

Research Article

The Impact of Artificial Intelligence Tools on Learning Modalities, Educational Dependency, and Cognitive Tendencies: A Comparative Cross-Institutional Study

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ABSTRACT

Background: The rapid proliferation of consumer-grade Artificial Intelligence (AI) platforms has significantly altered the educational landscape, yet comparative data regarding usage patterns and perceived cognitive impacts across diverse socio-institutional environments remain sparse.

Aims/Objectives: To evaluate and compare AI utilization models, help-seeking behaviours, and subjective cognitive impacts among secondary students between a CBSE school and a Non-CBSE school.

Methodology: A multi-centre, cross-sectional descriptive cohort study evaluated students across Grades 5-12 (N = 294; n = 147 per school). Data collection utilized an electronic multi-variable assessment tool. Statistical significance was verified using Chi-square (χ^2) analyses and Student's t-tests.

Results: Demographic parameters (age, gender, grade distribution) were statistically identical between cohorts ($p > 0.05$). The CBSE school demonstrated significantly higher daily AI interactions (55.8%) compared to the Non-CBSE school (22.4%; $p < 0.001$), primarily favouring generative Large Language Models (LLMs) (59.2% vs. 24.8%; $p < 0.001$). The Non-CBSE school heavily relied on standard search engines (62.4%). Perceptions of AI inducing cognitive passivity ("laziness") were significantly higher in the CBSE school (59.2%) than the Non-CBSE school (37.6%; $p < 0.001$). CBSE school students reported higher reductions in independent study time (56.7% vs. 39.2%; $p = 0.014$) and greater application in STEM fields (51.7% vs. 32.8%; $p = 0.004$). Academic oversight was significantly superior in the Non-CBSE school (40.8% actively monitored vs. 24.2% in the CBSE school; $p < 0.01$).

Conclusion: Institutional frameworks, curriculum structures, and oversight mechanisms strictly modulate adolescent AI engagement. CBSE environments correlate with high-frequency LLM utilization and elevated self-reported academic dependencies, highlighting the need for targeted digital hygiene guidelines.

Keywords: Artificial Intelligence, Education, Chatgpt, AI Awareness Cognitive Impact, Academic Dependency, Behavioural Dependency.

INTRODUCTION

The integration of consumer-grade Artificial Intelligence (AI) platforms and Generative Large Language Models (LLMs) into daily life has induced a paradigm shift in secondary education globally.^{1,2} Platforms such as OpenAI's ChatGPT, Google Gemini, and automated application-specific software offer immediate, conversational, and highly structured technical solutions to complex academic inquiries.³ While these technologies present powerful opportunities for personalized tutoring, conceptual scaffolding, and expedited text generation,^{4,5} they simultaneously introduce significant challenges regarding adolescent cognitive development, academic self-efficacy, and behavioral dependency.^{6,7}

During adolescence, executive functioning, metacognition, and independent study behaviors undergo critical refinement. Unrestricted access to immediate algorithmic validation may compromise these developmental processes by cultivating cognitive passivity—often subjectively described by students as perceived lethargy or "laziness"—and encouraging cognitive offloading.^{8,9} Furthermore, the impact of these platforms may be modulated by institutional contexts, parental oversight, socioeconomic baselines, and pedagogical device integration policies.^{5,10} CBSE schools frequently promote early digital immersion and technical integration, whereas Non-CBSE institutions may operate under traditional pedagogical

paradigms or alternative curriculum guidelines. Understanding how these different institutional ecosystems shape AI engagement, help-seeking behaviors, and academic integrity is essential for designing effective digital literacy interventions.^{1,11}

This study directly addresses this research gap. The purpose of this investigation was to evaluate and compare the utilization models, primary platform choices, transactional frequencies, help-seeking behaviors, and subjective cognitive impacts of consumer-grade AI platforms among students from two distinct educational institutions (CBSE school versus Non-CBSE school).

