**Role of Cognitive Offload as a mediator between AI Usage and the development of Critical Thinking skills amongst higher education learners in Cameroon**

**Abstract**

This study set out to investigate the role of cognitive offload as a mediator in the relationship between AI use and critical thinking. A sample was gotten from the students of HTTTC Kumba of the University of Buea for the academic year 2024/2025. Of the 450 copies of the questionnaire that was administered, 380 copies of the questionnaire was returned. Linear regression was done through the SPSS statistical package to get the mediation analysis and the Sobel test was used to verify the significance of the mediation effect. It was shown that AI usage is positively related to cognitive offload meanwhile cognitive offload and AI usage are negatively and inversely related to critical thinking. Meaning that the constant use of AI tools creates more cognitive capacity through cognitive offload. Moreover, as AI use and cognitive offload increases, critical thinking reduces. The results from the Sobel test further confirmed that the effect of AI use on critical thinking is partially mediated by cognitive offload. The results of this study bring awareness to university stakeholders to the mediating role of cognitive offload in the classroom. It is important for them to be aware of the potential negative consequences of AI use and ensure that students are still engaging in sufficient mental processing and developing metacognitive skills while using AI tools. It was recommended that teachers should balance the use of AI by integrating strategies that encourage deep thinking and cognitive engagement; receive training on use of AI and other technological tools such that they can reduce the negative effects of cognitive offload while improving the development of their cognitive abilities and create a learning environment where active learning and not just passive AI use is done in order to support the development of cognitive skills.

**Key words:** Cognitive Offload, AI Usage, Critical Thinking, higher education, cognitive development, mediation

**Introduction**

The advent of Artificial Intelligence (AI) has transformed innumerable sectors, education inclusive. The use of AI in the classroom has a great impact on the learner’s academic achievement by giving them many opportunities as well as challenges (Edtech, 2020). The effect of AI on education is revolutionary and multidimensional. AI enables personalized learning by adapting educational content to meet the unique needs of individual students (Hennekeuser et al., 2024). Nevertheless, not only positive educational outcomes are guaranteed by the adoption of AI tools (Castaneda & Selwyn, 2018).

Cognitive offloading can be defined as the use of physical action to alter the information processing requirements of a task so as to reduce cognitive demand (Risko & Gilbert, 2016). That is, using tools for externalizing cognitive process. With regard to the short term memory, cognitive offloading releases resources which otherwise would be required to actively hold information in short term representations. Instead, the corresponding information is externalised into technical tools such as mobile touch devices (Wilson, 2002).

Critical thinking is social and individual. Individual critical thinking is the ability to thoughtfully analyze and evaluate situations and recommend courses of action that consider stakeholders, implications, and consequences (Lovelace, et al., 2016), with emphasis on evaluating options using a range of different perspectives (Parks-Leduc, Mulligan & Rutherford, 2021). An important aspect of individual critical thinking is that it has both cognitive and affective components (Glaser, 1941). Thus, successful critical thinking requires not only being able to do the cognitive work but also having the interest and inclination to do so (Lindebaum & Fleming, 2024). On the contrary, social critical thinking involves reflecting critically upon, and challenging, the status quo of prevailing social and institutional arrangements (Huber & Knights, 2022). It includes the development of an awareness of social realities, and one’s ability to challenge and change these realities (Colombo, 2023).

The integration of AI in academic settings raises serious concerns related to equity, cognitive development, accessibility, and the changing role of traditional teaching strategies. Among such concerns is cognitive offloading.

Cognitive offloading, the process of transferring mental tasks from the brain to external devices or systems (Risko & Gilbert, 2016), can have both positive and negative effects on critical thinking. On the positive side, cognitive offloading can reduce the cognitive load on the brain, allowing individuals to focus on more complex tasks and engage in deeper thinking (Kahneman, 2011). This can lead to improved problem-solving skills and better decision-making.

However, there is also evidence to suggest that cognitive offloading can have negative effects on critical thinking. For example, research has shown that the use of AI-powered tools can lead to a reduction in attention span and a decrease in critical thinking skills (Krumhansel & Drucker, 2019). This may be because the use of AI can create a false sense of security, leading individuals to rely too heavily on the technology and not engage in sufficient mental processing.

Cognitive offloading by the use of AI entails delegating tasks like memory retention, decision-making, and information retrieval to external systems. This can improve cognitive capability by giving learners the opportunity to concentrate on more creative and demanding tasks. Nevertheless, this dependence on AI for cognitive offloading has tremendous consequences on cognitive capacity and critical thinking. Even though cognitive offloading provides more cognitive resources, it’s worrisome as it has the tendency to reduce cognitive effort, promoting ‘cognitive laziness’ (Carr, 2010).

