Cognitive Dependency on Artificial Intelligence Among Students: A Comparative Study of Independent Problem-Solving Performance After AI-Assisted Learning

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Abstract

This study investigates the relationship between artificial intelligence (AI) dependency and cognitive ability among students aged 15–18. Using a quantitative, survey-based design, data were collected from 38 respondents and analyzed across two primary hypotheses: (H1) that AI-assisted learners demonstrate lower independent problem-solving performance than low/non-AI users, and (H2) that AI dependency levels are negatively correlated with self-reported cognitive ability indicators. Results show that while AI-assisted learners scored lower on average in independent problem-solving than low/non-AI users ($M = 2.86$ vs. $M = 3.22$), this difference was not statistically significant ($p = 0.182$), leaving H1 unsupported. However, a strong and statistically significant negative correlation was found between AI dependency and cognitive ability ($r = -0.688$, $p < .001$), supporting H2. These findings suggest that dependency-oriented AI use, rather than AI use in general, may be associated with reduced cognitive engagement. The study is exploratory in scope and recommends larger, longitudinal follow-up research.

Keywords: AI dependency, cognitive ability, independent problem-solving, students, quantitative research

1. Introduction

1.1 Background of the Study

Artificial intelligence tools — most prominently large language models such as ChatGPT — have become embedded in students' everyday academic workflows at a pace that has outrun both institutional policy and empirical understanding. These systems can generate explanations, solve problems, write essays, and debug code within seconds, allowing learners to bypass the effortful cognitive processing that traditionally underpins skill development. Kasneci et al. (2023) note that AI-powered tools can substantially reduce the cognitive effort required from users by generating contextually coherent, human-like responses on demand. While this efficiency is genuinely useful, it raises a fundamental pedagogical question: when a tool does the thinking for the learner, what happens to the learner's thinking?

Researchers have begun framing this concern under the concept of cognitive dependency — a state in which individuals progressively defer reasoning and problem-solving to external systems rather than developing internal competence. Sbhatu et al. (2025) warn that overreliance on AI may diminish critical thinking and independent problem-solving abilities over time. This risk is particularly salient among school-age students, whose cognitive skills are still in development and whose academic environments increasingly permit or even encourage AI use without clear guidance on its limits. The present study is motivated by the need to empirically examine this concern using primary student data.

1.2 Growth of AI in Learning Environments

AI has rapidly expanded from a novelty into a multi-functional academic support system. Platforms such as ChatGPT provide real-time explanations of theoretical concepts, generate structured essays, and answer complex queries across disciplines, while tools like GitHub Copilot assist with programming tasks by predicting and completing code in context. Dwivedi et al. (2023) observe that generative AI technologies now allow students to produce high-quality academic content with minimal input effort — a transformation in the very nature of academic work. This shift is accelerating: Zawacki-Richter et al. (2019) identify ease of access and user-friendly interfaces as the primary drivers of AI adoption in educational settings.

Institutional responses remain inconsistent. Some schools and universities are integrating AI deliberately into pedagogy, using it to personalize learning or automate administrative feedback. Others have imposed blanket restrictions in response to plagiarism concerns. Neither extreme reflects a nuanced understanding of how AI use interacts with cognitive development. The present study contributes to this conversation by examining how different levels and patterns of AI use relate to students' reported cognitive functioning.

1.3 Student Adoption and Digital Learning Behaviour

Empirical data on student AI usage confirms that adoption is widespread and increasingly routine. Sallam (2023) found that a significant proportion of students report frequent or daily use of generative AI tools for academic purposes. The behavioral pattern that accompanies this usage is revealing: rather than using AI to deepen understanding, many students use it to locate final answers quickly, skipping the exploratory, trial-and-error engagement that builds durable knowledge. Kasneci et al. (2023) attribute this to AI's core appeal — the ability to provide quick and reliable responses with minimal effort — which makes it intrinsically rewarding to use, even when independent effort would be cognitively more beneficial.

When a behavior is consistently rewarded, it tends to become habitual. Dependency patterns appear to emerge not just for complex tasks but for foundational ones — basic problem-solving, concept retrieval, even simple factual recall. The present study examines whether these patterns, captured through self-report survey data, are associated with measurable differences in cognitive ability indicators among school students.

1.4 Problem Statement

The central concern animating this study is whether frequent, dependency-oriented use of AI tools erodes the cognitive skills that education is designed to build. Carr (2010) documents how the automation of cognitive tasks can reduce analytical processing and diminish engagement with complex problem-solving. When students consistently receive AI-generated answers without engaging in the reasoning process themselves, they may bypass the mental operations — evaluation, synthesis, inference — that constitute genuine intellectual development.

Compounding this problem is a documented gap in students' self-awareness. Firth et al. (2019) find that users tend to overestimate the benefits of digital assistance while underestimating its cognitive costs. A student who believes they understand a concept because an AI explained it fluently may not realize that passive receipt of an explanation is no substitute for the active construction of understanding. This study addresses the gap by comparing self-reported problem-solving performance and cognitive indicators across students with different AI usage profiles.

