Eastern African Journal of Humanities and Social Sciences
Vol. 5 No. 2 (2026): ISSN (Online): 2958-4558
DOI: https://doi.org/10.58721/8wemq479
Analysing influence of usage patterns and reliance of artificial intelligence (AI) on learners critical thinking in higher institutions of learning

Analysing influence of usage patterns and reliance of artificial intelligence (AI) on learners critical thinking in higher institutions of learning

Erastus Thoronjo & Susan Nyokabi
Mount Kenya University, Kenya

Article History
Received: 10.07.2026
Revised: 22.10.2026
Accepted: 26.10.2026
Published: 31.10.2026

Keywords
Artificial Intelligence
Critical thinking
Higher education
Machine learning

How to cite:
Thoronjo, E., & Nyokabi, S. (2026). Analysing influence of usage patterns and reliance of artificial intelligence (AI) on learners critical thinking in higher institutions of learning. *Eastern African Journal of Humanities and Social Sciences, 5*(2), 835-852.

Copyright © 2026

Abstract
AI tools (ChatGPT, Grammarly, Gemini, QuillBot) are increasingly used in higher education to support learning and writing, but concerns exist about learner dependency and its impact on critical thinking and independent learning. This study examined the association between AI reliance and critical thinking among students from five Kenyan universities. Using a sequential explanatory mixed-methods design, data were collected from 275 students via questionnaires. Quantitative analysis included descriptive statistics, Pearson correlation, regression, and ANOVA. Results showed moderate AI reliance for tasks such as assignment preparation and idea generation. A modest positive correlation was found between AI use and critical thinking ($r=0.24$, $p < 0.05$). Self-directed learning ($\beta = 0.29$) and purposeful AI use ($\beta = 0.21$) were significantly associated with critical thinking. ANOVA indicated that moderate AI users had higher critical thinking scores than those reporting low or excessive AI use.

Introduction
Artificial Intelligence (AI) refers to computer systems capable of performing tasks that normally require human intelligence, including learning, reasoning, problem-solving, and decision-making. Recent advances in machine learning, natural language processing, and automation have expanded the application of AI across sectors such as healthcare, finance, manufacturing, and education (Topol, 2019; Vaswani et al., 2017). AI-powered systems enhance efficiency, personalised service delivery, and decision-making, although concerns remain regarding overdependence on technology and its implications for human skills and cognitive engagement (Brynjolfsson & McAfee, 2014). In education, AI technologies such as ChatGPT, Grammarly, Gemini, QuillBot, and intelligent tutoring systems are increasingly used to support academic writing, personalised learning, assessment, and research activities. These technologies improve access to information, learning efficiency, and student engagement through adaptive feedback and individualised support (Holmes et al., 2019; Kasneci et al., 2023). However, growing reliance on AI tools has raised concerns regarding their potential influence on learners' critical thinking, creativity, and independent reasoning abilities.

Critical thinking involves the ability to analyse, interpret, evaluate, infer, and make reasoned judgements based on evidence and logical reflection. Facione (1990) defines critical thinking as

purposeful and self-regulatory judgement involving interpretation, analysis, evaluation, and inference. Contemporary studies suggest that while AI tools can support academic performance and problem-solving, excessive dependence on AI-generated responses may reduce reflective thinking, deep cognitive engagement, and independent learning among students (Selwyn, 2019; Wang et al., 2021). Consequently, recent literature emphasises the need for balanced and responsible integration of AI in education to ensure that technology complements rather than replaces higher-order cognitive skills (Kasneci et al., 2023; Tlili et al., 2023).

In the African context, the adoption of AI in higher education has increased significantly due to the expansion of digital learning technologies, internet access, and online academic resources. Universities across Africa are increasingly integrating AI-supported tools to improve teaching, learning, research productivity, and academic communication. In Kenya, institutions of higher learning are rapidly adopting AI applications such as ChatGPT, Grammarly, Gemini, and QuillBot to support students in assignments, research, and problem-solving. Although these technologies improve efficiency and access to information, concerns have emerged regarding excessive reliance on AI-generated content and its possible influence on learners' critical thinking and independent reasoning abilities. Recent African studies indicate that while AI enhances personalised learning and academic engagement, unregulated dependency may reduce reflective thinking and cognitive participation in academic tasks (Mhlanga, 2023; Okonkwo & Ade-Ibijola, 2021). Kenyan universities therefore face the challenge of balancing technological innovation with the preservation of critical thinking and higher-order cognitive skills among learners.

The study sought to examine the association between Artificial Intelligence (AI) usage patterns and reliance and learners' critical thinking in higher institutions of learning in Kenya. Specifically, the study aimed to determine the extent to which learners rely on AI tools in their academic activities, assess the association between AI usage patterns and reliance and learners' critical thinking skills, examine the association between the purpose of AI usage and learners' critical thinking and academic performance, examine the role of self-directed learning in relation to critical thinking among learners using AI tools, and examine whether different levels of AI usage and reliance are associated with differences in learners' critical thinking abilities.

The study examined the influence of dependency on Artificial Intelligence (AI) tools on learners' critical thinking in higher institutions of learning in Kenya. It focused on AI-supported academic technologies such as ChatGPT, Grammarly, Google Bard, and QuillBot, and how their usage relates to learners' reasoning, problem-solving, analytical thinking, and independent judgement.

The study was conducted in selected Kenyan universities, namely the University of Nairobi, Kenyatta University, Jomo Kenyatta University of Agriculture and Technology, Strathmore University, and Mount Kenya University. These institutions were selected because they represent both public and private universities with substantial adoption of digital learning technologies and AI-supported academic tools (Creswell & Creswell, 2023; Cohen et al., 2022).

