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Assessing the Effects of Artificial Intelligence Adoption on Higher Education Outcomes: Evidence from Ethiopian Public Universities

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Abstract**:** *Artificial Intelligence (AI) is transforming higher education by enhancing teaching, learning, research, and administrative processes. Technologies such as machine learning, learning analytics, intelligent tutoring systems, and generative AI provide significant opportunities to improve educational quality, relevance, and accessibility while addressing the demands of the digital era. Despite these advancements, empirical evidence on the impact of AI adoption in higher education remains limited in developing countries, particularly Ethiopia. This study examined the effect of AI adoption on higher education outcomes in Ethiopian public universities, focusing on relevance, quality, and accessibility. A quantitative research design was employed, and data were collected from academic and administrative staff using a structured questionnaire. Descriptive statistics and multiple regression analysis were used to analyze the data. The findings reveal that AI adoption is widely perceived as enhancing curriculum modernization, student engagement, personalized learning, research productivity, and educational inclusiveness. Regression results indicate that AI adoption has a positive and statistically significant effect on the relevance of higher education ($\beta = 0.220$, $p < 0.001$) and accessibility ($\beta = 0.151$, $p = 0.016$). Although AI also demonstrated a positive effect on educational quality ($\beta = 0.113$), the relationship was only marginally significant ($p = 0.074$). Overall, the findings suggest that AI adoption has considerable potential to strengthen higher education outcomes, particularly by improving relevance and accessibility. The study recommends increased investment in digital infrastructure, institutional capacity building, faculty development, and supportive policy frameworks to accelerate the effective integration of AI across Ethiopian public universities.*

Keywords: *Artificial Intelligence, Higher Education, AI Adoption, Educational Quality, Accessibility, Relevance, Ethiopian Public Universities.*

1. Introduction

1.1. Background of the Study

Artificial Intelligence (AI) has become one of the most transformative technologies of the Fourth Industrial Revolution, reshaping higher education by enhancing teaching, learning, research, and institutional management. AI applications, including intelligent tutoring systems, learning analytics, virtual assistants, automated assessment, and generative AI, are increasingly being adopted to support personalized learning, improve student engagement, facilitate data-driven decision-making, and strengthen institutional effectiveness (Popenici & Kerr, 2017; European Commission Joint Research Centre, 2019; Dan et al., 2024). Recent advances in generative AI have further expanded opportunities for knowledge creation, adaptive learning, and research support, enabling higher education institutions to transition from traditional teacher-centered approaches to more learner-centered and flexible learning environments (Glickman & Zhang, 2024). Consequently, AI is increasingly recognized as a strategic technology for improving the quality, relevance, and accessibility of higher education while preparing graduates for the demands of the knowledge economy and the digital labor market (OECD, 2022; Almufarreh & Arshad, 2023).

Despite these opportunities, higher education institutions worldwide continue to face persistent challenges related to educational quality, curriculum relevance, graduate employability, and equitable access to learning opportunities. These challenges are particularly evident in developing countries, where technological infrastructure, digital literacy, financial resources, and institutional readiness often constrain the effective adoption of emerging technologies (European Commission Joint Research Centre, 2019). In Ethiopia, although public universities are increasingly pursuing digital transformation initiatives and introducing AI-enabled technologies, empirical evidence regarding the extent of AI adoption and its contribution to improving higher education outcomes remains limited. Existing studies have primarily examined the opportunities, challenges, and institutional readiness associated with AI implementation, with most empirical evidence originating from developed countries. Moreover, previous research has seldom investigated how AI adoption influences the core higher education outcomes of quality, relevance, and accessibility within the Ethiopian higher education context (Heredia-Carroza & Stoica, 2023; Dan et al., 2024).

This lack of context-specific empirical evidence creates a significant knowledge gap and limits the ability of policymakers, university leaders, and educators to make informed decisions regarding AI investment, implementation, and policy formulation. Without a clear understanding of how AI adoption influences educational quality, relevance, and accessibility, higher education institutions may struggle to maximize the potential benefits of AI technologies and design effective implementation strategies. Therefore, this study examines the impact of Artificial Intelligence adoption on higher education outcomes—specifically quality, relevance, and accessibility—in selected Ethiopian public universities. By providing empirical evidence from the Ethiopian context, the study contributes to the growing body of literature on AI in higher education and offers practical insights for policymakers and university leaders seeking to strengthen the effective, inclusive, and sustainable integration of AI technologies within Ethiopian public universities (Heredia-Carroza & Stoica, 2023; OECD, 2022).

1.3. Research Questions

1) To what extent does artificial intelligence adoption influence the relevance of higher education in Ethiopian public universities?
4)
2) To what extent does artificial intelligence adoption influence the quality of higher education in Ethiopian public universities?
3) To what extent does artificial intelligence adoption influence the accessibility of higher education in Ethiopian public universities?

1.4. General Objective

To assess the effect of artificial intelligence adoption on the relevance, quality, and accessibility of higher education in Ethiopian public universities.

1.4.1. Specific Objective

1) To examine the effect of artificial intelligence adoption on the relevance of higher education in Ethiopian public universities.
2) To assess the effect of artificial intelligence adoption on the quality of higher education in Ethiopian public universities.
3) To investigate the effect of artificial intelligence adoption on the accessibility of higher education in Ethiopian public universities.

2. Materials and Methods

2.1. Description of the Study Area

This study examined the current status of artificial intelligence (AI) utilization and integration within the higher education system of Ethiopia, with a specific focus on four prominent public universities: Addis Ababa Science and Technology University, Adama Science and Technology University, Addis Ababa University, and Ethiopian Civil Service University. The research aimed to provide a comprehensive understanding of the key opportunities, challenges, and policy implications arising from the use of AI-driven technologies in the selected institutional contexts.

2.2. Research Design

In this study, I used the Technology Acceptance Model as the foundational framework. According to this model, the acceptance of a new innovation is influenced by perceived advantages and perceived ease of use. Therefore, the primary theoretical model guiding this research was the Technology Acceptance Model. The author employed a cross-sectional survey research design. This research design was essential, as it enabled the smooth execution of various research operations, leading to efficient research and the attainment of maximum information while minimizing effort, time, and financial resources (Kothari, 2004). The research design established the logical connection between the data collected and the conclusions drawn in relation to the initial questions of the study (Yin, 1994).

