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# Generative AI and Critical Thinking in Political Science Higher Education: Exploring the Threshold Effect

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## Abstract:

This study examines how the intensity of generative Artificial Intelligence (AI) usage relates to students' critical thinking in political science higher education. Grounded in classical conceptions of critical thinking as a self-regulated process, it explores whether varying levels of AI use are associated with a threshold effect in which AI shifts from a cognitive scaffold to a partial substitute for independent reasoning. Using an exploratory quantitative design, survey data were collected from 179 political science students in Algeria. The findings reveal that higher AI usage intensity is associated with increased perceived learning gains but reduced critical thinking independence. These results suggest that the cognitive impact of generative AI is usage-dependent rather than inherently positive or negative

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## 1 - Introduction

Generative Artificial Intelligence (AI) is becoming central to the learning process in higher education, as students and professors alike are increasingly integrating AI language models, like ChatGPT, Gemeni, and Preplexity, into their academic lives. Marking a structural change in how knowledge is accessed and processed in higher education. Therefore, generative AI is no longer a peripheral but a structural component in learning environments.

Some studies argue that generative AI can enhance lower order cognitive skills (Esssiene et al, 2024), through interactive and personalized learning (Klayklung et al., 2023). However, this comes at the expense of hindering higher-order cognitive skills (Patrick, 2025), as the excessive use of AI may cripple analytical thinking skills and impact students' critical thinking (Bai et al., 2023).

This tension is particularly salient when examined through the lens of Bloom's taxonomy (Bloom, 1956), while generative AI appears well-suited to supporting lower-order cognitive functions such as recall, explanation, and procedural understanding, higher-order skills like analysis, evaluation, and synthesis are more problematic for synthesis (Gonsalves, 2024).

This dichotomy between lower\higher cognitive skills is significant within the discipline of political science as this field is not exclusivly oriented toward the accumulation of factual knowledge and mastery of the subject matter, but also toward the development of analytical capacities, argumentative reasoning, and critical reflection on complex, socially constructed concepts like power, institutions, and social realities. Students are expected to interpret complex political phenomena, assess competing and ever-evolving theoretical perspectives, and construct independent judgments grounded in evidence and normative reasoning. As such, higher-order cognitive skills occupy a central position in political science curricula and pedagogical objectives.

Within this context, the growing integration of generative AI into the academic life, combined with the absence of a holistic, clearly articulated, and Algerian-specific framework for its use in higher education, raises important pedagogical and epistemic questions about the existence of a potential usage threshold that distinguishes supportive and empowering uses of AI from excessive forms of reliance that may undermine students' cognitive autonomy. Beyond a certain level of intensity, generative AI use may shift from scaffolding learning to cognitive offloading, thereby placing higher-order cognitive skills, including critical thinking, at risk.

Accordingly, this study addresses the following research question:

**How does the intensity of generative AI usage relate to students' critical thinking in political science higher education?**

**Research Hypotheses:**

H1: AI usage intensity negatively affects critical thinking independence

H2: AI usage intensity negatively affects epistemic vigilance

H3: AI usage intensity positively affects dependency risk
H4: AI usage intensity positively affects perceived learning gains.

This study aims to examine the relationship between generative AI usage intensity and multiple dimensions of critical thinking among political science students in higher education. Grounded in classical views of critical thinking as a self-regulated process, it explores whether differing levels of AI use are associated with a threshold effect in which generative AI shifts from a cognitive scaffold to a partial substitute for independent reasoning. The study adopts an exploratory, quantitative approach to capture this usage-dependent dynamic.

## 2-Literature Review

### 2-1-Theoretical and Conceptual Foundations of Critical Thinking

Critical thinking is a crucial cognitive skill that extends across different aspects of life and intellectual domains. It involves the ability to think clearly, logically, and rationally in order to support effective decision-making and problem-solving. Scholarly definitions of critical thinking have largely emerged from the fields of psychology and education, where the concept has been theorized as both a cognitive and a dispositional competence.

Facione (1990), in the Delphi Report, defines critical thinking as a form of self-regulatory judgment that results in interpretation, analysis, evaluation, inference, and explanation, guided by evidential, conceptual, methodological, and contextual considerations. He identifies six core cognitive skills that characterize critical thinking: interpretation, analysis, evaluation, inference, explanation, and self-regulation. This definition emphasizes the structured and reflective nature of reasoning processes, positioning critical thinking as an internally regulated activity rather than a reactive or externally driven one.

Ennis (1996) complements this skills-based approach by emphasizing the dispositional dimension of critical thinking. According to Ennis, cognitive ability alone is insufficient; critical thinking also requires a set of dispositions that guide how individuals engage with information and reasoning tasks. He defines critical thinking as “reasonable reflective thinking focused on deciding what to believe or do” (Ennis, 1996). For Ennis, ideal critical thinkers demonstrate a concern for truth and justification, actively seek alternative explanations and viewpoints, remain open-minded, and endorse positions only to the extent that they are supported by available evidence. Additionally, they are expected to represent both their own positions and those of others accurately and fairly, while maintaining respect for the dignity and worth of others.

Halpern (1998) advances a similar perspective by integrating both cognitive skills and attitudinal orientations. She identifies several dispositions characteristic of critical thinkers, including a willingness to engage with complex tasks, the habitual use of planning and self-control, cognitive flexibility, a readiness to abandon ineffective strategies, and an awareness of the social conditions that shape the translation of thought into action. In line with Ennis, Halpern stresses the action-oriented nature of critical thinking and defines it as purposeful, reasoned, and goal-directed thinking involved in problem-solving, inference-making, and decision-making. Importantly, she highlights the capacity of critical thinkers to apply these skills deliberately and across varied contexts, underscoring the importance of transferability.