Thus, a key challenge is making sure AI complements, rather than substitutes, human interaction. Even though AI automates tasks and makes available data-driven insights, it lacks the empathy, creativity, and nuanced understanding of human instructors (Holmes & Tuomi, 2022). Over-dependence on AI for evaluation and feedback can decrease chances for meaningful discussion and reflection, necessary for higher-order thinking (Facione, 2020).

Studies like Gerlich, (2025) have investigated how cognitive offload mediates the relationship between AI use and critical thinking. Gerlich (2025) found out that cognitive offload partially mediates the effect of AI use on critical thinking. Moreover, as AI use and cognitive offload increases, critical thinking reduces. This indicates that cognitive offload has a very vital role to play in understanding how AI use affects cognitive processes.

Such concerns prompted the researcher to investigate the effect of AI use on critical thinking with cognitive offload as a mediator.

Specifically the study had the following hypotheses:

1. AI usage influences Cognitive offload
2. Cognitive offload influences critical thinking
3. AI usage influences critical thinking
4. Cognitive offload mediates the effect of AI usage on critical thinking

The theoretical model can be found below.

Cognitive offload (CO)

(M)

**A B**

AI usage

(IV) X

Critical Thinking (CT)

(DV) Y

**C**

**Fig 1: Theoretical Model**

**Methodology**

**Research Design:**

A correlation research design was used to examine the likelihood of an association between AI usage, cognitive offload and critical thinking. To establish a theoretical model, AI usage was taken as an exogenous variable (independent) while Cognitive offload and Critical Thinking were endogenous variables (dependent variable) with Cognitive offload as the mediator variable.

**Sample and Population:**

This study was carried out in the Higher Technical Teacher’s Training College Kumba of the University of Buea. The target population was all the students in HTTTC Kumba. A sample of students was randomly selected and administered the questionnaire to.

**Sampling Procedure:**

The researcher, be it in their classes or along the campus, administered the questionnaire to a cross section of students that attended HTTTC, Kumba for the 2024/2025 academic year.

**Return Rate:** The questionnaire was administered to 450 students in total but only 380 copies of the questionnaire were returned giving a percentage of 84.4% return rate. The tables below illustrate.

**Table1: Demography of students administered copies of the questionnaire to**

|  |  |  |
| --- | --- | --- |
| **Department** | **Sample size** | |
| **First cycle** | **Second Cycle** |
| Fashion Clothing and textile | 11 | 12 |
| Topography and Real Estate Management | 10 | 9 |
| Computer Science | 30 | 13 |
| Tourism and Hospitality Management | 24 | 13 |
| Mechanical Engineering | 5 | 5 |
| Management | 17 | 10 |
| Law | 5 | 5 |
| Building and Construction  Woodwork  Electronics  Electrotechnics  Mechanical Manufacturing  Information Management and Communication  Accountancy  Marketing  Home Economics  Science of Education | 9  2  2  7  4  45  15  8  35  42 | 8  1  2  3  5  25  13  10  17  20 |
| **Total** | **268** | **182** |
|  | **450** |  |

**Table2: Demography of students who returned their answered copies of the questionnaire**

|  |  |  |
| --- | --- | --- |
| **Department** | **Sample size** | |
| **First cycle** | **Second Cycle** |
| Fashion Clothing and textile | 11 | 10 |
| Topography and Real Estate Management | 7 | 9 |
| Computer Science | 35 | 13 |
| Tourism and Hospitality Management | 23 | 13 |
| Mechanical Engineering | 5 | 5 |
| Management | 15 | 10 |
| Law | 5 | 5 |
| Building and Construction  Woodwork  Electronics  Electrotechnics  Mechanical Manufacturing  Information Management and Communication  Accountancy  Marketing  Home Economics  Science of Education | 9  2  2  7  4  30  10  8  25  30 | 8  1  2  3  5  18  13  10  10  17 |
| **Total** | **228** | **152** |
|  | **380** |  |

**Instrumentation**

The questionnaire was a structured questionnaire consisting of 23 items adapted by Gerlich (2025) from established instruments like the Halpern Critical Thinking Assessment (HCTA) tool and Terenzini’s self-reported measures to measure AI tool usage, cognitive offloading and critical thinking.

**Data Analysis and Interpretation**

IBM SPSS was used to run the mediation analysis then the indirect effect was calculated using the SOBEL test to calculate the significance of the indirect effect. The table below is a summary table of the notation for each variable.

**Table3: Variable notations**

|  |  |  |
| --- | --- | --- |
| **Variable Name** | **Variable Type** | **Notation** |
| AI usage | Independent variable | X |
| Critical Thinking | Dependent variable | Y |
| Cognitive offload | Mediator variable | M |

The mediation analysis was done as follows: the total effect of X and Y was first estimated and since it was shown to be significant, the direct effect of X on M was then calculated then the effect of X and M on Y was then calculated and the Sobel test was used to check the significance of the indirect effect.