1.5 Research Gap

The existing literature on AI in education is weighted toward descriptive and perception-based findings. Bond et al. (2023) observe that current studies predominantly examine user perceptions, acceptance, and frequency of AI tool usage, rather than directly assessing the impact on academic performance or cognitive functioning. Lim et al. (2023) further note a need for student-centered primary data, as most existing evidence derives from secondary analysis, controlled laboratory experiments, or theoretical modeling — none of which fully captures how real students experience and are affected by AI in authentic academic settings.

The present study addresses this gap by collecting primary survey data directly from students, capturing self-reported AI usage patterns, perceived dependency levels, and self-assessed cognitive and problem-solving performance. Although self-report measures carry limitations of their own (discussed in Section 11), they offer an ecologically valid window into student behavior that controlled experiments cannot.

1.6 Significance of the Study

This study contributes to three distinct audiences. For educators, it provides empirical grounding for pedagogical decisions about AI integration — specifically, evidence that dependency-oriented use may be more harmful than AI use per se, which points toward usage-pattern interventions rather than blanket restrictions. Luckin et al. (2016) argue that AI integration in education requires careful pedagogical planning to ensure it enhances rather than replaces cognitive effort; this study offers data to inform such planning.

For students, the findings serve as a prompt for self-reflection on how AI is being used and what may be lost through passive, answer-seeking engagement. For the broader academic community, the study contributes a preliminary empirical dataset on AI dependency and cognition in a school-age sample, a demographic that remains underrepresented in the AI-in-education literature. Fischer (2001) notes that awareness of technology's cognitive impact is essential for developing responsible learning habits — a principle this research aims to promote.

2. Review of Literature

2.1 AI Dependency Among Students

AI dependency in academic contexts encompasses both behavioral and psychological dimensions. Behaviorally, it involves repeated reliance on AI for tasks that could be completed independently; psychologically, it involves trust, perceived necessity, and reduced confidence in one's own abilities. Rosen et al. (2013) define technology dependency as occurring when users rely on digital systems to perform tasks they could otherwise accomplish independently, a definition that maps cleanly onto how many students report using AI tools.

Recent research has begun developing structured tools AI dependency scales to quantify this reliance across cognitive and behavioral dimensions (Sbhatu et al., 2025). Early findings from such instruments point to a consistent upward trend in dependency levels among regular AI users, suggesting that AI is transitioning from a supplementary tool to a primary cognitive intermediary for many students. As dependency increases, the proportion of cognitive work performed by the learner decreases, making this an area of pressing concern for educational research.

2.2 Cognitive Offloading and AI Use

Cognitive offloading the use of external tools to reduce the mental demands of a task — is a well-documented and often adaptive human behavior. Risko and Gilbert (2016) define it as occurring when individuals use external aids to reduce the cognitive demands of a task, noting that it can be rational and efficient when used appropriately. However, AI represents an unprecedented form of offloading because it can perform not just memory storage or arithmetic, but complex reasoning, explanation, and content generation — the very processes most central to learning.

Sparrow et al. (2011) demonstrate that offloading cognitive processes can impair memory formation and reduce understanding of underlying concepts. When students habitually outsource explanation and problem-solving to AI, they may not develop the cognitive representations needed to understand, retain, or transfer that knowledge. The efficiency gained in the short term of a completed assignment, a quick answer may come at the cost of the slower, messier cognitive work through which durable learning actually occurs.

2.3 Impact on Cognitive Abilities

Critical thinking, memory retention, and independent problem-solving are widely recognized as the core outputs of a successful education. Facione (2011) argues that critical thinking requires active engagement with information rather than passive reception of ready-made answers. AI tools that supply polished, authoritative-sounding responses may actively suppress this engagement by removing the ambiguity and productive difficulty that prompt analytical thinking in the first place.

Kirschner and Hendrick (2020) describe what they term the 'solution without understanding' phenomenon: students may achieve task completion without meaningful learning when external tools provide immediate solutions. In AI-assisted contexts, this manifests as students obtaining correct answers and believing they understand without having performed the cognitive operations that would produce genuine comprehension. Over time, this pattern weakens both retention and the capacity to apply knowledge in novel situations.

2.4 Learning Behaviour Transformation

AI adoption is associated with a documented shift from deep to surface learning approaches. Biggs (1999) characterizes surface learning as focused on task completion and answer retrieval rather than conceptual understanding. AI tools, by providing immediate, well-structured responses, naturally reward surface engagement — efficiency is maximized, and the penalty for not understanding is temporarily concealed. This creates a structural incentive within AI-assisted learning environments that runs counter to the goals of education.