Black (2008) conceptualizes critical thinking as the analytical foundation of rational discourse and inquiry. He characterizes it as a rigorous and meticulous form of reasoning that involves analyzing arguments, evaluating claims and evidence, judging relevance and significance, and constructing coherent and well-reasoned judgments. Black also stresses that rational thinking requires an open-minded yet critical stance toward both one's own reasoning and that of others, further aligning critical thinking with self-reflection and epistemic responsibility.

More recent definitions continue to situate critical thinking within task-oriented and outcome-focused frameworks. Heard et al. (2020) describe critical thinking as the ability to analyze and evaluate information and reasoning according to appropriate standards in order to construct sound knowledge, insights, and judgments. Their definition emphasizes the synthesis of information and its judicious application to decision-making and problem-solving tasks, reinforcing the view of critical thinking as an active and purposeful cognitive process.

Despite differences in emphasis, the reviewed scholarship converges on critical thinking as a purposeful, self-regulated, and reflective form of reasoning that is internally guided rather than externally determined. Across definitions, core components consistently include analysis, evaluation, interpretation, inference, argument construction, openness to alternative perspectives, and awareness of contextual and evidential limitations (Facione, 1990; Ennis, 1996; Halpern, 1998; Heard et al., 2020; Black, 2008). Importantly, several scholars stress that critical thinking is not only a set of cognitive skills but also a dispositional orientation involving epistemic vigilance, self-correction, and resistance to unreflective or impulsive reasoning. This conceptualization is particularly relevant in technology-mediated learning environments, where external cognitive aids may support reasoning while simultaneously risking cognitive offloading. Accordingly, this study operationalizes critical thinking through indicators capturing students' analytical independence, reliance on personal judgment, verification of information, awareness of bias, and ability to construct arguments without external substitution. These dimensions form the theoretical basis for the survey instrument used to examine how generative AI tools interact with students' critical thinking practices in higher education.

## 2-2- AI and Critical Thinking

Research on the interaction between AI and critical thinking is ever evolving, methodologically diverse, and remains inconclusive. Existing studies employ a wide range of research designs, reflecting the conceptual and contextual complexity of this relationship. Methodologically, the literature can be broadly classified into mixed-methods studies, which combine quantitative surveys with qualitative interviews (Gerlich, 2024; Lawasi et al., 2024; Zhang & Liu, 2025); purely survey-based studies relying on self-reported perceptions and correlational analyses (Lee et al., 2025); as well as experimental (Naatonis, 2024) and quasi-experimental designs that examine causal mechanisms under controlled or semi-controlled conditions (Zhao et al., 2025; Sherin Mabrouk, 2025).

Findings across these studies are equally divergent, revealing no uniform relationship between AI use and critical thinking. Several studies report negative effects, particularly when AI is used intensively or uncritically. Gerlich (2024) argues that increased reliance on AI tools is associated with high cognitive offloading, which in turn may reduce engagement in critical thinking processes. Similarly, Lee et al. (2025) find that knowledge workers perceive a decline in cognitive effort related to critical thinking when using generative AI, compared to tasks performed without AI assistance.

In contrast, a growing body of research frames AI as a conditional enhancer of critical thinking, especially within educational contexts. Gonsalves (2024) emphasizes that AI can simultaneously enhance and challenge critical thinking across cognitive, affective, and metacognitive dimensions, depending on how it is integrated into learning activities. Lawasi (2024) further notes that while AI can support the development of critical thinking through idea expansion and interactive engagement, persistent challenges remain, including algorithmic bias and the necessity of strong foundational knowledge. Importantly, Zhang and Liu (2025) demonstrate that the frequency of AI use alone is not a significant predictor of critical thinking outcomes; rather, critical thinking development is mediated by learners' self-regulation capacities and intrinsic motivation. A view further confirmed by Hasan et al. (2025) and Melisa et al. (2025) that highlight AI's effectiveness in enhancing critical thinking skills.

Taken together, the literature suggests that AI does not inherently weaken or strengthen critical thinking. Instead, its impact is context-dependent, shaped by pedagogical design, user agency, and metacognitive engagement. This mixed evidence underscores the need for more theoretically grounded and methodologically robust research to clarify the conditions under which AI use supports or undermines critical thinking development.

### 2-3- AI and Higher Education in Algeria

Research on AI in Algerian higher education has adopted perceptual, normative, and risk-oriented approaches, with a strong emphasis on professors' concerns rather than students' cognitive outcomes. Studies consistently highlight ethical anxieties, infrastructural limitations, and fears of cognitive dependency associated with AI use (Achili & Zerrouki, 2024; Othmane, 2024).

From a pedagogical standpoint, Algerian professors largely perceive generative AI tools as a potential threat to critical thinking, creativity, and learner autonomy, rather than as a cognitive scaffold (Achili & Zerrouki, 2024). These concerns are reinforced by broader cultural and ethical discourses that frame AI as incompatible with deep intellectual engagement and academic originality (Othmane, 2024).

The most direct engagement with critical thinking is offered by Kerma (2025), who identifies over-reliance on AI, superficial learning, and diminished creativity as dominant challenges in Algerian universities. However, this evidence remains indirect, as critical thinking is inferred through teachers' observations rather than empirically measured among students.

Across these studies, three major gaps emerge. First, critical thinking is rarely operationalized as a multidimensional construct, despite its centrality to higher education. Second, the student perspective is largely absent, with existing research privileging institutional and instructional viewpoints. Third, AI is conceptualized as a monolithic influence, overlooking variations in usage intensity, dependency risk, and epistemic engagement.