METHODOLOGY

Study Design and Setting

This study utilized a multi-centre, cross-sectional descriptive cohort design conducted over a single academic cycle. The investigation compared two distinct educational environments situated within an urban sector: a CBSE school (a highly technical urban private institution characterized by extensive digital infrastructure and permissive classroom device integration) and a Non-CBSE school (a classic urban institution characterized by traditional pedagogical structures and rigid restrictions regarding student laptop and mobile device utilization during active classroom hours). Both campuses maintained standard internet connectivity.

Study Population and Selection Criteria

The study population comprised secondary education students enrolled across Classes/Grades 5 through 12, encompassing an age spectrum of 10 to 16 years. A total of 294 participants were enrolled via consecutive sampling and allocated equally into two cohorts based on their institution (*n* = 147 for the CBSE school; *n* = 147 for the Non-CBSE school).

- **Inclusion Criteria:** Confirmed institutional enrollment within Grades 5 through 12; documented student assent; documented parental/legal guardian written informed

consent; and full completion of the electronic multi-variable assessment tool.

- **Exclusion Criteria:** Incomplete survey metrics; multi-variable data entry errors; or a complete absence of prior interactions with digital or web-based interfaces.

Data Collection Tools and Procedures

A secure, electronic, multi-variable assessment tool was administered cross-sectionally to all eligible students. The validated instrument captured metrics across five main domains:

1. Baseline socio-demographic parameters (age, gender, and grade level).
2. Prior tool awareness and preferred digital platforms (Generative LLMs vs. standard search engines vs. calculator applications).
3. Temporal metrics of interaction (daily, weekly, or rare frequencies).
4. Subjective behavioral parameters (perceived cognitive dependencies, motivations for academic cheating, and effects on independent study time).
5. Academic outcomes and environmental influences (primary homework application domain, subjective helpfulness index, future career adjustments, and active parental or teacher oversight rates).

Statistical Analysis

Data integrity was systematically reviewed before analysis. Continuous variables (age) were verified for normality and are expressed as Mean ± Standard Deviation (SD). Inter-group differences for continuous measures were analyzed using an independent Student's t-test. Categorical variables and percentage frequencies were analyzed using Pearson's Chi-square (χ^2) tests of independence to determine within-group and between-group variances. The alpha level for statistical significance was pre-established at *p* < 0.05. All statistical computations were executed using automated analytical software.

RESULTS & DISCUSSION

Table 1: Demographic and Baseline Characteristics

Baseline parameter	School 1(147)	School 2 (147)	
Age (Years), Mean± SD	13.4±1.5	13.6±1.6	

Gender	Male	73 (56.7%)	78 (60.0%)	X2 = 0.34 p = 0.554 (not significant)
	Female	74 (43.3%)	69 (40.0%)	
Grade Level Bracket, n (%)				
Lower Secondary (Grades 5–8)		66 (45.0%)	72 (48.8%)	X2 = 0.49 P = 0.483 (not significant)
Upper Secondary (Grades 9–10)		81 (55.0%)	75 (51.2%)	
Prior AI Tool Awareness, n (%)	Yes	140 (95.0%)	132 (89.6%)	X2 = 3.14 p = 0.076 (not significant)
	NO	7 (5.0%)	15 (10.4%)	

A total of 294 students ($n = 147$ per school) successfully completed the study. The cohorts exhibited strong baseline demographic homogeneity. The mean age was 13.4 ± 1.5 years for the CBSE school and 13.6 ± 1.6 years for the Non-CBSE school, demonstrating no statistically significant variation ($p > 0.05$). No statistically significant variances were observed

regarding gender distribution ($\chi^2 = 0.34$, $p = 0.554$) or grade level distribution ($\chi^2 = 0.49$, $p = 0.483$), confirming excellent comparability between the cohorts. Baseline awareness of AI tools was highly prevalent across both institutions (95.0% in the CBSE school vs. 89.6% in the Non-CBSE school), showing no significant divergence ($\chi^2 = 3.14$, $p = 0.076$).