Chi (2009) finds that when learners are provided with immediate solutions, their engagement in exploratory and reflective thinking decreases. Exploration attempting a problem, encountering difficulty, revising one's approach is not merely a precursor to learning; it is a central mechanism of it. When AI eliminates this exploratory phase, it may be eliminating the process through which durable knowledge and cognitive flexibility are actually built.

2.5 Psychological Impacts of AI Dependency

Beyond cognitive effects, AI dependency carries psychological consequences. Sweller (2011) notes that excessive reliance on digital tools can contribute to cognitive overload by disrupting sustained attention and deep processing — an effect that is paradoxical, given that AI is typically adopted to reduce workload. More commonly observed is the erosion of academic self-confidence: students who habitually use AI report reduced confidence in their independent abilities, creating a dependency loop in which low confidence motivates greater AI use, which in turn prevents the practice that would rebuild confidence.

Turkle (2017) documents the tendency for individuals to develop emotional and cognitive reliance on digital agents that consistently provide accurate, immediate responses. In academic settings, AI can function as a form of reassurance — a coping mechanism for performance anxiety and deadline pressure. While this offers short-term relief, it displaces the development of resilience and the internal problem-solving strategies that students need when AI is unavailable.

2.6 Academic Self-Efficacy and AI Dependency

Bandura (1997) defines academic self-efficacy as individuals' beliefs in their capacity to organize and execute the actions required to achieve academic outcomes. High self-efficacy is associated with persistence, greater effort, and better performance. AI use creates a complex and potentially distorted relationship with self-efficacy: by consistently delivering successful task outcomes, it inflates perceived competence without necessarily developing actual competence.

Bjork et al. (2013) describe how learners may develop inflated perceptions of understanding when supported by external cognitive aids — a phenomenon sometimes called the 'illusion of knowing.' Students who complete assignments successfully with AI assistance may believe they have mastered the material, only to discover otherwise when required to perform independently. Zimmerman (2000) warns that external support can produce inflated confidence without corresponding gains in competence, ultimately undermining the self-regulatory skills that successful independent learning requires.

2.7 Task Complexity and Dependency Behaviour

Paas and Sweller (2014) find that individuals are more likely to offload cognitive tasks when perceived difficulty exceeds their available cognitive resources — a rational response to overload. For students, AI tools are particularly appealing at precisely the moments when engagement would be most productive: during genuinely difficult problems that require sustained effort, strategy revision, and tolerance for uncertainty. AI resolves this discomfort instantly, but at the cost of the cognitive challenge that would have produced growth.

When students repeatedly turn to AI during difficult tasks, the behavior can transition from situational coping to habitual avoidance. Kool et al. (2010) observe that learners tend to minimize effort when alternative solutions are readily available, especially under high cognitive demand. This avoidance of productive struggle can progressively lower the threshold at which students seek AI help, making dependency increasingly entrenched over time.

2.8 Research Gap in Empirical Performance Studies

Winne and Nesbit (2010) highlight that a significant portion of studies in educational technology rely on self-reported data that may not correspond to actual learning performance, and Bond et al. (2023) confirm that current AI-in-education research is dominated by perception-based findings. The OECD (2021) identifies a notable absence of empirical evidence directly measuring the impact of digital tools on higher-order cognitive performance, a gap that limits the practical utility of existing research for educators and policymakers.

The present study does not claim to fill this gap fully; it adds self-report primary data from a school-age sample in a context India that is underrepresented in the literature. Its findings are intended as exploratory groundwork for future experimental and longitudinal work rather than as definitive causal evidence.

3. Theoretical Background

3.1 Cognitive Offloading Theory

Cognitive Offloading Theory, developed by Risko and Gilbert (2016), describes the tendency of individuals to reduce internal cognitive demands by delegating tasks to external tools or environments. Traditional offloading writing notes, using calculators, consulting dictionaries has long been considered cognitively adaptive. AI, however, represents an extreme and qualitatively different form of offloading: it can handle not just information storage or computation, but the full chain of reasoning, inference, and articulation. When AI performs these operations for the student, the student is deprived of the very processes that consolidate learning.

Storm et al. (2016) find that reliance on external memory aids can impair the ability to retain and recall information independently, a finding that extends logically to AI-assisted reasoning. The more consistently a student offloads thinking to AI, the less practice their internal cognitive systems receive, and the weaker those systems may become. This theory directly informs Hypothesis 2 of the present study, which predicts a negative relationship between AI dependency and self-reported cognitive ability.

3.2 Behavioural Dependency Theory

Skinner's (1953) operant conditioning framework provides a basis for understanding how AI use can evolve from deliberate choice to habitual dependency. Each time a student uses AI and receives an accurate, effortless answer, the behavior is positively reinforced. Over repeated trials, this reinforcement pattern can produce habitual AI-seeking behavior triggered not by a reasoned decision, but by the automatic association between academic difficulty and AI-mediated relief. LaRose (2010) documents this mechanism in digital media contexts, describing habitual technology use as driven by reinforcement cycles that prioritize convenience and immediate outcomes over deliberate goal pursuit.