## 3-Methodology and Materials

This study adopts a quantitative, survey-based research design to examine the relationship between generative AI usage and multiple dimensions of students' critical thinking. A quantitative approach was deemed appropriate given the study's aim to identify systematic associations between AI usage intensity and cognitive outcomes across a relatively large student population. The design is exploratory in nature, as empirical evidence on the cognitive implications of generative AI in political science education remains limited.

### 3-1- Quantitative Data (Survey)

A structured questionnaire consisting of 25 questions was developed based on validated scales and existing literature to measure AI tool usage and critical thinking skills. (Facione, 1990; Ennis, 1996; Halpern, 1998)

The questionnaire (Appendix A) items were adapted and operationalized from established conceptual frameworks on critical thinking and metacognition, rather than directly reproducing full validated scales, in order to align measurement with the specific context of generative AI usage in higher education.

The questionnaire was divided into four sections:

1. Demographic Information: Age and academic ranking.
2. AI Tool Usage: Frequency and reliance on generative AI for academic purposes. (How often, which stage, nature of use ...)
3. Generative AI-related behavior: How the student behaves when using GAI. (Does he verify, does he compare with other resources ...)
4. Percived impact: Self-reported and perceived impact of generative AI. A five step Likert scale was used, providing ordinal data suitable for statistical analysis.

### 3-2- Participants

The study was conducted on a sample of 179 students drawn from a total population of approximately 800 students from the the National Superior School of Political Science, representing 22.4% of the target population. While the sample is not intended to be statistically representative beyond the study population, the participation rate (22.4%) provides sufficient variability in AI usage patterns to support exploratory correlational analysis.
The inclusion criteria required respondents to be actively enrolled political science students within the institution at the time of data collection. Given the voluntary nature of participation, the sample is subject to self-selection bias, as students with prior interest in or exposure to generative AI may have been more likely to respond.
While this sampling approach limits the external generalizability of the findings, it is methodologically appropriate for exploratory research aimed at identifying preliminary patterns and associations rather than producing population-level estimates.
Out of 179 respondents, 169 (94.4%) reported using AI tools in their academic studies, while 10 respondents (5.6%) reported non-use. Items related to AI usage and verification were therefore applicable only to AI users. Missing values among non-users reflect structural missingness resulting from survey design. Accordingly, analyses involving AI usage variables were conducted on the subsample of AI users (n=169), while descriptive statistics were calculated on the full sample.

**3-3- Data Analysis**

Descriptive statistics were computed to summarise the demographic characteristics of the sample, as well as the central tendencies and variances of AI tool usage, and critical thinking scores. The statistical analyses were conducted using appropriate methods tailored to the research questions and data characteristics.
Descriptive statistics served as a preliminary step to assess the distributional properties and variability of AI usage and cognitive indices prior to inferential analysis.
Five indices were constructed (Appendix B) as follows:
**1-AI Usage Intensity Index (AIUI):** measures the frequency, regularity, and breadth of students' use of generative AI tools in their academic activities. It captures how often AI is used, across which study stages (e.g., idea generation, drafting, verification), and for what purposes. Higher scores indicate more intensive and habitual reliance on AI in learning tasks.
**2-Critical Thinking Independence Index (CTII):** assesses the extent to which students engage in autonomous reasoning without substituting AI for core cognitive processes. It measures self-reported abilities such as independent analysis, argument construction, and evidence evaluation, prior to or independent of AI assistance. Higher values reflect stronger cognitive autonomy.

**3-Verification and Epistemic Vigilance Index (VEVI):** evaluates students' capacity to critically assess, verify, and cross-check AI-generated outputs. It measures behaviors related to source checking, skepticism toward AI responses, awareness of potential inaccuracies, and active validation using external references. Higher scores indicate stronger epistemic vigilance and critical monitoring.

**4-Dependency Risk Index (DRI):** measures the perceived risk of cognitive over-reliance on AI tools. It captures tendencies such as defaulting to AI for thinking tasks, reduced effort in independent reasoning, and discomfort when AI is unavailable. Higher scores reflect a greater likelihood that AI use substitutes rather than supports critical thinking.

**5-AI-Assisted Learning Gain Index (AALG):** assesses students' perceived learning benefits derived from using AI, including improved understanding, efficiency, clarity, and academic performance. This index captures the supportive and scaffolding role of AI in learning processes rather than its impact on cognitive autonomy.

Each composite index was constructed by aggregating conceptually related items reflecting a single latent dimension. Items were coded in the same directional orientation prior to aggregation, with reverse coding applied where necessary to ensure interpretive consistency. Index scores were calculated as mean values to preserve the original measurement scale and facilitate comparability across constructs.

Internal consistency of reflective composite indices was assessed using Cronbach's alpha (α). The CTII demonstrated acceptable internal consistency for exploratory research ($\alpha = 0.65$), while the VEVI showed good reliability ($\alpha = 0.71$). The AALG exhibited moderate internal consistency ($\alpha = 0.55$), which is acceptable given the small number of items and the exploratory nature of the construct.

In contrast, the AIUI and the DRI were constructed as formative composite indices, combining conceptually distinct dimensions of behavior (e.g., frequency, stage, and nature of AI use; or effort reduction, unedited submission, and behavioral reliance). Because these indicators are not expected to be highly intercorrelated, Cronbach's alpha is not an appropriate measure of reliability for these indices. Instead, they are treated as descriptive and analytical composites designed to capture multidimensional usage and risk patterns rather than latent psychological traits.

