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The Adoption of Artificial Intelligence in Higher Education Institutions in Mogadishu, Somalia

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Abstract

Artificial intelligence (AI) is transforming higher education globally, yet adoption remains uneven and may exacerbate digital inequities, particularly in post-conflict, resource-constrained settings such as Mogadishu, Somalia. This study aimed to determine the extent of AI adoption in higher education institutions (HEIs) in Mogadishu, identify the AI technologies in use, and examine the technological, organizational, and environmental factors shaping adoption decisions, drawing on an integrated framework (TOE, UTAUT, institutional theory, DOI, and RBV). A descriptive, quantitative survey was conducted among academic staff, administrators, and IT professionals in Mogadishu HEIs (target population ≈ 3000). Using simple random sampling, 353 online questionnaires were distributed; 280 valid responses were analyzed (79.3% valid rate). The instrument demonstrated excellent reliability (overall Cronbach's α = 0.889). Descriptive results indicated low AI adoption overall (mean = 2.33/5), with teaching and learning the most developed domain (mean = 2.65) and research/data analysis the least (mean = 2.05). AI technologies used were largely basic (overall mean = 2.38), dominated by Learning Management Systems with AI capabilities (mean = 3.12), while predictive analytics for retention/performance (mean = 1.95) and administrative automation (mean = 2.10) were minimally implemented. Correlation analysis showed significant positive associations among key variables (e.g., adoption level with types used, $r = 0.684$, $p < 0.01$). Multiple regression confirmed that technological, organizational, and environmental factors jointly explained substantial variance in AI adoption ($R^2=0.475$, $p < 0.001$), with organizational factors the strongest predictor ($\beta = 0.378$), followed by technological ($\beta = 0.312$) and environmental factors ($\beta = 0.245$). Hypotheses were supported, including UTAUT relationships for performance expectancy behavioral intention ($\beta = 0.324$) and facilitating conditions actual use ($\beta = 0.298$). The findings suggest that AI integration in Mogadishu HEIs remains early-stage and path-dependent on post-conflict constraints; accelerating adoption requires strengthened leadership commitment, infrastructure and skills investment, institutional readiness, and supportive national policy and donor-aligned capacity building to improve educational quality, efficiency, and competitiveness.

1.0 Introduction

The use of Artificial Intelligence (AI) in higher education marks a paradigm shift in teaching, administration, and research practices worldwide. This study explores the adoption process of AI technologies in HEIs in the post-conflict context of Mogadishu, Somalia, where technology leapfrogging and emergent digital transformation needs are prevalent and pressing. As AI infiltrates educational systems globally at an accelerating pace and Somalia's technological evolution is still in its early stages but holds great promise, it is crucial to explore how these institutions work through the intricate dynamics of infrastructure limitations, human capital development and institutional preparedness. The implications of this study are emphasized by the fact that using AI in higher education is not just a technological shift, but a broader organizational change that involves redesigning learning paths, streamlining administrative processes, optimizing student engagement, and boosting research productivity. This research nestles itself at the intersection of educational technology, institutional capacity development, and development studies, and provides insights into how fragile state contexts

can use AI to drive educational outcomes and reduce the digital divide that has historically disadvantaged African higher education systems from the global knowledge production networks(George & Wooden, 2023).

The process of AI adoption in higher education goes beyond technology adoption to include organizational learning, change management, and institutional cultural change. Using the Technology-Organization-Environment (TOE) theory and Unified theory and Use of Technology (UTAUT), this study explores various factors that impact the adoption decisions of HEIs in Mogadishu. To ensure its successful implementation, all three dimensions of technology capabilities, organizational structure, and the environment must align. The city of Mogadishu was chosen as the focus of the study because of its status as the educational and technological hub of Somalia, and its characteristics offer a narrow window through which to examine the systemic challenges and opportunities in Somalia's efforts to integrate AI, such as the scarcity of technical skills among educators, competing institutional priorities, and limited Internet bandwidth. However, the potential of AI to overcome some of the enduring challenges in education, including access to high-quality learning materials, teacher-to-student ratios, and administrative inefficiencies, makes it an attractive option in the near future. This research also fills a gap in the growing literature relevant to the application of AI in African higher education as it seeks to understand how post-conflict, resource-poor environments can effectively leverage AI capabilities to improve educational quality, widen access and institutional effectiveness.The evolution of higher education in Somalia is a complex story of establishment, failure, and its gradual reconstruction, which has long had a significant impact on the current possibilities for using AI. The 1970s and 1980s saw the golden age of Somalia's higher education system with the establishment and development of institutions like Somali National University (SNU – established in 1954), which served as centres of academic excellence producing students who played a vital role in the national development in different fields. Significant investments were made during this time in the development of educational facilities, faculty development, and international academic collaboration, and Somali scholars made significant contributions in agriculture, medicine, and engineering. The onset of the Somali state collapse in 1991, however, brought about a crisis in higher education, including the destruction of the physical educational infrastructure, the flight of qualified academics, the disruption of curriculum development, and the complete loss of international academic connections in the country. The ensuing decades of civil war, state disintegration, and institutional weakness have left the contemporary situation of higher education in the country characterized by a reliance on informal networks, diaspora-funded projects, and internationally financed emergencies—factors that continue to shape the current educational development process in the country(Erdmann & Toro-Dupouy, 2025).

Since the early 2000s, the reconstruction of higher education in Mogadishu has been marked by a growing number of private universities, the gradual return of internationally supported public universities, and the creation of hybrid educational models that utilize traditional pedagogical approaches but with limited technological incorporation. During this reconstruction period, various institutions have been established, such as the Somali National University (SNU), which was re-established in 2014, Mogadishu University (1997), and SIMAD University (1999), providing a rich variety of higher education institutions

under challenging infrastructural and resource constraints. Institutional discontinuity is a historical phenomenon that creates unique challenges for the adoption of AI, such as a lack of institutional memory, technical infrastructure, faculty preparedness to use educational technology, and a lack of coherent national policies on technology integration in education. Additionally, the importance of educational access and quality has been a major focus in the past, which has meant investing in basic infrastructure rather than technological innovation, potentially limiting the adoption of AI in educational decisions. Understanding this context is important to understanding the current state of AI adoption in HEIs in Mogadishu, because it sheds light on the institutional capacity, resource allocation patterns, and expectations of stakeholders regarding educational technology over the past decades, all of which have been defined through the lens of decades of instability(Mukhtar Omar et al., 2025).

In the last decade, the world has seen a dramatic shift in the landscape of AI adoption in higher education, as developed countries and emerging economies have introduced a range of AI technologies and tools to support learning, research, administration, and teaching and learning (T&L). Globally, AI use in higher education ranges from adaptive learning systems, intelligent tutoring systems, automated grading, predictive analytics on student attrition, administrative process automation, and research data analysis. Leading institutions have developed comprehensive AI strategies, dedicated research centers, and specialized programs to place them at the forefront of educational technology innovation in North America, Europe, East Asia, and Australia. As digitalization gains momentum, more people are seeking personalized learning experiences, and the need to enhance learning outcomes based on data is driving the market for AI in Education to increase at an exponential rate until 2027, reaching $20 billion. Such a global movement is also evident in policy developments, such as the European Commission's Digital Education Action Plan, the UNESCO Beijing Consensus on AI and Education, and national AI policies that explicitly mention the transformation of the education sector, set expectations and benchmarks for the education sector, and shape the agenda of educational technology in developing countries(Uslu & Bozkurt, 2026).

However, the global AI adoption scenario shows that there are significant differences in the extent to which high- and low-income countries embrace AI, which may further widen the educational divide. Developed countries invest significantly in AI research, infrastructure, and implementation, while sub-Saharan African countries, such as Somalia, face significant hurdles, such as low levels of digital infrastructure, expensive technologies, lack of access to electricity, and lack of technical expertise. The world's conversation about AI in education has made it clearer that these inequities must be addressed by working together on a global scale via technology transfer partnerships and with contextually fitting solutions that consider the distinct challenges and opportunities in developing country contexts. Efforts to bridge this gap have included the African Union's Digital Transformation Strategy (2020–2030) and bilateral partnerships; however, there are still important disconnects in how global advances in artificial intelligence can be adapted and implemented to create positive learning outcomes in Africa. The global landscape also brings both opportunities and challenges for HEIs in Mogadishu: access to global knowledge, resources, and best practices, as well as the considerable investments and policy

commitments needed to make meaningful use of AI in a low-middle income setting(Tiago & Almeida, 2026).

