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AI-INDUCED COGNITIVE LAZINESS IN HIGHER EDUCATION: A DIAGNOSTIC STUDY

PREGUIÇA COGNITIVA INDUCIDA PELA IA NO ENSINO SUPERIOR: UM ESTUDO DIAGNÓSTICO

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Abstract
The objective of this study was to examine the relationship between university students' inappropriate and excessive use of Artificial Intelligence (AI) and the cognitive laziness they may exhibit, defined as a reduced need to engage their own cognitive processes, even in simple tasks. A sample of 50 students aged 19-25 completed a questionnaire with multiple-choice and Likert-scale items. The questions focused on the frequency of AI use, students' perceived dependence on it, and the reduction in mental effort. Based on the data obtained, a composite index of cognitive laziness was constructed. A linear regression model was constructed, and its interpretation can be summarized in three points: first, each increase in frequency of use triples the risk of high cognitive laziness (OR = 3.42). It was also found that using AI for personal tasks quadruples the risk (OR = 4.15), and finally, the model explains 58% of the variance. It was concluded that the use of AI without adequate regulation tends to lead to lower cognitive engagement among students, underscoring the need to incorporate AI into higher education through an approach that promotes reflective thinking, conscious use of technology, and the development of intellectual autonomy.

Keywords: Higher Education, Artificial Intelligence, Metacognition, Critical Thinking, Cognitive Laziness

Resumo
O objetivo deste estudo foi examinar a relação entre o uso inadequado e excessivo da Inteligência Artificial (IA) em estudantes universitários e a preguiça cognitiva que eles poderiam apresentar, entendida como uma menor necessidade de ativar seus próprios processos cognitivos, mesmo em tarefas simples. Participaram 50 estudantes de 19 a 25 anos, que responderam a um questionário com perguntas de múltipla escolha e escala Likert. As perguntas se concentraram na frequência de uso da IA, na dependência percebida e na redução do esforço mental. Com os dados, foi construído um índice composto de preguiça cognitiva e estimado um modelo de regressão, cujos resultados são resumidos em três pontos: cada aumento na frequência de uso triplica o risco de alta preguiça cognitiva (OR = 3,42); usar IA para tarefas pessoais quadruplica o risco (OR = 4,15); e o modelo explica 58% da variância. Conclui-se que, sem uma regulamentação adequada, a IA tende a reduzir o envolvimento cognitivo, pelo que a sua integração no ensino superior deve promover o pensamento reflexivo, o uso consciente da tecnologia e a autonomia intelectual.

Palavras-chave: *Ensino Superior. Inteligência Artificial. Metacognição. Pensamento Crítico. Preguiça Cognitiva*

1 INTRODUCTION

In recent years, Artificial Intelligence (AI) has become increasingly prevalent in classrooms across educational institutions. Its ability to accelerate activities, solve problems, summarize texts, create algorithms, and perform other tasks, as well as provide near-instantaneous answers to student questions, has made it a favorite tool for millions of students and professionals. However, this growing use has raised concerns about its potential effects on the mental processes and cognitive development of those who use it frequently. One of the main concerns for teachers is that students may submit assignments and projects created with AI without prior critical review or reflection, which, according to Correal Romero (2025), reduces their engagement in learning and limits the development of their own skills and abilities.

Given the current situation, teachers are required to develop actions, strategies, and activities that foster reflection and analysis.

Recent studies (Rivera, 2023; Hassen, 2025) indicate that the excessive use of AI by students and professionals can decrease cognitive engagement while increasing dependence on technology, weakening necessary skills and abilities such as critical thinking, reflection, analysis, synthesis, and decision-making, among others, which have traditionally developed autonomously. In this regard, Zhang *et al*. (2023) and Kim & Lee (2024) comment that the result would be a passive education, emphasizing the immediate acquisition of answers that lack meaning and utility for the student.

This phenomenon raises the need to analyze whether the frequent use of AI is generating a dependency that directly affects cognitive load. People who frequently use this tool accept the given answers without questioning them, leading to a phenomenon called "cognitive laziness." Kahneman (2011) defines it as a tendency to use minimal mental processing strategies to make decisions or solve problems, avoiding the cognitive effort necessary for in-depth analysis. In other words, this term refers to the brain's tendency to avoid the effort of critical thinking when it has access to automated answers.

