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The Impact of Barriers and Drivers of AI Technology Utilization on Adoption of AI through Educational Institutions' Readiness: A Case Study of the Arab Academy for Science, Technology, and Maritime Transport[1]

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ABSTRACT

The current study aims to explore how barriers to using AI technologies—such as economic barriers, organizational and managerial barriers, and technological barriers—and drivers of using AI technologies—such as institutional efficiency, R&D sector improvement, and immediate feedback loops—affect the adoption of AI in higher education institutions through the mediating role of educational institutions' readiness, which includes financial, technological, staff, and processes and operations readiness. Utilizing a positivist philosophy with a quantitative analysis approach, the researcher collected primary data via a questionnaire administered to faculty members and students at the Arab Academy for Maritime Transport, Science, and Technology in Alexandria. The findings indicate that both obstacles and motivators significantly impact educational institutions' readiness and the adoption of AI in higher education. Economic, organizational, and technological barriers were found to positively influence readiness, as did motivators such as enhancing institutional efficiency, improving R&D sectors, and establishing immediate feedback loops. Additionally, readiness within educational institutions was shown to positively affect AI adoption. Finally, Staff Readiness partially mediates Economic Barriers, Institutional Efficiency, and AI Adoption, fully mediating R&D Sector Improvement and Immediate Feedback Loop impacts. Processes and Operations Readiness partially mediates Economic and Organizational Barriers, Institutional Efficiency, and AI Adoption, fully mediating R&D Sector Improvement and Immediate Feedback Loop effects. The study suggests that policymakers should address barriers to AI adoption while enhancing readiness through strategic investments, policy development, collaboration promotion, and support for research and development initiatives.

Keywords: *Barriers of Using AI Technologies - Drivers of Using AI Technologies - Adoption of AI - Higher Education Institutions - Educational Institutions' Readiness.*

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1. INTRODUCTION

Artificial Intelligence (AI) holds significant potential for organizations, encompassing technologies like image recognition, data mining, machine learning, and natural language processing, which emulate human intellect. This technology offers various benefits, including increased efficiency, financial savings, improved product quality, and enhanced customer service, by rapidly analyzing vast amounts of data and automating previously time-consuming tasks (Chen et al., 2022).

Universities play a crucial role in national development by fostering innovation, facilitating information exchange, and promoting unity. They are pivotal in cultivating intellectual capacity and driving productivity growth in the knowledge-based economy. Integration of AI technologies in universities holds promise for advancing education and research, although it presents both opportunities and challenges. Collaboration between higher education institutions and industry partners can optimize benefits and enhance the competitiveness of the knowledge-based economy (Alvi et al., 2020).

Artificial Intelligence (AI) holds the potential to transform learning in higher education through personalized experiences for students. AI can offer tailored instructional strategies to meet each learner's unique needs, enhancing the overall learning experience. AI-powered libraries could complement this personalized approach. Although current AI technology may not fully support personalized experiences, future advancements are anticipated. Additionally, AI-enabled chatbots can provide individualized assistance to students, offering tailored answers and support outside of regular class times. Overall, AI has the capacity to greatly impact higher education by providing diverse forms of assistance and personalized learning experiences (Chatterjee and Bhattacharjee, 2020).

The readiness of educational institutions to use artificial intelligence represents an essential aspect of the efficiency of implementing these programs. The readiness of university institutions in terms of infrastructure, technologies, and human competencies constitutes the obstacle that stands between development.

When it comes to education and the application of artificial intelligence initiatives in the education sector, educational institutions must invest in training staff and upgrading systems to fully make use of AI's potential in education. Without proper readiness, the benefits of personalized learning and efficient problem-solving through chatbots may not be fully realized (Flavián et al., 2022).

Organizational readiness for change, originating from change management literature, initially focused on managers' efforts to mitigate resistance to organizational change. However, contemporary perspectives regard it as a proactive and critical factor for the success of organizational reforms. Extensively studied across management, human resources, marketing, and artificial intelligence adoption, this construct is crucial in diverse contexts within the artificial intelligence and information systems sector, encompassing the adoption and implementation of corporate information systems and AI projects (Shahrasbi and Paré, 2014).

Therefore, the current study aims to explore how the barriers to using ai technologies (economic barriers, organizational and managerial barriers, and technological barriers) and the drivers of using ai technologies (institutional efficiency, R&D sector improvement, and immediate feedback loop) affect the adoption of artificial intelligence in higher education institutions through the mediating role of educational institutions' readiness (financial readiness, technological readiness, staff readiness, and processes and operations readiness).

2. RESEARCH PROBLEM

The challenges and problems associated with the adoption and implementation of e-business in emerging markets, particularly in the context of Egypt, are multifaceted. Firstly, there are technological barriers such as inadequate infrastructure and limited access to reliable internet and advanced digital tools. Secondly, firms face organizational and managerial obstacles, including resistance to change, lack of digital literacy among staff, and insufficient training and development programs. Additionally, financial constraints pose a significant challenge, as the initial investment in e-business technologies and continuous upgrades can be substantial. There are also environmental and contextual factors, such as political instability, regulatory hurdles, and socio-cultural differences that can impede the smooth transition to e-business. Moreover, the empirical evidence on the benefits of e-business in emerging economies is limited, making it difficult to establish a clear link between e-business adoption and competitive advantage. This lack of robust data and theoretical frameworks hinders the ability of firms to make informed decisions about e-business strategies. Lastly, the digital divide between developed and developing countries adds another layer of complexity, as firms in emerging markets may not fully benefit from late adoption advantages due to unique local challenges that require tailored solutions. The adoption of AI technologies in Egyptian Higher Education Institutions (HEIS) is hindered by various barriers while simultaneously driven by several enablers. Despite the significant potential AI holds for transforming educational practices and enhancing institutional effectiveness, the actual implementation and integration of these technologies face numerous obstacles. These include economic barriers such as high costs and limited funding, organizational and managerial challenges like resistance to change and lack of strategic vision, and technological issues including inadequate infrastructure and digital literacy gaps. Additionally, privacy concerns and lack of experience among educators further complicate the adoption process. On the other hand, drivers such as institutional efficiency, improvements in the R&D sector, and the provision of immediate feedback loops can facilitate the adoption of AI in HEIS. The research problem thus focuses on understanding how these barriers and drivers impact the readiness of Egyptian HEIS to adopt AI technologies and how addressing these factors can enhance the integration and utilization of AI to improve educational outcomes (Shehata and Montash, 2020). Specifically, this study aims to explore the mediating role of educational institutions' readiness in terms of financial, technological, staff, and operational aspects in the relationship between the identified barriers and drivers and the overall adoption of AI technologies in Egyptian HEIS.

3. RESEARCH AIM AND OBJECTIVES

The current study aims to explore how the Barriers to Using AI Technologies (Economic Barriers, Organizational and Managerial Barriers, and Technological Barriers) and the Drivers of Using AI Technologies (Institutional Efficiency, R&D Sector Improvement, and Immediate Feedback Loop) affect the Adoption of Artificial intelligence in Higher Education Institutions through the mediating role of Educational Institutions' Readiness (Financial Readiness, Technological Readiness, Staff Readiness, and Processes and Operations Readiness). Moreover, the study addresses a set of objectives including:

3-1 Exploring how organizational and managerial challenges, including resistance to change and lack of strategic vision, affect the implementation of AI in Egyptian HEIS.

3-2 Investigating the mediation effect of readiness of educational institutions in terms of financial, technological, staff, and operational aspects on the relationship between the identified barriers and drivers and the overall adoption of AI technologies in Egyptian HEIS.

3-3 Determining the measures used to enhance the readiness of Egyptian HEIS to adopt AI technologies, thereby improving educational outcomes.

4. RESEARCH QUESTIONS

This research has several questions, as follows:

- How do organizational and managerial challenges, including resistance to change and lack of strategic vision, affect the implementation of AI in Egyptian HEIS?
- How does the readiness of educational institutions in terms of financial, technological, staff, and operational aspects mediate the relationship between the identified barriers and drivers and the overall adoption of AI technologies in Egyptian HEIS?
- What measures can be taken to enhance the readiness of Egyptian HEIS to adopt AI technologies, thereby improving educational outcomes?

These questions aim to explore various aspects of the challenges and drivers related to the adoption and implementation of e-business and AI technologies in Egypt, providing a comprehensive framework for further research and analysis.

5. RESEARCH IMPORTANCE

The current study aims to explore how the Barriers to Using AI Technologies and the Drivers of Using AI Technologies affect the Adoption of Artificial intelligence in Higher Education Institutions through the mediating role of Educational Institutions' Readiness. Therefore, the current study offers a variety of significant variables and an essential topic in modern technology adoption, the research significance are as follows:

5-1 Academic Importance

- The current study enriches the theoretical understanding of AI adoption in higher education by integrating barriers and drivers within the framework of institutional readiness.
- By applying the current study on Egyptian higher education institutions, the study provides empirical understanding specific to a region that faces unique challenges and opportunities in the technology adoption sector.
- Employing quantitative methods such as regression analysis and mediation/moderation analysis contributes to the methodological rigor in the field of educational technology research. It sets a precedent for future studies aiming to employ similar methods to explore the adoption of emerging technologies.