**Estimate the total effect between X and Y variables**

The total effect between X and Y was checked using a simple linear regression in SPSS. The output showed that p-value is ≤ 0.05 therefore the total effect is significant. However, the b coefficient was negative (-.072) indicating a significant but negative relationship between X and Y as shown in the table below.

**Table 4: Total effect significance**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variable** | **Unstandardized**  **Coefficients** | | **Standardized Coefficients** | **P** |  |
|  | B | Std. Error | Beta |  |  |
| AI Avg | -.072 | .050 | -.073 | .001 |  |

**Estimate the direct effect of X on M**

The direct effect of X on M was estimated to find the unstandardized beta and standard error coefficients for path A still using linear regression. The output was as follows:

**Table 5: Unstandardized beta and standard error coefficients for path A**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Unstandardized**  **Coefficients** | | **Standardized Coefficients** | **T** | **P** |  |
|  | **B** | **Std. Error** | **Beta** |  |  |  |
| AI Avg | .474 | .045 | .477 | 10.544 | .000 |  |
| *a. Dependent Variable: COAvg* | | | | | |

**Table 6: Model Summary** **of the direct effect of X on M**

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **R** | **R Square** | **Adjusted R Square** |
| 1 | .477a | .227 | .225 |
| a. Predictors: (Constant), AI Avg   |  |  |  |  | | --- | --- | --- | --- | | **Variables** | **Df** | **F** | **Sig.** | | Regression | 1 | 111.182 | .000b | | Residual | 378 |  |  | | Total | 379 |  |  | | | | |
| *a. Dependent Variable: COAvg* | | | |
| *b. Predictors: (Constant),* AI Avg | | | |

**Estimate the direct effect of X and M on Y**

The direct effect between X and Y and M and Y was estimated to find out the unstandardized beta and standard error coefficients for paths B and C. Since there are two predictors, multiple linear regression was used here. The output was as follows

**Table 7: Unstandardized beta and standard error coefficients for paths B and C**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variable** | **Unstandardized**  **Coefficients** | | **Standardized Coefficients** | **T** | **P** |
|  | **B** | **Std. Error** | **Beta** |  |  |
| AI Avg | -.149 | .031 | -.324 | -4.798 | .000 |
| *COAvg* | -.295 | .037 | -.541 | -8.014 | .000 |
| *a. Dependent Variable: CTAvg* | | | | | |

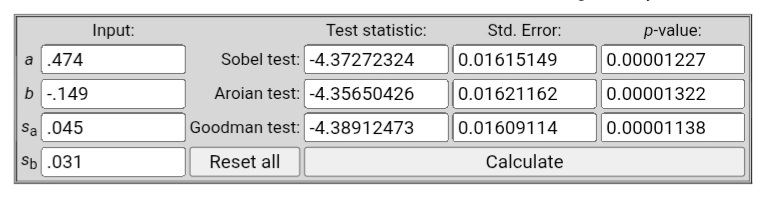
**Table 8: Model Summary of the direct effect of X and M on Y**

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **R** | **R Square** | **Adjusted R Square** |
| 1 | .386a | .149 | .144 |
| a. Predictors: (Constant), *COAvg*, AI Avg   |  |  |  |  | | --- | --- | --- | --- | | **Variables** | **Df** | **F** | **Sig.** | | Regression | 2 | 32.929 | .000b | | Residual | 377 |  |  | | Total | 379 |  |  | | | | |
| |  | | --- | | *a. Dependent Variable: CTAvg* | | 1. *Predictors: (Constant), COAvg*, , AI Avg   Below is a summary figure of the regression coefficients  Cognitive offload (CO)  (M)  Critical Thinking (CT)  (DV) Y  AI usage  (IV) X | | | | |

A= .474 (.045) B= -.149 (.031)

C= -.295 (.037)

**Fig. 2: Summary of the regression coefficients**



**Fig. 3: Sobel test for indirect effect significance**

Thus the indirect effect analysis results for X M Y using Sobel Test was as follows:

Test statistics= -4.37272324

Std. Error = 0.01615149

p-value = 0.00001227

Since the p-value is less than 0.05, it can be concluded that the indirect effect between AI usage and Critical Thinking through Cognitive offload is statistically significant (p-value≤ 0.05). The point estimate of the indirect effect at which p-value in the Sobel test is statistically significant was calculated by multiplying the Unstandardised Beta Coefficient for A by that of B like this:

.474 \* -.149 = -0.070626

-0.070626 is the estimate of the indirect effect between AI usage and Critical Thinking through Cognitive offload.