In educational terms, this means that dependency may become self-sustaining: the more students use AI, the more their behavior is reinforced, and the less they practice the independent effort that would reduce their dependency. This cycle is particularly concerning during the formative years of schooling, when cognitive habits are being established.

3.3 Cognitive Load Theory

Sweller's (1988) Cognitive Load Theory distinguishes between intrinsic load (the inherent difficulty of a task) and extraneous load (unnecessary cognitive burden from poor design). AI tools dramatically reduce extraneous load and often intrinsic load by simplifying, summarizing, and solving. This can be genuinely helpful when used to make instruction more accessible. However, Kirschner et al. (2006) caution that learning is hindered when cognitive effort is minimized to the point where meaningful processing does not occur. A certain level of cognitive struggle that Bjork (1994) calls 'desirable difficulty' is necessary for deep encoding and transfer.

AI use that eliminates this struggle may produce the appearance of efficiency while degrading actual learning outcomes. The theory implies that AI dependency is most harmful not when students use AI occasionally for genuine support, but when it systematically removes the productive cognitive challenge that drives skill development.

3.4 Self-Efficacy Theory

Bandura (1997) argues that self-efficacy beliefs one's confidence in one's ability to perform a task are among the strongest predictors of academic motivation and persistence. AI creates an interesting distortion of this mechanism: by enabling students to complete tasks successfully, it can produce high perceived self-efficacy, but this efficacy is built on AI-mediated performance rather than genuine independent competence. Zimmerman (2000) characterizes this as external support leading to inflated confidence without corresponding competence gains.

When students eventually face tasks without AI in examinations, oral presentations, or time-pressured problem-solving the gap between perceived and actual ability becomes apparent. This mismatch can be disorienting and may paradoxically reduce motivation rather than enhance it, as students realize their sense of competence was partly illusory.

3.5 Dual Process Theory

Kahneman's (2011) Dual Process Theory describes human cognition as operating through two systems: System 1, which is fast, automatic, and intuitive; and System 2, which is slow, deliberate, and analytical. Higher-order academic tasks constructing arguments, solving multi-step problems, evaluating evidence require System 2 engagement. AI tools, by instantly providing outputs, create conditions that favor System 1 processing: students receive answers that 'feel right' without engaging the effortful scrutiny that System 2 would apply.

Evans (2008) documents how overreliance on intuitive processing limits analytical reasoning and reduces decision-making quality. In academic contexts, habitual AI use may gradually reduce the frequency and depth of System 2 engagement, as students become accustomed to accepting AI outputs without critical evaluation. This erosion of deliberate analytical thinking is directly implicated in the cognitive ability outcomes examined in this study.

4. Objectives of the Study

Objective 1

To examine the relationship between AI-assisted learning and students' independent problem-solving performance by analyzing how frequency and pattern of AI reliance are associated with self-reported ability to solve academic tasks without external assistance.

Objective 2

To analyze the relationship between AI dependency levels and self-reported cognitive abilities particularly indicators of critical thinking, independent explanation, and deep-thinking engagement in order to evaluate whether increased AI reliance is associated with reduced cognitive functioning.

5. Hypotheses

H1: AI-assisted learners will demonstrate lower independent problem-solving performance than low/non-AI users.

H2: There is a significant negative correlation between AI dependency levels and self-reported cognitive ability indicators including critical thinking, independent explanation, and deep-thinking engagement among students.

6. Method

6.1 Research Design

This study employs a quantitative, cross-sectional survey design. Quantitative methods were selected because they allow structured, comparable measurement across respondents and facilitate statistical testing of the hypothesized relationships. The design is descriptive and correlational: it does not manipulate variables experimentally, but instead captures self-reported behavior and cognitive indicators at a single point in time. This design is appropriate for the study's exploratory goals but does not permit causal inference, a limitation explicitly acknowledged throughout the analysis and discussion.

6.2 Sample and Population

The target population comprised students aged 15–25 years who were actively engaged in academic learning and had sufficient familiarity with AI-based educational tools to form meaningful self-assessments. This age range was selected because it captures the demographic most actively using AI for academic purposes and the demographic at which long-term learning habits are being established.

The final sample consisted of 38 respondents (mean age = 16.39 years, SD = 1.53). The majority were aged 16 (73.7%), followed by age 17 (15.8%), with smaller numbers aged 15, 18, and 25. The age-25 respondent was retained in the analysis given the absence of other data quality issues, but represents an outlier relative to the predominantly school-age sample and should be treated with caution. Future studies should apply explicit age-based eligibility criteria at the point of data collection.