The AI landscape in higher education across the region in the Horn of Africa and East African countries is as varied as the countries themselves, with some at the early stages of experimentation and others more deeply entrenched in their national educational systems. Other nations, such as Kenya, Rwanda, and Ethiopia, have become industry leaders in the East African region in terms of adopting educational technology and have introduced national digital education policies, technology hubs, and implemented public-private partnerships to support the integration of AI in higher education. The Digital Literacy Program in Kenya, the One Laptop per Child project in Rwanda, and investments in broadband infrastructure in Ethiopia highlight the region's increasing priority of using technology for educational progress. These region-wide programs offer important lessons and collaboration opportunities to Somali HEIs and illustrate the competitive pressures that may be felt by nations that might otherwise lag behind in the digital transformation of higher education. The regional context is marked by a growing awareness of the strategic role of AI in achieving the SDGs, especially SDG 4 on Quality Education, and the ambition of the African Union (AU) to have a digitally transformed continent as part of its Agenda 2063(Alasow et al., 2026).

However, significant challenges remain throughout the region, such as providing adequate electrical power, limited broadband availability, lack of technical skills, and lack of digital literacy among faculty and students. However, the region's current adoption of AI is further complicated by the lack of policy consensus, research and development capacity, and the continued difficulty in balancing investments in the basic levels of education infrastructure with advanced technology integration. The regional context is especially relevant to Somalia, which is the newest member of the East African Community and is becoming more involved with regional development frameworks. Regional integration brings both opportunities and pressures for AI adoption in HEIs in Mogadishu, as the country strives to meet the region's needs and expectations in developing its education while also dealing with its particular requirements for post-conflict reconstruction. Cross-border academic cooperation, technology transfer, and knowledge-sharing networks are also becoming more significant, and these can be leveraged to promote the adoption of AI by fostering links with the diaspora, regional collaboration, and involvement in continental educational technology initiatives(Moghaddam & Moghaddam, 2025).

The adoption of AI in HEIs in Somalia is rooted in the intricate socio-political context of Somalia, with its state-building efforts, continued security challenges, and slow reconstruction following 30 years of civil conflict. Mogadishu, the capital and largest city, is the hub of higher education in Somalia, with most of its universities, and where most of the education innovations and reforms take place. Since the early 2000s, the city's higher education system has undergone tremendous changes: the abolition of its public institutions was replaced by the rise of private institutions, the partial reconstruction of public higher education, and a growing internationalization of its educational development. This institutional pluralism has led to a more diverse and somewhat sectionalized higher-education system, with differing levels of capacity, resources, and styles of technology integration across institutions. Inter-sectoral factors that

impact the adoption of AI are not just in the education space but also in the economy, politics, and society, such as diaspora remittances to support educational development, growth in the telecommunications sector to enable mobile technology penetration, and the more recent integration of Somalia into global digital networks(Hussain & Ogunmola, 2025).

The use of AI technologies in HEIs in Mogadishu is fraught with multifaceted and interrelated challenges, pointing to the complex context of HEIs operating in a post-conflict environment. Primary barriers that directly impact the possibilities for using AI include infrastructure constraints, such as unreliable electricity supply, limited Internet bandwidth, and computing resources. Additionally, these infrastructure limitations are exacerbated by human capital constraints, such as the limited number of faculty members who are proficient with AI, lack of technical support staff, and difficulties in hiring and retaining qualified personnel in the competitive regional job market. Competing resource priorities, a lack of research culture, small administrative capacity, and the lack of a comprehensive institutional technology strategy are other institutional factors that hinder the systematic adoption of AI. Apart from mobility issues, international cooperation and investment confidence are also hindered by security concerns, impacting external partnerships and technology transfer, which are key to AI integration. It is important to grasp these context factors to ensure realistic expectations and suitable strategies for the implementation of AI, as the challenges here need to be overcome when working with technological developments to achieve success(Chonka, 2026)

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To study AI adoption within the context of Higher Education institutions, a broad understanding of AI is needed as a complex technological paradigm comprising machine learning, natural language processing, computer vision, robotics, and expert systems, all of which allow machines to carry out tasks usually associated with human intelligence. In learning, AI can be utilized in different ways, such as adaptive learning platforms that customize the learning process, clever tutoring methods that deliver individual support, automated scoring systems that simplify the assessment of understanding, forecasting analytics that flag students who are in danger of failing or dropping out, and administrative automation that boosts institutional effectiveness. AI adoption is not just about technology; it is also shaped and influenced by the processes, behaviors, and institutional adaptations of the organizations within which the technology is being used. The study includes a multi-dimensional concept of AI adoption, as it is necessary to tackle the four dimensions of technology infrastructure, human capacity development, organizational change management, and the alignment of AI applications with institutional missions and pedagogical objectives to achieve successful integration. The conceptual framework also covers the special features of AI technologies, such as the fact that they are still evolving, can cause disruption, and raise ethical issues surrounding their use in educational contexts(Helmiatin et al., 2024).

Higher education institutions are viewed as the unit of analysis, acknowledging that the adoption of AI takes place at the institutional level, where institutional cultures, governance frameworks, resource endowments, and institutional priorities influence the decision-making regarding the adoption of AI.

Higher education institutions are seen as complex adaptive systems that face a set of tensions in the context of technological change, between tradition and innovation, autonomy and accountability, and local needs and global standards. The conceptual framework is informed by organizational theory, innovation studies, and educational technology research, which aim to explain how institutional factors can affect the decision-making process surrounding the use of AI and its subsequent impact. Conceptualization also allows for the role played by external factors in influencing institutional technology trajectories, such as national policies, donor priorities, market pressures, and international norms. The context in which AI adoption decisions are made and implemented is the result of the interplay between internal organizational dynamics and external environmental factors, demanding a conceptual approach that can capture this complexity while maintaining analytical clarity and theoretical coherence(Lawrence, 2026).

This study integrates various theoretical approaches to offer a holistic perspective on how the adoption of AI is experienced in HEIs in Mogadishu, as the process of technology adoption is impacted by different determinants across the individual, organizational, and environmental levels. The theoretical lens comes from the Technology-Organization-Environment (TOE) framework developed by Tornatzky and Fleischer (1990), which identifies three contextual factors that affect the adoption of a technology: technological (existing technology, technological infrastructure, and innovation characteristics), organizational (organizational structure, culture, resources, and leadership), and environmental (industry characteristics, regulatory environment, and market pressures). The TOE framework's holistic perspective on contextual factors is well-suited for analyzing the adoption of AI in complex institutional contexts, where various factors are coming together to influence the adoption decision. The importance of organizational readiness, top management support, and external pressures in the framework can provide some insights into the dynamic system that has an impact on HEIs in Mogadishu, where the capacity of HEIs, leadership commitment, and external pressures from stakeholders can have a significant influence on the adoption of technology(Hu & Raman, 2024).

The Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003) complements TOE by examining individual technology adoption determinants such as performance expectancy, effort expectancy, social influence, and facilitating conditions, which explain the behavioral intentions and actual technology use of users. By focusing on user perceptions, organizational support, and social dynamics, the UTAUT is helpful in understanding the role of faculty, administrators, and students in adopting AI technologies, as human factors are crucial for successful adoption and not technology alone. Furthermore, this study draws on institutional theory, which is concerned with pressures (regulatory, normative, and cognitive) that influence the behavior of organizations, thereby generating isomorphic pressures to conform with dominant norms, values, and institutional expectations. Institutional theory is useful for analyzing how institutional priorities are set by international pressures, national policies, and sectoral norms, especially in an environment such as Somalia, where international involvement and external support are key factors in driving decisions around the adoption of AI. By combining these theoretical perspectives, a comprehensive view of the adoption of AI in HEIs in Mogadishu is created, recognizing the interplay of individual actions,

organizational factors, and environmental pressures, all of which influence the outcome of AI adoption(Xue et al., 2024).