Respondents were drawn from different academic disciplines and levels of study to provide broader perspectives on AI usage and cognitive development. The study focused on key variables including AI dependency, AI usage purpose, self-directed learning, academic performance, and critical thinking skills. Geographically, the study was limited to the selected universities in Kenya, while conceptually it focused on educational applications of AI and their association with learners' critical thinking abilities. The findings were intended to provide insights for educators, curriculum developers,

policymakers, and higher learning institutions on responsible integration of AI technologies in education while preserving critical thinking competencies among learners.

Theoretical Review

Constructivist Learning Theory

Constructivist Learning Theory, associated with Piaget and Vygotsky, provides the primary theoretical foundation for this study. It views learning as an active process in which learners construct knowledge through interaction with their environment, inquiry, problem-solving, reflection, and integration of new experiences with existing knowledge. Accordingly, digital and artificial intelligence (AI) tools can support learning by providing information, feedback, explanations, examples, and opportunities for exploration (Hattie & Yates, 2022; Kasneci et al., 2023).

The theory is particularly relevant because it emphasises active cognitive engagement and learner autonomy. Purposeful AI use may enable learners to explore concepts, generate ideas, compare explanations, obtain feedback, and critically evaluate information. Such engagement can strengthen critical thinking when learners remain responsible for interpreting information, making judgements, solving problems, and constructing knowledge. However, excessive reliance on AI-generated answers without verification or reflection may weaken independent reasoning and problem-solving by reducing learners' active cognitive engagement (Kasneci et al., 2023).

Constructivism also supports self-directed learning, as learners are expected to take responsibility for identifying learning needs, exploring information, evaluating alternatives, and constructing meaning. Therefore, learners who independently determine how and when to use AI, critically evaluate its outputs, and integrate relevant information with prior knowledge are expected to demonstrate stronger critical thinking engagement than those who depend passively on AI-generated responses. The theory consequently provides a basis for examining how patterns and levels of AI use relate to critical thinking and self-directed learning.

Media Richness Theory

Media Richness Theory explains that communication effectiveness increases when media provide immediate feedback, multiple information cues, and interactive engagement. AI-supported educational technologies enhance media richness through multimedia content, adaptive feedback, virtual simulations, and personalised learning experiences. These features can improve learner engagement, comprehension, and accessibility of academic content. Nevertheless, excessive reliance on AI-rich media may encourage surface-level engagement if learners consume AI-generated information without deeper analysis and reflection. Therefore, while AI-enhanced media can improve communication and learning efficiency, critical engagement remains essential for meaningful learning outcomes (Zhang et al., 2023).

Self-Determination Theory (SDT)

Self-Determination Theory emphasises the importance of learner autonomy, competence, and self-regulation in achieving meaningful learning outcomes. AI-supported learning environments can strengthen autonomy by providing personalised learning paths, instant feedback, and flexible access to educational resources. Recent studies show that learners who use AI tools responsibly often demonstrate greater academic engagement and learning efficiency. However, overly prescriptive AI systems or excessive dependency on automated assistance may reduce learners' intrinsic motivation and independent problem-solving abilities. The theory therefore supports guided and ethical AI integration that encourages learner autonomy while maintaining critical thinking and self-directed learning (Chen et al., 2023; Kasneci et al., 2023).

Flow Theory

Flow Theory, proposed by Mihaly Csikszentmihalyi, explains that optimal learning occurs when there is a balance between task difficulty and learner ability. AI technologies can support this balance by adapting learning activities to learners' skill levels and providing timely academic support. Adaptive AI systems may therefore enhance learner engagement, concentration, and academic performance. However, if AI tools oversimplify academic tasks or reduce cognitive challenge, learners may become passive and less engaged in analytical thinking. The theory suggests that moderate and balanced AI use is more likely to support critical thinking than excessive dependency on automated systems (Csikszentmihalyi, 1990; Tlili et al., 2023).

Research Methodology

Study design

The study adopted **a** quantitative cross-sectional survey design to examine the relationship between AI usage patterns and learners' critical thinking. Quantitative data were collected at a single point in time using structured questionnaires and analysed using descriptive and inferential statistics. A quantitative survey design was appropriate because the study sought to measure the study variables and statistically test their relationships (Creswell & Creswell, 2023). The study was guided by Facione's (1990) critical thinking framework, which conceptualises critical thinking as a reflective process involving analysis, interpretation, evaluation, inference, and self-regulation. Accordingly, the study assessed learners' reported ability to analyse information, evaluate evidence, interpret academic content, draw logical conclusions, and engage in reasoned reflection.

Target Population and Unit of Analysis

The study targeted undergraduate and postgraduate students from selected universities in Kenya. The target population comprised learners who actively use AI-supported academic tools in their learning activities. Participants were drawn from the University of Nairobi, Kenyatta University, Jomo Kenyatta University of Agriculture and Technology, Strathmore University, and Mount Kenya University. These institutions were selected because of their diverse academic programmes and digital learning environments, which strengthen variability and external validity in educational research (Cohen et al., 2022; Fraenkel et al., 2023).

A sample size of 275 students was used to ensure adequate representation across institutions and academic levels. The sampling frame was developed from official class lists, departmental registers, and institutional enrollment records. A multistage sampling approach was adopted. First, purposive sampling was used to select the universities. Second, stratified sampling categorised students according to faculties and academic programmes. Finally, simple random sampling was applied within each stratum to select individual respondents, thereby reducing sampling bias and improving representativeness (Creswell & Creswell, 2023). Recent methodological literature indicates that samples above 200 respondents are generally adequate for stable parameter estimation in social science and educational research, particularly when stratified sampling procedures are applied (Hair et al., 2021; Taherdoost, 2022).