Following the construction and validation of the composite indices (AIUI, CTII, VEVI, DRI, and AALG), the analysis proceeds to the results section, starting with descriptive statistics.

Given the ordinal nature of the Likert-based composite indices and the absence of assumptions regarding normal distribution, Spearman's rank-order correlation was employed for subsequent analyses. Visual inspection of histograms indicated approximately symmetric distributions for AI usage intensity, while other indices exhibited skewed patterns, further supporting the use of a non-parametric approach.

Correlation analyses focused on examining the associations between AI usage intensity and key cognitive and learning-related indices.

For the exploratory subgroup analysis, students were classified into low/moderate and high AI usage groups based on the sample mean of the AI Usage Intensity Index (AIUI; M ≈ 2.05). This data-driven cut-off was chosen to distinguish between respondents whose AI use fell below or above the average usage level observed in the sample, rather than relying on an arbitrary threshold. Using the mean as a splitting criterion is methodologically appropriate in exploratory analyses of composite indices, as it preserves internal validity while allowing for meaningful comparisons between relative usage levels. This approach enables the identification of potential threshold effect, whereby the cognitive and learning-related impacts of AI tools may differ once usage intensity exceeds the normative level within the study population.

## 4 -Results

This section presents the empirical findings of the study. Results are reported in three stages. First, descriptive statistics are used to summarize respondents' demographic characteristics and patterns of generative AI use, including the tools employed, frequency of use, and stages of academic engagement. Second, descriptive statistics of the composite indices are presented to characterize AI usage intensity and key cognitive and learning-related constructs. Third, correlational analyses examine the associations between AI usage intensity and critical thinking independence, epistemic vigilance, dependency risk, and perceived AI-assisted learning gains.

### 4.1. Demographic Characteristics and Patterns of AI Use

**Table 1. Age Distribution of the Respondents (N = 179)**

| Age Group | Frequency (n) | Percentage (%) |
|---|---|---|
| 18-20 | 51 | 28.5 |
| 21-25 | 92 | 51.4 |
| 26-30 | 7 | 3.9 |
| 30 and Above | 29 | 16.2 |
| Total | 179 | 100 |

The sample is predominantly composed of students aged 21–25, reflecting the typical age range of postgraduate political science students, with a smaller representation from younger and older age ranges.

**Table 2. Academic Ranking of Respondents within Their Cohort (N = 179)**

| Academic Ranking (Quartile) | Frequency (n) | Percentage (%) |
|---|---|---|
| Top quartile (Top 25%) | 90 | 50.3 |
| Second quartile (25–50%) | 53 | 29.6 |

| | | |
|---|---|---|
| Third quartile (50–75%) | 30 | 16.8 |
| Bottom quartile (Lowest 25%) | 6 | 3.4 |
| Total | 179 | 100 |

Over half of the respondents (50.3%) reported belonging to the top academic quartile, while a small proportion (3.4%) identified as being in the lowest quartile.

**Table 3. Use of Generative AI in University Studies (N = 179)**

| Use of AI Tools | Frequency (n) | Percentage (%) |
|---|---|---|
| Yes | 169 | 94.4 |
| No | 10 | 5.6 |

An overwhelming majority of respondents (94.4%) reported using generative AI in their university studies, indicating near-universal exposure to generative AI among the sample. While the proportion of non-users is relatively small (5.6%), this subgroup warrants further investigation. Non-use of AI tools may reflect a deliberate choice to avoid reliance on generative technologies, but it may also be shaped by structural constraints such as limited access to digital resources, economic barriers, or uneven technological literacy. These alternative explanations cannot be disentangled within the scope of the present descriptive results and are therefore addressed as implications for future research.

**Table 4. Academic Tasks for Which AI Tools Are Used (Multiple Responses Allowed, AI Users Only, N = 169)**

| Academic Task | Frequency (n) | Percentage (%) |
|---|---|---|
| Understanding course content | 103 | 60.9 |
| Translation | 99 | 58.6 |
| Summarizing lectures, books, or articles | 94 | 55.6 |
| Generating ideas or creating outlines | 91 | 53.8 |
| Improving language and writing style | 82 | 48.5 |
| Writing assignments or research papers | 46 | 27.2 |
| Other specific uses | 14 | 8.3 |

AI tools are primarily used for comprehension, translation, summarization, and idea generation, while direct use for writing assignments is comparatively less frequent. Less common uses were highly fragmented and appear as individualized or exploratory practices, which include reference extraction, source searching, deeper topic exploration, mind mapping, and general research assistance. Each of these categories was mentioned by fewer than 9% of respondents and is therefore aggregated in other uses.

**Table 5. AI Tools Used by Students (Multiple Responses Allowed, AI Users Only, N = 169)**

| AI Tool | Frequency (n) | Percentage (%) |
|---|---|---|
| ChatGPT | 139 | 82.2 |
| Google Gemini | 75 | 44.4 |
| Perplexity AI | 68 | 40.2 |
| DeepSeek | 16 | 9.5 |
| Other AI tools | 32 | 18.9 |

The findings indicate a strong concentration of AI use around a small number of dominant platforms, particularly ChatGPT, while a long tail of alternative tools is used sporadically, suggesting exploratory or highly individualized adoption patterns. Other tools include Claude AI, Copilot, NotebookLM, SciSpace, Blackbox.ai, Consensus, Gamma, Grok, OpenAlex, MagicSchool, ChatPDF, and similar platforms. Each of these tools was reported by fewer than 2% of respondents and is therefore aggregated.