5-2 Practical Importance

- By addressing the crucial issues that must be addressed to improve AI adoption, policymakers in the education sector can benefit from the findings. Comprehending the obstacles and motivators facilitates the development of policies that enhance institutional preparedness and alleviate difficulties.
- Improved Institutional Efficiency: The study demonstrates how AI may spur advancements in R&D and institutional efficiency. This data may be used by educational institutions to support their investments in AI technology by highlighting the possible benefits in terms of improved academic performance and operational efficiency.
- Future Research Directions: The study lays the groundwork for future research by pointing out gaps and areas that require more exploration. On the basis of the results, researchers may investigate further facets of AI adoption, evaluate the suggested model in various settings, and create creative responses to new problems.

6. LITERATURE REVIEW

This section illustrates the literature regarding the studied variables and the relationships between them including the relationship between barriers of using ai technologies and educational institutions' readiness, the relationship between drivers of using ai technologies and educational institutions' readiness, and the relationship between educational institutions' readiness and adoption of artificial intelligence in higher education institutions.

6-1 The Relationship between Barriers of Using AI Technologies and Educational Institutions' Readiness

Stentoft et al. (2019) investigated the factors influencing Industry 4.0 readiness and implementation through a survey involving 308 small and medium-sized manufacturers. Their research uncovered that perceived drivers of Industry 4.0 positively contribute to organizational readiness for the technology, thereby increasing the adoption of Industry 4.0 practices. Interestingly, the study also found that while barriers may hinder an organization's readiness for Industry 4.0, they do not significantly impede the actual implementation of Industry 4.0 practices.

Caputo et al. (2019) conducted a study focusing on the relationship between information and communication technologies (ICTS) and human resources, aiming to identify barriers and challenges affecting institutional readiness. Their research provided a comprehensive conceptual framework for understanding how ICTS and human resources are interconnected within the context of Industry 4.0. They concluded that technology readiness plays a crucial role in determining how human resources respond to the introduction of new technologies and digital tools.

Salim et al. (2022) investigated the association between organization readiness and the desire to embrace blockchain, focusing on the mediation and moderating effects of perceived cost (economic aspects). All the framework assumptions were evaluated using partial least squares structural equation modeling (PLS-SEM), analytical approach, and data gathered from blockchain professionals. Utilizing Importance-Performance Map Analysis (IPMA), this topic's possible management ramifications were examined. The results indicated that the association between the Technology Readiness Index enablers and the Technology Readiness Index inhibitors with the desire to use blockchain is moderated by perceived cost rather than acting as a mediator.

Goswami and Daultani (2022) investigated the impact of various barriers and socio-technical consequences on the technological readiness of ten selected enterprises. Their research aimed to compare the macro-level differences between China's Made-in-China 2025, Germany's Industry 4.0, and India's Made-in-India initiatives. Utilizing a combination of methodological approaches, they found that the infrastructure project management sector exhibited the least preparedness for Industry 4.0 technologies, while the automobile and software industries showed the highest readiness for implementation.

According to the previous studies that were illustrated, the first hypothesis of the study can be suggested, which is that there is a statistically significant relationship between barriers of using AI technologies and educational institutions' readiness.

H1 There is a Significant Relationship between Barriers of Using AI Technologies and Educational Institutions' Readiness

6-2 The Relationship between Drivers of Using AI Technologies and Educational Institutions' Readiness

Damerji and Salimi (2021) investigated the influence of perceived ease of use (PEOU) and perceived usefulness (PU) on the relationship between technology readiness among accounting students and their decision to adopt AI. Their study examined students' attitudes towards technology readiness and adoption using an online questionnaire completed by participants, primarily students, consisting of 31 items covering demographic information, technology readiness, technology adoption, PEOU, and PU. The results indicated a significant impact of technology readiness on technology adoption.

Yousaf et al. (2022) explored the relationship between the innovation network and organizational innovativeness, with a focus on the mediating role of frugal innovation and the moderating effect of organizational readiness. Data collected from SMEs through a cross-sectional method involved 442 managers and proprietors. The findings revealed a positive association between the innovation network and organizational innovativeness, along with frugal innovation acting as a mediator between the two.

Flavián et al. (2022) examined how customers' technology readiness and service awareness influenced their intention to use analytical AI financial advisory services. Their study, based on data from 404 potential customers of robo-advisors in North America, also considered moderating factors such as gender, age, and previous experience with financial investment services. Surprisingly, the findings suggested that customers' technological optimism increased their intention to use robo-advisors, while feelings of technological unease positively influenced robo-advisor adoption, challenging traditional assumptions about technology adoption and value co-creation.

According to the previous studies that were illustrated, the second hypothesis of the study can be suggested, which is that there is a statistically significant relationship between drivers of using AI technologies and educational institutions' readiness.

H2There is a Significant Relationship between Drivers of Using AI Technologies and Educational Institutions' Readiness

6-3 The Relationship between Educational Institutions' Readiness and Adoption of AI in Higher Education Institutions

Paul (2020) conducted a study to explore how large businesses perceive their readiness for AI adoption and identified key internal and external factors influencing this readiness. Semi-structured interviewswith13Finnish organizations were analyzed using the technology-organization-environment (TOE) theory as the research framework. The study revealed that cultural characteristics, data-related challenges, business case and process comprehension, and strategic linkage were the most significant factors influencing AI adoption readiness in Finnish organizations.

Issa et al. (2022) investigated the impact of AI organizational readiness on AI adoption using a mixed-methods approach, including 236 e-surveys and 25 interviews conducted at a prominent AgriTech conference. Their findings emphasized the importance of data driven AgriTech companies dedicating sufficient time to analyze data points to make informed strategic decisions, necessitating the development of sustainable data processing channels as part of the AI readiness process.

Owolabi et al. (2022) examined the preparedness of academic librarians in Nigerian university libraries to adopt robotic technology using a questionnaire distributed to 100 academic librarians from ten purposefully selected institutions, employing a snowball sampling approach. Despite recognizing the benefits of robotic technology for library operations, the study found that university libraries in Nigeria are not adequately prepared to integrate this technology.

Flavián et al. (2022) investigated the relationship between consumers' intention to use analytical AI investment services and their level of service awareness and technological readiness. They collected data from 404 prospective robo-advisor clients in North America and found that consumers' inclination to adopt robo-advisors is influenced by increased technical optimism and decreased insecurity.

Nouraldeen (2023) assessed the effects of thought utility, perceived simplicity of use, and technical readiness on accounting and auditing students' adoption of AI. Data were collected through a questionnaire completed by 330 students enrolled at Lebanese private institutions, and hierarchical multiple regression analysis was used to analyze the hypotheses. The study revealed that perceived utility and technological readiness significantly influence AI adoption among students, while perceived ease of use does not impact their decisions to utilize AI.

According to the previous studies that were illustrated, the third hypothesis of the study can be suggested, which is the fact that that exist a statistically significant relationship between educational institutions' readiness and adoption of AI in higher education institutions.

H3There is a Significant Relationship between Educational Institutions' Readiness and Adoption of AI in Higher Education Institutions

6-4 The Relationship between Barriers of Using AI Technologies and the Adoption of AI in Higher Education Institutions

Chatterjee and Bhattacharjee (2020) conducted a study focusing on the adoption of AI in higher education in India and strategies for effective adoption by stakeholders. Drawing on various adoption theories and models, including the Unified Theory of Acceptance and Utilization of Technology (UTAUT), the researchers developed hypotheses and a conceptual model. These were subsequently validated through a survey involving 329 usable respondents. The methodology included gathering feedback from stakeholders to evaluate the feasibility and potential effectiveness of AI adoption in higher education. The results showed that the proposed model had a positive impact on higher education institutions.

Woodruff et al. (2023) conducted a study to explore K-12 educators' perceptions of artificial intelligence (AI), technology policies, training, and resources across all 50 states of the USA and Puerto Rico. Employing a mixed-methods approach, the researchers aimed to understand educators' comfort levels with technology. The methodology included distributing a survey via Qualtrics, which was approved by the Lindenwold University Institutional Review Board, using social media tags commonly associated with educators. The survey was distributed twice, approximately 10 days apart, to enhance participant diversity. Analysis of the data revealed an overall positive perception of AI among educators and a general openness towards its integration into the classroom.

Sharma et al. (2024) delved into the role of artificial intelligence (AI) within Indian university settings and delineated its various applications. It adopted a quantitative research approach, gathering data from faculty, students, and administrative staff across different higher education institutions in India. The investigation drew upon theoretical frameworks like the technological Model of Acceptance, social cognitive theory, and human-computer interaction theory to understand the factors influencing the acceptance and integration of AI in these institutions. The findings of the study revealed significant correlations among factors such as AI self-efficacy, the intention to adopt AI, AI adoption in higher education, efficiency, perceived usefulness organizational support, and risk perception.