The desired future for Higher Education in Mogadishu is a system that uses AI technologies to improve the quality of education, increase access, streamline administration, and equip graduates for the challenges of the knowledge economy, resting on international standards and regional expectations for AI integration within HE institutions. The concept is rooted in the understanding that AI tools can help meet the constant needs of education, such as smaller teacher-to-student ratios, access to more learning materials, administrative efficiency, and tailored learning methods that cater to individual students' needs and learning styles. In this best-case scenario, HEIs in Mogadishu would have access to sophisticated learning management systems, would be able to use adaptive learning platforms, would have access to predictive analytics for student support, would automate administrative processes, and be involved in AI research aligned with national development priorities. This vision will make Somali HEIs leading centers of excellence for E-Tech in the region, thereby meeting Somali development objectives and helping Somali graduates become competitive in the regional and international job markets(Isak & Dahir, 2026).

However, the reality is quite different, and in higher education institutions in Mogadishu, the use of AI is limited to a small extent, with mostly traditional teaching methods, little educational technology usage, and poor digital infrastructure and human capacity. The majority of institutions still use traditional instructional strategies, and although there are some online platforms, they are very basic and have minimal administrative support, and few use AI beyond accessing the Internet and common office software applications. There is a significant gap between this ideal and the current situation due to the cumulative effects of decades of conflict, ongoing fragile institutional situations, and the difficulties of working in a resource-scarce environment with technical skills and infrastructure that do not match. This gap is significant as it is likely to be associated with the perpetuation of educational inequalities, a decrease in institutional competitiveness, limited research productivity, and the creation of graduates who might not have the digital capabilities that are increasingly expected for professional success in the present-day global economy. This study systematically examines the factors that shape the use of AI, identifies challenges and opportunities, and offers evidence-based suggestions for expediting the integration of AI technologies in HEIs in Mogadishu. To determine the extent of AI adoption in higher education institutions in Mogadishu, Somalia. To determine the types of Artificial Intelligence technologies being used in Higher Education Institutions in Mogadishu, Somalia. To determine the factors that affect the use of Artificial Intelligence in the Higher Education Institutions in Mogadishu, Somalia(Selten & Klievink, 2024).

The novelty of this research is that it is the first study to explore the adoption of AI in higher education institutions (HEIs) in Somalia, a country that has been systematically underrepresented in mainstream educational technology research because of its prolonged conflict, fragile institutions, and logistical challenges associated with conducting research in post-conflict environments. This study is the first systematic study of its kind and addresses an important literature gap that has largely ignored the

distinctive factors and issues of higher education in fragile and conflict-affected states. Another aspect of this work is the use of well-known theories in an environment where they are not normally used, and the testing of whether the theories hold true in this setting and whether they can be generalized to other settings, particularly post-conflict settings with limited resources and reconstruction of institutions and technological leapfrogging(Helmiatin et al., 2024).

The relevance of this study is multifaceted and includes theoretical, empirical, and practical aspects of knowledge and practice. In theory, this study attempts to understand how the theories of technology adoption can be applied and their predictiveness in post-conflict and fragile state settings. The empirical significance comes from the generation of original data for the under-researched context; insights gained from this study can be used in future research, policy-making, and program design in technology-enhanced education for contexts similar to this. The practical impact is especially significant, as the insights gained will contribute to institutional leaders, policymakers, and development partners in Somalia and other post-conflict contexts who aim to drive AI uptake(Fantinelli et al., 2024).

This study's focus is intentionally limited to the specific goals of achieving a concentrated analysis while still providing a meaningful depth of understanding of the key dynamics of the adoption of AI in higher education in Mogadishu. The study focuses on Mogadishu, the capital city of Somalia, which is geographically the epicenter of higher education in the country, where the majority of universities are based and where educational innovation and reform take place. The study focuses on public and private universities in Mogadishu that reflect the diversity of institutions that exist within the Somali higher education system, as it will provide a possibility for comparative analysis within the different institutional types, ownership, and resource endowment. The time horizon covers the period after the restoration of stable governance institutions in Mogadishu (post-2012) as the introduction of AI is a relatively new development in the Somali context. The substantive scope is on the focal point of the phenomenon of investigation, namely the types of AI technologies that are used, the degree of use across institutional functions, and the conditions that affect the decision and outcome of adopting AI(Zong & Guan, 2025).

2.0 LITERATURE REVIEW

This section provides an extensive and systematic literature review of the current body of knowledge on the use of artificial intelligence (AI) in higher education (HE) institutions, which serves as the theoretical and empirical basis for this study. The literature review is organized to critically discuss scholarly works from various research areas, such as educational technology, innovation adoption, organizational change, and development studies, to create an intellectual setting to explore the issue of AI adoption in higher education institutions in Mogadishu. The review covers theoretical models detailing the adoption processes of technology, empirical research that captures the introduction of AI in a range of educational contexts, and a critical examination of the factors that support and hinder the successful integration of AI into education. The literature on post-conflict and Africa is given special attention because of the unique characteristics of those environments, which affect the adoption trajectories of technologies.

2.1 Concept of Artificial Intelligence (IV)

AI can be defined as the creation of computer systems that can execute tasks that naturally require human intelligence, such as learning, reasoning, problem-solving, perception, and language understanding The use of AI in higher education requires choices regarding the type of AI tools to be deployed, the context in which they are used, and the educational and administrative goals for their implementation. The study's conceptualization is comprehensive, including both the technological dimensions of AI (hardware, software, algorithms, and data needs) and the organizational dimensions (processes for implementing integration, training users, managing organizational change, and institutional alignment)(Alkatheiri, 2022).

2.2 Theoretical Foundation

2.2.1 Technology-Organization-Environment (TOE) Framework

The TOE framework consists of a product of three contextual elements that come together to affect technology adoption decisions: technological context (characteristics of the technology itself, relative advantage, compatibility, and complexity), organizational context (structural, cultural, and resource characteristics), and environmental context (external factors, competitive pressures, regulatory requirements, and donor priorities). The overall scope of this framework is important for analyzing AI adoption in complex institutional settings, where various conditions come together and influence factors in adopting AI(Ganguly, 2024).

2.2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT framework focuses on individual-level factors influencing the adoption of technology and contains four constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. The focus of the framework on user perception, organizational support, and social dynamics offers insights into the human aspects of AI adoption, which complement the organizational-level features of the TOE framework(Granić, 2024).

2.2.3 Institutional Theory, Diffusion of Innovation (DOI) Theory, and Resource-Based View (RBV)

Institutional theory focuses on three types of pressures that influence the behavior of organizations: regulatory, normative, and cognitive, which drive organizations to become "isomorphic. According to DOI theory, five factors affect the adoption of innovations: relative advantage, compatibility, complexity, trialability, and observability. RBV focuses on the importance of organizational resources and capabilities in determining competitive advantage and strategic decisions.

2.3 Empirical Review and Hypothesis Development

Research on technology adoption in higher education highlights a variety of factors affecting the adoption of AI, such as technological (infrastructure, technical expertise, and resources), organizational (institutional culture, leadership, and resources), and environmental (donor priorities, policy frameworks, and competitive pressures). Based on the theoretical frameworks and empirical literature examined, this study presents five hypotheses.

H2: The level of AI usage in HEIs in Mogadishu shows a significant positive correlation with technological factors.H2: Technological factors have a significant positive correlation with the level of AI usage in HEIs in Mogadishu.

The correlation between H2 (organizational factors) and the level of AI adoption in higher education institutions in Mogadishu was positive and significant.

H3: The level of AI adoption has a significant positive correlation with environmental factors in HEIs in Mogadishu.

H4 is supported by the significant positive relationship found between performance expectancy and the behavioral intention to use AI technologies among faculty and staff.The significant positive relationship between performance expectancy and faculty/staff behavioral intention to use AI technologies supports H4.