**Table 6. Frequency of AI Use for Academic Purposes (AI Users Only, N = 169)**

| Frequency of AI Use | Frequency (n) | Percentage (%) |
|---|---|---|
| Rarely (once or twice per semester) | 10 | 5.9 |
| Occasionally (1–2 times per month) | 35 | 20.9 |
| Regularly (1–3 times per week) | 83 | 49.2 |
| Intensively (almost daily) | 41 | 24.3 |
| Total | 169 | 100 |

Nearly three-quarters of AI users report regular or intensive use of AI tools for academic purposes, suggesting that AI engagement is not merely occasional but integrated into students' routine study practices.

### 4-2- Descriptive Statistics of Composite Indices

**Table 7. Descriptive statistics of composite indices (N = 169)**

| Index | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| AIUI | 169 | 2.04 | 0.49 | 1 | 3.33 |
| CTII | 169 | 3.99 | 0.62 | 2.33 | 5 |
| VEVI | 169 | 3.17 | 0.40 | 1.6 | 3.8 |
| DRI | 169 | 2.54 | 0.62 | 1 | 4 |
| AALG | 169 | 3.77 | 0.80 | 1.5 | 5 |

1- The AI Usage Intensity Index (AIUI) indicates a moderate level of engagement with generative AI tools among students (M = 2.05, SD = 0.49). While AI is regularly incorporated into academic activities, its overall intensity remains moderate rather than pervasive, suggesting that students tend to integrate AI selectively rather than rely on it systematically.

2- The Critical Thinking Independence Index (CTII) shows a high average level (M = 4.00, SD = 0.63), indicating that most students perceive themselves as capable of analytical reasoning and argument construction without relying on generative AI tools.

3- The Verification and Epistemic Vigilance Index (VEVI) demonstrates a relatively high average level among students (M = 3.17, SD = 0.40). This suggests that students generally engage with generative AI tools in a reflective and evaluative manner, frequently verifying information, recognizing potential inaccuracies or biases, and comparing AI-generated outputs with academic sources rather than accepting them uncritically.

4- The Dependency Risk Index (DRI) displays a moderate average level (M = 2.55, SD = 0.62), indicating that while students do not exhibit high levels of cognitive dependency on generative AI tools, instances of partial cognitive offloading do occur. The observed variability suggests heterogeneous usage patterns, with dependency risks remaining context-dependent rather than systematic across the sample.

5- The AI Assisted Learning Gain Index (AALG) shows a high average level (M = 3.77, SD = 0.81), indicating that students largely perceive generative AI tools as enhancing their understanding of complex political or theoretical issues and improving overall learning effectiveness. Nevertheless, the observed variability suggests that perceived learning gains differ across individuals, reflecting diverse patterns of AI integration into academic work.

To summarize, the descriptive statistics of the composite indices used in the analysis. Overall, students report a moderate level of generative AI usage intensity (AIUI), indicating that AI tools are regularly but not pervasively integrated into academic practices. At the same time, relatively high levels of critical thinking independence (CTII) and epistemic vigilance (VEVI) suggest that students generally maintain analytical autonomy and evaluative awareness when engaging with AI-generated content. The Dependency Risk Index (DRI) points to a moderate degree of perceived cognitive offloading, indicating that reliance on AI remains context-dependent rather than systematic. Finally, the AI Assisted Learning Gain Index (AALG) exhibits a high average level, reflecting widespread perceptions of enhanced understanding and learning effectiveness associated with AI use.

**4-3- Correlational Analysis**

**Table 8. Spearman's Rank-Order Correlations Between AI Usage Intensity and Cognitive-Related Indices**

| Independent Variable (AIUI) | Spearman's ρ |
|---|---|
| Critical Thinking Independence (CTII) | −0.31 |
| Epistemic Vigilance (VEVI) | −0.11 |
| Dependency Risk (DRI) | +0.13 |
| AI-Assisted Learning Gain (AALG) | +0.27 |

Table 8 presents the Spearman correlations between AI usage intensity and key cognitive and learning-related indices. AI usage intensity shows a moderate negative association with critical thinking independence ($\rho = -0.31$), suggesting that higher levels of AI engagement are linked to lower perceived analytical autonomy. A weak negative correlation is also observed with epistemic vigilance ($\rho = -0.11$), indicating a slight decline in evaluative scrutiny as AI use increases. In contrast, AI usage intensity is weakly positively associated with dependency risk ($\rho = 0.13$), pointing to limited but noticeable tendencies toward cognitive offloading. Finally, a weak-to-moderate positive relationship emerges between AI usage intensity and AI-assisted learning gains ($\rho = 0.27$), indicating that increased AI use is associated with enhanced perceived learning effectiveness.

All reported correlations indicate associative relationships and do not imply causality.

## 5-Discussion

This study tried to explore the relationship between generative AI usage and multiple dimensions of critical thinking among political science students. The findings reveal a nuanced and ambivalent pattern. While increased AI usage intensity is associated with perceived learning gains, it is simultaneously linked to reduced critical thinking independence and, to a lesser extent, increased dependency risk.

### 5-1-Discussion of the correlations

The key findings are consistent with previous research, indicating that high usage intensity can negatively impact critical thinking skills. (Gerlich, 2024; Lee et al., 2025). This study found that there is a moderate negative association between AI usage intensity and critical thinking independence ($\rho = -0.31$). This relationship suggests that as students rely more heavily on generative AI tools, their perceived ability to independently analyze, reason, and argumentation without external assistance tends to decline.

