0.814		
Enterprise	less than 10000	45	3.89	0.535	0.826	0.438
	From 10000 to 30000	56	3.77	0.813		
	More than 30000	283	3.90	0.719		
Leaders	less than 10000	45	4.00	0.521	4.617	0.010
	From 10000 to 30000	56	3.63	0.729		
	More than 30000	283	3.89	0.666		
Targets	less than 10000	45	3.92	0.533	2.951	0.053
	From 10000 to 30000	56	3.61	0.738		
	More than 30000	283	3.80	0.664		
Technology	less than 10000	45	3.98	0.468	2.074	0.127
	From 10000 to 30000	56	3.70	0.820		
	More than 30000	283	3.85	0.703		
Analysts	less than 10000	45	3.86	0.434	1.890	0.153
	From 10000 to 30000	56	3.66	0.730		
	More than 30000	283	3.87	0.793		
Big-Data Readiness	less than 10000	45	3.92	0.415	2.622	0.074
	From 10000 to 30000	56	3.68	0.748		
	More than 30000	283	3.88	0.640		

Table 15 shows the results. No significant differences were found across most dimensions, except Leaders ($p = 0.010$). Universities with fewer than 10,000 students and those with more than 30,000 students scored higher, while mid-sized universities (10,000–30,000 students) scored lowest, University capacity has limited influence on readiness, with significant variation observed only in leadership readiness.

8.2.6 The sixth Hypothesis: (University Type Differences)

The sixth Hypothesis: There is a signification difference in level of big-data readiness of higher education institutions (DELTTA) and its subdimensions according to the type of the university

Table 16: Shows the results of the sixth Hypothesis

The type of the university		N	Mean	Std. Deviation	t	P.Value
Data	Public	313	3.90	0.880	0.513	0.016
	Private	71	3.96	0.609		
Enterprise	Public	313	3.88	0.746	0.263	0.018
	Private	71	3.90	0.565		
Leaders	Public	313	3.84	0.711	1.427	0.012
	Private	71	3.97	0.409		
Targets	Public	313	3.76	0.700	1.454	0.015
	Private	71	3.89	0.473		
Technology	Public	313	3.79	0.731	3.252	0.001
	Private	71	4.08	0.482		
Analysts	Public	313	3.83	0.797	0.404	0.017
	Private	71	3.87	0.520		
Big-Data Readiness	Public	313	3.83	0.678	1.331	0.018
	Private	71	3.95	0.408		

Table 16 shows the results. Private universities reported higher mean scores across all DELTTA dimensions compared to public universities, and these differences were statistically significant ($p < 0.05$), university type significantly affects readiness, with private universities demonstrating greater preparedness for big-data analytics adoption than public institutions.

9. Conclusion

Inferential tests—t-tests and ANOVA—show that there are statistically significant differences in big-data readiness on demographic and institutional dimensions like gender, age, years of experience, institutional role, university capacity, and type (private vs. public). To be precise, administrative staff, private universities, and people with fewer years of experience always reported higher levels of readiness. The chapter also synthesizes qualitative remarks from open-ended responses, with a strong consensus on the necessity of big-data adoption to improve educational quality, operational efficiency, and competitiveness of institutions. Overall, the findings provide an elaborate and sophisticated comprehension of the drivers of big-data readiness in higher education.

10. Discussion of the results

- Egyptian HEIs are moderately to highly ready across DELTTA dimensions, with strengths in data quality, IT infrastructure, and leadership engagement.
- Gender had no significant effect on readiness, except for slight male advantage in the Analysts dimension.
- Age showed significant differences: the 30–40 age group reported highest readiness, while respondents over 50 showed lowest.
- Experience influenced readiness: staff with less than 10 years of experience showed higher readiness, while those with 11–15 years scored lowest.
- Institutional position was highly significant: administrative staff reported greater readiness than academic staff across all dimensions.
- University size had minimal impact, except in leadership, where smaller universities showed stronger readiness.
- University type was decisive: private universities consistently scored higher than public universities.
- Overall, the findings suggest that organizational culture, leadership, and adaptability are stronger predictors of readiness than institutional size or resources.