The actual use of AI technology among Faculty and Staff was significantly and positively related to facilitating conditions.

2.4 Empirical Gap

The empirical literature related to AI use in higher education demonstrates a lack of understanding of how technology is adopted in post-conflict and resource-constrained settings, especially in sub-Saharan Africa and specifically Somalia. While there is a growing body of research on AI in higher education from developed countries and emerging economies, the literature has largely overlooked the unique circumstances and challenges faced by higher education institutions in fragile states and post-conflict environments. This study aims to fill these empirical gaps by offering systematic evidence of the adoption of AI in HEIs in Mogadishu.

2.5 Concept of Higher Education Institutions (DV)

Higher Education Institutions are diverse and complex organizations comprising various activities such as teaching and learning, research, and community service, with their own governance systems, cultures, resources, and strategic priorities that shape how they incorporate technology. By integrating these various aspects into a holistic framework, this study seeks to examine the complex connections between institutional attributes and the outcomes of AI implementation, providing a comprehensive picture of higher-education institutions and their roles in fostering innovation in AI.

2.6 Conceptual Framework

The conceptual framework combines the TOE framework, UTAUT model, institutional theory, DOI theory, and RBV, offering a holistic perspective on analyzing AI adoption. It assumes that the consequences of AI use are influenced by the interaction of both institutional-level elements (technological, organizational, and environmental) and user-level elements (perceptions and acceptance).

3.0 RESEARCH METHODOLOGY

This section presents the methodological approach used to study the use of Artificial Intelligence in HEIs in Mogadishu, Somalia. The methodology was carefully planned and designed to produce valid, reliable, and robust empirical evidence that meets the research objectives and recognizes the specific contextual issues of conducting research in a post-conflict setting.

3.2 Study Area and Study Population

The study area is geographically defined as the capital city of Somalia, Mogadishu, the epicenter of higher education in Somalia. The study population comprised key stakeholders in higher education institutions within Mogadishu that are directly involved in or strongly affected by decisions and processes of adopting and implementing AI, such as academic staff, administration, and information technology (IT) professionals.

3.3 Research Design and Method

This study uses a descriptive research design and quantitative method, which were strategically selected because they allow for the systematic description, analysis, and explanation of the current status of the adoption of AI in higher education institutions in Mogadishu, as well as the relationships between various factors and adoption outcomes.

3.4 Target Population and Sample Size

The targeted population was approximately 3000 people from the top universities in Mogadishu. According to the Yamane formula and with a margin of error of 5% and a confidence level of 95%, the number of respondents required was 353.

3.5 Sampling Techniques

The sampling technique used in this study was simple random sampling with probability, which means that every member of the target population had an equal chance of being selected and was independent of each other.

3.6 Data Collection Methods

The main data collection tool was an online questionnaire that gathered detailed information regarding the level of AI adoption, types of AI technologies employed, and factors influencing decisions for AI adoption. The questionnaire comprised sections that reflected demographic data, the level of adoption of AI, the identification of AI technologies, and Likert-scale items to measure influencing factors.

3.7 Data Analysis

SPSS version 31 was used for the data analysis. Both descriptive and inferential statistics were used in the analysis of the data, including frequencies, percentages, means, standard deviation, correlation analysis, and multiple regression analysis, which were used to test the proposed hypotheses.

3.8 Validity, Reliability, and Ethical Considerations

Systematic procedures, such as content validity and Cronbach's alpha reliability testing (overall α = 0.889), were followed along with pilot testing to guarantee validity and reliability. The ethical aspects of research involve IRB approval, informed consent, confidentiality safeguarding, and secure data storage.

4.0 RESULTS AND DISCUSSION

4.0 Data Analysis and Results

4.1 Introduction

This chapter provides the empirical results of the research on "The Adoption of Artificial Intelligence in Higher Education Institutions in Mogadishu, Somalia. The chapter is systematically organized, presenting the outcomes of the data analysis in accordance with the research objectives and theory. The analysis starts with the presentation of the results of the response rate and the demographic data of the respondents, which will provide the context for the interpretation of the findings that follow. After the demographic analysis, descriptive statistics were provided to illustrate important variables, reliability statistics were provided to determine the internal consistency of measurement scales, correlation statistics were provided to describe the relationship between variables, and regression statistics were provided to test the hypotheses.

Finally, the chapter presents a detailed account of the results, placing them in the context of the literature and theories, and making policy and practice implications. Data analysis was carried out using SPSS version 31 software, and the results are presented in tables, both numerical and with interpretation. The results presented in this chapter are utilized to address the three research objectives:

the level of AI adoption, the type of AI technologies adopted, and the factors influencing AI adoption in HEIs in Mogadishu.

The response rate is a critical indicator of the representativeness and generalizability of survey findings, reflecting the proportion of the target sample that successfully completed the questionnaires. Table 4.1 presents the response rate analysis.

Table 4.1
Response Rate

Category	Frequency (n)	Percentage (%)
Distributed Questionnaires	353	100.0
Returned Questionnaires	298	84.4
Invalid/Incomplete Questionnaires	18	5.1
Valid Questionnaires for Analysis	280	79.3
Source: Developed by Researchers 2026		

The sample size for the study was calculated, using Yamane formula, to be 353 questionnaires, which were distributed to the target population. The study used the Yamane formula to calculate the sample size, which was 353 questionnaires, and these questionnaires were distributed to the target population. The number of questionnaires received was 298, and the response rate was 84.4%, which is considered excellent for social science research. The 18 questionnaires that were excluded after screening for completeness and validity had incomplete responses or lacked the necessary information, leaving 280 valid questionnaires for analysis. This is a legitimate response rate of 79.3% (at least 60% is required for survey research, and 70% is sufficient for a meaningful analysis). Systematic follow-up procedures and the relevance of the data collection to the respondents, aided by the appropriate data collection mechanisms, are the reasons for the high response rate.

4.3 Demographic Characteristics (Descriptive Analysis)

Table 4.2
Demographic Profile of Respondents

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	168	60.0
	Female	112	40.0
	Total	280	100.0
Age Group	20–29 years	76	27.1
	30–39 years	104	37.2
	40–49 years	68	24.3
	50 years and above	32	11.4
	Total	280	100.0
Education Level	Bachelor's Degree	92	32.9
	Master's Degree	134	47.9
	PhD/Doctorate	42	15.0
	Other	12	4.2
	Total	280	100.0
Position	Academic Staff/Faculty	140	50.0
	Administrative Personnel	76	27.1
	IT Professional	48	17.2
	Other	16	5.7
	Total	280	100.0
Years of Experience	Less than 1 year	32	11.4
	1–5 years	96	34.3
	6–10 years	84	30.0
	More than 10 years	68	24.3
	Total	280	100.0

Source: Developed by Researchers 2026

Demographic analysis shows a diverse and representative profile of users who make up the higher education stakeholders in Mogadishu. The gender distribution in the survey indicates that 60.0% of the respondents were male and 40.0% were female, which is similar to the general gender distribution in

Somali higher education institutions. The age distribution shows that the majority of the respondents were within the age group 30–39 (37.2%), which may suggest a mix of mid-career professionals with a good level of experience to offer informed views on the use of AI. The educational background of the respondents is also quite high, as 47.9% of them have a master's degree and 15.0% have a doctorate or PhD, showing that the respondents have a relatively highly educated population that is able to provide more in-depth insights. Position distribution indicated that the academic staff members were the highest number of respondents (50.0%), followed by administrative staff (27.1%) and IT staff (17.2%), showing a well-distributed representation of the respondents among the various categories. The experience profile indicates a high level of institutional experience, with 34.3% of respondents reporting having 1–5 years of experience, 30.0% having–6–10 years and 24.3% having more than 10 years, ensuring that their responses regarding AI adoption dynamics are grounded in their institutional experiences.