Table 2: Platform Selection and Temporal Engagement Frequencies

Variable Analysed	School 1 (n=147)	School 2 (n=147)	
Primary Platform Chosen, n (%)			X ² = 36.84 P < 0.001 (very significant)
• ChatGPT / Generative LLMs	87 (59.2%)	36 (24.8%)	
• Google Search / Reference Web	47 (31.7%)	92 (62.4%)	
• Specialized Apps (Calculators)	12 (9.1%)	19 (12.8%)	
Frequency of Daily Interaction, n (%)			X ² = 36.54 p < 0.001 (very significant)
• Daily (Every day)	82 (55.8%)	33 (22.4%)	
• Weekly / Periodic	50 (34.2%)	75 (51.2%)	
• Rarely / Never	15 (10.0%)	39 (26.4%)	

Marked differences emerged regarding the selection of primary platforms and frequency of use. CBSE school students heavily favoured generative LLMs/ChatGPT (59.2%), whereas Non-CBSE school students predominantly utilized standard Google Search/reference web interfaces (62.4%). This structural difference in tool selection was highly significant ($\chi^2 = 36.84$, $p < 0.001$). Furthermore, temporal engagement patterns indicated accelerated daily interaction in the

CBSE setting. Over half of the CBSE school cohort (55.8%) interacted with AI platforms daily, whereas the majority of the Non-CBSE school cohort (51.2%) engaged on a weekly or periodic basis. A substantial portion of the Non-CBSE cohort reported rare or zero interaction (26.4%), establishing a highly significant variance in temporal frequency ($\chi^2 = 36.54$, $p < 0.001$).

Table 3: Perceived Behavioural Dependencies and Tendencies

Survey Query Metric	School 1 (n=147)	School 2 (n=147)	
"Does AI usage make you lazy?"			
• Yes	87 (59.2%)	55 (37.6%)	X ² = 14.17 P < 0.001 (V. significant)
• No	42 (28.3%)	61 (41.6%)	
• Maybe / Not Sure	18 (12.5%)	31 (20.8%)	
"Would you cheat using AI?"			
• Always / Frequently	23 (15.8%)	13 (8.8%)	X ² =5.67 P< 0.059 (not significant)
• Sometimes	76 (51.7%)	69 (47.2%)	
• Never	48 (32.5%)	65 (44.0%)	

Students' subjective evaluations of their cognitive habits revealed notable behavioral dependencies. When asked if AI platform usage induced cognitive passivity ("lazy habits"), a significant majority of CBSE school students (59.2%) answered affirmatively, compared to 37.6% in the Non-CBSE school ($\chi^2 = 14.17$,

$p < 0.001$). Conversely, self-reported tendencies to use AI for academic dishonesty (cheating) did not differ significantly between the institutions, with similar proportions acknowledging frequent or situational usage ($\chi^2 = 5.67$, $p = 0.059$).

Table 4: Academic Self-Efficacy, Task Resolution, and Secondary Environmental Variables

Functional Outcome Metric	School 1 (n=147)	School 2 (n=147)	
Primary Use in Homework, n (%)			
• Fast Verification / Fact Checking	100 (68.3%)	93 (63.2%)	X ² =4.80 P< 0.091 (not significant)
• Outlining / Full Text Generation	32 (21.7%)	26 (17.6%)	
• Direct Copying / No Modification	15 (10.0%)	28 (19.2%)	
Perceived AI Helpfulness (Scale 1-5)			
• High Helpfulness Rating (Scores 4–5)	115 (78.3%)	107 (72.8%)	X ² = 0.90 P< 0.342 (not significant)
• Moderate / Low Rating (Scores 1–3)	32 (21.7%)	40 (27.2%)	
Alters Long-Term Career Plans?			
• Yes	17 (11.7%)	13 (8.8%)	X ² =0.78 P< 0.678 (not significant)
• No	99 (67.5%)	105 (71.2%)	
• Maybe	31 (20.8%)	29 (20.0%)	