2.3. Research approach

In the proposal for the study on artificial intelligence and the future of higher education in Ethiopia: practice, challenges, and opportunities, the researchers employed a mixed research approach to generate comprehensive knowledge and theories (George & Bennett, 2004). This methodological choice was influenced by the desire to obtain more reliable data for addressing the research questions. The study utilized both qualitative and quantitative research methods. The qualitative approach explored the attitudes, behaviors, and experiences of the participants through in-depth interviews and open-ended questions, enabling a comprehensive understanding of the phenomenon (Kothari, 2004). Conversely, the quantitative approach involved the collection of statistical data via large-scale surveys using closed-ended questionnaires. The rationale for employing a mixed research method, as highlighted by Kumar (2011), was to enhance the quality of the research by mitigating the biases inherent in relying solely on either quantitative or qualitative methods.

2.4. Data Type and Source

2.4.1. Data Type

In this study, the researchers utilized both qualitative and quantitative research approaches, along with primary and secondary types of data. The inclusion of primary and secondary data, as well as qualitative and quantitative data, was crucial for triangulating and complementing the diverse data obtained from various sources. Ultimately, this integrated approach aimed to enhance the reliability of the data and the research findings. The qualitative component of the study involved in-depth interviews and open-ended questions to explore the attitudes, behaviors, and experiences of the participants. This approach provided a comprehensive understanding of the phenomenon from the participants' perspectives. Concurrently, the quantitative component encompassed the collection of statistical data through large-scale surveys using closed-ended questionnaires. This enabled the researchers to identify trends, patterns, and relationships within the data, complementing the insights gained from the qualitative analysis.

2.4.2. Data Source

In this study, the researchers employed both primary and secondary data sources to obtain reliable information. The primary data was gathered directly from sources by utilizing survey questionnaires, conducting interviews, engaging in focus group discussions (FGDs), and making field observations. This approach enabled the researchers to collect firsthand information from key stakeholders, such as university administrators, faculty members, and quality assurance experts, to gain a deeper understanding of their attitudes, perceptions, and experiences regarding the implementation of artificial intelligence in higher education quality assurance.

Concurrently, the researchers utilized secondary data sources, including policy documents, periodic reports, scholarly articles, relevant books, published and unpublished materials, and various websites, to support the research based on existing theoretical and empirical evidence. This integration of primary and secondary data sources allowed for a comprehensive and reliable investigation of artificial intelligence and higher education in Ethiopia, triangulating the findings from diverse data points. By employing both primary and secondary data, the researchers strived to develop a well-rounded understanding of the opportunities, challenges, and best practices associated with the utilization of artificial intelligence for higher education quality assurance in Ethiopia, drawing upon both empirical observations and the existing body of knowledge in the field.

2.5. Instruments and procedure of data collection

2.5.1. Instruments of data collection

The researchers employ both quantitative and qualitative data collection methods to obtain primary and secondary data, utilizing a mixed research approach to address the study's objectives. The data collection instruments employed are outlined below.

Quantitative Data Collection

The quantitative component of the study involved the administration of structured survey questionnaires to a representative sample of higher education institutions in Ethiopia. The survey collected numerical data on various aspects of artificial intelligence implementation, such as the extent of utilization, integration into quality assurance processes, and perceived impact on institutional performance metrics. This quantitative data enabled the researchers to identify trends, patterns, and relationships within the data using statistical analysis techniques.

Qualitative Data Collection

The qualitative component of the study included in-depth interviews and focus group discussions with key stakeholders, such as university administrators, faculty members, students, and university leaders. These qualitative methods provided the researchers with a deeper understanding of the experiences, perceptions, and contextual factors influencing the integration of artificial intelligence and higher education in Ethiopia. The data collected through these methods offered insights that complemented the quantitative findings.

Secondary Data Collection

In addition to the primary data collection, the researchers also reviewed and analyzed secondary data sources, including policy documents, periodic reports, scholarly articles, relevant books, and other published and unpublished materials. This secondary data helped contextualize the findings, establish theoretical and empirical foundations, and provide a comprehensive understanding of the research topic.

2.5.2. Procedure of data collection

In the study, the data-gathering process began with a review of relevant literature and secondary data sources to identify the important issues to be included in the data collection instruments. Following this initial review, the primary data collection instruments—such as survey questionnaires, key informant interview protocols, and focus group discussion topics—were designed based on a comprehensive review of the existing knowledge. A pilot test of the survey questionnaire was conducted with a purposively selected group of respondents, including students and staff members of Addis Ababa University, Ethiopian Civil Service University, and Addis Ababa Science and Technology University. The purpose of the pilot test was to refine and make necessary corrections to the final questionnaire before the actual survey was carried out. The actual survey was conducted by trained enumerators who were selected based on their educational background and familiarity with the local culture. To ensure the quality of data collection, an orientation workshop was organized, providing an introduction to the data collection tools and facilitating discussions with the enumerators. Throughout the data collection phase, the researchers closely supervised the data collectors and obtained information from key informants. The primary data for the study were collected from the specified sources between October and December 2024.

2.6. Target population and sampling Techniques

2.6.1. Target Population

The target population included academic staff, university leaders, quality assurance personnel, students, and other members of the university community from Addis Ababa Science and Technology University, Adama Science and Technology University, Addis Ababa University, and Ethiopian Civil Service University. These institutions were purposively selected to capture a wide range of perspectives: Adama Science and Technology University and Addis Ababa Science and Technology University are specialized institutions focusing on science and technology; Addis Ababa University is the oldest and most resource-rich university in the country; and the Ethiopian Civil Service University serves as a founding institution dedicated to building public sector capacity.

2.6.2. Sampling techniques and sample size determination

The research sites were selected using a purposive sampling technique. The study was conducted at Addis Ababa Science and Technology University, Adama Science and Technology University, Addis Ababa University, and Ethiopian Civil Service University due to their geographic proximity, long-standing academic experience, and well-established internet infrastructure. To collect quantitative data, a simple random sampling method was applied, targeting university staff, university leaders, quality assurance personnel, students, and other members of the university community. The survey sample was drawn by randomly selecting appropriate respondents from each of the target universities. The estimated population sizes of the universities were as follows: AASTU (10,000), ASTU (25,000), AAU (40,000), and ECSU (7,000). These figures were used to determine a statistically significant and representative sample size for the study.

2.6.2.1. Sample size determination

In this study, determining the sample size was a crucial consideration. The sample size was carefully chosen to strike a balance between manageability and representativeness (Kothari, 2004). Among the various sample size calculation methods available in the literature, Yamane's (1967) formula n=N/(1+N(e)2)n = N / (1 + N(e)^2) was used to determine the total sample size. The calculation was based on a ±5% precision level and a 95% confidence level for the total population.

$n = \frac{N}{1+N\,(e)^2}$ Where: N = Total Population

$n = \frac{122{,}000}{1+122{,}000(0.05)^2}$ e =Sampling Error/precision level/

$n = \frac{122{,}0000}{306}$ n = Sample size

n = <u>400</u>

The sample size will be administered proportionally among selected universities for this study.