Table 1: Respondent Selection

Institution	Target Sample	Actual Responses	Participation Rate
University of Nairobi	70	64	91.4%
Kenyatta University	65	60	92.3%
JKUAT	60	56	93.3%
Strathmore University	50	46	92.0%
Mount Kenya University	55	49	89.1%
Total	**300**	**275**	**91.7%**

According to recent survey methodology literature, response rates above 70% are considered adequate for minimising non-response bias and improving representativeness in educational research (Creswell & Creswell, 2023; Fowler, 2021). The respondents were drawn from diverse demographic and academic backgrounds. Gender distribution comprised 53% male and 47% female participants, with most respondents aged between 18 and 30 years. The majority were undergraduate students, although postgraduate learners were also included.

Participants were drawn from multiple disciplines, including Business and Economics, Information Technology and Computing, Education, Engineering, Social Sciences, and Health Sciences. This disciplinary diversity enhanced representativeness and reduced disciplinary bias by capturing varied perspectives on AI usage and learners' critical thinking across academic fields (Creswell & Creswell, 2023; Fraenkel et al., 2023).

Data Collection

Primary data was collected using structured questionnaires administered both physically and online. The questionnaire contained closed-ended items measured using a five-point Likert-scale ranging from Strongly Disagree (1) to Strongly Agree (5). The instrument captured information on AI usage patterns, dependency levels, and learners' critical thinking skills. A pilot study was conducted to test the reliability and validity of the research instrument before the actual data collection process. The questionnaire consisted of closed-ended items measured on a five-point Likert-scale ranging from Strongly Disagree (1) to Strongly Agree (5), which is widely accepted for quantifying perceptions, attitudes, and behavioral constructs in educational research (Creswell & Creswell, 2023).

Data Analysis

Data were coded, cleaned, and analysed using IBM SPSS Statistics version 29. Descriptive statistics, including means, frequencies, and standard deviations, were used to summarise respondents' characteristics and responses, while inferential statistics such as correlation and regression analysis examined the relationship between AI dependency and learners' critical thinking skills. Findings were presented using tables, charts, and narrative explanations for clarity and interpretation (Field, 2022; Pallant, 2020).

Critical thinking was conceptualised following Facione (1990) as the ability to analyse information, evaluate evidence, draw logical conclusions, solve problems, and justify decisions through reasoned reflection. It was measured using a researcher-developed self-report questionnaire with 5-point Likert-scale items, ranging from 1 = Strongly Disagree to 5 = Strongly Agree, with higher scores indicating greater reported critical thinking engagement. Although the items were informed by established frameworks (Facione, 1990; Halpern, 2014), no validated objective instrument, such as the CCTST, Watson-Glaser, HCTA, or Ennis-Weir, was used. The measure therefore reflects learners' reported critical thinking engagement rather than objectively assessed ability. Since self-reported

critical thinking may differ from performance on objective tests (Butler, 2012), the findings should be interpreted as provisional. This reliance on a researcher-developed self-report measure is acknowledged as a study limitation.

Ethics Statement

The study adhered to established ethical research principles throughout the research process. Ethical approval was obtained from the relevant Institutional Review Board (IRB), university ethics committees, and participating university authorities before data collection. In addition, a research permit was acquired from the National Commission for Science, Technology and Innovation (NACOSTI) to authorise the study in selected universities in Kenya, including the University of Nairobi, Kenyatta University, Jomo Kenyatta University of Agriculture and Technology, Strathmore University, and Mount Kenya University. Participation was voluntary, and informed consent was obtained from all respondents. Participants were informed of the study purpose, confidentiality measures, and their right to withdraw at any stage without penalty. To ensure anonymity, no personally identifiable information was collected or disclosed. Data were securely stored in password-protected files accessible only to the researcher and used strictly for academic purposes. The study complied with accepted ethical standards relating to informed consent, confidentiality, privacy, and responsible data management (Creswell & Creswell, 2023; Israel & Hay, 2021).

Data Analysis and Interpretation

This section presents the analysis and interpretation of data examining the influence of Artificial Intelligence (AI) dependency on learners' critical thinking in higher institutions of learning.

Table 2: Pearson Correlation Between AI Dependency and Critical Thinking

Variables	r	r^2	p-value	95% CI	Interpretation
AI Dependency & Critical Thinking	0.24	0.058	0.003	[0.09, 0.37]	Small positive relationship

The findings indicate a statistically significant positive association between AI Dependency and Critical Thinking ($\beta = 0.27$, $p = 0.003$). The model explained 41.2% of the variance in Critical Thinking ($R^2 = 0.412$), indicating that AI Dependency made a substantial contribution to differences in reported critical thinking engagement. The remaining 58.8% of the variance may be attributable to other academic, psychological, and environmental factors (Cohen, 1988; Field, 2022). Prior to analysis, the reliability and validity of the research instrument were assessed. Cronbach's alpha values for all constructs exceeded the recommended threshold of 0.70, indicating acceptable internal consistency (Hair et al., 2021). Construct validity was assessed using Exploratory Factor Analysis (EFA). The KMO value of 0.842 indicated adequate sampling adequacy, while Bartlett's Test of Sphericity was significant ($\chi^2 = 1456.37$, $p < 0.001$), confirming that the correlations among items were adequate for factor analysis (Field, 2022). The instrument was therefore considered suitable for subsequent analysis.