6.3 Sampling Method

Participants were recruited using non-probability convenience sampling. The survey was distributed digitally via a Google Form link shared through the researcher's school peer network and family contacts. Participation was voluntary and anonymous. While this method was appropriate given the study's time and resource constraints, it carries significant limitations: the sample is not representative of any defined population, and results cannot be generalized beyond this exploratory context. Social homophily within peer networks (participants likely share similar academic environments and AI exposure) may further limit the diversity of the sample.

6.4 Sample Size

The final sample of 38 respondents falls within the range specified in the study's design (30–40 participants). It is sufficient for exploratory descriptive and correlational analysis, but carries inherent power limitations for group-comparison tests. Post-hoc power analysis (not conducted here, but recommended for future studies) would likely confirm that the H1 group comparison (n = 25 vs. n = 13) was underpowered for detecting a moderate effect size at the conventional alpha level of .05. This is acknowledged as a key limitation in the interpretation of H1.

6.5 Tools and Instruments

Data were collected using an 18-item self-report questionnaire developed and administered through Google Forms. Items were rated on a 4-point Likert scale (1 = Strongly Disagree, 4 = Strongly Agree). The questionnaire measured AI usage frequency (Q1), dependency behaviors (Q2, Q5, Q6, Q9, Q10, Q13, Q17), independent problem-solving difficulty (Q7, Q8, Q9, Q11, Q12, Q13, Q17), cognitive ability indicators (Q7, Q8, Q11, Q12, Q14, Q18), and perceived AI learning benefits (Q3, Q4, Q15). Several items were reverse-coded such that higher composite scores consistently represent stronger independent performance and cognitive ability. Full item wording is provided in Appendix A.

6.6 Data Collection Procedure

The survey link was circulated digitally over a fixed collection period. Respondents were briefed on the study's academic purpose prior to participation. Completion was estimated at 5–8 minutes. Responses were recorded automatically through the Google Forms platform and exported for analysis. No incentives were offered for participation.

6.7 Ethical Considerations

All participation was voluntary, and respondents were informed of the study's purpose before completing the survey. No personally identifying information was collected. Responses were stored and analyzed anonymously and used exclusively for academic research purposes. The study involved no deception, no sensitive procedures, and no collection of data beyond self-reported academic behaviors and perceptions, representing a minimal-risk protocol.

7. Data Analysis

7.1 Variable Construction

Construct	Items Used	Coding	Interpretation
AI-assisted learning group	Q1	Q1 ≥ 3 = AI-assisted; Q1 ≤ 2 = low/non-AI	Used for H1 group comparison
AI Dependency Level	Q2, Q5, Q6, Q9, Q10, Q13, Q17	Mean of items; higher = more dependent	Predictor for H2
Independent Problem-Solving Performance	Q7, Q8, Q9, Q11, Q12, Q13, Q17	Reverse-coded; higher = stronger independent performance	Outcome for H1
Cognitive Ability Index	Q7, Q8, Q11, Q12, Q14, Q18	Reverse-coded; higher = stronger cognitive ability	Outcome for H2
AI Learning Benefit	Q3, Q4, Q15	Mean of items; higher = stronger perceived benefit	Descriptive only

7.2 Descriptive Statistics

Sample Characteristics

The final dataset included 38 respondents. The mean age was 16.39 years (SD = 1.53). One response recorded an age of 25; this participant was retained as no other data quality issues were identified, but the response should be interpreted cautiously given the predominantly 15–17 age distribution. Of the 38 respondents, 25 (65.8%) were classified as AI-assisted learners (Q1 ≥ 3) and 13 (34.2%) as low/non-AI users (Q1 ≤ 2).

Category	n	%
Age 15	2	5.3%
Age 16	28	73.7%
Age 17	6	15.8%
Age 18	1	2.6%
Age 25 (outlier — verify)	1	2.6%
AI-assisted learners	25	65.8%
Low/non-AI users	13	34.2%

Item-Level Descriptive Statistics

The highest mean was recorded for Q16 ("AI makes students dependent", M = 3.29), with 84.2% of respondents agreeing or strongly agreeing. This indicates widespread awareness among students of the dependency risks associated with AI. Strong agreement was also found for Q1 (frequent AI use, M = 2.92) and Q15 (AI improves learning, M = 2.79), reflecting high prevalence of use alongside perceived benefit. Lower means were observed for items capturing passive or uncritical AI reliance such as trusting AI without verification (Q14, M = 1.87) and preferring AI over traditional methods (Q5, M = 1.87) suggesting that students retain some degree of discernment in their engagement.