According to the previous studies that were illustrated, the fourth hypothesis of the study can be suggested, which is that that exist a statistically significant relationship between Barriers to Using AI Technologies and Adoption of AI in Higher Education Institutions

H4 There is a Significant Relationship between Barriers to Using AI Technologies and the Adoption of AI in Higher Education Institutions

6-5 The Relationship between Drivers of Using AI Technologies and the Adoption of AI in Higher Education Institutions

Rahim et al. (2022) explored factors influencing chatbot adoption in higher education institutions (HEIS) by adapting the UTAUT2 model. They surveyed 302 postgraduate students in Malaysian HEIS over three months, using a two-stage analytical approach (SEM-ANN). Results emphasized interactivity, ethics, and perceived trust as crucial for students' behavioral intention toward chatbot adoption. Positive interactions with chatbots enhanced trust, facilitating information retrieval and fostering preference for chatbot usage. Additionally, ethical considerations significantly influenced trust, with positive values and effective communication encouraging adoption.

Ivanov et al. (2024) investigated the relationship between Theory of Planned Behavior (TPB) variables and the intention to use GenAI tools in higher education, employing an online questionnaire with 130 lecturers and 168 students from multiple nations. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used for data analysis. Results showed that perceived strengths positively influenced attitudes, subjective norms, and perceived behavioral control. These TPB variables significantly influenced intentions to use GenAI tools, subsequently impacting adoption.

Polyportis (2024) studied ChatGPT adoption among 222 students in Dutch higher education over eight months, noting a decrease in usage over time. Factors like trust, emotional perception, and perceived control were found to influence this decline. These findings offer insights into AI adoption dynamics in educational settings.

According to the previous studies that were illustrated, the fifth hypothesis of the study can be suggested, which is that there is a statistically significant relationship between drivers of using ai technologies and adoption of ai in higher education institutions.

H5 There is a Significant Relationship between Drivers of Using AI Technologies and the Adoption of AI in Higher Education Institutions

7. RESEARCH GAP

The literature review identifies several research gaps in the study of AI adoption in educational institutions:

- Previous studies have not specifically examined the relationship between barriers and drivers of AI technologies and their adoption in educational institutions. Most studies have focused on barriers or drivers in organizations generally, without detailing the specific factors relevant to educational institutions. Enriching the understanding of these factors could enhance organizations' readiness to adopt AI programs.

- There is a lack of research on the mediating role of educational institutions' readiness in facilitating successful AI implementation. Additionally, integrated frameworks combining barriers, drivers, and organizational readiness are scarce.

Specifically, there is a gap in understanding the impact of financial readiness, technological readiness, staff readiness, and processes and operations readiness on AI adoption in higher education institutions. This is particularly crucial as universities, including those in Egypt, are in the process of integrating AI into their operations. Further research in this area is essential for universities to prepare effectively for AI adoption, addressing both challenges and opportunities.

8. RESEARCH METHODOLOGY

The study is applied to Egyptian higher education institutions, which is a special scope due to the unique challenges and opportunities present in the region. Therefore, the current research attempts to investigate how the Barriers to Using AI Technologies (Economic Barriers - Organizational and Managerial Barriers - Technological Barriers) and the Drivers of Using AI Technologies (Institutional Efficiency - R&D Sector Improvement - Immediate Feedback Loop) affect the Adoption of AI in Higher Education Institutions through the mediating role of Educational Institutions' Readiness (Financial Readiness - Technological Readiness - Staff Readiness - Processes and Operations Readiness). To employ positivist philosophy, quantitative techniques, a deductive approach, and a questionnaire in measuring the research, the study begins by embracing a positivist stance, prioritizing empirical evidence and scientific methods. It designs a quantitative research study, formulating hypotheses based on existing literature and theoretical frameworks, and develops a questionnaire aligned with research objectives. This questionnaire gathers numerical data on variables such as barriers and drivers of AI adoption, educational institutions' readiness, and other pertinent factors. After determining the appropriate sampling method, data is collected from participants and analyzed using quantitative techniques like regression analysis and mediation/moderation analysis. The study interprets findings within the context of its hypotheses, theory, and literature review, concluding with implications for theory, practice, and future research. Therefore, the research variables are represented as follows;

- **Independent Variable:**
  - Barriers to Using AI Technologies and its dimensions (Economic Barriers, Organizational and Managerial Barriers, and Technological Barriers)
  - Drivers of Drivers of Using AI Technologies and its dimensions (Institutional Efficiency, R&D Sector Improvement, and Immediate Feedback Loop)
  - **Dependent Variable:** Adoption of AI in Higher Education Institutions
  - **MediatorVariables:** Educational Institutions' Readiness (Financial Readiness, Technological Readiness, Staff Readiness, and Processes and Operations Readiness)

Therefore, the current research framework could be expressed using the following figure:

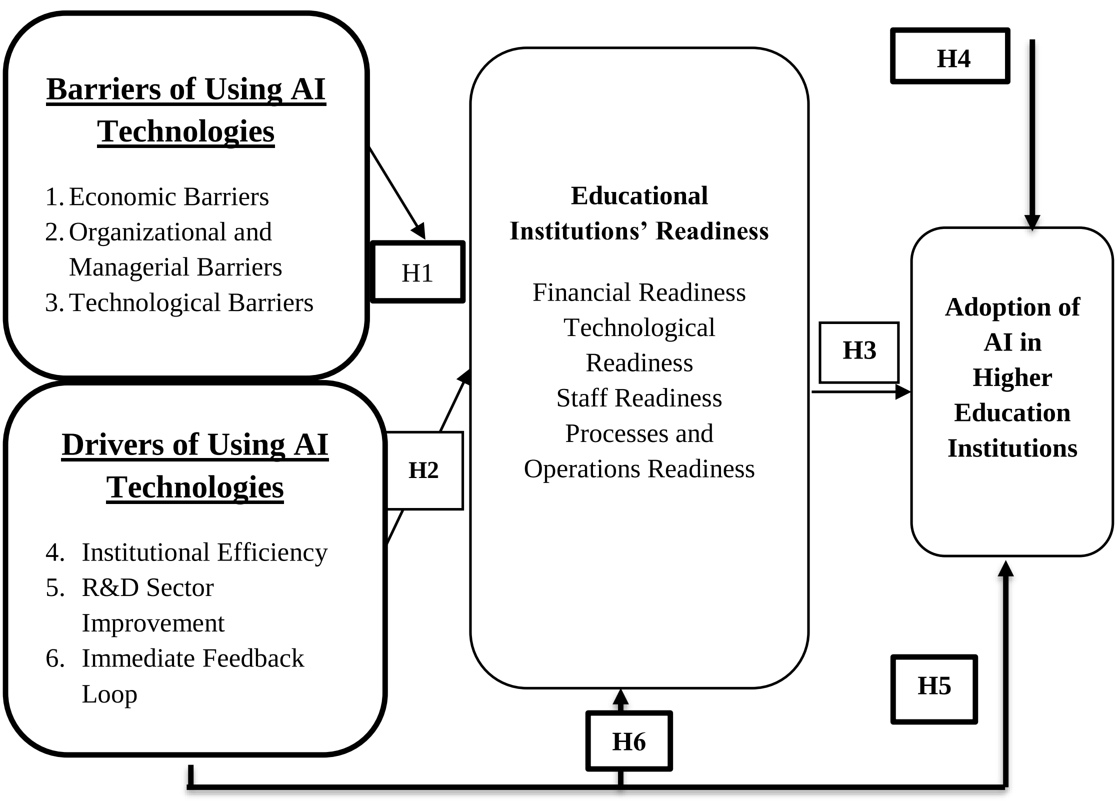

Figure 1: Conceptual Model (by the researcher)

Accordingly, from the framework, these could be the research hypothesis expressed:

H1 There is a Significant Relationship between Barriers of Using AI Technologies and Educational Institutions' Readiness

H_{1-1}: There is a Significant Relationship between Economic Barriers and Educational Institutions' Readiness.

H_{1-2}: There is a Significant Relationship between Organizational and Managerial Barriers and Educational Institutions' Readiness.

H_{1-3}: There is a Significant Relationship between Technological Barriers and Educational Institutions' Readiness.

***H2** There is a Significant Relationship between Drivers of Using AI Technologies and Educational Institutions' Readiness*

H_{2-1}: There is a Significant Relationship between Institutional Efficiency and Educational Institutions' Readiness.

H_{2-2}: There is a Significant Relationship between R&D Sector Improvement and Educational Institutions' Readiness.

H_{2-3}: There is a Significant Relationship between the Immediate Feedback Loop and Educational Institutions' Readiness.

H3 There is a Significant Relationship between Educational Institutions' Readiness and Adoption of AI in Higher Education Institutions

H_{3-1}: There is a Significant Relationship between Financial Readiness and Adoption of AI in Higher Education Institutions.

H_{3-2}: There is a Significant Relationship between Technological Readiness and Adoption of AI in Higher Education Institutions.

H_{3-3}: There is a Significant Relationship between Staff Readiness and Adoption of AI in Higher Education Institutions.

H_{3-4}: There is a Significant Relationship between Processes and Operations Readiness and Adoption of AI in Higher Education Institutions.

H4 There is a Significant Relationship between Barriers to Using AI Technologies and the Adoption of AI in Higher Education Institutions

H_{4-1}: There is a Significant Relationship between Economic Barriers and Adoption of AI in Higher Education Institutions.

H_{4-2}: There is a Significant Relationship between Organizational and Managerial Barriers and the Adoption of AI in Higher Education Institutions.