Table No. 5: Comparative Analysis of Secondary Behavioural Variables and Environmental Influences

Functional Outcome Metric	School 1 (n=147)	School 2 (n=147)	
Reduces Independent Study Time?			X ² =8.59

YES	83 (56.7%)	58 (39.2%)	P< 0.014 (significant)
NO	48 (32.5%)	65 (44.0%)	
Unsure/ no response	16(10.8%)	24(16.8%)	
Primary Domain of Application			X ² = 11.11 P< 0.004 (very significant)
STEM (Math/Science)	76 (51.7%)	48 (32.8%)	
Humanities (Essays/Languages)	54 (36.7%)	78 (52.8%)	
Arts / Other Subjects	17 (11.6%)	21 (14.4%)	
Peer Pressure to Use AI Tools			X ² =3.20 P< 0.202 (not significant)
High Influence	29 (20.0%)	18 (12.0%)	
Moderate Influence	65 (44.2%)	68 (46.4%)	
No Influence	53 (35.8%)	61 (41.6%)	
Parental / Teacher Oversight Rate			X ² = 9.22 P < 0.01 (highly significant)
Actively Monitored	36 (24.2%)	60 (40.8%)	
Intermittently Checked	75 (50.8%)	62 (42.4%)	
Completely Unmonitored	36(25.0%)	25 (16.8%)	

Regarding homework execution, fast verification or fact-checking was the predominant use case across both institutions (68.3% in the CBSE school vs. 63.2% in the Non-CBSE school; $\chi^2 = 4.80$, $p = 0.091$). The perceived helpfulness index remained uniformly elevated, with 78.3% of the CBSE school and 72.8% of the Non-CBSE school reporting scores of 4 or 5 ($\chi^2 = 0.90$, $p = 0.342$). Long-term career adjustments attributable to AI disruption were minimal and statistical parity was maintained between institutions ($\chi^2 = 0.78$, $p = 0.678$).

However, CBSE school students experienced a significant reduction in independent study time (56.7%) compared to Non-CBSE school students (39.2%; $\chi^2 = 8.59$, $p = 0.014$). Academic application domains also shifted significantly: the CBSE school focused primarily on STEM disciplines (51.7%), while the Non-CBSE school focused on Humanities and languages (52.8%; $\chi^2 = 11.11$, $p = 0.004$). Peer pressure showed no significant differences ($\chi^2 = 3.20$, $p = 0.202$). Crucially, active parental and teacher oversight rates were significantly higher in the Non-CBSE school (40.8%) compared to the CBSE school (24.2%; $\chi^2 = 9.22$, $p < 0.01$).

DISCUSSION & CONCLUSION

Interpretation and Comparative Insights

This study reveals distinct patterns of behavioral adaptation, tool prioritization, and subjective cognitive impacts among secondary students exposed to consumer-grade AI platforms. Despite baseline demographic homogeneity and equivalent fundamental awareness of AI technologies across both cohorts, curriculum frameworks, institutional policies, infrastructure, and socio-environmental factors appeared to strongly modulate actual engagement patterns.^{12,13} Students within the CBSE school demonstrated high-frequency, daily utilization profiles dominated by conversational, generative LLMs (59.2%). In contrast, students in the Non-CBSE school relied primarily on traditional search engine networks (62.4%) and periodic usage models. This variance likely stems from differences in institutional constraints: the CBSE school permits continuous mobile and laptop integration within active classroom structures, whereas the Non-CBSE school enforces traditional, non-device pedagogies. Continuous device availability lowers the friction required to access algorithmic answers, transitioning AI