Table 1: Summary of sample size determination of the study area

No.	Target Population	Population size	Formula	Sample size taken	Sampling technique
1	Addis Ababa Science and Technology University	10,000	ni= $(\frac{Ni}{N}n)$	50	Simple random
2	Adama Science and Technology University	25,000	ni= $(\frac{Ni}{N}n)$	121	Simple random
3	Addis Ababa University	40,000	ni= $(\frac{Ni}{N}n)$	195	Simple random
4	Ethiopian Civil Service University	7,000	ni= $(\frac{Ni}{N}n)$	34	Simple random
	Total	82,000	---	400	

Source: Author's estimations

2.6.3. Sampling for Qualitative Data

The study employed a purposive non-probability sampling technique to deliberately select key informants based on their knowledge and capacity to provide relevant data on the research theme. Detailed information was collected through in-depth interviews with key informants, including academic staff, university leaders, quality assurance personnel, students, and other members of the university community at Addis Ababa Science and Technology University, Adama Science and Technology University, Addis Ababa University, and Ethiopian Civil Service University. Specifically, four individuals were selected from each university for the interviews. In addition, three focus group discussions, each comprising eight participants, were conducted at each university to gather further insights on the topic.

2.7. Method of Data Analysis

The collected data were analyzed using both quantitative and qualitative techniques in accordance with the mixed-methods research design. Quantitative data were cleaned, coded, and entered into the Statistical Package for the Social Sciences (SPSS) Version 25 for analysis. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were used to summarize respondents' demographic characteristics and perceptions regarding artificial intelligence (AI) adoption and higher education outcomes.

To examine the effect of AI adoption on higher education outcomes, multiple regression analysis was employed. Three separate regression models were estimated to assess the influence of AI adoption on the relevance, quality, and accessibility of higher education while controlling for selected demographic and digital readiness variables. Prior to conducting the regression analyses, key assumptions of linear regression, including normality, linearity, homoscedasticity, multicollinearity, and independence of residuals, were assessed to ensure the validity of the models.

Qualitative data obtained through interviews and focus group discussions were analyzed using thematic analysis. The data were transcribed, coded, and organized into themes and subthemes that reflected participants' experiences, perceptions, and perspectives regarding AI adoption in higher education.

The study adopted a convergent mixed-methods approach, whereby quantitative and qualitative data were analyzed independently and integrated during the interpretation stage. The qualitative findings were used to complement, explain, and enrich the quantitative results, thereby enhancing the validity, credibility, and comprehensiveness of the study findings.

Multiple Linear Regressions

To evaluate the impact of AI utilization on the accessibility, quality, and relevance of higher education, multiple linear regression analysis was conducted. This analysis examined the influence of AI utilization alongside other explanatory variables on these outcomes. Data spanning the past ten years were analyzed to identify key factors affecting accessibility, quality, and relevance, with a primary focus on understanding the specific contributions of AI utilization within the higher education sector.

$$\boldsymbol{Accessibility_{it} = \beta_0 + \beta_1 AI\ adpotion_{it} + \beta_2 Exog_{it} + \varepsilon_{it}}$$

$$\boldsymbol{Quality_{it} = \gamma_0 + \gamma_1 AI\ adoption_{it} + \gamma_2 Exog_{it} + \mu_{it}}$$

$$\boldsymbol{Relevance_{it} = \delta_0 + \delta_1 AIadoption_{it} + \delta_2 Exog_{it} + \tau_{it}}$$

The model incorporated additional exogenous variables that potentially influenced the outcome variables. These included institutional characteristics, student demographics, technological infrastructure, faculty characteristics, policy and regulatory environment, curriculum and program offerings, assessment and evaluation practices, and external partnerships.

2.8. Data validation

A pilot study was conducted with participants selected from Addis Ababa University, Ethiopian Civil Service University, and Addis Ababa Science and Technology University, who possessed characteristics similar to those of the main study sample. The objective of the pilot study was to assess the validity of the data collection instruments prior to the main survey, allowing for verification of reliability and refinement of the instruments based on the test results. Participants in the pilot study were excluded from the final sample. Additionally, expert opinions were solicited to confirm the content validity of the instruments. Feedback from these experts was utilized to enhance the data collection tools by identifying and addressing potential issues that could affect data quality. Prior to data analysis and interpretation, validation procedures were performed in SPSS to check for missing data, percentage mismatches, and encoding errors. To evaluate the extent to which the research instruments represented the intended constructs, the Content Validity Index (CVI) was employed. Experts rated the relevance and clarity of each item using a Likert scale, and the CVI was calculated by dividing the number of experts who rated an item as relevant or highly relevant by the total number of experts. A higher CVI score indicated stronger content validity, thereby enhancing the reliability and validity of the measurements used in the study.

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2.9. Reliability

The reliability of this study was ensured by providing a detailed account of the research procedures and employing standardized data collection instruments that can be replicated by other researchers. Internal consistency and data accuracy were assessed using Cronbach's alpha coefficient, which measures the reliability of scales on a range from 0 to 1. A Cronbach's alpha value of 0.70 or higher was considered satisfactory. Accordingly, the coefficient was calculated using SPSS to confirm it fell within the acceptable range. Additionally, the test-retest method was applied to evaluate the reliability of the instruments. This involved administering the instruments to participants on two separate occasions, with a time interval between administrations. The consistency of responses over time was assessed by computing the correlation coefficient between the two sets of results.

2.10. Ethical consideration

Ethical approval for this study was obtained from the appropriate Research Ethics Review Committee of Ethiopian Public Service University prior to data collection. The study was conducted in accordance with established ethical principles governing research involving human participants. Informed consent was obtained from all participants before their involvement in the study. Participants were provided with detailed information regarding the purpose of the research, data collection procedures, expected duration of participation, potential benefits, and their right to decline participation or withdraw from the study at any stage without any consequences. Participation was entirely voluntary. To ensure privacy and confidentiality, no personally identifiable information was collected or disclosed. All responses were treated anonymously and used solely for research purposes. The collected data were securely stored and accessed only by the research team. The study complied with institutional ethical guidelines for research involving human subjects.

3. Results and Discussion

3.1. Cross-tabulation between Institution and Gender

The following table presents the distribution of respondents by institution and gender. It shows the number and percentage of male and female respondents within each of the four participating universities, providing an overview of the demographic composition of the study sample across institutions.