H_{4-3}: There is a Significant Relationship between Technological Barriers and Adoption of AI in Higher Education Institutions.

H5 There is a Significant Relationship between Drivers of Using AI Technologies and the Adoption of AI in Higher Education Institutions

H_{5-1}: There is a Significant Relationship between Institutional Efficiency and the Adoption of AI in Higher Education Institutions

H_{5-2}: There is a Significant Relationship between R&D Sector Improvement and the Adoption of AI in Higher Education Institutions

H_{5-3}: There is a Significant Relationship between the Immediate Feedback Loop and the Adoption of AI in Higher Education Institutions

H6 There is a significant effect of the mediation role of Educational Institutions' Readiness between Barriers, Drivers of Using AI Technologies, and Adoption of AI.

In this study, primary data collection involved administering a questionnaire to faculty members and students at the Arab Academy for Technology, Science, and Maritime Transport in Alexandria. The questionnaire utilized a five-point Likert scale to gather data on how barriers to using AI technologies (economic, organizational, and technological barriers) and drivers of using AI technologies (institutional efficiency, R&D sector improvement, and immediate feedback loop) impact the adoption of AI in higher education institutions. Additionally, the questionnaire aimed to measure the mediating role of educational institutions' readiness (financial, technological, staff, and processes and operations readiness). Responses were recorded on a scale where 1 indicated "strongly disagree," 3 represented "neither agree nor disagree" (neutral), and 5 denoted "strongly agree."

The following statements are mentioned in Table 1 as the ones that were utilized to measure the study variables:

Table 1: Research Variables Measurement

Variables	Statements	References
Barriers of Using AI Technologies		
Economic Barriers	– AI usage boosts productivity in business processes. – AI usage boosts efficiency in Business processes. – AI usage enables deep learning-based innovation. – The cost of AI usage is affordable – AI usage enables reduced equipment costs. – AI usage enables reduced human error.	Cubric (2020)
Organizational and Managerial Barriers	– AI usage offers new risks in addition to the opportunities. – AI usage worries the stakeholders in educational institutions. – The usage of AI needs many requirements and objectives. – The usage of AI needs procurement and partnership.	**Bodea et al. (2020)**
Technological Barriers	– AI usage offers availability of large training datasets. – AI shows an inability to read unstructured data. – Lack of training data may result in performance degradation. – Most of the data is unstructured and difficult to share. – Project data sets are difficult to collect and maintain. – It is difficult to reuse AI models for different problems.	Cubric (2020)
Drivers of Using AI Technologies		
Institutional Efficiency	– The institution has clear outline for the ethical and responsible use of AI technology. – Staff members receive regular training on how to effectively use AI tools. – The institution regularly evaluates the performance and impact of AI systems to ensure they are meeting their intended views. – Feedback from staff and clients is considered in the implementation and improvement of AI technologies within the institution.	**Lee and Wohn (2016)**
R&D Sector Improvement	– The institution benefits from prompt input in every procedure. – The institution enjoys effective systems in place to move technology from research to product development. – The institution benefits greatly from consumer and market input during the technical innovation process.	**Yam et al. (2011)**
Immediate Feedback Loop	– The quantity and timing of AI feedback fits the needs of users. – The AI feedback quality is high and reliable. – The feedback provided by AI is useful. – The AI feedback offers new dimensions to learning and examination.	**Agricola et al. (2020)**
Educational Institutions' Readiness		
Financial Readiness	– The institution enjoys the financial resources to adopt the AI applications.	**Shahrasbi and Paré (2014)**

Variables	Statements	References
	– the institution enjoys the financial resources to implement and support the AI programs in all departments. – The information systems budget fits the cost of developing and maintaining this system.	
Technological Readiness	– The institution enjoys the technical resources to adopt the AI programs. – The institution is well computerized with LAN and WAN techniques. – The institution enjoys high bandwidth connectivity to the Internet. – The institution enjoys sufficient experience with network-based applications. – The institution enjoys the technical knowledge and skills to implement AI Programs.	**Shahrasbi and Paré (2014)**
Staff Readiness	– The employees have enough IT skills to apply and use AI programs. – Most of the employees are computer literate and proficient. – The institution enjoys enough skilled personnel to apply the AI applications. – Management actively works to alleviate employee concerns of the AI implementation. – Roles of employees under the AI change are clarified.	**Shahrasbi and Paré (2014)**
Processes and Operations Readiness	– AI programs are compatible with the preferred work practices. – AI programs are compatible with the existing work practices. – The institutions' processes that can be automated have already been automated. – Evaluating and prioritizing which shared business processes should be automated is undertaken.	**Shahrasbi and Paré (2014)**
Adoption of AI in Higher Education Institutions	– The adoption of AI in higher education is good for society. – The adoption of AI in higher education will make education more interactive. – The adoption of AI in higher education will make it cost effective. – The adoption of AI in higher education will make the teaching-learning activity more interesting.	**Chatterjee and Bhattacharjee (2020)**

The current study determines its sample size based on the most common confidence interval (95%) and margin of error (5%), resulting in a targeted sample size of 400 faculty members and students at the Arab Academy for Science, Technology, and Maritime Transport in Alexandria. This sample size is deemed sufficient as it aligns with Hair et al. (2019) recommendation of obtaining at least five responses per item. It meets established literature recommendations, considers a significant number of respondents for this study, and matches the required statistical calculations for quantitative research sample estimation. Using a convenient non-random sample technique, the researcher distributed 600 survey questionnaires to staff members and students at the Arab Academy for, Technology, and Science Maritime Transport in Alexandria. The researchers received survey forms from 409 respondents in total, and they freely and voluntarily answered the questions. Nine of the 409 surveys that were received were disqualified because the respondents provided inaccurate information. Consequently, 400 accurate and filled questionnaires were sent to the researcher, who then conducted additional analysis on them.

Descriptive Analysis for Respondents Profile

Table 1 provides insights into the demographic characteristics of the sample population, consisting of 512 individuals. Regarding gender, the majority are male, accounting for 59.6% (305 individuals), while females constitute 40.4% (207 individuals) of the sample. In terms of age distribution, the highest proportion falls within the range of 22 to less than 30 years, representing 56.4% (289 individuals) of the sample. The next largest age group is 30 to less than 40 years, comprising 20.1% (103 individuals), followed by 40 to less than 50 years with 13.7% (70 individuals), and 50 to less than 60 years with 9.8% (50 individuals). When considering education level, the distribution shows that the highest percentage of individuals hold a Master's degree, accounting for 34.6% (177 individuals), followed by those with another educational qualification at 31.1% (159 individuals). Additionally, 28.5% (146 individuals) possess a Bachelor's degree, while 5.9% (30 individuals) have a Doctorate.

Table 1: Descriptive Statistics of Respondents Profile

	Frequency (n=512)	Percent
Gender		
Male	305	59.6
Female	207	40.4
Age		
22-Less than 30	289	56.4
30- Less than 40	103	20.1

	Frequency (n=512)	Percent
40- Less than 50	70	13.7
50- Less than 60	50	9.8
Education level		
Bachelor's degree	146	28.5
Master's degree	177	34.6
Doctorate	30	5.9
Other	159	31.1

9. RESULTS AND FINDINGS

To examine the research hypotheses comprehensively, the data were subjected to structural equation modeling (SEM) analysis, employing AMOS version 24. Initially, a measurement model was established to validate the underlying structure of the research model. Factor of confirmation examination (CFA) was used to assess the suitability of the measurement model regarding the dataset. Subsequently, assessments were made to confirm the normality and multicollinearity assumptions. Additionally, descriptive analyses, encompassing the study variables and respondent profiles, were conducted using SPSS version 25.

9-1 Descriptive Analysis for Research Variables

Table 2 illustrates the research variables' descriptive analysis. The standard deviation and mean values for various variables in the study were calculated to provide insights into the center tendency and variability of the data. For "Application Development," the mean score was 3.6571 with a standard deviation of 1.24690. Examining other indicators, "Economic Barriers" exhibited an average of 3.6738 with a standard deviation of 0.98574, "Organizational and Managerial Barriers" showed an average of 3.6758 utilizing a standard deviation of 1.01474, and "Technological Barriers" displayed an average of 3.6738 with a standard deviation of 1.02085. Additionally, "Institutional Efficiency" had an average of 3.6367 with a standard deviation of 1.01499, "R&D Sector Improvement" showed an average of 3.6289 with a standard deviation of 1.02368, and "Immediate Feedback Loop" exhibited an average of 3.6113 with a standard deviation of 1.01617.

Furthermore, "Financial Readiness" displayed an average of 3.8633 with a standard deviation of 0.97767, "Technological Readiness" showed an average of 3.8223 with a standard deviation of 1.00179, "Staff Readiness" had a mean of 3.7559 with a standard deviation of 1.04730, "Processes and Operations Readiness" exhibited an average of 3.8418 with a standard deviation of 0.98341, and "Adoption of AI" showed a mean of 3.6563 utilizing a standard deviation of 1.00244. These descriptive statistics offer valuable insights into the perceived levels and variability of each aspect under study, contributing to a deeper understanding of organizational dynamics and challenges.