Item	Statement	Mean	SD	Median	Agree/Strongly Agree %
Q1	Frequent AI use for studying	2.92	1.02	3.00	65.8%
Q2	Uses AI before attempting questions	2.03	1.08	2.00	31.6%
Q3	Relies on AI for difficult concepts	2.66	1.07	3.00	57.9%
Q4	AI makes studying faster	2.76	0.94	3.00	57.9%

Q5	Prefers AI over traditional methods	1.87	1.04	1.50	26.3%
Q6	Uses AI even when able to solve	1.87	1.09	1.00	31.6%
Q7	Less confident without AI	1.95	1.04	2.00	28.9%
Q8	Struggles to solve independently	2.08	1.17	2.00	39.5%
Q9	Attempts fewer problems independently	2.24	1.20	2.00	42.1%
Q10	Depends on AI when stuck	2.76	1.10	3.00	57.9%
Q11	Difficult to explain without AI	1.74	0.86	1.50	21.1%
Q12	Problem-solving ability has decreased	2.18	1.11	2.00	44.7%
Q13	Feels stuck without AI	1.97	0.94	2.00	26.3%
Q14	Trusts AI without verification	1.87	1.02	2.00	23.7%
Q15	AI improves learning/understanding	2.79	0.99	3.00	65.8%
Q16	AI makes students dependent	3.29	0.98	4.00	84.2%
Q17	Would perform worse without AI	1.95	1.01	2.00	31.6%
Q18	AI reduces deep thinking	2.82	1.23	3.00	57.9%

Construct-Level Descriptive Statistics

Construct	Mean	SD	Median	Min	Max
AI Dependency Level	2.10	0.79	2.07	1.00	4.00

Independent Problem-Solving Performance	2.98	0.78	3.07	1.00	4.00
Cognitive Ability Index	2.89	0.64	2.92	1.00	4.00
AI Learning Benefit	2.74	0.81	2.83	1.00	4.00

7.3 Reliability and Validity

Reliability

Internal consistency was assessed using Cronbach's alpha. Values above .70 are generally considered acceptable; values around .60 are questionable but may be tolerated in exploratory research with small samples.

Scale	Items	No. of Items	Cronbach's α	Interpretation
Overall scale	Q1–Q18	18	0.865	Good
AI Dependency Level	Q2, Q5, Q6, Q9, Q10, Q13, Q17	7	0.859	Good
Independent Problem-Solving Performance	Reverse-coded Q7, Q8, Q9, Q11, Q12, Q13, Q17	7	0.864	Good
Cognitive Ability Index	Reverse-coded Q7, Q8, Q11, Q12, Q14, Q18	6	0.640	Questionable; acceptable for exploratory use only
AI Learning Benefit	Q3, Q4, Q15	3	0.732	Acceptable

Validity

Content validity is supported by the direct correspondence between questionnaire items and the constructs under investigation: AI usage behavior, dependency patterns, independent problem-solving confidence, verification habits, and deep-thinking perceptions. Construct validity is partially supported by the observed negative relationship between AI dependency and cognitive ability, which aligns with the theoretical framework outlined in Section 3.

An important caveat applies to the Cognitive Ability Index: the questionnaire does not include objective memory or reasoning tests, only self-reported perceptions. This index should therefore be interpreted as a proxy for self-assessed critical thinking, independent explanation ability, and deep-thinking engagement not as a direct measure of cognitive performance. All conclusions drawn from this construct are subject to this limitation.

7.4 Correlation Analysis

Relationship	Test	Coefficient	p-value	Interpretation
AI Dependency × Cognitive Ability	Pearson r	-0.688	< .001	Strong negative; supports H2
AI Dependency × Cognitive Ability	Spearman rho	-0.699	< .001	Consistent rank-order confirmation
AI Dependency × Independent Problem-Solving	Pearson r	-0.914	< .001	Very strong negative relationship
AI Dependency × Cognitive Difficulty Index	Pearson r	0.688	< .001	Strong positive; higher dependency = more cognitive difficulty

The Pearson and Spearman coefficients for the AI Dependency × Cognitive Ability relationship are nearly identical (r = -0.688, rho = -0.699), indicating that the result is robust to distributional assumptions. The very strong correlation between AI dependency and independent problem-solving performance (r = -0.914) should be interpreted with caution, as both constructs draw on overlapping items (Q9, Q13, Q17), which may inflate the coefficient through shared-item variance.

7.5 Hypothesis Testing

H1: Group Comparison

Group	n	Mean Performance	SD	SE
AI-assisted learners	25	2.86	0.79	0.16
Low/non-AI users	13	3.22	0.75	0.21

Hypothesis	Analysis	Statistic	p-value	Decision

H1	Welch independent-samples t-test	t(25.50) = -1.371; Cohen's d = -0.462	0.182	Not supported at .05 level
H1 robustness	Mann-Whitney U test	U = 114.5	0.142	Same conclusion
H2	Pearson correlation	r = -0.688	< .001	Supported

AI-assisted learners recorded a lower mean performance score ($M = 2.86$, $SD = 0.79$) than low/non-AI users ($M = 3.22$, $SD = 0.75$), with a medium effect size (Cohen's $d = -0.462$). However, neither the parametric Welch t-test ($p = 0.182$) nor the non-parametric Mann-Whitney U test ($p = 0.142$) reached statistical significance. H1 is therefore not statistically supported within this sample. The observed medium effect size is nonetheless meaningful: with a larger sample, this effect could plausibly reach significance, and the direction of results is entirely consistent with the hypothesis. The failure to achieve significance most plausibly reflects low statistical power ($n = 25$ vs. $n = 13$) rather than a true null effect.