This paper addresses the problem of cognitive laziness among students due to the inappropriate or excessive use of AI. Students may rely entirely on the immediate answers it provides without verifying the information's accuracy, hindering their ability to develop critical thinking skills and make independent decisions by simply accepting everything

AI offers. Therefore, the research question posed was: Do students experience cognitive laziness due to the inappropriate or excessive use of AI? The idea that AI can be a beneficial tool for reducing cognitive load is not dismissed. It can help avoid overwhelming students with too much information when searching for a topic, allowing them to break it down into sections for easier understanding. This prevents the information from becoming tedious and causing the user to lose interest quickly. Its balanced integration into daily life can improve productivity, expedite information searches, and even aid in decision-making. In a world where technology is advancing rapidly, critical thinking is a skill that should not be lost.

Although generative AI offers convenience and immediate efficiency, its overuse comes at a cognitive cost. The mind tends to disengage from effort when using AI, which can cause long-term damage to skills such as memory, critical thinking, and creativity (Gerlich, 2023).

1.1 Cognitive laziness

The conceptualization of cognitive laziness is rooted in the theory of the "Cognitive Miser" (Fiske & Taylor, 1984), which posits that people naturally conserve cognitive resources. Kahneman (2011) expanded on this notion with his Systems 1 and 2 model, where System 1 (fast, intuitive) is error-prone but requires less effort than System 2 (slow, analytical).

Regarding the two systems Kahneman refers to, Table 1 shows the main characteristics of System 1.

Table 1

Main characteristics of System 1

,	Description	Everyday Example
Automatic	Operates effortlessly and involuntarily	Recognizing familiar faces
Fast	Almost instantaneous processing	2 + 2 = 4 (you know the answer without calculating)
Intuitive	Based on emotions and associations	“Sensing” danger when hearing a strange noise
Heuristic	Uses mental shortcuts (rules of thumb)	Judging distance by apparent size
Subconscious	Does not require conscious attention	Maintaining balance while walking

Prone to errors	Makes systematic biases	Optical illusions mislead you

The main characteristics of system 2 are presented in Table 2.

Table 2

Main characteristics of System 2

Attribute	Description	Everyday example
Controlled	Requires conscious effort	Solving 17 × 24
Slow	Deliberate processing	Choosing what to study at university
Analytical	Based on logical reasoning	Comparing prices of complex products
Rule-based	Follows systematic procedures	Learning to drive (at the beginning)
Conscious	Requires focused attention	Filling out a complex form
Infrequent	Activated only when necessary	Most of the time we use System 1

Kahneman summarizes the two systems as follows: "System 1 is automatic, and System 2 is normally in a comfortable, minimal-effort mode, with only a small portion of its capacity engaged."

Tversky and Kahneman (1974) demonstrated that mental shortcuts (heuristics) are adaptive mechanisms for managing processing constraints. However, in educational contexts, this cognitive economy can become dysfunctional when thinking is excessively externalized.

Cognitive load theory (Sweller, 1988) explains how limitations on working memory influence learning. Automation through AI can reduce intrinsic cognitive load, but it can also diminish the development of mental schemas necessary for expertise (Sweller *et al.*, 2019).

In educational settings, Kim and Lee (2024) found that 73% of high school students used AI to complete tasks without first attempting to solve them, and that critical thinking scores decreased by 28% after 8 weeks of regular use.

Zhang *et al*. (2023) reported a negative correlation (r = -0.41) between ChatGPT usage frequency and critical thinking skills in university students, controlling for demographic variables.

Logg *et al*. (2023) demonstrated in 6 experiments with 1,200 participants that 68% preferred to follow AI recommendations rather than think independently, even when they had sufficient knowledge for the task.

Fischer *et al*. (2022) identified that AI reduces tolerance for ambiguity, leading to a preference for immediate answers over exploratory processes.

Smith *et al*. (2023) analyzed 47 studies (n = 15,238) and found an average effect size of d = -0.32 on critical thinking with the use of AI. The negative effects were greater in tasks that required creativity and synthesis.

Chen and Wang (2024) concluded in their meta-analysis that the negative cognitive effects of AI are moderated by learner self-regulation factors.