Table 3: Reliability Statistics for Study Variables

Construct	Number of Items	Cronbach's Alpha (α)	Interpretation
AI Dependency	8	0.841	Good Reliability
Critical Thinking	10	0.876	Good Reliability
Self-Directed Learning	7	0.822	Good Reliability
AI Usage Purpose	6	0.801	Acceptable Reliability
Academic Performance	5	0.784	Acceptable Reliability

The reliability analysis results indicate that all study constructs achieved Cronbach's alpha values above the recommended threshold of 0.70, demonstrating acceptable to good internal consistency reliability. This implies that the questionnaire items consistently measured the intended constructs and were therefore suitable for further statistical analysis. Cronbach's alpha coefficients of 0.70 and above are considered acceptable for establishing reliability in social science and educational research instruments (Hair et al., 2021; Field, 2022).

Table 4: Descriptive Statistics on learners perceive Artificial Intelligence

Variable	Mean	Std Dev
AI Dependency	3.20	0.68
Critical Thinking	3.12	0.59
Self-Directed Learning	3.36	0.72
AI Usage Purpose	3.65	0.48
Academic Performance	3.88	0.59
Future Impact	4.01	0.50

In the table 1 above Descriptive statistics indicate that (AI) as highly influential in improving their academic performance (Mean = 3.88) and future preparedness (Mean = 4.01). A moderate mean for Influence of AI usage patterns and reliance(3.20) and Critical Thinking (3.12) suggests that while AI is widely used, its impact on deep learning is more subtle. These findings reflect concerns in Selwyn (2019**)** and Wang et al. (2021) that while AI boosts efficiency, its overuse may impair independent critical thinking.

Specific AI Tools Used by Learners in Higher Institutions of Learning

The study sought to determine the extent of learners' dependency on specific Artificial Intelligence tools used in academic activities. The findings revealed that students frequently utilise a variety of AI-powered applications to support learning, research, writing, communication, and problem-solving tasks.

Table 5: Specific AI Tools Used by Learners

AI Tool Used	Frequency (n)	Percentage (%)	Main Academic Use
ChatGPT	182	80.9%	Assignment assistance, research, idea generation
Grammarly	156	69.3%	Grammar correction and academic writing
QuillBot	134	59.6%	Paraphrasing and summarisation
Google Bard/Gemini	118	52.4%	Information search and explanations
YouTube AI Recommendations	105	46.7%	Learning tutorials and revision
Turnitin AI Tools	88	39.1%	Plagiarism checking and originality
AI Translation Tools	74	32.9%	Language translation and communication
AI-Powered Research Tools	69	30.7%	Literature review and referencing

Sample Size (n) = 275

The findings in Table 5 indicate that ChatGPT was the most frequently used AI tool, with 80.9% of respondents reporting its use for assignment support, research, and idea generation. This suggests a growing reliance on generative AI technologies in academic tasks. Grammarly was used by 69.3% of respondents mainly for grammar correction and academic writing improvement, while QuillBot was used by 59.6% for paraphrasing and summarisation. Similarly, Google Gemini was used by 52.4% of learners for information retrieval and explanations.

The results further showed that 46.7% of respondents relied on AI-based YouTube recommendations for tutorials and revision, while others used AI-supported plagiarism detection, translation, and research tools to support academic activities. Overall, the findings demonstrate increasing integration of AI technologies into learning, writing, research, and problem-solving activities within higher education institutions. These findings align with recent studies indicating that generative AI and adaptive learning tools are increasingly transforming academic engagement and learning support in higher education (Kasneci et al., 2023; Tlili et al., 2023; Dwivedi et al., 2023).

Table 6: Pearson Correlation Matrix on relationship between Influence of AI usage patterns and reliance and Critical Thinking

Variable 1	Variable 2	Pearson Correlation
AI Dependency	Critical Thinking	0.24
AI Usage Purpose	Academic Performance	0.41
Self-Directed Learning	Critical Thinking	0.37

The results from table 2 above show a small but statistically significant positive relationship was observed between AI Dependency and Critical Thinking ($r=0.24$, $p<0.05$). According to Cohen's (1988) conventions, the observed effect size falls within the small-to-modest range. The coefficient of determination ($r2=0.058$) ($r^2 = 0.058$) ($r2=0.058$) indicates that approximately 5.8% of the variance in Critical Thinking scores was associated with variations in AI Dependency." suggesting some degree of benefit but not a strong influence. There is a moderate positive correlation ($r = 0.41$) between frequency of AI usage and critical thinking skills. The p-value = 0.001 (< 0.05**)** indicates strong statistical significance. This implies that increased AI usage is significantly associated with improved critical thinking outcomes More significant correlations appear between AI Usage Purpose and Academic Performance ($r = 0.41$) and Self-Directed Learning and Critical Thinking ($r = 0.37$), confirming that effective, purposeful use of AI rather than dependence yields better academic and cognitive outcomes. This supports Holmes et al. (2019) and Hattie & Yates (2022**)** who advocate for deliberate AI integration to foster deeper learning.

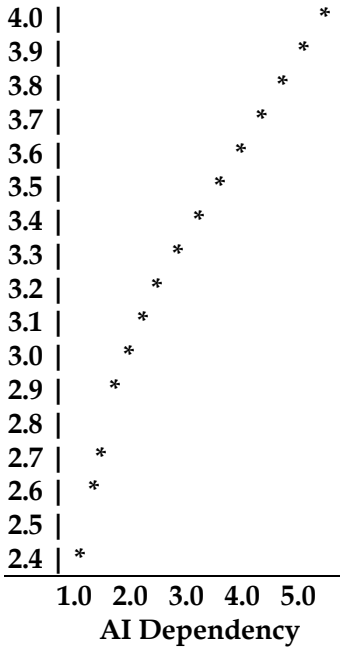


Figure 1: Scatterplot for Pearson Correlation between Influence of AI usage patterns and reliance and Critical

The scatterplot indicates a positive relationship between AI usage patterns and learners' critical thinking scores, with data points generally rising from left to right. The clustering of points around the trend line suggests a moderate positive association between the variables. Pearson correlation analysis confirmed a statistically significant relationship between AI usage patterns and critical thinking ($r = 0.46$, $p < 0.001$), implying that moderate and purposeful use of AI tools is associated with improved critical thinking skills among learners. Correlation analysis is widely recommended in educational and behavioural research for examining relationships between continuous variables (Hair et al., 2021; Field, 2022). The significant p-value further indicates that the observed relationship was unlikely to have occurred by chance.