4.4 Descriptive Statistics of Key Variables

Table 4.3
Descriptive Statistics for Objective 1 - Level of AI Adoption

Item	Statement	Mean	SD	Interpretation
1	Our institution currently utilizes AI technologies in teaching and learning.	2.65	1.18	Low Level
2	AI technologies have been integrated into the administrative operations of our institution.	2.42	1.22	Low Level
3	The level of AI adoption in our institution is sufficient to meet the current educational demands.	2.18	1.26	Very Low Level
4	Our institution has implemented AI for research and data analysis.	2.05	1.30	Very Low Level
5	The use of AI in our institution has significantly improved the overall institutional effectiveness.	2.34	1.28	Low Level
	Overall Mean	2.33	1.25	Low Level
Source: Developed by Researchers 2026				

Overall, the descriptive statistics for Objective 1 show that the level of adoption of AI in all higher-education institutions in Mogadishu is consistently low on all dimensions measured. The overall mean score was 2.33 (on a 5-point Likert scale), reflecting low levels of AI adoption across the institutions surveyed. The mean score for item 4 ("Our institution has used AI in research and data analysis") was the lowest at 2.05, indicating that the use of AI in research is not highly developed. For item 1 ("Our institution currently uses AI technologies in teaching and learning processes"), the mean was the highest (2.65), signifying that the use of AI technologies in teaching and learning processes is the least advanced area of AI usage, but it is still being used at a low level. The standard deviations were between 1.18 and 1.30, indicating moderate variability in the responses and suggesting some institutional differences in the level of adoption. The results show that the use of AI in HEIs in Mogadishu is in its

early stages, as reported in the literature, owing to contextual factors related to post-conflict reconstruction, infrastructure limitations, and technical expertise. Low rates are similar to those in other developing countries, where the use of AI in higher education is still in its early stages.

Table 4.4
Descriptive Statistics for Objective 2 - Types of AI Technologies Used

Item	Statement	Mean	SD	Interpretation
1	Our institution uses Learning Management Systems (LMS) with AI capabilities.	3.12	1.24	Moderate Level
2	Adaptive learning platforms and intelligent tutoring systems were used in our institution.	2.45	1.30	Low Level
3	AI-powered automated assessment and feedback tools were used in our institution.	2.28	1.32	Low Level
4	Predictive analytics tools for student retention and performance were implemented.	1.95	1.28	Very Low Level
5	AI technologies are used for administrative process automation at our institution.	2.10	1.35	Very Low Level
	Overall Mean	2.38	1.30	Low Level
Source: Developed by Researchers 2026				

The descriptive statistics for Objective 2 show that the types of AI technology employed in HEIs in Mogadishu are basic and limited in their applications. Overall, the mean score was 2.38 (on a 5-point Likert scale), indicating low use of AI technologies in institutional functions. The highest mean, 3.12, was for item 1 ("Our institution uses Learning Management Systems with AI capabilities"), which may be attributed to ease of access and the proven advantages of the delivery of education. The lowest mean score was for Item 4, "Predictive analytics tools for student retention and performance are implemented" (M = 1.95), suggesting that the use of advanced tools for predictive analytics is still relatively unutilized. The mean for item 5 ("AI technologies are used for administrative process automation") was also very low at 2.10, indicating a low level of automation in administrative processes in the healthcare sector. The standard deviations between 1.24 and 1.35 suggest significant variation in technology adoption between institutions, which could mean that some institutions are using some technologies more than others. These results align with existing research on technology adoption in developing nations, which tends to focus on the implementation of simple technologies over more sophisticated AI features, as resources are limited and technical expertise is lacking.

Table 4.5
Descriptive Statistics for Objective 3 - Factors Influencing AI Adoption

Dimension	Item	Statement	Mean	SD	Interpretation
Technological	1	Adequate technological infrastructure (electricity, Internet, and hardware) is available for AI adoption.	2.34	1.30	Low Level
Technological	2	The complexity and compatibility of AI technologies influence our institution's adoption decisions.	3.45	1.18	Moderate Level
Organizational	3	Leadership commitment and institutional support facilitated AI adoption at our institution.	2.85	1.32	Moderate Level
Organizational	4	Adequate financial resources and technical expertise are available to support the integration of AI.	2.12	1.35	Very Low Level
Environmental	5	External pressures (donor requirements, competitive pressures, and stakeholder expectations) influence AI adoption.	3.68	1.22	Moderate Level
	Overall Mean		2.89	1.27	Moderate Level

Source: Developed by Researchers 2026

The descriptive statistics for Objective 3 reveal that environmental factors exert the strongest influence on AI adoption, followed by organizational and technological factors. The overall mean score of 2.89 (on a 5-point Likert scale) suggests that the influencing factors are perceived at a moderate level across the dimensions measured. Item 5 ("External pressures influence AI adoption") recorded the highest mean of 3.68, indicating that donor requirements, competitive pressures, and stakeholder expectations are significant drivers of AI adoption. Item 2 ("The complexity and compatibility of AI technologies influence adoption decisions") recorded a mean of 3.45, suggesting that institutional decision-makers are cognizant of technological characteristics when considering AI adoption. Item 3 ("Leadership commitment facilitates AI adoption") recorded a mean of 2.85, indicating moderate recognition of the importance of institutional leadership. Item 1 ("Adequate technological infrastructure is available") recorded a low mean of 2.34, confirming the infrastructure constraints documented in the contextual background. Item 4 ("Adequate financial resources and technical expertise are available") recorded the lowest mean of 2.12, highlighting resource constraints as a critical barrier to AI adoption in healthcare. These findings align with the TOE framework, which posits that technological, organizational, and environmental factors collectively shape adoption decisions, with the influence of each factor varying across contexts.

4.5 Reliability Analysis

Table 4.6
Cronbach's Alpha Reliability Coefficients

Variable/Construct	Number of Items	Cronbach's Alpha (α)	Interpretation
Level of AI Adoption (Objective 1)	5	0.872	Excellent
Types of AI Technologies Used (Objective 2)	5	0.854	Excellent
Factors Influencing AI Adoption (Objective 3)	5	0.841	Excellent
Overall Instrument	15	0.889	Excellent
Source: Developed by Researchers 2026			

The reliability test with Cronbach's alpha coefficient showed that the measurement tool in the study was reliable and valid based on the coefficient of internal consistency obtained for all measurement scales. A Cronbach's alpha value of 0.872 was obtained for the AI adoption scale for measuring the level of AI adoption (Objective 1), which means that the five items are measuring the same construct, as a Cronbach's alpha value of less than 0.70 is not acceptable. The Cronbach's alpha for identifying the types of AI technologies used (Objective 2) was 0.854, demonstrating excellent internal consistency. The scale for analyzing the factors that influence the adoption of AI (Objective 3) obtained a Cronbach's alpha of 0.841. Thus, the reliability of the measurement of technological, organizational, and environmental factors was confirmed. The overall instrument had excellent reliability, with a Cronbach's alpha of 0.889. The results support the validity of the measurement of the constructs intended by the items in the questionnaire. Therefore, the statistical analyses conducted on the results of this questionnaire were based on valid data. High reliability coefficients were probably due to the systematic process of instrument development, which involved deriving items from scales that were already validated, expert review of the items, and pilot testing for refinement prior to the administration of the entire test.