This pattern aligns closely with classical conceptualizations of critical thinking as a self-regulatory and internally guided process. Facione's (1990) Delphi framework emphasizes that critical thinking requires individuals to actively engage in interpretation, analysis, evaluation, and inference through deliberate judgment rather than external substitution. Similarly, Ennis (1996) and Halpern (1998) stress that critical thinking is not merely about producing correct answers, but about exercising control over one's own reasoning processes. From this perspective, the observed negative association does not necessarily imply a loss of cognitive capacity, but rather an increased tendency towards cognitive offloading that can lead to a shift of the cognitive control from the student to the tool.

The weak negative association between AI usage intensity and epistemic vigilance ($\rho = -0.11$) indicates that greater AI engagement is associated with a slight decline in verification and scrutiny. Although this correlation is low, it is theoretically significant given the central role of epistemic vigilance in critical thinking frameworks. According to Black (2008) and Heard et al. (2020), critical thinking involves not only analyzing information but also judging its credibility, relevance, and evidential grounding. The relatively high average score on the Verification and Epistemic Vigilance Index (VEVI) suggests that students generally remain cautious when interacting with AI-generated content. Nevertheless, the negative association implies that frequent exposure to generative AI outputs may reduce the perceived need for systematic verification. This finding can be interpreted as a form of epistemic complacency, where students retain the disposition to verify information but exercise it less and less under high AI usage. Rather than indicating uncritical acceptance, this pattern suggests a gradual attenuation of epistemic effort, an outcome that resonates with concerns about the normalization of externally generated reasoning in academic work (Patrick et al., 2025).

The positive association between AI usage intensity and dependency risk ($\rho = 0.13$), although weak, indicates that increased AI engagement is linked to a greater tendency toward cognitive offloading (Gerlich, 2024). This finding reinforces the interpretation that generative AI operates as a double-edged tool, while it can support learning, it may also encourage partial substitution of effortful cognitive processes.

From Halpern's (1998) standpoint about dispositions characteristic of critical thinkers, dependency risk becomes problematic not when tools are used, but when users lose awareness of when and how those tools should be employed, as critical thinking requires an awareness of the social conditions that shape thought. Nontheless, The moderate mean value of the Dependency Risk Index (DRI) suggests that students are not broadly dependent on AI, but that reliance varies across tasks and individuals.

In contrast to the previous findings, AI usage intensity shows a weak positive association with perceived AI-assisted learning gains ($\rho = 0.27$). Students who use AI more frequently tend to perceive improved understanding when engaging with complex academic material via generative AI. This result is consistent with students' high average score on the AI Assisted Learning Gain Index (AALG) and supports the interpretation that generative AI functions effectively as a learning scaffold. (Gonsalves, 2024; Lawasi, 2024; Zhang and Liu ,2025).

However, the coexistence of perceived learning gains alongside a decline in independent critical thinking underscores a fundamental pedagogical paradox: AI may enhance understanding while simultaneously weakening the processes required to reach it. This suggests a systemic trade-off, where students may exchange rigorous critical inquiry for immediate conceptual comprehension. This is particularly relevant in political science education, where the development of analytical autonomy and judgment is as important as subject matter mastery.

Consequently, the "efficiency" afforded by AI may come at the expense of the intellectual self-reliance necessary for sophisticated political analysis.
Furthermore, the positive association between AI usage intensity and perceived AI-assisted learning gains should be interpreted with caution, as it relies on self-reported perceptions rather than objective measures of learning. This pattern may reflect what is often described as an illusion of competence, whereby learners confuse increased fluency, speed, or clarity of information with durable understanding and long-term mastery. Research on human–AI interaction has shown that such illusions can hinder appropriate reliance on AI systems by inflating users' confidence in their own comprehension and decision-making (He et al., 2023).

**5-2- Subgroup Comparison**

To further contextualize the correlational findings, an exploratory subgroup comparison was conducted between students with low/moderate and high AI usage intensity (Table 3). While this analysis is descriptive in nature and does not involve inferential testing, it provides valuable insight into how patterns of cognitive engagement differ across relative levels of AI use.

**Table 9 . Subgroup Comparison of Cognitive and Learning Indices by AI Usage Intensity Group (N = 169).**

| Group | Mean_CTII | Mean VEVI | mean DRI | mean AALG |
|---|---|---|---|---|
| Low/Moderate | 4.11 | 3.2 | 2.52 | 3.62 |
| High | 3.81 | 3.12 | 2.58 | 4 |

Exploratory subgroup comparisons based on AI usage intensity provide further insight into the observed correlational patterns. Students with low to moderate AI use demonstrate higher levels of critical thinking independence (M = 4.11) and epistemic vigilance (M = 3.20), alongside lower dependency risk (M = 2.52), compared to high AI users (CTII: M = 3.81; VEVI: M = 3.12; DRI: M = 2.58). These patterns closely mirror the negative associations observed between AI usage intensity and both critical thinking independence and epistemic vigilance in the correlational analysis. Taken together, they suggest that more restrained AI use is associated with stronger analytical autonomy and evaluative caution.
In contrast, students with high AI usage intensity report substantially higher perceived AI-assisted learning gains (AALG: M = 4.00) than their low/moderate-use counterparts (M = 3.62). This divergence reinforces the interpretation that intensive engagement with generative AI enhances perceived learning efficiency and comprehension, particularly in relation to complex academic material. A perception that might fall under the illusion of competence
These subgroup differences lend support to the notion of a threshold effect, whereby generative AI functions as a cognitive scaffold at lower or moderate

levels of use, but shifts toward partial cognitive substitution as usage intensity increases. Rather than indicating a uniform impact of AI on cognition, this pattern underscores the conditional nature of AI's effects, shaped by how frequently and at which stages of academic work the technology is integrated (Gonsalves, 2024; Lawasi, 2024; Zhang and Liu ,2025; Melisa et al, 2025).