Table 2: **Institution of respondents * Gender of respondents Crosstabulation**

Institution of respondents * Gender of respondents Crosstabulation					
			Gender of respondents		Total
			Female	Male	
Institution of respondents	Addis Ababa Science and Technology University	Count	21_a	108_b	129
		% within Institution of respondents	16.3%	83.7%	100.0%
	Ethiopian Civil Service University	Count	3_a	81_b	84
		% within Institution of respondents	3.6%	96.4%	100.0%
	Addis Ababa University	Count	9_a	50_a	59
		% within Institution of respondents	15.3%	84.7%	100.0%
	Adama Science and Technology University	Count	1_a	45_b	46
		% within Institution of respondents	2.2%	97.8%	100.0%
Total		Count	34	284	318

	% within Institution of respondents	10.7%	89.3%	100.0%
Each subscript letter denotes a subset of Gender of respondents categories whose column proportions do not differ significantly from each other at the .05 level.				

The table shows that a total of 318 respondents participated in the study, of whom 34 (10.7%) were female and 284 (89.3%) were male. Addis Ababa Science and Technology University contributed the largest number of respondents (129), followed by Ethiopian Civil Service University (84), Addis Ababa University (59), and Adama Science and Technology University (46). Within Addis Ababa Science and Technology University, 108 respondents (83.7%) were male and 21 (16.3%) were female. Similarly, Addis Ababa University had 50 male respondents (84.7%) and 9 female respondents (15.3%). Ethiopian Civil Service University included 81 male respondents (96.4%) and 3 female respondents (3.6%), while Adama Science and Technology University comprised 45 male respondents (97.8%) and 1 female respondent (2.2%). The results further indicate that Addis Ababa Science and Technology University and Addis Ababa University shared similar gender distributions, as evidenced by the common subscript letter (a) for female respondents and the absence of statistically significant differences in column proportions at the 0.05 significance level. Likewise, Ethiopian Civil Service University and Adama Science and Technology University exhibited comparable gender distributions. Overall, the table demonstrates the distribution of respondents across institutions and gender categories, reflecting the characteristics of the study participants selected for the survey.

3.2. Digital Readiness and AI Capacity Assessment

The following table presents respondents' digital readiness and AI capacity assessment. Specifically, it provides information on respondents' access to a stable internet connection at their institutions, their perceived level of training in using digital tools relevant to their roles, and their exposure to formal training on artificial intelligence (AI) or related digital technologies. These indicators help describe the digital environment and preparedness of the study participants.

Table 3: Digital Readiness and AI Capacity Assessment

		Count	Column N %
Do you have access to a stable internet connection at your institution	Yes	242	76.1%
	No	74	23.3%
Do you feel adequately trained to use digital tools relevant to your role	Yes	150	47.3%
	No	54	17.0%
	Somewhat	113	35.6%
Have you received any formal training on AI or related digital technologies	Yes	82	25.8%
	No	221	69.5%

The results indicate that the majority of respondents, 242 (76.1%), reported having access to a stable internet connection at their institutions, while 74 respondents (23.3%) indicated that they did not have such access. This suggests that most participants operate in an environment where internet connectivity is available to support digital activities. Regarding training in the use of digital tools relevant to their roles, 150 respondents (47.3%) reported that they felt adequately trained, while 113 respondents (35.6%) indicated that they were somewhat trained. In contrast, 54 respondents (17.0%) reported that they did not feel adequately trained. Taken together, these findings show that a considerable proportion of respondents perceived themselves as having at least some level of preparation to utilize digital tools in their professional activities. With respect to formal training on AI or related digital technologies, 82 respondents (25.8%) indicated that they had received such training, whereas 221 respondents (69.5%) reported that they had not. This finding

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suggests that although respondents generally have access to digital infrastructure and some level of preparedness in using digital tools, participation in formal AI-related training programs is less common among the study participants.

3.3. AI Adoption Level

The following table presents respondents' perceptions of the level of AI adoption within their institutions. The assessment was conducted using five indicators related to AI integration in curricula, faculty use of AI tools, student engagement with AI applications, AI-related training opportunities, and institutional involvement in AI projects. Responses were measured on a five-point Likert scale ranging from *Strongly Disagree* to *Strongly Agree*. The mean scores provide an overall indication of the perceived level of AI adoption for each statement.

Table 4: AI Adoption Level

		Strongly Disagree	Disagree	Neutral	Agree	Strongly agree	Mean
AI technologies are effectively integrated into our course curriculum.	Count	48	94	54	58	55	3.30
	%	15.4%	30.1%	17.3%	18.6%	17.6%	
Faculty members regularly use AI tools in their teaching and research activities.	Count	40	63	95	77	37	3.03
	%	12.8%	20.2%	30.4%	24.7%	11.9%	
Students actively engage with AI-based applications and tools as part of their learning process.	Count	12	44	63	112	79	3.65
	%	3.9%	14.2%	20.3%	36.1%	25.5%	
Faculty and staff receive adequate training on AI technologies to enhance	Count	26	55	107	81	41	3.18
	%	8.4%	17.7%	34.5%	26.1%	13.2%	

their skills and knowledge.							
Our institution has a significant number of ongoing or completed projects related to AI.	Count	22	60	126	62	39	3.18
	Row N %	7.1%	19.4%	40.6 %	20.0 %	12.6%	

The findings show varying levels of agreement regarding AI adoption across different institutional dimensions. Among the five indicators, the statement *"Students actively engage with AI-based applications and tools as part of their learning process"* recorded the highest mean score (M = 3.65). More than sixty percent of respondents either agreed (36.1%) or strongly agreed (25.5%) with this statement, indicating that students are actively interacting with AI technologies in their learning activities. The statement *"AI technologies are effectively integrated into our course curriculum"* obtained a mean score of 3.30. While 36.2% of respondents agreed or strongly agreed with the statement, 45.5% expressed disagreement or strong disagreement. This suggests differing perceptions regarding the extent to which AI has been incorporated into academic curricula. Regarding faculty engagement, the statement *"Faculty members regularly use AI tools in their teaching and research activities"* yielded a mean score of 3.03. The largest proportion of respondents (30.4%) selected the neutral option, while 36.6% agreed or strongly agreed. These findings indicate a moderate level of faculty utilization of AI tools in teaching and research activities. Similarly, the statement *"Faculty and staff receive adequate training on AI technologies to enhance their skills and knowledge"* produced a mean score of 3.18. A substantial proportion of respondents (34.5%) remained neutral, while 39.3% agreed or strongly agreed that adequate AI training opportunities were available. This suggests that respondents perceived a moderate level of institutional support for AI-related capacity development. The statement *"Our institution has a significant number of ongoing or completed projects related to AI"* also recorded a mean score of 3.18. The largest group of respondents (40.6%) selected the neutral category, whereas 32.6% agreed or strongly agreed with the statement. These results indicate that respondents perceived a moderate level of institutional involvement in AI-related projects and initiatives.