Table 2: Descriptive Analysis for the Research Variables

Variables	N	Mean	Std. Deviation	Frequency				
				1	2	3	4	5
Economic Barriers	512	3.6738	.98574	18	26	173	183	112
Organizational and Managerial Barriers	512	3.6758	1.01474	25	19	166	189	113
Technological Barriers	512	3.6738	1.02085	26	18	167	187	114
Institutional Efficiency	512	3.6367	1.01499	30	14	168	200	100
R&D Sector Improvement	512	3.6289	1.02368	27	17	185	173	110
Immediate Feedback Loop	512	3.6113	1.01617	30	14	180	189	99
Financial Readiness	512	3.8633	.97767	19	25	95	241	132
Technological Readiness	512	3.8223	1.00179	24	20	106	235	127
Staff Readiness	512	3.7559	1.04730	26	18	148	183	137
Processes and Operations Readiness	512	3.8418	.98341	19	25	105	232	131
Adoption of AI	512	3.6563	1.00244	15	29	198	145	125

9-2 Data Testing using Validity and Reliability

Validity and reliability of the data were rigorously assessed, with Kaiser-Meyer-Olkin (KMO) measures and Average Variance Extracted (AVE%) values indicating suitability for factor analysis and the extent of variable explanation, respectively. KMO values ranging from 0.752 to 0.941 signified data suitability, while high AVE% values (80.423% to 84.552%) indicated substantial variance explanation. Reliability, gauged via Cronbach's alpha coefficients, demonstrated high internal consistency (0.896 to 0.954), exceeding the 0.7 threshold. Factor loadings above 0.8 reinforced strong item-construct relationships, further affirming measurement model reliability. These results underscore the exploratory factor analysis of the data, ensuring confidence in the study's findings.

Table 3: Exploratory Factor Analysis

Variables	KMO	AVE %	Cronbach's α	Items	Factor Loading
Economic Barriers	0.939	80.423	0.951	EB1	0.808
				EB2	0.811
				EB3	0.791
				EB4	0.807
				EB5	0.806
				EB6	0.802
Organizational and Managerial Barriers	0.866	83.137	0.932	OMB1	0.832
				OMB2	0.823
				OMB3	0.844
				OMB4	0.827
Technological Barriers	0.941	81.419	0.954	TB1	0.795
				TB2	0.816
				TB3	0.803
				TB4	0.822
				TB5	0.818
				TB6	0.831
Institutional Efficiency	0.867	83.713	0.935	IE1	0.838
				IE2	0.844
				IE3	0.835
				IE4	0.831
R&D Sector Improvement	0.757	84.552	0.908	RDSI1	0.847
				RDSI2	0.839
				RDSI3	0.850
Immediate Feedback Loop	0.863	82.993	0.932	IFL1	0.826
				IFL2	0.830
				IFL3	0.830
				IFL4	0.834
Financial Readiness	0.752	82.858	0.896	FR1	0.835
				FR2	0.829
				FR3	0.822
Technological Readiness	0.915	81.411	0.943	TR1	0.818
				TR2	0.823

Variables	KMO	AVE %	Cronbach's α	Items	Factor Loading
				TR3	0.810
				TR4	0.824
				TR5	0.795
Staff Readiness	0.915	81.445	0.943	SR1	0.813
				SR2	0.807
				SR3	0.830
				SR4	0.807
				SR5	0.815
Processes and Operations Readiness	0.866	83.163	0.933	POR1	0.819
				POR2	0.837
				POR3	0.833
				POR4	0.838
Adoption of AI	0.863	83.517	0.934	ADAI1	0.828
				ADAI2	0.833
				ADAI3	0.845
				ADAI4	0.835

9-3 The measurement model utilizing Confirmatory Factor Analysis

The measurement model underwent thorough scrutiny, with confirmatory factor analysis revealing a well-fitting model. The chi-square split by the degrees of freedom (CMIN/DF) yielded a value of 1.039, well below the recommended threshold of 2.00, with a significantly low p-value of 0.000, affirming the model's adequacy. Goodness of fit indices including GFI (0.922) and AGFI (0.911) surpassed desirable thresholds, while NFI (0.960), TLI (0.998), and CFI (0.998) all exceeded 0.90, indicating robust model fit. Additionally, both RMR (0.019) and RMSEA (0.009) fell below the recommended threshold of 0.1, further affirming model appropriateness. Visual representation in Figure 1 depicted strong factor loadings, validating the efficacy of the confirmatory factor analysis.

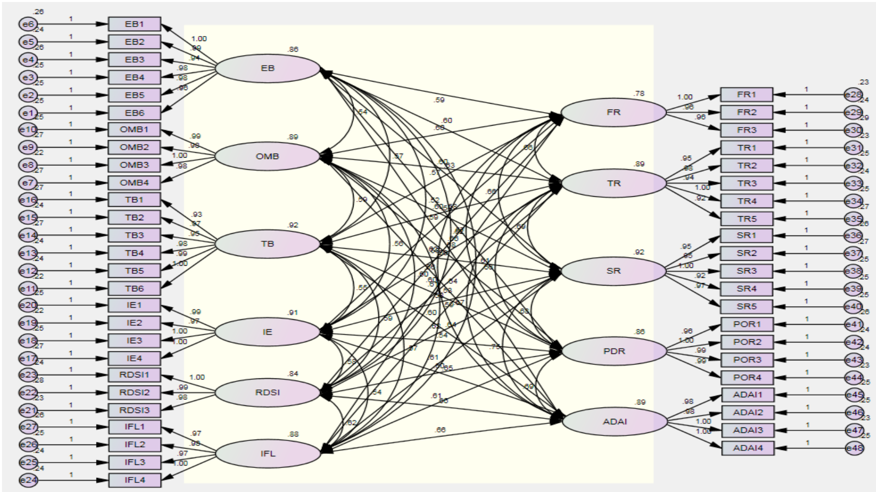

Figure 1: CFA for the Measurement Model

After confirming that the model fit indices are acceptable, the measurement model was examined. Table 4 demonstrates the factor loadings for the statements assigned to each construct. All factor loadings ranged from 0.922 to 1.000, and all P-values were less than 0.05. This indicates that all factor loadings were greater than 0.4, demonstrating good validity and a well-fitting model.

Table 4: Item Loading after Confirmatory Factor Analysis

			Estimate	S.E.	C.R.	P
EB6	<---	EB	.965	.034	27.991	***
EB5	<---	EB	.978	.035	28.037	***
EB4	<---	EB	.980	.035	28.268	***
EB3	<---	EB	.942	.034	27.377	***
EB2	<---	EB	.992	.035	28.485	***
EB1	<---	EB	1.000			
OMB4	<---	OMB	.983	.035	28.416	***
OMB3	<---	OMB	1.000			
OMB2	<---	OMB	.980	.034	28.538	***
OMB1	<---	OMB	.991	.034	29.110	***
TB6	<---	TB	1.000			
TB5	<---	TB	.995	.032	30.651	***
TB4	<---	TB	.978	.032	30.480	***
TB3	<---	TB	.951	.033	29.085	***
TB2	<---	TB	.969	.032	30.064	***
TB1	<---	TB	.929	.033	28.521	***
IE4	<---	IE	.997	.035	28.265	***

			Estimate	S.E.	C.R.	P
IE3	<---	IE	1.000			
IE2	<---	IE	.972	.033	29.263	***
IE1	<---	IE	.993	.035	28.702	***
RDSI3	<---	RDSI	.975	.035	27.484	***
RDSI2	<---	RDSI	.991	.037	26.496	***
RDSI1	<---	RDSI	1.000			
IFL4	<---	IFL	1.000			
IFL3	<---	IFL	.971	.034	28.507	***
IFL2	<---	IFL	.976	.034	28.288	***
IFL1	<---	IFL	.967	.035	28.005	***
FR1	<---	FR	1.000			
FR2	<---	FR	.958	.037	26.110	***
FR3	<---	FR	.963	.038	25.121	***
TR1	<---	TR	.946	.033	28.757	***
TR2	<---	TR	.982	.034	28.904	***
TR3	<---	TR	.938	.033	28.495	***
TR4	<---	TR	1.000			
TR5	<---	TR	.923	.034	27.330	***
SR1	<---	SR	.948	.033	28.469	***
SR2	<---	SR	.947	.033	28.275	***
SR3	<---	SR	1.000			
SR4	<---	SR	.922	.032	28.436	***
SR5	<---	SR	.966	.033	28.994	***
POR1	<---	PDR	.958	.035	27.638	***
POR2	<---	PDR	1.000			
POR3	<---	PDR	.995	.034	28.869	***
POR4	<---	PDR	.989	.034	28.956	***
ADAI1	<---	ADAI	.980	.034	29.223	***
ADAI2	<---	ADAI	.977	.034	29.135	***
ADAI3	<---	ADAI	1.000			
ADAI4	<---	ADAI	.999	.034	29.472	***

9-4 Normality Testing for the Research Variables

Table 5 presents the outcomes of the Kolmogorov-Smirnov examination of normality, which constitutes a formal evaluation of the normality assumption for the variables under investigation in this study. The results indicate a departure from normal distribution, as evidenced by the statistical significance of the associated P-values, all of which fall below the conventional alpha level of 0.05. This implies that the data deviates from a normal distribution, and this departure should be considered when conducting subsequent statistical analyses and interpreting the findings.