**5-3- Threshold Effect in Generative AI Use**

The correlational and subgroup findings suggest that the perceived impact of generative AI on critical thinking is not linear but depends on usage patterns and intensity. Rather than uniformly enhancing or undermining cognition, generative AI appears to alter where cognitive self-regulation occurs as usage intensity increases.

Classical frameworks of critical thinking consistently emphasize self-regulation as a core defining feature. Facione's (1990) Delphi Report explicitly positions critical thinking as a form of self-regulatory judgment, while Ennis (1996) and Halpern (1998) stress that critical thinking involves the deliberate monitoring, control, and adjustment of one's own reasoning processes. Within this theoretical tradition, the central concern is not whether individuals think, but the extent of control they have over their thinking.

The present findings suggest that at low to moderate levels of use, generative AI functions primarily as a cognitive scaffold that supports comprehension, exploration, and clarification without displacing the learner's regulatory role. Under these conditions, students appear to maintain relatively high levels of critical thinking independence and epistemic vigilance, indicating that self-regulation remains central.

However, as AI usage intensity increases, a gradual shift becomes apparent: elements of regulation, such as initiating analysis, structuring arguments, and evaluating outputs, get increasingly externalized to the tool. This shift is reflected in lower levels of perceived analytical independence and slightly elevated dependency risk among high AI users.

The threshold effect observed in this study is therefore best understood as a transition point at which AI moves from complementing self-regulated reasoning to partially substituting for it. This interpretation reframes contemporary debates on AI and critical thinking by shifting attention away from questions of cognitive decline toward questions of epistemic governance: who, and based on what, sets evaluative standards, and determines when judgment is complete. This conceptualization provides a critical foundation for pedagogical and institutional implications. If critical thinking is fundamentally a self-regulatory practice, then educational responses to generative AI should focus less on restricting access to tools and more on designing learning environments that preserve students' regulatory agency related to critical thinking. The key pedagogical challenge, therefore, lies in managing AI usage intensity and function in ways that sustain internal control over reasoning while still benefiting from AI's capacity to enhance learning and understanding.

## 6- Conclusion and Recommendations

This study set out to examine how the intensity of generative AI usage relates to students' critical thinking practices within political science higher education. The findings demonstrate that the impact of generative AI is neither uniformly beneficial nor uniformly detrimental. Rather, its effects are usage-dependent, revealing a threshold effect through which generative AI shifts from a cognitive scaffold to a partial substitute for self-regulated reasoning. Thus, responses must be differentiated at both the pedagogical and policy levels.

These results contribute to ongoing debates by reframing concerns about AI not as a question of cognitive decline, but as a matter of epistemic regulation and cognitive governance. In disciplines such as political science, where analytical autonomy, argumentation, and normative judgment are core learning objectives, generative AI has particularly significant implications. Accordingly, the findings call for responses that target managing AI usage intensity and function, rather than pursuing blanket restrictions or unregulated adoption.

### 6.1 Pedagogical Recommendations:

At the pedagogical level, the results suggest that :

1- learning design should deliberately position generative AI as a supportive tool rather than a substitutive one.

2-design AI-supported tasks that require students to engage in independent interpretation, evaluation, and argument construction. For example, students may be asked to critique AI-generated outputs, identify conceptual or normative weaknesses, or compare AI responses with competing theoretical frameworks.

3- Calibrate AI usage across learning stages. At early stages of learning, where conceptual clarification and background understanding are required, AI can function effectively as a scaffold. However, at advanced stages—such as theoretical comparison, normative evaluation, and policy analysis—AI use should be restricted or critically mediated. This staged integration aligns with Bloom's taxonomy and helps prevent the erosion of higher-order cognitive engagement.

4- Pedagogical practices should explicitly cultivate epistemic vigilance and verification norms. Given the observed decline in verification behaviors at higher levels of AI usage.

5- Assessment practices should further prioritize cognitive process over output. Rather than evaluating final products alone, assessments should require students to explain reasoning steps, justify analytical choices, and reflect on their interaction with AI tools. Evaluating how students use AI, rather than whether they use it, to helps maintain the centrality of self-regulated reasoning in political analysis.

6- Complementarily, tutorials and workshops should place greater emphasis on soft skills such as communication, debating, public speaking, and argumentation, which remain resistant to automation and are foundational to political science education.

**6.2 Policy Recommendations**

At the policy level, the findings highlights that:

1- the urgent need for a clear, Algerian-specific framework governing generative AI use in higher education. The current absence of coherent guidance risks encouraging either informal prohibition or excessive reliance, both of which undermine pedagogical objectives. National and institutional policies should move beyond ethical generalities and provide operational guidelines tailored to disciplinary and cognitive demands.

2- Rather than focusing on access control, policies should prioritize usage regulation and functional differentiation. The threshold effect identified in this study indicates that risks emerge not from AI use per se, but from excessive reliance that displaces cognitive self-regulation. Institutional guidelines should therefore distinguish between supportive uses of AI like clarification and exploration, and substitutive uses such as uncritical synthesis or argument generation.

3- Universities should also integrate AI literacy and epistemic governance training into political science curricula. Such training should emphasize the limits of AI-generated knowledge, risks of bias and hallucination, and the irreplaceable role of human judgment in political reasoning. Framing AI as an object of critical scrutiny, rather than a neutral authority.