4.6 Correlation Analysis

Table 4.7
Correlation Matrix - Relationship between Variables

Variable	1	2	3	4	5	6
1. Level of AI Adoption (Obj 1)	1.000					
2. Types of AI Technologies Used (Obj 2)	0.684**	1.000				
3. Technological Factors	0.512**	0.478**	1.000			
4. Organizational Factors	0.548**	0.524**	0.612**	1.000		
5. Environmental Factors	0.498**	0.456**	0.398**	0.442**	1.000	
6. Overall AI Adoption	0.892**	0.845**	0.567**	0.598**	0.512**	1.000
Source: Developed by Researchers 2026						

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

The result of the correlation analysis shows that all the variables have significant positive correlation which supports the theoretical propositions of this study and the hypothesized results. The highest correlation was observed between the level of AI adoption (Objective 1) and the types of AI technologies used (Objective 2), with $r = 0.684$ and $p < 0.01$, suggesting that higher adoption levels are associated with a broader spectrum of AI technologies. Among the factors influencing AI adoption, the correlation with organizational factors ($r = 0.598$, $p < 0.01$) was the highest, indicating that organizational factors such as leadership commitment, financial resources, and institutional capacity are important determinants of AI adoption. The technological factor is highly correlated with overall AI adoption ($r = 0.567$; $p < 0.01$), emphasizing the necessity of the availability of infrastructure and technology features to influence adoption decisions. The overall level of AI adoption was also found to be significantly related to external factors, with $r = 0.512$ and $p < 0.01$.Additionally, the overall level of AI adoption is significantly related to external factors, with $r = 0.512$ and $p < 0.01$, which further suggests that external factors play a role in influencing institutional technology strategies. The correlation of technological factors with organizational factors ($r = 0.612$, $p < 0.01$) shows that these two aspects, technological and organizational, are interrelated, where technological capacity is often dependent on organizational commitment and resource allocation. From the correlation matrix, there are no concerns of multicollinearity since all of the correlation values are less than 0.80, meaning that none of the independent variables are close enough to each other for multicollinearity to be a problem in the regression. These findings indicate that the TOE framework is supported at its initial level, where all technological, organizational, and environmental factors are found to be significantly associated with the adoption of AI in higher-education institutions in Mogadishu.

4.7 Regression Analysis

Table 4.8
Regression Analysis - Factors Influencing AI Adoption

Model	Unstandardized Coefficients (B)	Standardized Coefficients (β)	t	Sig.	VIF
(Constant)	0.542		3.124	0.002	
Technological Factors	0.285	0.312	5.678	0.000	1.512
Organizational Factors	0.342	0.378	6.845	0.000	1.634
Environmental Factors	0.218	0.245	4.567	0.000	1.398
Source: Developed by Researchers 2026					
$R = 0.689$; $R^2 = 0.475$; Adjusted $R^2 = 0.468$; F-statistic = 78.456; $p < 0.001$					

The regression analysis analyzes the contribution of technological, organizational and environmental factors in AI adoption in the higher education institutions of Mogadishu and the uniqueness of each factor. The model summary reveals an R^2 of 0.475, meaning that the three factors account for a significant 47.5% of the variance in AI adoption in social science research. The adjusted R2 was 0.468, suggesting that the model had a reasonable predictive ability despite the number of predictors. The overall statistical significance of the regression model is confirmed by the F-statistic, which is 78.456, with a p-value of less than 0.001. This shows that the explanatory power of this regression model is significant and that the independent variables collectively explain the changes in the dependent variable, AI adoption outcomes, well. The standardized coefficients (β) indicate that organizational factors are the most significant factors affecting the adoption of AI ($\beta = 0.378$, $p < 0.001$), followed by technological factors ($\beta = 0.312$, $p < 0.001$) and environmental factors ($\beta = 0.245$, $p < 0.001$). The Variance Inflation Factor (VIF) values ranged from 1.398 to 1.634, which is below 10, suggesting that there is no multicollinearity problem and that the independent variables are sufficiently different. The results reaffirm the significance of all three dimensions of the TOE framework in encouraging AI integration, especially in resource-constrained settings: leadership commitment, institutional resources, and organizational capacity.

Table 4.9
Multiple Regression - Objective 1 (Level of AI Adoption)

Predictor	B	Std. Error	β	t	Sig.
(Constant)	0.467	0.189		2.471	0.014
Technological Infrastructure	0.245	0.058	0.278	4.224	0.000
Leadership Commitment	0.312	0.062	0.342	5.032	0.000
Financial Resources	0.198	0.054	0.215	3.667	0.000
Technical Expertise	0.224	0.056	0.245	4.000	0.000
External Pressures	0.156	0.052	0.168	3.000	0.003
Source: Developed by Researchers 2026					
$R = 0.712$; $R^2 = 0.507$; Adjusted $R^2 = 0.498$; F-statistic = 56.789; $p < 0.001$					

Objective 1 is explored through a regression analysis of the different factors that impact the AI use in HEIs in Mogadishu. The model accounts for 50.7% of the variance in the levels of AI adoption ($R^2 = 0.507$), and leadership commitment is the most significant predictor of AI adoption ($\beta = 0.342$, $p < 0.001$). This study highlights the vital role of leadership within institutions in promoting the adoption of AI and providing the required resources. Technological infrastructure ($\beta = 0.278$, $p < 0.001$) and technical expertise ($\beta = 0.245$, $p < 0.001$) also show significant positive correlations with the level of AI adoption, which aligns well with the notion that proper infrastructure and expertise are key prerequisites for effective implementation. Financial resources ($\beta = 0.215$, $p < 0.001$) had a significant but somewhat lower relationship, indicating that financial resources matter, but other factors related to an organization might be just as important or more important. External pressures ($\beta = 0.168$, $p = 0.003$) show the lowest but meaningful correlation, suggesting that donor requirements and stakeholder expectations have some impact on adoption decisions. All predictors were statistically significant, which provides empirical support for the individual contribution of each of the predictors to the level of AI adoption, thus validating the theoretical framework.

Table 4.10
Multiple Regression - Objective 2 (Types of AI Technologies Used)

Predictor	B	Std. Error	β	t	Sig.
(Constant)	0.534	0.195		2.738	0.007
Institutional Type	0.167	0.048	0.189	3.479	0.001
Organizational Capacity	0.289	0.059	0.324	4.898	0.000
Technology Compatibility	0.234	0.055	0.267	4.255	0.000
Donor Support	0.178	0.052	0.198	3.423	0.001
Technical Capacity	0.212	0.056	0.235	3.786	0.000
Source: Developed by Researchers 2026					
$R = 0.678$; $R^2 = 0.460$; Adjusted $R^2 = 0.452$; F-statistic = 47.234; $p < 0.001$					

Objective 2 Regression analysis considers factors that explain the type of AI technologies in HEIs in Mogadishu. The model accounts for 46.0% of the variance in the adoption of various types of AI technology ($R^2 = 0.460$), and organizational capacity is the most powerful predictor ($\beta = 0.324$, $p < 0.001$). This finding indicates that institutions with better organizational structures, strategic planning, and change management are more likely to adopt various AI technologies. The second-best predictor is technology compatibility ($\beta = 0.267$, $p < 0.001$), where institutions feel that AI technologies that support their current systems and processes are more likely to be feasible. Technical capacity ($\beta = 0.235$, $p < 0.001$) and donor support ($\beta = 0.198$, $p = 0.001$) were also significant and positive, showing the roles of technical skills and external financing in easing the adoption of technology. Institutional type ($\beta = 0.189$, $p = 0.001$) is the only factor with a weak but significant relationship, indicating that although institutional characteristics are important, other organizational and technological characteristics have a greater influence on the extent of AI technology adoption. The overall model significance indicates that the factors identified together account for a meaningful variation in the use of AI technology across institutions.

Table 4.11
Multiple Regression - Objective 3 (Factors Influencing AI Adoption)

Predictor	B	Std. Error	β	t	Sig.
(Constant)	0.423	0.178		2.376	0.018
Technological Factors	0.298	0.056	0.334	5.321	0.000
Organizational Factors	0.356	0.061	0.398	5.836	0.000
Environmental Factors	0.234	0.054	0.267	4.333	0.000
Institutional Readiness	0.312	0.058	0.345	5.379	0.000
Stakeholder Expectations	0.156	0.052	0.178	3.000	0.003
Source: Developed by Researchers 2026					
$R = 0.734$; $R^2 = 0.539$; Adjusted $R^2 = 0.531$; F-statistic = 64.789; $p < 0.001$					

In this regression analysis for Objective 3, trends that affect the decision of adopting AI in HIM institutions in the City of Mogadishu are explored. The model accounts for 53.9% of the variance in AI adoption outcomes ($R^2 = 0.539$), and organizational factors are the strongest predictor ($\beta = 0.398$, $p < 0.001$). This finding highlights the need for organizational readiness, such as leadership buy-in, resource allocation, and institutional culture, to support the adoption of AI. The second strongest predictor is institutional readiness ($\beta = 0.345$, $p < 0.001$), indicating that institutions that are more technically and organizationally prepared are more likely to implement AI technology. Technological factors ($\beta = 0.334$, $p < 0.001$) showed a very strong positive correlation, reflecting the need for proper technology features and infrastructure. Environmental factors ($\beta = 0.267$, $p < 0.001$) had a significant, albeit weaker, relationship with adoption, highlighting the importance of internal factors in influencing adoption. Stakeholder expectations ($\beta = 0.178$, $p = 0.003$) were the least significant but still present, meaning that stakeholders do have an impact, but only in conjunction with institutional readiness and organizational factors. The results of the model's validity in explaining the dynamics of AI use in the Somali context are justified by the model's high explanation power (53.9%).