Table 5: Formal Testing of Normality

	Kolmogorov-Smirnov[a]		
	Statistic	Df	Sig.
Economic Barriers	.206	512	.000
Organizational and Managerial Barriers	.215	512	.000
Technological Barriers	.213	512	.000
Institutional Efficiency	.226	512	.000
R&D Sector Improvement	.194	512	.000
Immediate Feedback Loop	.211	512	.000
Financial Readiness	.284	512	.000
Technological Readiness	.277	512	.000
Staff Readiness	.217	512	.000
Processes and Operations Readiness	.273	512	.000
Adoption of AI	.216	512	.000

In cases where formal normality tests reveal non-normal distributions in the data, researchers may resort to informal normality tests to gauge the extent of departure from normality. The results of these informal tests are presented in Table 6, indicating that both skewness and kurtosis values drop to the acceptable range of ±1.This divergence implies that the data conform to a normal distribution pattern.

Table 6: Informal Testing of Normality

	Skewness		Kurtosis	
	Statistic	Std. Error	Statistic	Std. Error
Economic Barriers	-.516	.108	.145	.215
Organizational and Managerial Barriers	-.660	.108	.373	.215
Technological Barriers	-.665	.108	.372	.215
Institutional Efficiency	-.736	.108	.578	.215
R&D Sector Improvement	-.582	.108	.282	.215
Immediate Feedback Loop	-.670	.108	.486	.215
Financial Readiness	-.997	.108	.995	.215
Technological Readiness	-.998	.108	.985	.215
Staff Readiness	-.751	.108	.353	.215
Processes and Operations Readiness	-.930	.108	.826	.215
Adoption of AI	-.311	.108	-.250	.215

9-5 Testing Multicollinearity Assumption

This section examines and validates the assumption of multicollinearity among the independent variables in the model under study. Multicollinearity occurs when two or more predictors in a model are highly correlated with each other, potentially leading to redundancy of information and technical issues in regression analysis. Testing the Variance Inflation Factors (VIFS) for the independent variables in Table 7 reveals that all VIFS are less than 5, indicating no significant multicollinearity issue among the independent variables.

Table 7: VIF values for Research Variables

Independent Variables	VIF
Economic Barriers	2.685
Organizational and Managerial Barriers	2.570
Technological Barriers	2.660
Institutional Efficiency	2.323
R&D Sector Improvement	2.852
Immediate Feedback Loop	2.918

9-6 Testing the Research Hypotheses

This section presents the findings concerning the influence of independent variables on dependent variables. Within Table 8, the correlation matrix has been derived, revealing notable observations:

The analysis reveals numerous significant direct correlations between various factors and outcome measures. Notably, strong positive correlations are observed across several pairs, including Economic Barriers and Financial Readiness ($r = 0.729$, $p < 0.05$), Organizational and Managerial Barriers and Financial Readiness ($r = 0.703$, $p < 0.05$), Technological Barriers and Financial Readiness ($r = 0.661$, $p < 0.05$), Institutional Efficiency and Financial Readiness ($r = 0.693$, $p < 0.05$), R&D Sector Improvement and Financial Readiness ($r = 0.722$, $p < 0.05$), and Immediate Feedback Loop and Financial Readiness ($r = 0.695$, $p < 0.05$).

Additionally, significant positive correlations are noted between other pairs, such as Economic Barriers and Technological Readiness ($r = 0.736$, $p < 0.05$), Organizational and Managerial Barriers and Technological Readiness ($r = 0.673$,

$p < 0.05$), Technological Barriers and Technological Readiness ($r = 0.680$, $p < 0.05$), Institutional Efficiency and Technological Readiness ($r = 0.664$, $p < 0.05$), R&D Sector Improvement and Technological Readiness ($r = 0.718$, $p < 0.05$), and Immediate Feedback Loop and Technological Readiness ($r = 0.689$, $p < 0.05$).

Furthermore, significant positive correlations are observed between pairs like Economic Barriers and Staff Readiness ($r = 0.723$, $p < 0.05$), Organizational and Managerial Barriers and Staff Readiness ($r = 0.651$, $p < 0.05$), Technological Barriers and Staff Readiness ($r = 0.639$, $p < 0.05$), Institutional Efficiency and Staff Readiness ($r=0.642$, $p<0.05$), R&D Sector Improvement and Staff Readiness ($r = 0.682$, $p < 0.05$), and Immediate Feedback Loop and Staff Readiness ($r = 0.709$, $p < 0.05$).

Moreover, significant positive correlations are observed between pairs like Economic Barriers and Processes and Operations Readiness ($r = 0.716$, $p < 0.05$), Organizational and Managerial Barriers and Processes and Operations Readiness ($r = 0.672$, $p < 0.05$), Technological Barriers and Processes and Operations Readiness ($r = 0.623$, $p < 0.05$), Institutional Efficiency and Processes and Operations Readiness ($r = 0.632$, $p < 0.05$), R&D Sector Improvement and Processes and Operations Readiness ($r = 0.698$, $p<0.05$), and Immediate Feedback Loop and Processes and Operations Readiness ($r = 0.716$, $p < 0.05$).

Finally, significant positive correlations are noted between pairs such as Economic Barriers and Adoption of AI ($r = 0.778$, $p < 0.05$), Organizational and Managerial Barriers and Adoption of AI ($r = 0.746$, $p < 0.05$), Technological Barriers and Adoption of AI ($r = 0.753$, $p < 0.05$), Institutional Efficiency and Adoption of AI ($r = 0.735$, $p < 0.05$), R&D Sector Improvement and Adoption of AI ($r = 0.760$, $p < 0.05$), Immediate Feedback Loop and Adoption of AI ($r = 0.754$, $p < 0.05$), Financial Readiness and Adoption of AI ($r = 0.761$, $p < 0.05$), Technological Readiness and Adoption of AI ($r = 0.769$, $p < 0.05$), Staff Readiness and Adoption of AI ($r = 0.800$, $p< 0.05$), and Processes and Operations Readiness and Adoption of AI ($r = 0.780$, $p < 0.05$).

Table 8: Correlation Matrix for the Research Variables

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Economic Barriers	R	1										
	Sig.											
	N	512										
2. Organizational and Managerial Barriers	R	.649**	1									
	Sig.	.000										
	N	512	512									
3. Technological Barriers	R	.688**	.670**	1								
	Sig.	.000	.000									
	N	512	512	512								
4. Institutional Efficiency	R	.636**	.655**	.658**	1							
	Sig.	.000	.000	.000								
	N	512	512	512	512							
5. R&D Sector Improvement	R	.681**	.703**	.687**	.670**	1						
	Sig.	.000	.000	.000	.000							
	N	512	512	512	512	512						
6. Immediate Feedback Loop	R	.727**	.680**	.694**	.643**	.710**	1					
	Sig.	.000	.000	.000	.000	.000						
	N	512	512	512	512	512	512					
7. Financial Readiness	R	.729**	.703**	.661**	.693**	.722**	.695**	1				
	Sig.	.000	.000	.000	.000	.000	.000					
	N	512	512	512	512	512	512	512				
8. Technological Readiness	R	.736**	.673**	.680**	.664**	.718**	.689**	.734**	1			
	Sig.	.000	.000	.000	.000	.000	.000	.000				
	N	512	512	512	512	512	512	512	512			
9. Staff Readiness	R	.723**	.651**	.639**	.642**	.682**	.709**	.762**	.759**	1		
	Sig.	.000	.000	.000	.000	.000	.000	.000	.000			
	N	512	512	512	512	512	512	512	512	512		
10. Processes and Operations Readiness	R	.716**	.672**	.623**	.632**	.698**	.716**	.731**	.758**	.778**	1	
	Sig.	.000	.000	.000	.000	.000	.000	.000	.000	.000		
	N	512	512	512	512	512	512	512	512	512	512	
11. Adoption of AI	R	.778**	.746**	.753**	.735**	.760**	.754**	.761**	.769**	.800**	.780**	1
	Sig.	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	
	N	512	512	512	512	512	512	512	512	512	512	512

**. Correlation is significant at the 0.01 level (2-tailed).

Table 9 shows the SEM analysis for the impact of the research variables. The first hypothesis examines the significant relationship between Barriers of Using AI Technologies and Educational Institutions' Readiness, comprising four sub-hypotheses. In the first sub-hypothesis, Economic Barriers and Organizational and Managerial Barriers were found to positively impact Financial Readiness significantly, with P-values less than 0.05 and estimates of 0.197 and 0.151, respectively. However, Technological Barriers showed an insignificant effect on Financial Readiness (P-value > 0.05). Moving to the second sub-hypothesis, Economic Barriers, Technological Barriers, and Organizational and Managerial Barriers were found to significantly positively influence Technological Readiness, supported by P-values below 0.05 and estimates of 0.217, 0.144, and 0.114, respectively. Transitioning to the third sub-hypothesis, it was observed that Economic Barriers had a significant positive impact on Staff Readiness, with a P-value below 0.05 and an estimate of 0.292, while Organizational and Managerial Barriers and Technological Barriers showed an insignificant effect on Staff Readiness (P-value > 0.05). Lastly, in the fourth sub-hypothesis, Economic Barriers and Organizational and Managerial Barriers significantly positively impacted Processes and Operations Readiness, with P-values below 0.05 and estimates of 0.203 and 0.159, respectively, while Technological Barriers had an insignificant effect on Processes and Operations Readiness (P-value > 0.05).