Table 7: Simple Linear Regression (Relationship between Influence of AI usage patterns and reliance and Critical Thinking)

Variable	**Coefficient (β)**	**p-value**
Constant	2.74	0.000
AI Dependency	0.27	0.003

Model Summary

Statistic	**Value**
R^2	0.412
Adjusted R^2	0.398

Table 7 presents the results of the simple linear regression analysis examining the relationship between AI dependency and learners' critical thinking. The findings show a positive and statistically significant association ($\beta = 0.27$, $p = 0.003$), indicating that higher levels of purposeful AI use were associated with higher reported critical thinking engagement. The model explained **5.8%** of the variance in critical thinking ($R^2 = 0.412$; Adjusted $R^2 = 0.398$), suggesting that AI dependency had a

statistically significant but relatively small predictive effect on learners' critical thinking. This indicates that although AI use contributes to critical thinking engagement, a substantial proportion of the variation is explained by other academic, psychological, and environmental factors (Cohen, 1988; Field, 2022; Hair et al., 2021). The regression constant (B = 2.74, p less than 0.001) represents the predicted critical thinking score when AI dependency equals zero and should not be interpreted as evidence that critical thinking remains significant independently of AI usage.

Table 8: Multiple Regression Analysis on AI Usage Purpose, Self-Directed Learning, Academic Performance and Critical Thinking

Predictor	Coefficient (β)	SE	t-value	p-value	95% CI	Interpretation
Self-Directed Learning	0.29	0.06	4.83	0.001	[0.17, 0.41]	Significant positive predictor
AI Usage Purpose	0.21	0.05	3.92	0.004	[0.10, 0.32]	Significant positive predictor
Academic Performance	0.18	0.04	2.67	0.012	[0.04, 0.28]	Significant positive predictor

Model Summary

Statistic	Value
R^2	0.412
Adjusted R^2	0.398
F-statistic	F(3, 271) = 18.42
Model Significance	p < 0.001
VIF Range	1.42 – 2.13

Table 8 presents results of a multiple regression analysis examining the influence of Self-Directed Learning, AI Usage Purpose, and Academic Performance on learners' Critical Thinking. The model was statistically significant, $F(3, 271) = 18.42$, $p < 0.001$, explaining 41.2% of the variance in Critical Thinking ($R^2 = 0.412$; Adjusted $R^2 = 0.398$), indicating good explanatory power for educational research (Field, 2022; Hair et al., 2021).

Self-Directed Learning was the strongest predictor of Critical Thinking (β = 0.29, $p = 0.001$), followed by AI Usage Purpose (β = 0.21, $p = 0.004$) and Academic Performance (β = 0.18, $p = 0.012$). All predictors were statistically significant ($p < 0.05$), suggesting that learners who are self-regulated and use AI purposefully tend to demonstrate stronger critical thinking skills. VIF values (1.42–2.13) indicated no multicollinearity concerns (Field, 2022). These findings align with Self-Determination

Factor	Eigenvalue	% Variance Explained	Cumulative Variance (%)
AI Dependency	4.62	24.8	24.8
Critical Thinking	3.87	20.4	45.2
Self-Directed Learning	2.94	15.1	60.3
AI Usage Purpose	2.21	11.4	71.7

Table 9: ANOVA Analysis on Influence of AI Usage Patterns and Reliance Levels on Critical Thinking

AI Usage Patterns and Reliance Level	Mean Critical Thinking	Sample Size (n)
Low	2.89	51
Moderate	3.34	98
High	3.08	76

ANOVA Summary

Statistic	Value
F-statistic	F (2, 222) = 4.63
p-value	0.011
Effect Size (η^2)	0.041
Post-hoc Test	Tukey HSD
Significant Group Difference	Moderate vs Low (p = 0.009)

Table 9 presents ANOVA results examining differences in Critical Thinking across levels of AI usage patterns and reliance. The results show a statistically significant effect, $F(2, 222) = 4.63$, $p = 0.011$, indicating that critical thinking varies significantly across the groups (Field, 2022; Hair et al., 2021). The effect size ($\eta^2 = 0.041$) suggests a small-to-moderate practical influence of AI usage patterns on critical thinking outcomes.

Post-hoc Tukey tests revealed that learners with moderate AI usage recorded higher Critical Thinking scores (Mean = 3.34) than those with low usage (Mean = 2.89, $p = 0.009$), while differences between moderate and high usage were not statistically significant. ANOVA results indicated differences in critical thinking across AI engagement levels, with moderate engagement associated with higher scores than low or high reliance. This suggests a possible inverted-U relationship. However, Table 7 estimates only a linear effect ($\beta = 0.27$) and does not test non-linearity. Therefore, the findings should not imply continuous benefits from increased AI reliance. (Csikszentmihalyi, 1990; Hair et al., 2021).