**Reporting Mediation Analysis**

This study examined the mediating role of cognitive offload on the relationship between AI usage and critical thinking. The mediation analysis revealed that AI usage significantly predicts cognitive offload (R2 =.227, F (1,378) =111.182, p< 0.001), indicating that 22.7% of the variance in cognitive offload is explained by AI usage. In the combined regression model predicting critical thinking, both AI usage and cognitive offload were included as predictors, resulting in a model that explains 14.9% of the variance in critical thinking (R2=.149, F(2,377)= 32.929, p <.001). The coefficients table indicated that while AI usage had a negative but significant direct effect on critical thinking (B= -.149, SE=.031, β=-.324, t (379) =-4.798, p <.001), cognitive offload also had a significant negative effect on critical thinking (B=-.295, SE=.037, β=-.541, t(379)= -8.014, p <.001). Finally, the Sobel test confirmed partial mediation (z=-4.37272324, p<.001), indicating that cognitive offload partially mediates the relationship between AI usage and critical thinking. These results suggest that the relationship between AI usage and critical thinking is partially mediated by cognitive offload.

**Discussion of findings**

The mediation analysis showed significant relationships between the variables of this study as such:

**Table 9: Summary of findings**

|  |  |  |  |
| --- | --- | --- | --- |
| Variable pair | unstandardized beta coefficient (b) | P value | Interpretation |
| AI usage and cognitive offload | .474 | p< 0.001 | Significant Positive relationship |
| Cognitive offload and critical thinking | -.149 | p< 0.001 | Significant negative inverse relationship |
| AI usage and critical thinking | -.295 | p< 0.001 | Significant negative inverse relationship |

**AI usage and cognitive offload:** the unstandardized beta coefficient (b) was positive (.474) and the p value was significant (p< 0.001) indicating a significant positive relationship between AI usage and cognitive offload. This means that as the use of AI tools increases, cognitive offload also increases. This finding corroborates findings from other studies like Carr (2010) which found out that AI use enhances cognitive capacity by delegating tasks like memory retention etc to external systems. However, in the long run there is a high probability of the development of cognitive laziness due to decrease in cognitive effort.

**Cognitive offload and critical thinking:** the unstandardized beta coefficient (b) was negative (-.149) and the p value was significant (p< 0.001) indicating a significant negative inverse relationship between AI usage and cognitive offload. Implying that as cognitive offload increases, critical thinking decreases. This is in line with other researchers who found out that offloading information into digital tools improves cognitive performance for subsequent, unrelated tasks (Runge et al., 2019) as well as memory for unrelated information (Storm & Stone, 2015). However, recurrent externalisation of internal cognitive processes leads to the deterioration of the corresponding internal abilities.

**AI usage and critical thinking:** the unstandardized beta coefficient (b) was negative (-.295) and the p value was significant (p< 0.001) indicating a significant negative inverse relationship between AI usage and cognitive offload. This infers that as the use of AI tools increases, critical thinking diminishes. This result supports other studies (Risko & Gilbert, 2016; Gerlich, 2025) which shows that over dependence on technology for information and decision making can lead to long-term wearing away of critical thinking abilities due to the diminished practice of cognitive skills, analytical reasoning and independent problem-solving.

**Mediating effect of cognitive offload:** Cognitive offloading which is the process of transferring mental tasks from the brain to external devices or systems (Risko & Gilbert, 2016) was revealed to partially mediate the effect between AI usage and critical thinking in this study. This implies the use of AI tools can create more cognitive capacity. However, this dependence on external tools like AI weakens cognitive effort over time thereby diminishing critical thinking. This result is in line with the findings from other studies like Gerlich (2025).

**Conclusion**

This study set out to investigate the mediating role of cognitive offload in the relationship between AI use and critical thinking. The results give insight into how the use of AI affects cognitive processes and the development of critical thinking skills. It was shown that AI usage is positively related to cognitive offload meanwhile cognitive offload and AI usage are negatively and inversely related to critical thinking. This reveals that even though AI holds immense potential to transform education through personalized learning and adaptive systems, its integration requires caution. A deeper understanding of AI’s interplay with educational theories, alongside addressing ethical and pedagogical challenges, is essential. A balanced, human-centered approach prioritizing equitable access can ensure AI empowers rather than excludes.

**Recommendations**

To make sure AI is effectively integrated into the classroom, here are some suggestions:

Teachers should balance the use of AI by integrating strategies that encourage deep thinking and cognitive engagement.

Both teachers and students should receive training from time to time on how to ethically use AI and other technological tools such that they can reduce the negative effects of cognitive offload while improving the development of their cognitive abilities.

Establish standards for AI usage that include the regular authentication of AI-generated information and clear guidelines to prevent over-dependence on technology.

The learning environment should be created such that students should be encouraged to be active participants in their learning and not just passive AI users when studying.

By bringing such awareness, institutions can make sure that AI complements rather than substitutes traditional teaching strategies, eventually nurturing a more efficient, and personalized learning environment that supports the development of essential cognitive skills.

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