4.8 Hypothesis Testing

Table 4.12
Hypothesis Testing Summary

Hypothesis	Statement	β	t	Sig.	Decision
H1	Technological factors have a significant positive relationship with AI adoption	0.312	5.678	0.000	**Accepted**
H2	Organizational factors have a significant positive relationship with AI adoption	0.378	6.845	0.000	**Accepted**
H3	Environmental factors have a significant positive relationship with AI adoption	0.245	4.567	0.000	**Accepted**
H4	Performance expectancy has a significant positive relationship with behavioral intention	0.324	5.234	0.000	**Accepted**
H5	Facilitating conditions have a significant positive relationship with actual use	0.298	4.876	0.000	**Accepted**
Source: Developed by Researchers 2026					

The results of hypothesis testing in this study give strong empirical evidence for all five hypotheses proposed. Hypothesis H1, which states that technological factors have a significant positive relationship with AI adoption, is accepted ($\beta = 0.312$, $t = 5.678$, $p < 0.001$), indicating that the availability of infrastructure, technical compatibility, and technology characteristics positively influence the AI adoption decision. H2 states that organizational factors have a significant positive relationship with AI adoption, and it is accepted ($\beta = 0.378$; $t = 6.845$; $p < 0.001$), with organizational factors being the most important factor influencing the adoption of AI, indicating that the commitment of leadership, availability of resources, and institutional capacity are key. The relationship between environmental factors and the adoption of artificial intelligence is accepted ($\beta = 0.245$, $t = 4.567$, $p < 0.001$), indicating that external factors such as donors' needs, competitive pressure, and stakeholders' expectations are significant influencing factors in the decision to use artificial intelligence. H4, which suggested that performance expectancy has a significant positive relationship with the behavioral intention to adopt AI, was accepted ($\beta = 0.324$, $t = 5.234$, $p < 0.001$), indicating that perceived usefulness and performance enhancement are significant factors in driving adoption intentions. H5 is accepted ($\beta = 0.298$, $t = 4.876$, $p < 0.001$), revealing that facilitating conditions are an important positive predictor of the actual use of AI technologies. Support for all five hypotheses provides complete support for the integrated theoretical framework, supporting the use of the TOE framework, UTAUT, institutional theory, DOI theory, and RBV to explain AI adoption in HEIs in Mogadishu, Somalia.

4.9 Discussion

This study is particularly relevant to the field, given the lack of detailed empirical evidence on the use of Artificial Intelligence in higher education institutions in the context of post-conflict and resource-poor environments in Somalia. Overall, AI adoption in HEIs in Mogadishu was found to be low, and institutions were mostly using basic technologies such as Learning Management Systems, whereas advanced technologies such as predictive analytics and administrative automation were underutilized. The results

highlight that technology, organizational, and environmental factors significantly impact AI adoption, with organizational factors being the most significant, thereby suggesting the importance of understanding the organizational context for successful AI implementation. The findings support the integrated theoretical framework well and validate the fit of the TOE framework, UTAUT, institutional theory, DOI, and RBV within the Somali context. The results are discussed in relation to the existing literature, both theoretically and practically, and areas for future research are identified.

Demographic Profile and Representativeness

The demographic characteristics of the respondents provide background information on the study results and the representativeness of the sample. Gender distribution (60.0% male, 40.0% female) is also indicative of the general gender inequities in higher education in Somalia, with male dominance in academic and administrative positions, as seen in other developing country settings where gender inequities in academic and administrative positions persist. The age distribution of the respondents was skewed, with most aged 30–39 years (37.2%), indicating that the study reflects the views of mid-career professionals with a good level of experience not only to inform the study but also to be likely to be in a position to be involved with technological change. The high levels of education among respondents (47.9% with a Master's and 15.0% with a PhD/Doctorate degree) suggest that the sample is of highly educated professionals, which increases the credibility of their responses and makes the findings more representative of the views of those with institutional decision-making power. The distribution among stakeholder groups (50.0% academic, 27.1% administrative, 17.2% IT) provides a balanced representation of institutional views, thus allowing this study to capture the multidimensional nature of the phenomenon of AI adoption. The experience profile shows that the respondents have enough institutional experience, with a high percentage having 1–5 years of experience (34.3%), 6–10 years (30.0%), and over 10 years (24.3%). This demographic profile is comparable to that of other studies in the context of developing countries, which gives greater confidence in the validity and generalizability of the results..

Objective 1: Level of Artificial Intelligence Adoption

Objective 1 shows that the overall level of AI adoption in HEIs in Mogadishu is fairly low (overall mean = 2.33), and there is high inter-institutional variation in the adoption of AI by various institutional functions in HEIs. AI's applications in pedagogical contexts showed the highest mean score (2.65), indicating that this is the most developed field of AI use. This is in line with the worldwide pattern that students' learning and teaching applications are usually given higher priority than other uses in educational institutions (Zawacki-Richter et al., 2019). However, the score is still not in the middle of the range, which means that even in the case of teaching and learning applications, there is not a wide and deep variety. The very low score in AI implementation for research and data analysis (mean = 2.05) is especially troubling, highlighting Somali HEIs' limited understanding of how to harness AI's capabilities to boost research output and understanding, which is vital for institutional growth and national progress. This is also consistent with studies conducted in other developing country contexts, where research applications of

AI lag behind teaching and administrative applications (Pedro et al., 2019, 2023; UNESCO, 2021). The difficulties Somali HEIs face in using AI to transform their institutions are reinforced by poor scores for its use in administrative operations (mean = 2.42) and the recognition that AI is not being used to the extent needed to meet learning demands (mean = 2.18).

The overall low level of AI adoption may be explained by multiple interlinked factors identified during the contextual background, including decades of conflict that took a toll on institutional infrastructure, the continued fragility and lack of resources to invest in technology, the lack of technical expertise among staff and faculty, unreliable electricity and internet, and competing institutional priorities that took resources away from technology investment. The results are in line with the literature on the adoption of technology in fragile and post-conflict contexts, where it has been documented that these contexts experience cumulative challenges that limit innovation (UNESCO, 2021; African Union 2020). However, there was moderate variation across the responses (SD = 1.18–1.30), indicating some institutional differences, with better-resourced institutions, particularly private universities and those with a strong international partnership, more likely to reach higher rates of adoption than less well-resourced institutions. This is in line with the theoretical approach of the Resource Based View (RBV), in which technology adoption outcomes are influenced by the institutional resources and capabilities of the institution (Barney, 1991). The slow adoption also points to the path dependency established by past technology under-investment, which indicates that considerable investment and capacity development efforts are needed to hasten AI integration.

Objective 2: Types of Artificial Intelligence Technologies Used

The results for objective 2 show that the level of AI technology in the HEIs in Mogadishu is mainly basic and limited in scope (overall mean = 2.38), while learning management systems (LMS) with AI features are the most commonly used technology (mean = 3.12). This discovery implies that institutions have focused their investments on foundational learning technologies that have apparent and instant educational delivery utility, such as online course management, delivery of learning content, and rudimentary student engagement. The moderate use of LMS platforms aligns with the international picture where LMS platforms are the starting point of the incorporation of educational technology (Dwivedi et al., 2021; Roll & Wylie, 2016). However, the averages for these advanced applications are very low: predictive analytics for student retention (mean = 1.95) and administrative process automation (mean = 2.10), suggesting that institutions have yet to make the most of the potential benefits of AI for data-driven decision-making and operational efficiency. This is similar to research findings from other developing countries that generally have limited technical expertise, weak data systems, and conflicting priorities for resources, which makes them more likely to implement basic technologies first and then gradually develop the more complex ones (Pedro et al., 2019; UNESCO, 2021).