11. Recommendations

Based on the results and the objectives of the study the following recommendations are proposed:

- Develop standardized definitions, data governance policies, and periodic audits to ensure accuracy and consistency.
- Public universities, in particular, should prioritize funding for digital transformation and analytics capacity.
- Expand leadership training and strategic workshops to deepen engagement in analytics adoption.
- Provide training for middle and non-executive staff to broaden analytics use beyond senior management.
- Address gaps in public institutions by building smart campuses and advanced analytics platforms.
- Partner with industry to create training pipelines and retain qualified data professionals.
- Encourage collaboration between public and private universities to share knowledge and resources.
- Integrate big-data practices with Egypt's Vision 2030 and the Ministry of Higher Education's digital transformation plans.

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Appendices

BDA Readiness Survey

AAST

The purpose of this research project is to determine what higher education executive leadership perceive as the readiness of their institutions to utilize big data within HEI environments. The research shall analyze the determinants associated with HEI readiness of big data analytics.

Survey Elements for Big-Data Readiness:

-**Data** is the most basic component of a big-data set up and is a key determinant of the success of a big-data initiative. Data can be obtained from external or internal sources and can be in structured or unstructured form.

-An **enterprise** approach to big data is a crucial step toward achieving big-data readiness and maturity. It entails unifying a big-data initiative across the entire organization.

-**Leaders** in big-data-ready institutions should be passionate and committed during the adoption and implementation of the technologies. They must have a disruptive mindset, meaning that they are ready to disrupt the status quo and try new, risky approaches and are also willing to experiment with data on a large scale.

-**Targets** implies that an institution must identify where big-data analytics will be applied within the institution.

-**Technology** aids in the management and analysis of data. Big data not only entails large volumes of structured and unstructured data but also the relevant technologies which enable data processing and analysis.

-**Analysts** represent the human side of big data and are crucial to the success of the initiative. Adopting and deriving meaningful information from big data requires a workforce that is data literate, as well as data scientists who focus specifically on data operations.

1- Gender

Male

Female

2- Age

Less than 30 years

From 30 to 40 years

From 41 to 50 years

Above 50 years

3- Years of experience

Less than 5 years

From 5 to 10 years

From 11 to 15 years

Above 15 years

Q2 Institutional Position:

Academic

Administrative

Q3 Institution Enrollment Size (Undergraduates and Graduates):

Small (0-4,999)

Medium (5,000-15,000)

Large (15,000-Greater)

Q4 Your institution can best be categorized as:

Public

Private

Q6 Data (Agree - Disagree)

- We have access to very large, unstructured, or fast- moving data for analysis.
- We integrate data from multiple internal sources into a data warehouse or mart for easy access.
- We integrate external data with internal to facilitate high-value analysis of our business environment.
- We maintain consistent definitions and standards across the data we use for analysis.
- Users, decision makers, and product developers trust the quality of our data.

Q7 Enterprise (Agree - Disagree)

- We employ a combination of big data and traditional analytics approaches to achieve our organization's goals.
- Our organization's management ensures that business units and functions collaborate to determine big data and analytics priorities for the organization.

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- We structure our data scientists and analytical professionals to enable learning and capabilities sharing across the organization.
 - Our big data and analytics initiatives and infrastructure receive adequate funding and other resources to build the capabilities we need.
 - We collaborate with channel partners, customers, and other members of our business ecosystem to share big data content and applications.

Q8 Leadership (Agree - Disagree)

- Our senior executives regularly consider the opportunities that big data and analytics might bring to our business.
- Our senior executives challenge business unit and functional leaders to incorporate big data and analytics into their decision- making and business processes.
- Senior executives in our organization utilize big data and analytics to guide both strategic and tactical decisions.
- Non-executive level managers in our organization utilize big data and analytics to guide their decisions.
- Our process for prioritizing and deploying our big data assets (data, people, software and hardware) is directed and reviewed by senior management

Q9 Targets (Agree - Disagree)

- Our senior executives regularly consider the opportunities that big data and analytics might bring to our business.
- Our senior executives challenge business unit and functional leaders to incorporate big data and analytics into their decision- making and business processes.
- Senior executives in our organization utilize big data and analytics to guide both strategic and tactical decisions.
- Non-executive level managers in our organization utilize big data and analytics to guide their decisions.
- Our process for prioritizing and deploying our big data assets (data, people, software and hardware) is directed and reviewed by senior management.

Q10 Technology (Agree - Disagree)

- Our senior executives regularly consider the opportunities that big data and analytics might bring to our business.