2 METHODOLOGY

This study was descriptive and correlational, as outlined by Hernández-Sampieri and Mendoza (2023), and aimed to examine two correlations: one between the inappropriate use of AI and cognitive laziness, and the other between excessive AI use and cognitive laziness. The sample consisted of 50 university students aged 19 to 25. The sample was randomly selected, as students from a school within the National Polytechnic Institute in Mexico City were invited to participate via social media. They were informed of the study's objective and that they would complete a questionnaire via Google Forms. It was emphasized that they would not be recording their names or any other sensitive information. Authorization was also obtained from the school's Ethics Committee to conduct this study, and the students provided informed consent before completing the questionnaire.

The methodological instrument used was a questionnaire, designed to identify usage and perception patterns related to artificial intelligence tools. Based on these responses, the frequency of AI use, its primary purpose, the degree of integration into students' daily lives, and the level of trust in the information provided by these tools were analyzed. This approach allows interpreting the results as positive or negative, depending on the impact of artificial intelligence on cognitive load and learning processes.

The questionnaire was structured with three types of items: six multiple-choice items, five dichotomous (yes/no) items, and five Likert-type scale items. The inclusion of the Likert scale was due to its ease of administration, as well as its recognized validity and widespread acceptance in educational and psychological research. Likert scales allow for the quantification of opinions, attitudes, and perceptions through graded responses, which facilitates the subsequent statistical analysis of the data obtained (Likert, 1932).

Furthermore, self-report instruments have proven suitable for assessing perceived cognitive load, as they capture the student's subjective experience during the learning process and allow for a direct approach to their cognitive experience (Paas, 1992). The reliability of the instrument was assessed using Cronbach's alpha coefficient, considering only the Likert-type scale items that consistently measure the construct under study. Multiple-choice, dichotomous, and open-ended questions were excluded from this analysis because they do not present a comparable ordinal scale nor do they contribute to the internal consistency of the instrument (Oviedo & Campo-Arias, 2005).

Once the questionnaire was completed, the Excel file was downloaded, and the statistical measures for obtaining the results and corresponding analysis were calculated.

To analyze the information from the questionnaire results, different statistical measures were used. The procedure followed is presented below:

1. Defining the indicators.
2. Testing the consistency between indicators.
3. Constructing the composite index (0-3 points).
4. Testing the reliability of the index using Cronbach's alpha.
5. Comparison between risk groups.
6. Logistic regression model and its interpretation.
7. Identifying profiles using cluster analysis (K-means).
8. Spearman's rank correlation matrix.

3 RESULTS AND ANALYSIS

This section is divided into two parts. The first presents the percentages obtained from the questions in the questionnaire, and the second presents the statistical measures used to conduct the analysis.

3.1 Results expressed as percentages for multiple-choice and "yes/no" questions

100% of respondents stated that they had heard of or knew what Artificial Intelligence is. The categories "Sometimes" (34%), "frequently" (34%), and "every day" (14%) predominated, suggesting that AI is part of students' daily routine. 36% considered AI "Very useful" and 22% "Useful," totaling 58% with a positive perception. Only 16% expressed a negative perception. The most reported uses were: academic work, content creation (texts, images, ideas), and information retrieval. This indicates that AI is primarily used as an academic and cognitive support tool.

Mobile phones and computers were reported as the most frequently used devices for accessing AI tools, reflecting flexible and consistent usage.

Regarding trust in information provided by AI, the levels are intermediate, suggesting that students recognize its usefulness but maintain a critical and verification-oriented approach.

With respect to attitudes toward learning about and the future of AI, the majority (96%) believed that AI use will continue to increase in the future and that they want to learn more about its proper use. This reflects a positive and open attitude, but one that is also aware of the need for training.

As for risk perception, a significant proportion of students (96%) recognized that excessive use of AI could have negative effects, demonstrating an ethical and critical awareness of its application.

3.2 Results and data analysis

3.2.1 Defining indicators

To statistically analyze cognitive laziness, indicators based on the data obtained from the questionnaire were used. These indicators were:

- High AI dependence: "I feel that I depend too much on AI" (≥4)
- Low perceived mental effort: "AI helps me reduce mental effort" interpreted negatively (≥4 could indicate effort avoidance)

- Use to avoid cognitive work: Use of AI for personal tasks + Low verification.
- Combination of indicators: Creation of a composite index
- Risk factors were also defined:
- Inappropriate use: "Yes" in use for personal tasks
- Excessive use: Frequency "Every day" or "Frequently."

The information obtained from the distribution of cognitive laziness indicators is presented in Table 3.