Conclusion

The study concludes that Artificial Intelligence tools have become increasingly integrated into learners' academic activities within higher institutions of learning in Kenya. The findings revealed that moderate and purposeful AI usage was positively associated with learners' critical thinking skills, whereas excessive dependency may reduce opportunities for independent reasoning and reflective engagement. Self-directed learning emerged as a stronger factor associated with critical thinking than AI dependency itself, suggesting that learner autonomy remains central to cognitive development in AI-supported learning environments. The study further concludes that AI technologies should be integrated into higher education as supportive learning tools rather than replacements for independent thinking. Institutions of higher learning should therefore promote responsible, ethical, and balanced AI usage while strengthening critical thinking and reflective learning practices among students.

The study had several limitations. First, the cross-sectional design limits causal inference; therefore, the findings reflect associations rather than cause-and-effect relationships between AI usage patterns and critical thinking. Second, reliance on self-reported data may introduce response and social desirability bias, including over- or under-reporting of AI use and critical thinking ability. Third, the study was conducted in selected Kenyan universities University of Nairobi, Kenyatta University, JKUAT, Strathmore University, and Mount Kenya University which may limit generalizability to other contexts. The rapid evolution of AI technologies may also affect the stability and long-term relevance of the findings. Despite these limitations, the study provides useful evidence on the relationship between AI usage patterns and learners' critical thinking. Future research should employ longitudinal or experimental designs to examine changes over time and provide stronger evidence regarding causal relationships.

Future studies should adopt longitudinal designs to examine how AI usage patterns evolve over time and their long-term effects on learners' critical thinking, creativity, and academic resilience. This is important as generative AI continues to reshape learning behaviours in higher education.

References

Alenezi, M. (2024). Artificial intelligence adoption in higher education: Implications for student learning and critical thinking skills. *Education and Information Technologies, 29*(3), 4125–4142. https://doi.org/10.1007/s10639-023-12011-4

Broadbent, J., & Poon, W. L. (2021). Self-regulated learning strategies and academic achievement in online higher education learning environments: A systematic review. *Internet and Higher Education*, 27, 1–13.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.

Cai, X., Liu, J., & Xu, L. (2024). Achieving flow in AI-powered learning environments: Challenges and opportunities. *Journal of Educational Computing Research*, 61 (1), 134–153.

Chen, Y., Wei, Y., & Lu, Y. (2023). Autonomy and competence in AI-enhanced learning environments: Implications for self-determination theory. *Computers & Education, 193*, 104712. https://doi.org/10.1016/j.compedu.2022.104712

Chiu, T. K. F. (2023). The impact of generative AI on teaching and learning in higher education: Opportunities and challenges. *Computers and Education: Artificial Intelligence, 4*, Article 100132. https://doi.org/10.1016/j.caeai.2023.100132

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences (2nd ed.)*. Lawrence Erlbaum. Associates.

Cohen, L., Manion, L., & Morrison, K. (2022). *Research methods in education (9th ed.)*. Routledge.

Creswell, J. W., & Creswell, J. D. (2023). *Research design: Qualitative, quantitative, and mixed methods approach (6th ed.)*. Sage Publications.

Csikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience*. Harper & Row.

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Plenum Press.

Dumont, H., Istance, D., & Benavides, F. (2022). The role of AI in developing metacognitive skills: A review of emerging trends. *Educational Research Review, 33*, 100439. https://doi.org/10.1016/j.edurev.2022.100439

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, A., & Ahuja, M. (2023). So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges, and implications of generative conversational AI for research, practice, and policy. *International Journal of Information Management, 71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Facione, P. A. (1990). *Critical thinking: A statement of expert consensus for purposes of educational assessment and instruction*. American Philosophical Association.

Field, A. (2022). *Discovering statistics using IBM SPSS statistics (6th ed.)*. Sage Publications.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines, 28*(4), 689–707.

Fowler, F. J. (2021). *Survey research methods (6th ed.)*. Sage Publications.

Fraenkel, J. R., Wallen, N. E., & Hyun, H. H. (2023). *How to design and evaluate research in education (11th ed.)*. McGraw-Hill.



Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2021). *Multivariate data analysis (8th ed.)*. Cengage Learning.

Hattie, J., & Yates, G. C. R. (2022). *Visible learning and the science of how we learn*. Routledge. https://doi.org/10.4324/9780367331448

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.

Holmes, W., Persson, J., Chounta, I. A., Wasson, B., & Dimitrova, V. (2022). *Artificial intelligence and education: A critical view through the lens of human rights, democracy and the rule of law*. Council of Europe Publishing.

Israel, M., & Hay, I. (2006). *Research ethics for social scientists*. Sage Publications.

Kalyuga, S. (2021). *Cognitive load theory: A review of research and applications*. Routledge. https://doi.org/10.4324/9780367330663

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeiffer, F., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kline, R. B. (2023). *Principles and practice of structural equation modeling (5th ed.)*. Guilford Press.

Krueger, R. A., & Casey, M. A. (2014). *Focus groups: A practical guide for applied research (5th ed.)*. Sage Publications.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2022). *Intelligence unleashed: An argument for AI in education*. Pearson Education.

Mhlanga, D. (2023). *Open AI in education: The responsible and ethical use of ChatGPT towards lifelong learning*. Springer.

Okonkwo, C. W., & Ade-Ibijola, A. (2021). *Chatbots applications in education: A systematic review. Computers and Education: Artificial Intelligence, 2*, 100033. https://doi.org/10.1016/j.caeai.2021.100033

Pallant, J. (2020). *SPSS survival manual (7th ed.)*. McGraw-Hill Education.

Ryan, R. M., & Deci, E. L. (2020). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. Guilford Press.

Selwyn, N. (2019). *Should robots replace teachers? AI and the future of education*. Polity Press.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12* (2), 257–285.