3.4. AI and the Relevance for Higher Education

The following table presents the results of the multiple regression analysis examining the effect of AI adoption on the relevance of higher education institutions. The analysis was conducted to determine whether the level of AI adoption significantly influences perceptions of higher education relevance while controlling for selected demographic and digital readiness variables. The standardized beta coefficients, t-values, and significance levels were used to assess the magnitude and significance of the relationships.

Table 5: Regression Result

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3.136	.431		7.274	.000		
	AI Adoption Level	.186	.052	.220	3.554	.000	.844	1.185
	Institution of	-.022	.043	-.030	-.517	.606	.963	1.038

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	respondents							
	What is your highest level of education?	.081	.054	.090	1.488	.138	.888	1.126
	What is your current role at the institution?	.017	.074	.014	.233	.816	.947	1.056
	What is your primary mode of accessing digital resources?	-.133	.043	-.180	-3.102	.002	.962	1.040
	How often do you use digital tools in your daily tasks	.084	.040	.124	2.103	.036	.923	1.083
	Do you have access to a stable internet connection at your institution	-.059	.090	-.039	-.658	.511	.933	1.072
	Do you feel adequately trained to use digital tools relevant to your role	.142	.053	.160	2.699	.007	.923	1.084

a. Dependent Variable: Relevance

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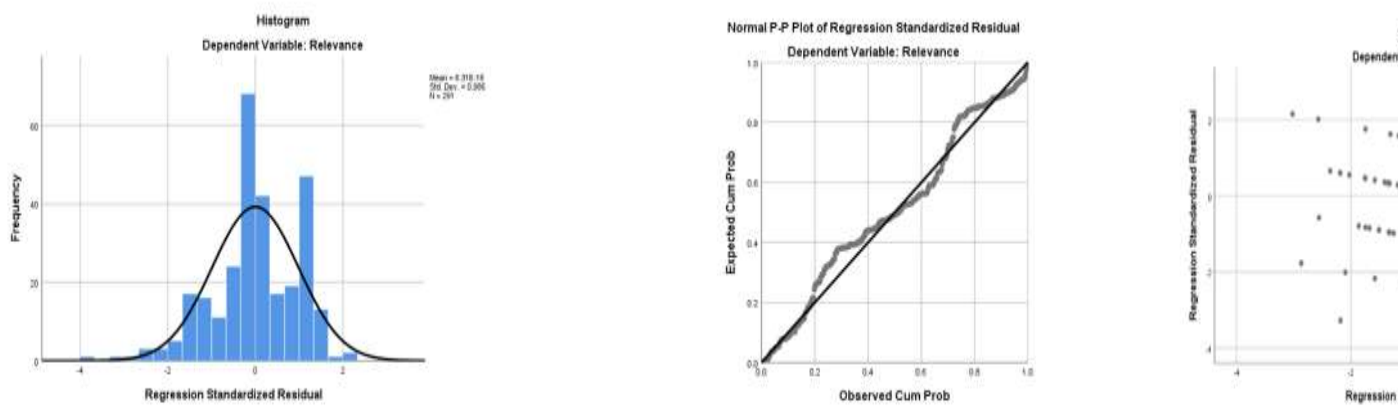
The findings revealed that AI adoption has a positive and statistically significant effect on the relevance of higher education (β = .220, $p < .001$). This suggests that universities with higher levels of AI integration are better positioned to align their educational programs with emerging technological trends and labor market demands. The descriptive results further showed strong agreement among respondents that AI contributes to curriculum modernization, student engagement, career planning, and evidence-based decision-making. These findings are consistent with the work of Holmes et al. (2019), who argued that AI can enhance the responsiveness of higher education institutions by enabling personalized learning and supporting data-driven educational planning. Similarly, Zawacki-Richter et al. (2019) found that AI technologies help universities adapt to rapidly changing knowledge economies and workforce requirements. The finding also supports the Technology Acceptance Model (TAM), which suggests that perceived usefulness encourages technology adoption and improves organizational outcomes. The positive relationship observed in this study indicates that AI is increasingly viewed as a strategic tool for ensuring the relevance of Ethiopian higher education institutions. As universities face growing pressure to prepare graduates for digitally driven workplaces, AI can support curriculum innovation, labor market alignment, and informed institutional decision-making. The analysis further shows that respondents' digital preparedness, measured through perceived adequacy of digital tool training (β = .160, p = .007) and frequency of digital tool usage (β = .124, p = .036), also contributed positively to perceptions of higher education relevance. However, their effects were smaller than that of AI adoption. Other control variables, including institution, educational level, current role, and internet access, did not have statistically significant effects on the dependent variable.

3.5. Assumption of Linear Regression

The regression diagnostic plots were examined to evaluate the normality of residuals and the homoscedasticity assumption of the regression model, where the dependent variable is Relevance of Higher Education. The results indicate that the model assumptions are adequately satisfied.

Figure 1: Diagnostic Plots for Regression Assumption Testing



The histogram and Normal P-P Plot show that the standardized residuals are approximately normally distributed, with residuals centred around zero and most points following the expected diagonal line. The scatterplot shows a random distribution of residuals around the zero line without a clear pattern, indicating that the variance of errors is relatively constant and the homoscedasticity assumption is supported.

3.6. AI and the Quality for Higher Education

The following table presents the results of the multiple regression analysis examining the impact of AI adoption on the quality of higher education. The analysis was conducted to determine whether the level of AI adoption significantly influences perceptions of educational quality while controlling for selected demographic and digital readiness variables. Standardized beta coefficients, t-values, and significance levels were used to assess the magnitude and significance of the relationships.

Table 6: Regression Result

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3.735	.395		9.464	.000		
	AI Adoption Level	.086	.048	.113	1.794	.074	.852	1.174
	Institution of respondents	-.029	.040	-.042	-.713	.476	.960	1.042
	What is your highest level of education?	.055	.050	.068	1.106	.270	.889	1.124
	What is your current role at the institution?	.017	.069	.015	.251	.802	.949	1.054
	What is your primary mode of accessing digital resources?	-.073	.039	-.111	-1.865	.063	.958	1.044
	How often do you use digital tools in your daily tasks	.070	.037	.116	1.923	.055	.928	1.078
	Do you have	-.105	.082	-.077	-1.277	.203	.935	1.070