The second hypothesis explores the significant relationship between Drivers of Using AI Technologies and Educational Institutions' Readiness, comprising four sub-hypotheses. In the first sub-hypothesis, Institutional Efficiency, R&D Sector Improvement, and Immediate Feedback Loop were found to significantly positively impact Financial Readiness, with P-values less than 0.05 and estimates of 0.172,0.275, and 0.113, respectively. Transitioning to the second sub-hypothesis, Institutional Efficiency, R&D Sector Improvement, and Immediate Feedback Loop were noted to significantly positively influence Technological Readiness, supported by P-values below 0.05 and estimates of 0.153, 0.236, and 0.110, respectively. Moving to the third sub-hypothesis, it was discerned that Institutional Efficiency, R&D Sector Improvement, and Immediate Feedback Loop had a significant positive impact on Staff Readiness, with P-values below 0.05 and estimates of 0.167, 0.272, and 0.149, respectively. Lastly, addressing the fourth sub-hypothesis, Institutional Efficiency, R&D Sector Improvement, and Immediate Feedback Loop were found to significantly positively impact Processes and Operations Readiness, demonstrated by P-values below 0.05 and estimates of 0.106, 0.252, and 0.227, respectively.

The third hypothesis explores the significant relationship between Educational Institutions' Readiness and Adoption of AI in Higher Education Institutions. The findings indicate that Staff Readiness and Processes and Operations Readiness have a significant positive impact on Adoption of AI, with P-values below 0.05 and estimates of 0.285 and 0.167, respectively. However, Financial Readiness and Technological Readiness demonstrated insignificant effects on Adoption of AI, with P-values greater than 0.05.

Regarding the fourth hypothesis, it investigates the significant relationship between Barriers of Using AI Technologies and Adoption of AI. The analysis revealed that Economic Barriers, Technological Barriers, and Organizational and Managerial Barriers significantly positively influence Technological Readiness, with P-values below 0.05 and estimates of 0.126, 0.093, and 0.106, respectively.

Furthermore, the fifth hypothesis investigates the significant relationship between Drivers of Using AI Technologies and Adoption of AI. It is observed that Institutional Efficiency has a significant positive influence on Adoption of AI, with a P-value less than 0.05 and an estimate of 0.146. However, R&D Sector Improvement and Immediate Feedback Loop exhibit insignificant effects on Adoption of AI, with P-values greater than 0.05.

The sixth hypothesis explores the potential mediation role of Educational Institutions' Readiness between Barriers, Drivers of Using AI Technologies, and Adoption of AI. Findings suggest that Staff Readiness and Processes and Operations Readiness directly impact Adoption of AI, while Financial Readiness and Technological Readiness do not. Significant effects of Economic Barriers, Institutional Efficiency, R&D Sector Improvement, and Immediate Feedback Loop on Staff Readiness, as well as on Processes and Operations Readiness, were identified. Consequently, Staff Readiness may act as a mediator between Economic Barriers, Institutional Efficiency, R&D Sector Improvement, Immediate Feedback Loop, and Adoption of AI. Similarly, Processes and Operations Readiness could potentially mediate the relationship between Economic Barriers, Organizational and Managerial Barriers, Institutional Efficiency, R&D Sector Improvement, Immediate Feedback Loop, and Adoption of AI.

Notably, Staff Readiness acts as a partial mediator in the relationship between Economic Barriers, Institutional Efficiency, and Adoption of AI, as these effects remain significant even when Staff Readiness is considered. However, it fully mediates the relationship between R&D Sector Improvement, Immediate Feedback Loop, and Adoption of AI, as these effects become insignificant in the presence of Staff Readiness. Similarly, Processes and Operations Readiness partially mediate the relationship between Economic Barriers, Organizational and Managerial Barriers, Institutional Efficiency, and Adoption of AI, as these effects remain significant even with Processes and Operations Readiness included.

Conversely, it fully mediates the relationship between R&D Sector Improvement, Immediate Feedback Loop, and Adoption of AI, as these effects become insignificant in the presence of Processes and Operations Readiness.

Table 9: SEM Analysis for the Research Variables

			Estimate	P	R^2
Financial Readiness	<---	Economic Barriers	.197	***	.754
Financial Readiness	<---	Organizational and Managerial Barriers	.151	***	
Financial Readiness	<---	Technological Barriers	.055	.179	
Financial Readiness	<---	Institutional Efficiency	.172	***	
Financial Readiness	<---	R&D Sector Improvement	.275	***	
Financial Readiness	<---	Immediate Feedback Loop	.113	.017	
Technological Readiness	<---	Economic Barriers	.217	***	.665
Technological Readiness	<---	Organizational and Managerial Barriers	.144	.003	
Technological Readiness	<---	Technological Barriers	.114	.013	
Technological Readiness	<---	Institutional Efficiency	.153	***	
Technological Readiness	<---	R&D Sector Improvement	.236	***	
Technological Readiness	<---	Immediate Feedback Loop	.110	.037	
Staff Readiness	<---	Economic Barriers	.292	***	.652
Staff Readiness	<---	Organizational and Managerial Barriers	.089	.078	
Staff Readiness	<---	Technological Barriers	.006	.906	
Staff Readiness	<---	Institutional Efficiency	.167	***	
Staff Readiness	<---	R&D Sector Improvement	.272	***	
Staff Readiness	<---	Immediate Feedback Loop	.149	.007	
Processes and Operations Readiness	<---	Economic Barriers	.203	***	.651
Processes and Operations Readiness	<---	Organizational and Managerial Barriers	.159	.001	
Processes and Operations Readiness	<---	Technological Barriers	-.011	.811	
Processes and Operations Readiness	<---	Institutional Efficiency	.106	.018	

			Estimate	P	R^2
Processes and Operations Readiness	<---	R&D Sector Improvement	.252	***	
Processes and Operations Readiness	<---	Immediate Feedback Loop	.227	***	
Adoption of AI	<---	Economic Barriers	.126	.005	.821
Adoption of AI	<---	Organizational and Managerial Barriers	.093	.023	
Adoption of AI	<---	Technological Barriers	.106	.004	
Adoption of AI	<---	Institutional Efficiency	.146	***	
Adoption of AI	<---	R&D Sector Improvement	.059	.291	
Adoption of AI	<---	Immediate Feedback Loop	.065	.145	
Adoption of AI	<---	Financial Readiness	.048	.428	
Adoption of AI	<---	Technological Readiness	-.024	.581	
Adoption of AI	<---	Staff Readiness	.285	***	
Adoption of AI	<---	Processes and Operations Readiness	.167	***	

The model fit indices, including CMIN/DF = 1.194, GFI = 0.908, CFI = 0.992, AGFI = 0.895, and RMSEA = 0.019, are all within acceptable ranges. Figure 2 depicts the SEM model conducted to analyze the impact of the study model.

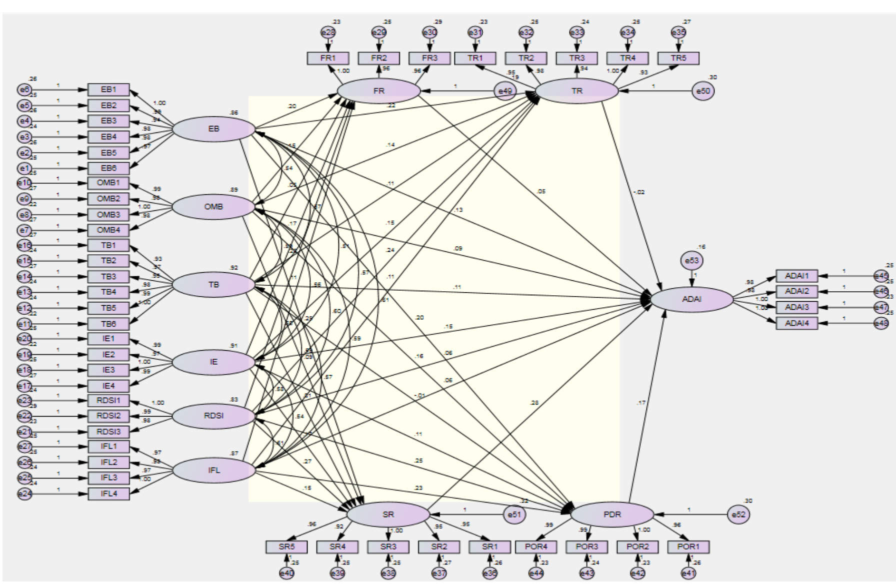

Figure 2: SEM for the Research Variables

10. RESEARCH DISCUSSION AND CONCLUSION

The study investigates how obstacles and motivators impacting AI technologies in higher education institutions influence the readiness of these establishments and ultimately, the adoption of AI itself. It examines various barriers to AI implementation, such as economic, organizational, and technological challenges, alongside drivers of AI use like improving efficiency and research and development. The research aims to understand how these factors impact the readiness of educational institutions in terms of financial, technological, and staff preparedness, as well as operational readiness. Through hypotheses testing, it's perceptions of seeks to establish significant relationships between these variables. This study provides perceptions of the complexities of AI adoption in higher education and highlights the significance of readiness in facilitating successful implementation.