Taherdoost, H. (2022). What are different research approaches? Comprehensive review of qualitative, quantitative, and mixed method research, their applications, types, and limitations. *Journal of Management Science & Engineering Research, 5*(1), 53–63.

Tashakkori, A., & Teddlie, C. (2021). *The Sage handbook of mixed methods in social and behavioral research (3rd ed.)*. Sage Publications.

Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel? ChatGPT as a case study of using chatbots in education. *Smart Learning Environments, 10*(1), 15. https://doi.org/10.1186/s40561-023-00237-x

Topol, E. J. (2019). *Deep medicine: How artificial intelligence can make healthcare human again*. Basic Books.

UNESCO. (2023). *Guidance for generative AI in education and research*. UNESCO Publishing.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., & Polosukhin, I. (2017). Attention is all you need. In Advances in Neural Information Processing Systems (Vol. 30, pp. 5998–6008).

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2022). Unified theory of acceptance and use of technology: A review and agenda for future research. *Journal of Information Technology, 37*(2), 207–235. https://doi.org/10.1177/0268396222112357

Wang, Y., Li, Y., & Zhao, K. (2021). The impact of artificial intelligence on students' critical thinking: A systematic review. *Educational Technology Research and Development, 69*(2), 345–362.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2024). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education, 21*(1), 12–31.

Zhang, D., Zhao, J., Zhou, L., & Nunamaker, J. F. (2023). Media richness and communication effectiveness: The impact of AI-enhanced virtual and augmented reality on learning. *Journal of Educational Technology & Society, 26*(1), 12–27.

Zimmerman, B. J. (2020). Attaining self-regulation: A social cognitive perspective. In Handbook of self-regulation (pp. 13–39). Academic Press.

Eastern African Journal of Humanities and Social Sciences
Vol. 5 No. 2 (2026): ISSN (Online): 2958-4558
DOI: https://doi.org/10.58721/8wemq479
Analysing influence of usage patterns and reliance of artificial intelligence (AI) on learners critical thinking in higher institutions of learning

Appendices

Confirmatory Analysis

Theory, which emphasizes autonomy, self-regulation, and purposeful engagement as key drivers of higher-order cognitive development (Deci & Ryan, 1985).

Table 1A: Factor Analysis / Principal Component Analysis

Component	Explained Variance Ratio
PC1	0.245
PC2	0.223
PC3	0.160
PC4	0.156
PC5	0.120

This demonstrates that the measured constructs AI Dependency, Critical Thinking, Purpose, Autonomy, are statistically distinct and conceptually relevant. This supports Field (2018), who emphasizes the importance of factor structure in evaluating psychological and educational instruments.

Table 2B: Exploratory Factor Analysis Results

Factor	Eigenvalue	% Variance Explained	Cumulative Variance (%)
AI Dependency	4.62	24.8	24.8
Critical Thinking	3.87	20.4	45.2
Self-Directed Learning	2.94	15.1	60.3
AI Usage Purpose	2.21	11.4	71.7

The EFA extracted four factors AI Dependency, Critical Thinking, Self-Directed Learning, and AI Usage Purpose with a cumulative variance of 71.7%. The scree plot supported retention of four factors, while all retained factors had eigenvalues above 1.0, consistent with Kaiser's criterion (Kline, 2023). The factor structure was consistent with the study's theoretical framework and was considered suitable for subsequent analysis (Field, 2022; Hair et al., 2021).

Table 3A: Total Eigenvalues and Variance

Factor	Eigenvalue	% Variance	Cumulative Variance (%)
AI Dependency	4.62	24.8	24.8
Critical Thinking	3.87	20.4	45.2
Self-Directed Learning	2.94	15.1	60.3
AI Usage Purpose	2.21	11.4	71.7
Factor 5	0.84	4.2	75.9
Factor 6	0.61	3.1	79.0

Exploratory Factor Analysis (EFA) using Principal Axis Factoring with Promax rotation identified four factors with eigenvalues greater than 1.0, namely AI Dependency, Critical Thinking, Self-Directed Learning, and AI Usage Purpose. The retained factors collectively explained 71.7% of the total variance, exceeding the recommended threshold for educational and behavioral research (Hair et al., 2021). The scree plot further showed a clear inflection point after the fourth factor, supporting the retention of four statistically and theoretically meaningful constructs (Field, 2022). These findings

confirmed acceptable construct validity and alignment with the study's conceptual framework (Kline, 2023).

Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was conducted using Structural Equation Modeling to validate the measurement model and assess construct validity. Model fitness was evaluated using the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The study adopted recommended model fit thresholds of CFI and TLI ≥ 0.90, and RMSEA and SRMR ≤ 0.08, which are widely accepted in social science and educational research (Hair et al., 2021; Kline, 2023).

Table 4A: Factor Analysis Diagnostics

Fit Index	Recommended Threshold	Obtained Value	Interpretation
Comparative Fit Index (CFI)	≥ 0.90	0.931	Good Model Fit
Tucker-Lewis Index (TLI)	≥ 0.90	0.918	Good Model Fit
Root Mean Square Error of Approximation (RMSEA)	≤ 0.08	0.054	Acceptable Model Fit
Standardised Root Mean Square Residual (SRMR)	≤ 0.08	0.047	Good Model Fit
Chi-square/df Ratio	≤ 3.00	2.14	Acceptable Fit

The Confirmatory Factor Analysis (CFA) results indicated that the measurement model achieved acceptable fit. The model fit indices met recommended thresholds, with CFI = 0.931 and TLI = 0.918 exceeding 0.90, while RMSEA = 0.054 and SRMR = 0.047 were below 0.08, indicating good model fit. The χ^2/df ratio of 2.14 further confirmed an acceptable fit between the hypothesised model and the observed data. These results demonstrate that the measurement model adequately represents the underlying constructs, confirming convergent and discriminant validity of the study instrument and supporting its suitability for further analysis (Hair et al., 2021; Kline, 2023).