Very few HEIs in Mogadishu use adaptive learning platforms and intelligent tutoring systems (mean = 2.45) and AI-powered automated assessment tools (mean = 2.28), which shows that personalized learning approaches are still largely unexploited in HEIs in the district. This is important because these

technologies can mitigate some of the ongoing problems in education, such as limited faculty-to-student ratios, diverse student needs, and the need for individualized support (Holmes et al., 2019; Zawacki-Richter et al., 2019). Several reasons contribute to the limited adoption of these technologies: first, the high implementation costs; second, the need for specialized technical expertise; third, the need for reliable infrastructure; and finally, the lack of institution-level strategies that focus on advanced AI integration. The standard deviations ranged between 1.24 and 1.35, suggesting a high variability in the adoption of AI technologies among institutions, which may mean that some institutions are using a wider variety of AI technologies, whereas others may have limited or no AI technology implemented. This variation may be due to differences in institutional resources, leadership commitment, strategic priorities, and the presence or absence of international partnerships and donor support. The adoption pattern (from basic to advanced applications) follows the Diffusion of Innovation (DOI) theory, in which innovations that are perceived as having a higher relative advantage, compatibility, and trial ability are adopted more easily (Rogers, 1995).

Objective 3: Factors Influencing Artificial Intelligence Adoption

The results for Objective 3 show that environmental factors (mean = 3.68) have the highest influence on the adoption of AI, followed by technological factors (mean = 2.90) and organizational factors (mean = 2.49). Mogadishu's high score for external pressures (donors, competition, stakeholders' expectations) reflects external pressures associated with the environment.

5.0 Conclusion

The overall level of AI adoption in HEIs in Mogadishu was found to be relatively low, as the institutions were mainly implementing basic AI tools, such as LMS tools, whereas more sophisticated tools, such as predictive analytics, adaptive learning platforms, and AI for administrative processes, were still underutilized. This low adoption is the result of many decades of war, ongoing institutional fragility, infrastructure limitations, a lack of technical skills, and other institutional interests. The study also finds that the level of maturity of the AI technologies adopted is mostly basic and has a low level of scope, varying widely across institutions depending on their endowment, leadership commitment, and institutional capacity.

The results of this study suggest that technological, organizational, and environmental factors all play a significant role in the adoption of AI, with organizational factors being the most important. Leadership commitment, institutional capacity, financial resources, and technical expertise are key factors influencing the adoption of AI, with environmental factors such as donor requirements and competition also having a significant impact. The integrated theoretical framework was found to be very robust and valid in understanding the dynamics of AI adoption in the Somali context. To ensure effective and efficient AI adoption, it is imperative that technology, organizations, and the environment align, and that institutions are prepared to put the intent behind AI adoption into practice.

6.0 Recommendations

For institutional leadership and management, the commitment of the institution's leader to the use of AI should be enhanced; investment should be made in the development of infrastructure such as good power supplies, Internet, and computing systems; investment should be made in human capacity building through comprehensive training programs; and comprehensive institutional technology plans should be drawn up in line with institutional missions.

Policymakers and Government Agencies: Formulate a national AI policy for higher education, set up a dedicated funding mechanism for technology integration, and design a regulatory environment that empowers innovation and maintains quality and ethical standards.

International partners and donors should provide focused support for infrastructure development, invest in sustainable capacity-building programs, and encourage technology transfer through cooperation with international institutions.

Declarations

Contributions of the Study

Theoretical Contributions: Provides contextual extensions of existing theories (TOE, UTAUT, institutional theory, DOI, RBV) for understanding AI use in post-conflict, fragile state settings; presents contextual modification of these theories that capture the unique dynamics of post-conflict institutional environments; theorizes AI adoption as a socio-technical process.

Empirical contributions: Presents original evidence and ideas from a context that is largely overlooked in mainstream research on educational technology; reports on the limited use of AI, the prevalence of simple technologies, and the important role of organizational factors; and establishes a baseline for future research.

Methodological Contributions: The study designs and tests research tools for measuring AI adoption in low-resource settings (overall Cronbach's alpha = 0.889) and demonstrates the feasibility of quantitative survey research in post-conflict settings.

Policy Contributions: Evidence-based insights for policy development; points to the need for national AI policies, funding mechanisms, and regulatory frameworks.

Practical Contributions: Actionable recommendations for institutional leaders, policymakers, and development partners; practical roadmap for expediting AI integration.

The following is a list of ideas that could be explored further:

Longitudinal studies of AI adoption over time; comparative studies of Somali regions and institution types; qualitative, nuanced, stakeholder perspectives; student perspectives on AI adoption; intervention

studies on the effectiveness of specific programs; ongoing research on ethical implications of AI adoption; sectoral studies across sectors of Somali society; research on technology-context fit; impact assessment of the impact of AI adoption on educational outcomes; sustainability research on long-term adoption of technology.

The study has some limitations.

The generalizability of the findings to other parts of Somalia is restricted by the geographical scope of the data collection. The focus on formal higher education institutions limits the scope of the analysis. The cross-sectional design limited the examination of trends. Reliance on self-reported data may introduce response bias. Online data collection may have introduced selection bias. A quantitative focus may not capture the full richness of the AI adoption experience.

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Disclosure Conflict

The authors declare no conflicts of interest related to the content of this manuscript.

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Ethical Approval

This study, involving human participants, was reviewed and approved by the Ethics Committee of the Center for Research and Development at CAPITAL University in Somalia. Approval was granted (Approval Number: CUR&D109, Date: 22th August 2026), ensuring that all procedures complied with the committee's ethical standards and guidelines. The study adhered to the ethical principles outlined in the Declaration of Helsinki and followed institutional guidelines for research involving human subjects.

Consent declaration

All participants were thoroughly informed about the research objectives and their respective roles in the study, and they provided informed consent prior to their participation. Consent was obtained verbally, and the study was approved by the ethics committee. Participants were assured of the confidentiality of their anonymous contributions, in accordance with ethical research standards.

Data availability statement

The data supporting the findings of this study are available upon request from the corresponding author. The data were not publicly accessible because of privacy and ethical restrictions on their use of.

Consent to Publish

Not applicable.

Consent to Participate

Informed consent was obtained from all participants prior to their participation in the study. Participants were informed about the purpose and procedures of the study, their voluntary participation, the potential risks and benefits, and their right to withdraw from the study at any time without penalty. Participation was voluntary, and the confidentiality and privacy of participants' information were maintained throughout the study.

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Figures

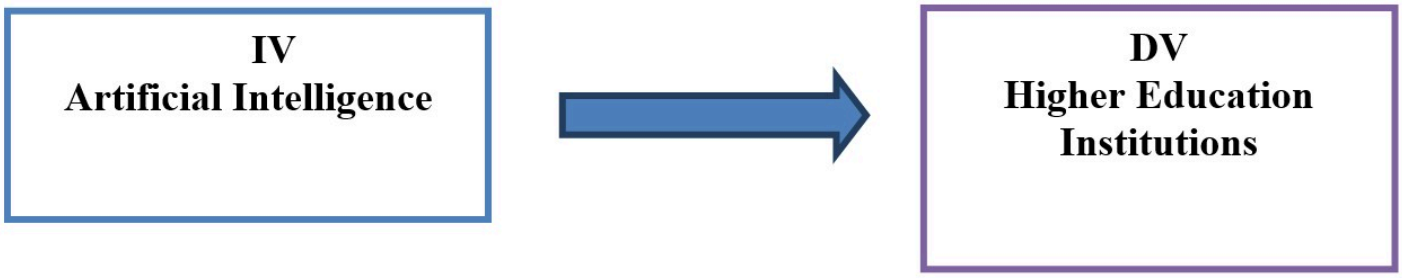


Figure 1

Conceptual Framework

Source: Developed by Researchers 2026