Most studies on Barriers of Using AI Technologies and its dimensions (Economic, Organizational, and Managerial Barriers, and Technological Barriers) were found to have positive significant effects on Educational Institutions' Readiness. Accordingly, the adopted result is in line with the investigation of previous studies (Caputo et al. 2019; Goswami and Daultani 2022; Salim et al. 2022; Govindan and Arampatzis. 2023). However, studies by Stentoft et al. (2019) were found to have insignificant effects on Educational Institutions' Readiness. Accordingly, the researcher will discuss the main hypotheses as follows: The Relationship between Barriers of Using AI Technologies and Educational Institutions' Readiness is Partially Supported.

Most studies on Drivers of Using AI Technologies and its dimensions (Institutional Efficiency, R&D Sector Improvement, and Immediate Feedback Loop) were found to have positive significant effects on Educational Institutions' Readiness. Accordingly, the adopted result is consistent with the investigation of previous studies (Damerji and Salimi. 2021; Yousaf et al. 2022; Flavián et al., 2022). Accordingly, the researcher will discuss the main hypothesis that there is a Significant Relationship between Drivers of Using AI Technologies and Educational Institutions' Readiness Supported.

Firstly, they ought to prioritize investments and resource allocation towards initiatives that enhance institutional efficiency, facilitate R&D sector improvement, and establish immediate feedback loops within educational settings. This could involve funding for technology infrastructure upgrades, training programs for educators and staff, and the establishment of feedback mechanisms to continuously improve AI integration

Most studies on Educational Institutions' Readiness were found to have positive significant effects on the Adoption of AI in Higher Education Institutions. Accordingly, the adopted result is in keeping with the investigation of previous studies (Nouraldeen, 2023; Flavián et al., 2022; Owolabi et al. 2022; Issa et al. 2022; Paul 2020). Accordingly, the researcher will discuss the main hypotheses as follows there is a Significant Relationship between Educational Institutions' Readiness and Adoption of AI in Higher Education Institutions Partially Supported.

Barriers of Using AI Technologies and its dimensions (Economic Barriers, Organizational and Managerial Barriers, and Technological Barriers) were found to have positive significant effects on the Adoption of AI in Higher Education Institutions. Accordingly, the adopted result is in line with the investigation of previous studies (Sharma et al., 2024; Woodruff et al., 2023; Chatterjee and Bhattacharjee, 2020). There is a Significant Relationship between Barriers to Using AI Technologies and the Adoption of AI in Higher Education Institutions supported.

Drivers of Using AI Technologies and its dimensions (Institutional Efficiency, R&D Sector Improvement, and Immediate Feedback Loop) were found to have positive significant effects on the Adoption of AI in Higher Education Institutions. Accordingly, the adopted result is consistent with the investigation of previous studies (Ivanov et al., 2024; Polyportis, 2024; Rahim et al., 2022). There is a Significant Relationship between Drivers of Using AI Technologies and the Adoption of AI in Higher Education Institutions Partially Supported.

After thoroughly analyzing the products and confirming their alignment with previous studies, the decision maker must implement these findings to effectively integrate AI in educational institutions. This requires a comprehensive approach: start by identifying and analyzing economic, organizational, and technological barriers using surveys, interviews, and data analysis. Evaluate drivers like institutional efficiency, R&D enhancements, and the advantages of immediate feedback for AI adoption. Review financial resources, identify potential funding sources, and perform a cost-benefit analysis to justify AI investments. Assess the need for technological upgrades and determine training requirements to boost AI literacy among staff. Develop a detailed roadmap with clear short-term and long-term goals, specific milestones, and timelines. Allocate resources strategically based on readiness assessments, prioritize pilot projects to test AI technologies, and use gathered data to refine the strategy. Scale up AI implementation following pilot successes, maintain continuous monitoring and evaluation, and establish feedback mechanisms for ongoing improvement. Encourage inter-departmental collaboration and invest in R&D to integrate the latest AI advancements into the institution's strategy.

II. RESEARCH RECOMMENDATION

Based on the study's objectives, focusing on the relationship between barriers, drivers, and the adoption of AI in higher education institutions, mediated by educational institutions' readiness, multiple recommendations can be proposed:

To effectively navigate the complexities of AI adoption in higher education institutions, policymakers and stakeholders should undertake a comprehensive approach encompassing the assessment of barriers and drivers influencing adoption, along with targeted interventions to bolster educational institutions' readiness. This involves the following;

- Allocating resources to enhance financial, technological, staff, and operational readiness while leveraging drivers such as institutional efficiency and R&D sector improvement to promote adoption.
- Continuous monitoring and evaluation, coupled with knowledge sharing and collaboration among stakeholders, are crucial for refining strategies, overcoming challenges, and making certain the sustainable integration of AI technologies into higher education practices.
- Additionally,fostering aculture of innovation and experimentation, providing ongoing training and support, and adapting policies and regulations to the evolving landscape of AI in education are essential components of a successful adoption strategy.
- Through these concerted efforts, higher education institutions can harness the transformative potential of AI to enhance student learning outcomes, facilitate groundbreaking research, and drive institutional effectiveness in the digital age.

12. LIMITATIONS AND FUTURE RESEARCHER'S SUGGESTIONS

The study's limitations stem from the narrow scope of the research sample, which only included faculty members and students from a single institution, potentially limiting thegeneralizability of the findings.Toenhance representativeness, future researchers could expand the sample size and include participants from various educational institutions. Additionally, reliance solely on self-reported data from questionnaires may introduce response biases and social desirability effects, potentially affecting result validity. Future studies could employ mixed methods approaches, incorporating qualitative interviews or observations to gain a deeper understanding of the variables influencing AI adoption in higher education. Furthermore, while the current study focused on educational institutions' readiness as a mediator between barriers/drivers and AI adoption, future research could explore additional variables that may impact this relationship, such as institutional culture or leadership support. Lastly, conducting longitudinal studies could assess the long-term effects of AI adoption in higher education institutions and identify evolving trends and challenges over time.

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تأثير العوائق ومحفزات استخدام تقنيات الذكاء الاصطناعي على تبني الذكاء الاصطناعي من خلال جاهزية المؤسسات التعليمية: دراسة حالة الأكاديمية العربية للعلوم والتكنولوجيا والنقل البحري

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ملخص البحث باللغة العربية

تسعى الدراسة الحالية إلى استكشاف كيفية تأثير العوائق أمام استخدام تقنيات الذكاء الاصطناعي - مثل العوائق الاقتصادية، العوائق التنظيمية والإدارية، والعوائق التكنولوجية - ومحفزات استخدام تقنيات الذكاء الاصطناعي - مثل الكفاءة المؤسسية، تحسين قطاع البحث والتطوير، والحلقات الفورية للتغذية الراجعة - على تبني الذكاء الاصطناعي في مؤسسات التعليم العالي من خلال الدور الوسيط لاستعداد المؤسسات التعليمية، والذي يشمل الجاهزية المالية، التكنولوجية، جاهزية الموظفين، وجاهزية العمليات والإجراءات. باستخدام فلسفة الوضعية مع نهج التحليل الكمي، جمع الباحث بيانات أولية من خلال استبيان تم توزيعه على أعضاء هيئة التدريس والطلاب في الأكاديمية العربية للعلوم والتكنولوجيا والنقل البحري في الإسكندرية. وتشير النتائج إلى أن كل من العوائق والمحركات تؤثر بشكل كبير على جاهزية المؤسسات التعليمية وتبني الذكاء الاصطناعي في التعليم العالي. وقد تبين أن العوائق الاقتصادية والتنظيمية والتكنولوجية تؤثر إيجابياً على الجاهزية، وكذلك المحركات مثل تعزيز الكفاءة المؤسسية، تحسين قطاعات البحث والتطوير، وإنشاء حلقات فورية للتغذية الراجعة. بالإضافة إلى ذلك، تبين أن الجاهزية داخل المؤسسات التعليمية تؤثر إيجابياً على تبني الذكاء الاصطناعي. أخيرا، الجاهزية الإدارية للموظفين تعمل كوسيط جزئي في العلاقة بين العوائق الاقتصادية والكفاءة المؤسسية وتبني الذكاء الاصطناعي، وتعمل كوسيط كامل في العلاقة بين تحسين قطاع البحث والتطوير وحلقات التغذية الراجعة الفورية وتبني الذكاء الاصطناعي. كذلك، تعمل الجاهزية في العمليات والإجراءات كوسيط جزئي في العلاقة بين العوائق الاقتصادية والتنظيمية، والكفاءة المؤسسية وتبني الذكاء الاصطناعي، وتعمل كوسيط كامل في العلاقة بين تحسين قطاع البحث والتطوير وحلقات التغذية الراجعة الفورية وتبني الذكاء الاصطناعي.

تقترح الدراسة أن على صناع القرار معالجة العوائق أمام تبني الذكاء الاصطناعي مع تعزيز الجاهزية من خلال الاستثمارات الاستراتيجية، تطوير السياسات، تعزيز التعاون، ودعم مبادرات البحث والتطوير.

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