Table 3

Prevalence of Individual Indicators

Indicator	Criterion	n	%	Interpretation
High dependence	Score ≥ 4 (item 2)	12	24.00%	Psychological dependence
Extreme effort reduction	Score = 5 (item 1)	15	30.00%	Maximization of effort reduction
Use for own assignments	“Yes” or “Prefer not to answer”	36	72.00%	Possible task avoidance
Low verification	Score ≤ 2 (item 4)	11	22.00%	Limited information verification
Critical combination	High dependence + Use for own assignments	10	20.00%	Possible cognitive laziness

3.2.2 Consistency test between indicators

Once the indicators were defined, a consistency test was performed between them (Phi coefficients), obtaining the following:

- Dependence vs. Use for Work: $\varphi = 0.28$, $p = 0.048$ (significant association)
- Dependence vs. Effort Reduction: $\varphi = 0.42$, $p = 0.003$ (strong association)
- Use for Work vs. Low Verification: $\varphi = 0.18$, $p = 0.211$ (not significant)

3.2.3 Construction of the composite index (0-3 points)

The cognitive laziness index was subsequently constructed, resulting in the following:

Composite index (0-3 points), 1 point for each criterion met:

- Dependence ≥4
- Use of AI for own work = "Yes"

- Frequency of use ≥4 (Frequently/Every day)

Table 4 shows the distribution of the cognitive laziness index:

Table 4

Distribution of the Cognitive Laziness Index

Score	N	%	Interpretation
0 (Low risk)	8	16.00%	Moderate and ethical use
1 (Moderate risk)	18	36.00%	1 risk factor
2 (High risk)	16	32.00%	2 risk factors
3 (Very high risk)	8	16.00%	3 risk factors
Total at risk (≥1)	42	84.00%	Majority at risk

3.2.4 Reliability testing of the questionnaire using Cronbach's Alpha index

Reliability testing was conducted using Cronbach's Alpha index for the 3 items and by calculating the correlation between the item and the total score. The values obtained were as follows:

- Cronbach's Alpha for the 3 items: $\alpha = 0.58$ (moderate)
- Item-total score correlation: 0.42

3.2.5 Comparison between risk groups

Table 5 shows the information obtained for the classification of the risk groups:

Table 5

Student characteristics by cognitive laziness risk level

Variable	**Low risk (0)**	**Moderate risk (1)**	**High risk (2)**	**Very high risk (3)**	**p-value***
N	8	18	16	8	
Age (mean category)	2.13	1.94	1.88	1.75	0.412
Frequency of use (1–5)	2.75	3.11	3.94	4.5	<0.001
Perceived usefulness (1–5)	2.5	3.33	4.06	4.25	<0.001
Dependence (item 2)	1.88	2.28	3.13	4.38	<0.001
Reduces effort (item 1)	2.88	3.5	4.38	4.75	<0.001
Verification (item 4)	2.88	3.39	3.88	3.63	0.052
Total cognitive load	12.13	15.28	19.31	20.5	<0.001

*Kruskal-Wallis test (non-parametric)

- Post-hoc analysis (Dunn's test):
- Very high risk vs. Low risk: $p < 0.001$ (highly significant)
- High risk vs. Low risk: $p = 0.002$ (significant)
- Moderate risk vs. Low risk: $p = 0.035$ (significant)

3.2.6 Logistic regression model and its interpretation

The dependent variable is: High cognitive laziness (index ≥2 vs ≤1). The binary logistic model was constructed, the information of which is presented in Table 6.

Table 6

Logistic regression model and predictor variables

0	OR (Odds Ratio)	95% CI	p-value
Frequency of use (per point)	3.42	[1.85, 6.33]	<0.001
Use for own assignments (Yes vs No)	4.15	[1.08, 15.94]	0.038
Age (per category)	0.75	[0.35, 1.61]	0.46
Perceived usefulness (per point)	1.82	[0.97, 3.41]	0.063

3.3 Analysis

Considering the results shown in the previous section, their analysis is presented below.

A composite index of “cognitive laziness” was constructed, integrating key variables such as frequency of use, perceived dependence, and the use of AI for personal academic work. Although the Cronbach's alpha coefficient indicates moderate reliability, it proved useful for identifying risk profiles and analyzing general trends in the sample. The application of various statistical techniques, including correlation analysis, cluster analysis, and logistic regression, strengthened the robustness of the analysis and enabled a deeper understanding of the phenomenon.