from an occasional reference tool into an active workspace companion.¹⁴

This difference in usage frequency clarifies why 59.2% of CBSE school participants reported that AI usage induced behavioral passivity ("laziness"), compared to only 37.6% in the Non-CBSE school. When automated networks immediately generate structured paragraphs or resolve STEM formula brackets, the neurological effort required for cognitive processing drops substantially, driving cognitive offloading and learning inertia.^{8,15} Over time, this convenience can reduce tolerance for academic frustration and diminish executive stamina, contributing to problematic engagement habits.^{7,9} This is further evidenced by the significant reduction in independent study time reported by CBSE school students (56.7%), corroborating findings on AI-induced reductions in student effort and academic engagement.^{6,15}

The distinct domains of application between the institutions (51.7% STEM in the CBSE school vs. 52.8% Humanities in the Non-CBSE school) further clarify these usage profiles. LLMs are highly effective at generating code, parsing formulas, and structuring step-by-step logic, aligning well with the technical curriculum standards frequently emphasized in CBSE streams.³

Crucially, the higher rate of active academic and parental monitoring observed in the Non-CBSE school (40.8% vs. 24.2% in the CBSE school) may serve as a protective barrier against cognitive over-reliance. When adult oversight is continuous rather than intermittent, students are more likely to use digital platforms for targeted verification rather than direct text generation or unreflective task resolution.^{5,10} Interestingly, despite differences in tool reliance and perceived passivity, both cohorts exhibited similar self-reported rates of situational academic cheating. This suggests that the baseline motivation for academic shortcutting remains stable across student populations,⁶ but the technical capacity to execute it scales with institutional access and platform availability.^{4,7}

Literature Comparison

These outcomes align with emerging digital literacy models in adolescent populations.^{1,5} Earlier research indicates that while conversational agents can accelerate initial information gathering and boost self-reported academic emotions,^{3,12} they risk replacing the deeper cognitive synthesis typically developed

through traditional, independent study frameworks.^{8,9} The high rates of perceived helpfulness reported across both cohorts (78.3% and 72.8%) mirror global trends showing strong student satisfaction with AI integrations.^{3,11}

However, as highlighted in broader educational frameworks, without explicit instructions on prompt engineering, critical validation, and ethical use, students frequently cross the threshold from constructive help-seeking to total dependency.^{2,10} This study expands upon existing literature by showing that uniform access to internet connectivity is not the primary driver of AI dependency. Instead, the specific type of technology used (LLMs vs. search engines) combined with institutional device policies and active adult oversight are the critical factors shaping student outcomes.^{5,15}

Study Limitations

1. **Limited Geographic Scope:** The investigation drew samples exclusively from two urban institutions within a single localized educational sector, limiting the generalizability of the findings to rural settings or different socio-economic regions.
2. **Self-Reported Data Biases:** The data collection method relied on self-reported survey matrices, which may introduce social desirability bias—particularly regarding sensitive topics like academic dishonesty and cheating.
3. **Cross-Sectional Constraints:** The cross-sectional design captures student behaviors at a single point in time, preventing the identification of long-term longitudinal trajectories or causal links between AI tool use and objective academic performance.

Conclusion and Future Recommendations

In conclusion, institutional framework conditions, curriculum streams, device integration rules, and adult oversight mechanisms are key factors shaping adolescent interactions with artificial intelligence. High-frequency exposure to generative LLMs within permissive CBSE school environments correlates with greater self-reported behavioral passivity and reductions in independent study hours. However, it does not alter long-term career aspirations or inherently change baseline academic cheating rates compared to traditional Non-CBSE settings.

Educational policymakers should implement structured digital hygiene guidelines rather than total device bans.⁵ Schools must intentionally design curricula that reward metacognitive processes, critical analysis, and oral defense over standard textual or calculation outputs.^{8,10} Future research should prioritize longitudinal tracking of objective academic metrics alongside automated usage analytics to better understand the long-term cognitive impacts of these tools.^{6,14}

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