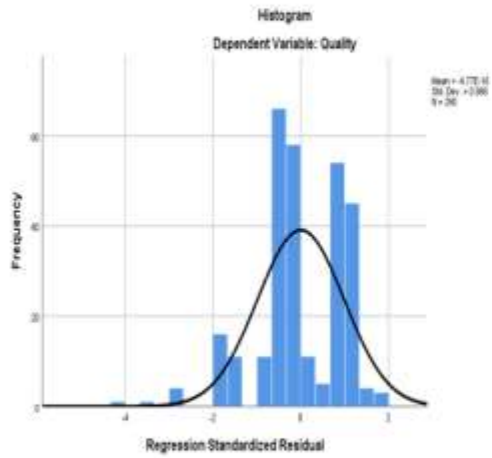
	access to a stable internet connection at your institution							
	Do you feel adequately trained to use digital tools relevant to your role	.101	.048	.127	2.101	.037	.928	1.078
a. Dependent Variable: Quality								

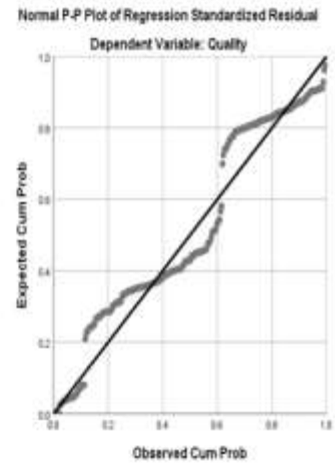
The study found that AI adoption positively influences the quality of higher education (β = .113, p = .074), although the relationship was significant only at the 10 percent level. Respondents strongly agreed that AI improves personalized learning, supports virtual laboratories, enhances student support services, and strengthens research through big data analytics. This finding aligns with the literature suggesting that AI can improve educational quality by enabling adaptive learning environments and individualized instructional support. For example, Luckin (2018) emphasized that AI-driven systems can tailor educational experiences to learners' needs, thereby improving learning outcomes. Likewise, Chen et al. (2020) reported that AI-based learning systems enhance student performance through personalized recommendations and timely feedback. However, the relatively weaker statistical significance may reflect the limited institutional capacity and AI expertise reported by respondents. Only a minority had received formal AI training, suggesting that the full benefits of AI for educational quality may not yet have been realized in Ethiopian universities. This finding supports previous studies that emphasize the importance of faculty competence, digital infrastructure, and institutional readiness for successful AI implementation. Among the control variables, perceived adequacy of training in digital tools relevant to respondents' roles had a positive and statistically significant effect on the quality of higher education (β = .127, p = .037). This finding suggests that respondents who feel adequately trained in digital technologies are more likely to perceive higher levels of educational quality. Other variables, including institution, educational level, current role, frequency of digital tool use, access to a stable internet connection, and primary mode of accessing digital resources, did not have statistically significant effects on the quality of higher education. Although frequency of digital tool use (p = .055) and primary mode of accessing digital resources (p = .063) were close to the significance threshold, their effects were not statistically significant.

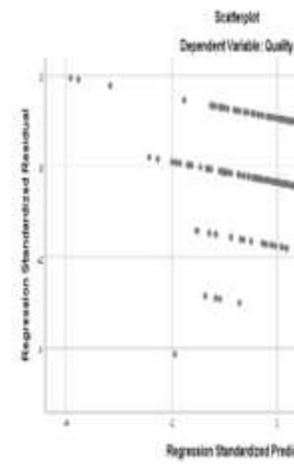
Regression Assumption Testing

The assumptions of normality and homoscedasticity for the regression model were assessed using a histogram, a Normal P–P plot, and a scatterplot of standardized residuals for the dependent variable Quality.

Figure 2: Diagnostic Plots for Regression Assumption Testing of the Quality Regression Model







The diagnostic plots indicate that the regression assumptions are reasonably satisfied. The histogram shows that the standardized residuals are approximately normally distributed (Mean = –4.77E–16; SD = 0.986), while the Normal P–P plot demonstrates that most observations closely follow the diagonal reference line with only minor deviations. Similarly, the scatterplot shows a random dispersion of residuals around the zero line without a clear funnel-shaped pattern, suggesting that the homoscedasticity assumption is also met. Overall, these results support the validity and reliability of the regression model for the Quality variable.

3.7. AI and Accessibility in Higher Education

The following table presents the results of the multiple regression analysis examining the effect of AI adoption on the accessibility of higher education. The analysis was conducted to determine whether the level of AI adoption significantly influences perceptions of accessibility while controlling for selected demographic characteristics and digital readiness variables. Standardized beta coefficients, t-values, significance levels, and collinearity statistics were used to assess the strength, direction, and significance of the relationships among the variables.

Table 7: Regression Result

Coefficients[a]							
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinea Statisti
		B	Std. Error	Beta			Tolerance
1	(Constant)	.952	.403		9.811	.000	
	AI Adoption Level	116	.048	.151	2.420	.016	.845
	Institution of respondents	034	.041	.050	.848	.397	.959
	What is your highest level of education?	.047	.050	-.058	-.950	.343	.885
	What is your current role at the institution?	.037	.069	-.031	-.534	.594	.962
	What is your primary mode of accessing digital resources?	.119	.040	-.175	-2.987	.003	.961
	How often do you use digital tools in your daily tasks	116	.038	.185	3.079	.002	.910

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	Do you have access to a stable internet connection at your institution	.175	.092	-.114	-1.905	.058	.914
	Do you feel adequately trained to use digital tools relevant to your role	056	.049	.068	1.125	.262	.910
a. Dependent Variable: Accessibility							

The results showed that AI adoption has a positive and statistically significant effect on accessibility (β = .151, p = .016). Respondents strongly agreed that AI expands educational opportunities for remote learners, supports multilingual education, provides continuous academic assistance, and enhances learning opportunities for students with disabilities. This finding is consistent with previous research highlighting AI's role in promoting educational inclusion. UNESCO (2021) noted that AI technologies can improve educational access through adaptive learning platforms, automated translation systems, and assistive technologies. Similarly, Tuomi (2018) argued that AI has the potential to democratize access to education by overcoming geographical, linguistic, and physical barriers. The Ethiopian context further reinforces the importance of AI for accessibility. Given the geographical dispersion of learners and variations in educational resources across regions, AI-enabled learning platforms can help bridge access gaps and support lifelong learning opportunities. The findings therefore suggest that AI can serve as a powerful mechanism for advancing equitable and inclusive higher education. Among the control variables, **frequency of digital tool use in daily tasks** emerged as the strongest positive predictor of accessibility (**β = .185, t = 3.079, p = .002**). This result indicates that respondents who frequently utilize digital technologies are more likely to perceive higher levels of educational accessibility. In contrast, **the primary mode of accessing digital resources** showed a negative and statistically significant relationship with accessibility (**β = -.175, t = -2.987, p = .003**), suggesting that certain modes of digital access may be associated with lower perceptions of accessibility. Additionally, **access to a stable internet connection** demonstrated a negative relationship that was marginally significant at the 10 percent level (**β = -.114, p = .058**). However, other variables, including institution, educational level, current role, and perceived adequacy of digital tool training, did not have statistically significant effects on accessibility. The collinearity statistics indicate no multicollinearity concerns, as all tolerance values exceed 0.10 and all VIF values are well below the commonly accepted threshold of 10. Overall, the findings suggest that AI adoption plays a significant role in enhancing the accessibility of higher education. The results further highlight the importance of regular digital technology use in supporting accessible educational environments, while also emphasizing the need to address barriers associated with different modes of digital access.