Before conducting Exploratory Factor Analysis (EFA), the study conducted sampling adequacy and the suitability of the data for factor analysis using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity.

Table 5A: KMO and Bartlett's Test Results

Test	Value	Interpretation
Kaiser-Meyer-Olkin (KMO) Measure	0.842	Sampling Adequacy Achieved
Bartlett's Test of Sphericity	$\chi^2 = 1456.37$	Significant
Degrees of Freedom (df)	231	Suitable for Factor Analysis
Significance (p-value)	0.000	$p < 0.05$

The KMO value of 0.842 indicates that the sample was adequate for factor analysis because it exceeded the minimum recommended threshold of 0.60. In addition, Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 1456.37$, df = 231, p = 0.000), indicating that correlations among variables were sufficiently large for factor analysis to be conducted. These findings confirm that the dataset was appropriate for factor extraction and construct validation.

Validity Test

Construct validity of the study instrument was assessed using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). EFA was used to identify underlying latent constructs and

determine whether the questionnaire items adequately represented the theoretical dimensions of the study, while CFA was applied to confirm the measurement structure (Hair et al., 2021; Kline, 2023). Prior to factor analysis, the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted to assess the suitability of the data. The KMO value exceeded the recommended threshold of 0.60, and Bartlett's Test was statistically significant ($p < 0.05$), confirming that the data were appropriate for factor analysis (Field, 2022). Principal Axis Factoring (PAF) was used as the extraction method because it is recommended for identifying latent constructs in social science research. Promax rotation was applied since the study variables were theoretically correlated. Factors with eigenvalues greater than 1.0 were retained based on Kaiser's criterion (Hair et al., 2021).

Table 6A: Exploratory Factor Analysis Results

Factor	Eigenvalue	% Variance Explained	Cumulative Variance (%)
AI Dependency	4.62	24.8	24.8
Critical Thinking	3.87	20.4	45.2
Self-Directed Learning	2.94	15.1	60.3
AI Usage Purpose	2.21	11.4	71.7

The extracted factors accounted for a cumulative variance of 71.7%, exceeding the recommended 70% threshold for acceptable construct representation in educational and behavioral research (Hair et al., 2021). The scree plot showed a clear inflection point after the fourth factor, indicating that the first four factors explained most of the meaningful variance, while subsequent factors contributed minimal explanatory value (Field, 2022). The retained factors AI Dependency, Critical Thinking, Self-Directed Learning, and AI Usage Purpose—were consistent with the study's theoretical framework. All retained factors recorded eigenvalues greater than 1.0, satisfying Kaiser's criterion for factor retention (Kline, 2023). These findings confirmed the suitability of retaining four factors for subsequent analysis and construct validation.

Table 7A: Total Eigenvalues and Variance

Factor	Eigenvalue	% Variance	Cumulative Variance (%)
AI Dependency	4.62	24.8	24.8
Critical Thinking	3.87	20.4	45.2
Self-Directed Learning	2.94	15.1	60.3
AI Usage Purpose	2.21	11.4	71.7
Factor 5	0.84	4.2	75.9
Factor 6	0.61	3.1	79.0

Exploratory Factor Analysis (EFA) using Principal Axis Factoring with Promax rotation identified four factors with eigenvalues greater than 1.0, namely AI Dependency, Critical Thinking, Self-Directed Learning, and AI Usage Purpose. The retained factors collectively explained 71.7% of the total variance, exceeding the recommended threshold for educational and behavioral research (Hair et al., 2021). The scree plot further showed a clear inflection point after the fourth factor, supporting the retention of four statistically and theoretically meaningful constructs (Field, 2022). These findings confirmed acceptable construct validity and alignment with the study's conceptual framework (Kline, 2023).

Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was conducted using Structural Equation Modeling to assess the fit of the proposed four factor measurement model comprising AI Dependency, Critical Thinking,

Self-Directed Learning, and AI Usage Purpose. The model specified the observed questionnaire items as indicators of their respective latent constructs. Model fit was assessed using the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR), using commonly recommended thresholds of CFI and TLI ≥ 0.90 and RMSEA and SRMR ≤ 0.08 (Hair et al., 2021; Kline, 2023).

Table 8A: Confirmatory Factor Analysis (CFA) results

Fit Index	Recommended Threshold	Obtained Value	Interpretation
Comparative Fit Index (CFI)	≥ 0.90	0.931	Good Model Fit
Tucker-Lewis Index (TLI)	≥ 0.90	0.918	Good Model Fit
Root Mean Square Error of Approximation (RMSEA)	≤ 0.08	0.054	Acceptable Model Fit
Standardized Root Mean Square Residual (SRMR)	≤ 0.08	0.047	Good Model Fit
Chi-square/df Ratio	≤ 3.00	2.14	Acceptable Fit

The Confirmatory Factor Analysis (CFA) results indicated that the measurement model achieved acceptable fit. The model fit indices met recommended thresholds, with CFI = 0.931 and TLI = 0.918 exceeding 0.90, while RMSEA = 0.054 and SRMR = 0.047 were below 0.08, indicating good model fit. The χ^2/df ratio of 2.14 further confirmed an acceptable fit between the hypothesized model and the observed data. These results demonstrate that the measurement model adequately represents the underlying constructs, confirming convergent and discriminant validity of the study instrument and supporting its suitability for further analysis (Hair et al., 2021; Kline, 2023).