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- Our senior executives challenge business unit and functional leaders to incorporate big data and analytics into their decision- making and business processes.
 - Senior executives in our organization utilize big data and analytics to guide both strategic and tactical decisions.
 - Non-executive level managers in our organization utilize big data and analytics to guide their decisions.
 - Our process for prioritizing and deploying our big data assets (data, people, software and hardware) is directed and reviewed by senior management.

Q11 Analysts and Data Scientists (Agree - Disagree)

- We have a sufficient number of capable data scientists and analytics professionals to achieve our analytical objectives.
- Our data scientists and analytics professionals act as trusted consultants to our senior executives on key decisions and data-driven innovation.
- Our data scientists and analytical professionals understand the business disciplines and processes to which big data and analytics are being applied.
- Our data scientists, quantitative analysts, and data management professionals operate effectively in teams to address big data and analytics projects.
- We have programs (either internal or in partnership with external organizations) to develop data science and analytical skills in our employees.

Q12 Please briefly explain why you do or do not believe big data acceptance/adoption is necessary for higher education institutions.

المستخلص

تهدف هذه الدراسة إلى فهم مدى جاهزية واستعداد مؤسسات التعليم العالي لتبني تحليلات البيانات الضخمة من خلال التنقيب في البيانات في مؤسسات التعليم العالي في مصر والكويت والولايات المتحدة – استناداً إلى مدى توافر الموارد. خاصة في أعقاب جائحة كوفيد-19، واجهت منظومة التعليم العالي في مصر وحول العالم تحديات جسيمة من منظور تشغيلي وقد تصل إلى التهديد الوجودي، بما في ذلك انخفاضات قياسية في معدلات الالتحاق، والاستبقاء، ومعدلات التخرج. إلى جانب التطبيقات التكنولوجية المتسارعة والتنافسية والتجارية والديناميكية في التعليم؛ فقد كافح صانعو القرار في مؤسسات التعليم العالي لفهم ومعالجة التحديات التشغيلية المعقدة التي تواجههم بشكل فعال، دون نجاح كبير. ونتيجة لذلك، تطور التعليم العالي بسرعة لتلبية المتطلبات الجديدة الناشئة عن التقدم التكنولوجي. وقد تم تحديد تطبيق تحليلات البيانات الضخمة من خلال التنقيب في البيانات كحل محتمل للعديد من التحديات التي تواجه التعليم العالي.

وتتحقق الجاهزية لتطبيق تحليلات البيانات الضخمة عندما تسمح قيادات مؤسسات التعليم العالي وتلتزم بتطبيق هذه التحليلات. يستمد الباحث إلهامه ودافعه من الرغبة في اكتساب المعرفة اللازمة لاستغلال التكنولوجيا ومواردها من أجل تحسين وتمكين اتخاذ القرار القائم على البيانات داخل مؤسساتهم. وتجدر الإشارة إلى أن مفهوم التنقيب في البيانات وُجد في قطاع الأعمال قبل أن تكون لتحليلات البيانات الضخمة أي تطبيقات أكاديمية، وقد مهدت النجاحات في الاستراتيجيات التسويقية والتجارية الطريق لتطبيقات التنقيب في البيانات في المجال الأكاديمي.

ولقياس جاهزية هذه المؤسسات لتبني تحليلات البيانات الضخمة، سيستخدم الباحث منهجاً مختلطاً. حيث سيتم استخدام طريقة دلفي بالدرجة الأولى لجمع البيانات الأولية من المديرين التنفيذيين في عينة مختارة من مؤسسات التعليم العالي. ثم سيتم تنظيم هذه الاستبيانات بينما يحاول الباحث تحديد مقدار "تقييم جاهزية البيانات الضخمة (BDRA)" بعد ذلك، سيتم استخدام هذا التقييم لقياس تبني وجاهزية تحليل البيانات الضخمة. كما سيتم إجراء دراسة كمية مقطعية باستخدام نموذج DELTTA، الذي يتكون من ستة عناصر: البيانات، المؤسسة، القيادة، الأهداف، التكنولوجيا، والمحللون (علماء البيانات).

وقد افترض الباحث أن مستوى الجاهزية سيختلف بين هذه العناصر الستة، وأن هناك فروقات ستظهر بناءً على طبيعة إدارة المؤسسة، والقدرات المالية، وحجم مؤسسات التعليم العالي.

الكلمات المفتاحية: تحليل البيانات، الذكاء الاصطناعي، التعليم العالي، أصحاب المصلحة.