H2 was strongly supported. AI dependency was negatively correlated with cognitive ability ($r = -0.688$, $p < .001$), confirmed by both Pearson and Spearman tests. Students reporting higher dependency on AI tended to report weaker indicators of independent cognition, including reduced confidence in explanation, lower engagement in deep thinking, and greater difficulty verifying information independently.

8. Results and Discussion

8.1 AI Usage Patterns

The survey confirmed high prevalence of AI use within the sample: 65.8% were classified as AI-assisted learners, and 84.2% agreed that AI makes students more dependent on external help, a strikingly candid self-assessment. Frequent use (Q1, 65.8% agreement) coexists with perceived benefit (Q15, 65.8% agreement), suggesting that students view AI favorably while simultaneously recognizing its dependency risks. This dual awareness is a promising foundation for AI literacy interventions: students are not unaware of the trade-offs; they may simply lack the strategies to manage them.

8.2 Problem-Solving Performance (H1)

Low/non-AI users outperformed AI-assisted learners on the independent problem-solving composite ($M = 3.22$ vs. $M = 2.86$), a difference representing a medium effect size (Cohen's $d = -0.462$). This directional result is consistent with H1 and with the cognitive offloading literature reviewed in Section 2. However, statistical significance was not reached ($p = 0.182$), and the result must therefore be treated as a trend rather than a confirmed finding.

Two interpretations are plausible. First, the null result may be a Type II error driven by low statistical power; the group sizes (25 and 13) provide limited ability to detect medium effects. Second, the relationship between AI use and independent problem-solving may be genuinely more complex than H1 assumes: it may be mediated by how students use AI (dependency-oriented versus supplementary) rather than simply whether they use it at all. The H2 result discussed below supports this interpretation.

8.3 Cognitive Ability and AI Dependency (H2)

The strong, significant negative correlation between AI dependency and cognitive ability ($r = -0.688$, $p < .001$) provides the clearest finding of the study. Students who reported higher reliance on AI for problem-solving, explanation, and task completion tended to report lower confidence in independent reasoning, reduced engagement in deep thinking, and greater difficulty explaining concepts without AI assistance. This pattern is consistent with the cognitive offloading, behavioral dependency, and self-efficacy frameworks outlined in Section 3.

Crucially, this correlation involves the AI Dependency Level construct — a measure of habitual, reliance-oriented AI use — rather than simple AI use frequency. This suggests that the cognitive risk may be specific to dependency-oriented patterns of use rather than AI use per se. A student who uses AI to check their own independently derived answer behaves very differently from one who uses AI to obtain the answer in place of attempting it — and the data suggest these behavioral differences have corresponding cognitive correlates.

8.4 The 'Illusion of Competence' Pattern

A notable finding in the item-level data deserves specific attention. Q15 ("AI improves learning/understanding") received 65.8% agreement, while items directly assessing whether students could explain, reason, or solve without AI scored substantially lower. This gap between perceived benefit and reported independent competence is consistent with the 'illusion of knowing' documented by Bjork et al. (2013): students may attribute their fluency with AI-assisted tasks to genuine understanding, without recognizing that the AI performed the cognitive work. This represents a self-efficacy distortion with direct implications for academic performance in non-AI contexts such as examinations.

8.5 Interpretation and Limitations of Results

The findings suggest that it is dependency-oriented AI use — not AI use itself — that is associated with reduced cognitive indicators. This nuance is important for practical recommendations: the goal should not be to eliminate AI from education, but to shift students from passive, answer-seeking patterns toward active, supplementary-use patterns in which AI is consulted after independent effort rather than in place of it.

These results are correlational and self-reported. Causation cannot be inferred: it is equally plausible that students with weaker cognitive skills are more likely to become dependent on AI (reverse causation) as it is that AI dependency causes cognitive decline. Separating these pathways requires longitudinal or experimental design. Additionally, the Cognitive Ability Index's moderate reliability (α = 0.640) and its reliance on self-report rather than objective measurement introduce noise into the H2 finding, which should be interpreted with appropriate caution.

9. Conclusion

9.1 Summary of Findings

This study examined the relationship between AI dependency and cognitive ability among a sample of 38 school-age students. The central findings are as follows. First, AI-assisted learners showed lower mean independent problem-solving performance than low/non-AI users, with a medium effect size (Cohen's $d = -0.462$), but this difference was not statistically significant ($p = 0.182$), leaving H1 unsupported. Second, AI dependency level was strongly and significantly negatively correlated with self-reported cognitive ability ($r = -0.688$, $p < .001$), supporting H2. Third, students were broadly aware of AI's dependency risks: 84.2% agreed that AI makes students more dependent on external help, even as they reported frequent use and perceived benefit.