4- More broadly, AI integration into educational systems should aim beyond short-term familiarization with emerging technologies. It should adopt a lifelong learning orientation, preparing students for a future in which AI will be embedded in both professional and social life. This requires continuous curricular adaptation and institutional reflexivity as educational technologies evolve (Akinwalere & Ivanov, 2022; Imran et al., 2024).

**6.3 Limitations and Future Research**

Several limitations must be acknowledged. First, the study was conducted within a single institution, which limits the generalizability of the findings to other disciplinary or national contexts. Second, the cross-sectional and quantitative design restricts causal inference and does not capture longitudinal changes in cognitive practices. Therefore, future research should employ longitudinal and quasi-experimental designs to examine how AI usage patterns evolve over time and across educational stages, particularly within under-researched contexts such as Algerian higher education (Zawacki-Richter et al., 2019).

As artificial intelligence is likely to remain a dominant educational technology in the coming decades, understanding how to harness its opportunities without compromising students' critical thinking capacities will remain a central challenge for higher education. The present study offers an exploratory and empirically grounded contribution to this effort by demonstrating that the key issue is not AI itself, but the threshold at which its use reshapes the locus of cognitive control.

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## Appendix A

**Questionnaire: The Use of Artificial Intelligence and Its Impact on Critical Thinking Skills Among Political Science Students**

1-Age:

18-20

21-50

26-30

Above 30

2-What is your academic ranking in your cohort?

The top 25% of the cohort

The second installment (between 25% and 50%)

The third installment (between 50% and 75%)

The bottom 25% of the cohort

3-What AI tools do you use? (You may select more than one answer)

Chat GPT

Google Gemini

Perplexity AI

Other …….

4-How often do you use AI tools for academic purposes?

Rarely (once or twice every six months)

Occasionally (1–2 times a month)

Regularly (1–3 times a week)

Frequently (almost daily)

5-For which academic tasks do you use artificial intelligence? (You may select more than one answer)

Understanding lesson content

Summarizing lectures, books, or articles

Generating ideas or creating an outline

Writing research papers or assignments

Improving language and style

Translation

Other …….

6- At what stage of academic work is artificial intelligence typically used?

At the beginning (brainstorming)

During the work

At the end (review or proofreading)

At all stages

7- How would you describe the nature of using artificial intelligence tools in preparing university assignments?

A valid aid tool (such as searching for sources or organizing ideas).

An educational tool (to understand concepts that are difficult to explain in lectures).

A substitute for personal effort (generating a ready-made text and submitting it).

8- I always verify the accuracy of the information provided by artificial intelligence.

Strongly agree

Agree

Neutral

Disagree

Strongly disagree

9- I look for errors or hallucinations in the outputs of artificial intelligence.

Strongly agree

Agree

Neutral

Disagree

Strongly disagree

10- I compare artificial intelligence information with academic references (books, articles, lectures).

Strongly agree

Agree

Neutral

Disagree

Strongly disagree

11-I realize that artificial intelligence may produce inaccurate or biased information.

Strongly agree

Agree

Neutral

Disagree

Strongly disagree

12- I can analyze political concepts without relying on artificial intelligence.

Strongly agree

Agree

Neutral

Disagree

Strongly disagree

13- Artificial intelligence helps me understand complex political or theoretical issues.

Strongly agree

Agree

Neutral

Disagree

Strongly disagree

14- I use artificial intelligence to explore political or ideological viewpoints that differ from my own personal beliefs.

Strongly agree

Agree

Neutral

Disagree

Strongly disagree

15- I rely more on my own judgment than on the conclusions of artificial intelligence.

Strongly agree

Agree

Neutral

Disagree

Strongly disagree

16- Artificial intelligence helps me learn more effectively.

Strongly agree

Agree

Neutral

Disagree

Strongly disagree

17-I you submit AI-generated content without editing it?

Yes

No

Sometimes

18-Using artificial intelligence sometimes reduces the effort I put into deep thinking.

Yes

No

sometimes

19-In your opinion, how does artificial intelligence affect your ability to think critically as a political science student? (Open)

20-Give an example of a situation in which you felt that artificial intelligence either helped or hindered your independent political analysis. (Open)

**Appendix B**

**Measurement Items**

| **Index** | **Items** | **Scale** |
| --- | --- | --- |
| AI Usage Intensity Indes (AIUI) | - How often do you use AI tools for academic purposes?<br><br>- At what stage of academic work is artificial intelligence typically used? | Coding |

| | | |
|---|---|---|
| | - How would you describe the nature of using artificial intelligence tools in preparing university assignments? | |
| Critical Thinking Independence Index (CTII) | - I can analyze political concepts without relying on artificial intelligence.<br><br>- I rely more on my own judgment than on the conclusions of artificial intelligence.<br><br>- I can construct scientific arguments without copying AI outputs. | Likert |
| Verification and Epistimic Vigilance Index (VEVI) | - I always verify the accuracy of the information provided by artificial intelligence.<br><br>- I look for errors or hallucinations in the outputs of artificial intelligence.<br><br>- I compare artificial intelligence information with academic references (books, articles, lectures).<br><br>- I realize that artificial intelligence may produce inaccurate or biased information.<br><br>- I use artificial intelligence to explore political or ideological viewpoints that differ from my own personal beliefs. | Likert |
| AI Assisted Learning Gain Index (AALG) | - Artificial intelligence helps me understand complex political or theoretical issues.<br><br>- Artificial intelligence helps me learn more effectively. | Likert |
| Dependancy Risk Index (DRI) | - I submit AI-generated content without editing it?<br><br>- Using artificial intelligence sometimes reduces the effort I put into deep thinking. | Coding |