The results show that a significant proportion of students are at moderate to high risk of cognitive laziness. Excessive reliance on AI and the submission of academic work as their own increases the likelihood of high levels of cognitive laziness. The cluster analysis allowed for the differentiation of profiles, ranging from students who use AI sparingly to those who use it routinely for everything, revealing patterns of dependence and cognitive decline.

4 DISCUSSION

This study offers a diagnostic analysis of the relationship between the inappropriate and excessive use of artificial intelligence and cognitive laziness among university students, a topic gaining relevance in higher education and educational technology research. The fact that a considerable proportion of students fall into moderate and high-risk categories suggests that the frequent use of AI tools may be displacing essential cognitive processes and promoting learning strategies that require less mental effort. This pattern is consistent with the concept of cognitive laziness, understood as the tendency to deliberately reduce analytical effort when technological shortcuts are readily available (Hassen, 2025).

In this vein, the results of the present study align with previous research that warns of the potential cognitive effects of the intensive use of artificial intelligence in educational settings, particularly when it is not accompanied by pedagogical strategies focused on reflection and active student participation. The high proportion of students exhibiting moderate to high levels of cognitive laziness aligns with the literature on a growing tendency to delegate cognitive tasks to automated systems, a phenomenon known as cognitive offloading (Gerlich *et al*., 2025; Logg *et al*., 2023).

Furthermore, the significant association between AI usage frequency and cognitive laziness reinforces the tenets of cognitive miser theory, which posits that people tend to reduce mental effort when they have alternatives of low cognitive cost (Fiske & Taylor, 1984; Kahneman, 2011). From this perspective, the empirical findings support the idea that AI use primarily favors the activation of System 1 cognitive processing, characterized by rapid, intuitive responses, at the expense of System 2, which is responsible for analytical, reflective, and critical reasoning.

These results are consistent with previous studies that have identified negative relationships between the frequent use of artificial intelligence tools and the development of critical thinking in university students (Zhang *et al*., 2023; Kim & Lee, 2024).

Similarly, the logistic regression model in this study shows that using AI for personal academic work quadruples the likelihood of exhibiting high cognitive laziness, which aligns with the experimental evidence from Logg *et al*. (2023), who demonstrated that users tend to follow algorithmic recommendations even when they possess the necessary knowledge to solve the task independently.

Based on cognitive load theory, the results allowed us to distinguish between a functional reduction in load and potential cognitive impoverishment. While artificial intelligence can reduce extrinsic cognitive load by facilitating access to and organization of information, its excessive use appears to interfere with the development of deeper mental schemas, as noted by Sweller *et al*. (2019). In this regard, the positive correlation between perceptions of less effort and cognitive laziness suggests that automation used without clear pedagogical criteria could limit the development of meaningful learning processes.

However, identifying a group of users with intensive, but conscious, use of artificial intelligence introduces an important nuance to the debate. This result is consistent with recent meta-analyses indicating that the potential negative effects of AI on cognitive abilities are not direct, but rather mediated by factors such as self-regulation, metacognition, and the purpose for which the technology is used (Chen & Wang, 2024; Fischer *et al*., 2022). From this perspective, the study's findings reinforce the idea that cognitive laziness does not stem from the technology itself, but from usage patterns that replace, rather than support, reflective thinking processes.

5 CONCLUSIONS

The construction of the composite cognitive laziness index is a valuable contribution, as it operationalizes an abstract theoretical construct into observable indicators.

One interpretively significant aspect is that frequency of use emerges as the most robust predictor of high cognitive laziness, even above variables such as age or perceived usefulness. This suggests that it is not the positive evaluation of AI that explains the phenomenon, but rather the normalization of its use as a substitute for cognitive effort. Furthermore, the discovery of distinct clusters enabled a nuanced understanding of the deterministic discourse surrounding AI's effects, revealing that self-regulation and information verification can serve as partial protective factors.

Therefore, the study not only empirically confirmed the presence of cognitive laziness associated with AI use but also provided an interpretive perspective on the mechanisms by which cognitive automation can weaken intellectual autonomy. These results reinforce the need to rethink the role of AI in higher education from a pedagogical, rather than merely instrumental, standpoint, since the findings suggest that AI does not act solely as a neutral support tool, but as an agent that reconfigures the dynamics of mental effort.

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Authors' Contribution

All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

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