Regression Assumption Testing

The assumptions of normality and homoscedasticity were assessed using the histogram, Normal P–P plot, and scatterplot of standardized residuals for the Accessibility model. The results are presented in Figure below.

Figure 3: Diagnostic Plots for Regression Assumption Testing

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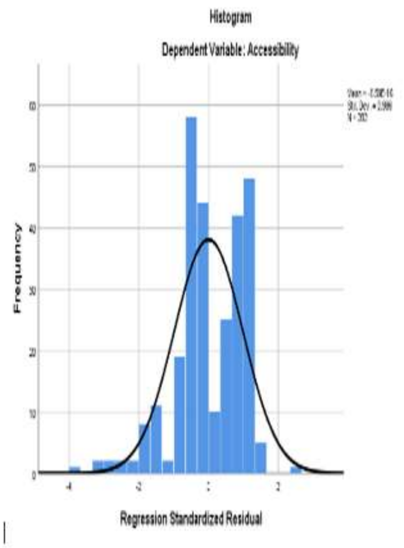

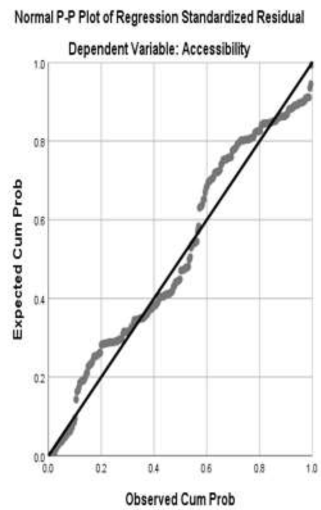

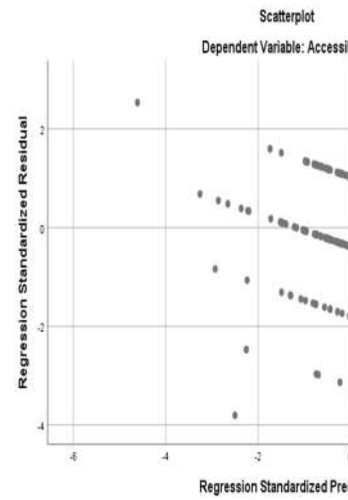

As shown in Figure 7, the histogram indicates that the standardized residuals are approximately normally distributed (Mean = –6.59E–16; SD = 0.986), while the Normal P–P plot shows that most observations closely follow the diagonal reference line with only minor deviations. The scatterplot also demonstrates a random distribution of residuals with no clear funnel-shaped pattern, indicating that the assumption of homoscedasticity is satisfied. Overall, the diagnostic plots confirm that the regression assumptions are reasonably met, supporting the validity of the regression analysis.

4. Conclusion and Recommendation

4.1. Conclusion

This study examined the effect of Artificial Intelligence (AI) adoption on higher education outcomes, specifically relevance, quality, and accessibility, in Ethiopian public universities. The findings demonstrate that respondents generally hold positive perceptions regarding the role of AI in transforming higher education. AI was perceived as a valuable tool for modernizing academic programs, supporting data-driven decision-making, enhancing student engagement, facilitating personalized learning, strengthening research capabilities, expanding educational access, and promoting inclusivity for diverse groups of learners.

The regression analysis revealed that AI adoption has a positive and statistically significant effect on the relevance of higher education. This suggests that increased integration of AI technologies contributes to aligning educational programs and learning experiences with emerging technological developments, labor market demands, and societal needs. The findings also showed that AI adoption has a positive and statistically significant effect on the accessibility of higher education, indicating that AI-enabled technologies support flexible learning opportunities, continuous academic support, multilingual education, and inclusive learning environments. Furthermore, AI adoption demonstrated a positive relationship with the quality of higher education. Although the effect was statistically significant only at the 10 percent level, the results provide evidence that AI has the potential to improve educational quality through personalized learning, enhanced research capabilities, and targeted student support mechanisms.

Overall, the study concludes that AI adoption is an important contributor to improving higher education outcomes in Ethiopian public universities. The findings suggest that universities that effectively integrate AI technologies are more likely to enhance the relevance, quality, and accessibility of higher education. Therefore, strengthening AI adoption through improved digital infrastructure, institutional readiness, capacity-building initiatives, and supportive policy frameworks can play a significant role in advancing the effectiveness and inclusiveness of higher education in Ethiopia. Furthermore, the study contributes to the growing body of knowledge on AI in higher education and provides empirical evidence that can inform policymakers, university leaders, and other stakeholders seeking to leverage AI technologies for educational transformation.

4.2. Recommendation

The findings indicate that Ethiopian public universities should strengthen the integration of Artificial Intelligence (AI) into teaching, learning, research, and institutional management. This requires improving digital infrastructure, expanding access to AI-enabled learning technologies, and providing continuous capacity-building programs to enhance the AI competencies of academic staff, administrators, and students.

The Ministry of Education and other relevant stakeholders should establish clear policies, ethical guidelines, and sustainable investment strategies to support the responsible adoption of AI in higher education. Strengthening institutional readiness and digital transformation initiatives will enhance educational quality, relevance, and accessibility across public universities.

Future research should examine the long-term effects of AI adoption using longitudinal and comparative studies and explore its influence on broader higher education outcomes, including student performance, graduate employability, research productivity, innovation, and institutional effectiveness.

4. Reference

[1]. Akinwalere, S.N. and Ivanov, V. (2022) 'Artificial intelligence in higher education: Challenges and opportunities', *Border Crossing*, 12(1), pp. 1–15. Available at: https://doi.org/10.33182/bc.v12i1.2015.
[2]. Almufarreh, A. and Arshad, M. (2023) 'Promising emerging technologies for teaching and learning: Recent developments and future challenges', *Sustainability*, 15(8), p. 6917. Available at: https://doi.org/10.3390/su15086917.
[3]. Alpaydin, E. (2020) *Introduction to machine learning*. 4th edn. Cambridge, MA: MIT Press.
[4]. Altbach, P.G., Reisberg, L. and Rumbley, L.E. (2019) *Trends in global higher education: Tracking an academic revolution*. Paris: UNESCO.
[5]. Bates, T. (2019) *Teaching in a digital age*. 2nd edn. Vancouver: Tony Bates Associates Ltd.
[6]. Bostrom, R.P. and Heinen, J.S. (1977) 'MIS problems and failures: A socio-technical perspective, part I: The causes', *MIS Quarterly*, 1(3), pp. 17–32.
[7]. Brennan, J. and Teichler, U. (2008) 'The future of higher education and of higher education research', *Higher Education*, 56(3), pp. 259–264.
[8]. Buelow, J.R., Barry, T. and Rich, L.E. (2018) 'Supporting learning engagement with the learning management system', *Online Learning*, 22(4), pp. 313–328.
[9]. Creswell, J.W. and Creswell, J.D. (2018) *Research design: Qualitative, quantitative, and mixed methods approaches*. 5th edn. Thousand Oaks, CA: SAGE Publications.
[10]. Dan, V., George, C. and Tin, L. (2024) 'Harnessing the power of artificial intelligence in education', *Article*, 0(0), p. 56.
[11]. Davis, F.D. (1989) 'Perceived usefulness, perceived ease of use, and user acceptance of information technology', *MIS Quarterly*, 13(3), pp. 319–340.
[12]. European Commission Joint Research Centre (2019) *The impact of artificial intelligence on learning, teaching, and education*. Available at: https://publications.jrc.ec.europa.eu/repository/handle/JRC113226.
[13]. Glickman, M. and Zhang, Y. (2024) 'AI and generative AI for research discovery and summarization', *Harvard Data Science Review*, 6(2). Available at: https://doi.org/10.1162/99608f92.7f9220.
[14]. Heredia-Carroza, J. and Stoica, R. (2023) 'Artificial intelligence in higher education: A literature review', *Journal of Public Administration, Finance and Law*, 30, pp. 97–113.
[15]. Hew, K.F., Huang, B., Chu, K.W.S. and Chiu, D.K. (2016) 'Engaging Asian students through game mechanics: Findings from two experimental studies', *Computers & Education*, 92, pp. 221–236.
[16]. Huisman, J. and Pausits, A. (eds.) (2010) *Higher education management and development: A compendium for managers*. Münster: Waxmann.
[17]. Jindal, P., Jain, V. and Rao, P.B. (2023) 'Study on utilizing ChatGPT for student engagement and educational support', *International Journal of Advance Research and Innovative Ideas in Education*, 9(6), pp. 1676–1677.
[18]. Legris, P., Ingham, J. and Collerette, P. (2003) 'Why do people use information technology? A critical review of the technology acceptance model', *Information & Management*, 40(3), pp. 191–204.
[19]. Ministry of Science and Higher Education (2022) *Higher education institutions in Ethiopia*.
[20]. Mumford, E. (2006) 'The story of socio-technical design: Reflections on its successes, failures and potential', *Information Systems Journal*, 16(4), pp. 317–342.
[21]. Ngoan, P.T. and Duc, N.M. (2021) 'Challenges and opportunities of implementing e-learning in teaching English at tertiary level from teachers' perspective', in *18th International Conference of the Asia Association of Computer-Assisted Language Learning (AsiaCALL–2-2021)*. Paris: Atlantis Press, pp. 168–175. Available at: https://doi.org/10.2991/assehr.k.210917.024.
[22]. OECD (2022) *What is higher education?* Available at: https://www.oecd.org/education/higher-education/.
[23]. Oyelere, S.S., Paliktzoglou, V. and Suhonen, J. (2019) 'M-learning in Nigerian higher education: An experimental study with Edmodo', *International Journal of*

Social Media and Interactive Learning Environments, 5(1), pp. 53–71.

[24]. Pasquale, F. (2020) *The black box society: The secret algorithms that control money and information*. Cambridge, MA: Harvard University Press.

[25]. Popenici, S.A. and Kerr, S. (2017) 'Exploring the impact of artificial intelligence on teaching and learning in higher education', *Research and Practice in Technology Enhanced Learning*, 12(1), pp. 1–13.

[26]. Rogers, E.M. (2003) *Diffusion of innovations*. 5th edn. New York: Free Press.

[27]. Russell, S.J. and Norvig, P. (2016) *Artificial intelligence: A modern approach*. 3rd edn. Harlow: Pearson.

[28]. Scherer, R., Siddiq, F. and Tondeur, J. (2019) 'The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education', *Computers & Education*, 128, pp. 13–35.

[29]. Semela, T. (2011) 'Breakneck expansion and quality assurance in Ethiopian higher education: Ideological rationales and economic impediments', *Higher Education Policy*, 24(3), pp. 399–425.

[30]. Subaveerapandiyan, A., Radhakrishnan, S., Tiwary, N. and Guangul, S.M. (2024) 'Student satisfaction with artificial intelligence chatbots in Ethiopian academia', *IFLA Journal*, pp. 1–15. Available at: https://doi.org/10.1177/03400352241252974.

[31]. Surry, D.W. and Farquhar, J.D. (1997) 'Diffusion theory and instructional technology', *Journal of Instructional Science and Technology*, 2(1).

[32]. Szeliski, R. (2010) *Computer vision: Algorithms and applications*. London: Springer.

[33]. Tadesse, T. (2014) 'Quality assurance in Ethiopian higher education: Boon or bandwagon in light of quality improvement?', *Journal of Higher Education in Africa*, 12(2), pp. 131–157.

[34]. Teferra, T. et al. (2018) *Ethiopian education development roadmap (2018–2030): An integrated executive summary*. Addis Ababa: Ministry of Education.

[35]. Thille, C. et al. (2014) 'The future of data-enriched assessment', *Research & Practice in Assessment*, 9, pp. 5–16.

[36]. Tiwari, C.K. et al. (2023) 'What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT', *Interactive Technology and Smart Education*. Available at: https://doi.org/10.1108/ITSE-04-2023-0061.

[37]. UNESCO (2015) *Rethinking education: Towards a global common good?* Paris: UNESCO.

[38]. UNESCO Institute for Statistics (2012) *International standard classification of education: ISCED 2011*. Montreal: UNESCO Institute for Statistics.

[39]. Venkatesh, V. and Davis, F.D. (2000) 'A theoretical extension of the technology acceptance model: Four longitudinal field studies', *Management Science*, 46(2), pp. 186–204.

[40]. Zawacki-Richter, O., Marín, V.I., Bond, M. and Gouverneur, F. (2019) 'Systematic review of research on artificial intelligence applications in higher education: Where are the educators?', *International Journal of Educational Technology in Higher Education*, 16(1), pp. 1–27.