Taken together, these findings suggest that the concern is less about AI use per se and more about dependency-oriented usage patterns habitual reliance that displaces independent cognitive engagement. The study is exploratory and its conclusions are preliminary, but the effect sizes and directionality of results are consistent with the theoretical framework and with the broader empirical literature.

9.2 Behavioural Insights

The data reveal a coherent behavioral profile associated with higher AI dependency: reduced independent problem-solving attempts, lower confidence in self-explanation, weaker deep-thinking engagement, and a subjective sense of cognitive dependence on AI tools. This profile aligns with the dependency loop predicted by Behavioral Dependency Theory (Skinner, 1953; LaRose, 2010): habitual use is reinforced by convenience, which reduces practice at independent effort, which increases reliance, completing the cycle. Interrupting this cycle through structured AI-use protocols, deliberate independent practice, or AI literacy education represents a practical direction for intervention.

10. Recommendations

10.1 Attempt-First Protocol

Students should adopt an 'attempt-first' rule: engage with any problem independently before consulting AI. This preserves productive struggle, the mechanism through which understanding is consolidated while still allowing AI to serve a checking, clarifying, or supplementary function. Educators can enforce this structurally through staged assignments (submit an independent attempt before receiving AI-assisted resources) or through reflective prompts that require students to articulate their independent reasoning before presenting an AI-generated answer.

10.2 Educational Policy Design

Institutions should develop differentiated AI use policies that distinguish between dependency-oriented use (submitting AI outputs without independent engagement) and supplementary use (using AI after independent effort, for verification or elaboration). Assessment redesign is also warranted: greater emphasis on oral examinations, process-based evaluation, and in-class problem-solving without AI access would create accountability structures that incentivize genuine skill development alongside AI fluency.

10.3 Cognitive Skill Development

Curriculum design should actively embed opportunities for productive struggle — open-ended problems, case-based reasoning, argumentation tasks — that require students to exercise the cognitive processes AI would otherwise perform for them. Regular low-stakes independent practice builds the cognitive habits and confidence that sustained learning requires, and reduces the anxiety that often drives students toward AI as a coping mechanism.

10.4 AI Literacy Programs

Schools should introduce structured AI literacy programs that go beyond digital citizenship to address the cognitive economics of AI use: what students gain in efficiency, what they risk losing in skill development, and how to calibrate AI use to maximize learning rather than merely task completion. Students who understand the mechanisms underlying cognitive offloading and dependency are better positioned to make deliberate, beneficial choices about when and how to use AI tools.

11. Limitations of the Study

Several limitations constrain the interpretation of these findings and should be addressed in future work.

Sample size and power. The sample of 38 respondents, divided into groups of 25 and 13 for H1 testing, provides insufficient statistical power to detect moderate effect sizes reliably. The non-significant H1 result should not be interpreted as evidence of no effect; it may reflect inadequate power rather than a true null. Future studies should target minimum samples of 80–100 for group comparison analyses.

Convenience sampling. The survey was distributed through the researcher's personal network, producing a sample that is not representative of any defined student population. Social homophily within the recruitment network likely reduced the diversity of AI usage patterns and academic contexts captured in the data.

Self-report validity. All measures are self-reported, introducing bias from inaccurate self-assessment, social desirability effects, and the general difficulty of introspecting accurately on cognitive habits. The Cognitive Ability Index in particular, which asks students to evaluate their own reasoning, explanation ability, and deep-thinking engagement, should be validated against objective cognitive measures in future research.

Cross-sectional design. The study captures a single time point and cannot distinguish between the hypothesis that AI dependency causes cognitive decline and the alternative that students with weaker independent cognitive skills are more likely to become AI-dependent. Longitudinal designs are required to address this directionality.

Age outlier. The single age-25 respondent is an outlier relative to the 15–18 age range of the remaining sample and may represent a qualitatively different AI usage context (post-secondary education). Future studies should define and enforce eligibility criteria at the point of data collection.

No objective cognitive measures. The absence of standardized cognitive tests means that all cognitive findings rest on self-perception rather than performance. This is a fundamental limitation of the Cognitive Ability Index and should be treated as a key priority for methodological improvement in follow-up studies.

12. Future Scope of Research

The most pressing need identified by this study is for longitudinal research that tracks the same students over time as their AI usage patterns evolve, enabling causal inferences about whether dependency precedes or follows cognitive changes. Experimental designs randomly assigning students to AI-permitted versus AI-restricted conditions across a semester would similarly allow causal conclusions that correlational surveys cannot support.

Future studies should expand sample size and diversity, including participants from different educational systems, socioeconomic contexts, and geographic regions, to improve generalizability. Subject-specific analysis would also be valuable: AI dependency may have different cognitive implications in mathematics, where procedural practice is critical to skill development, than in essay-based subjects where AI assistance in drafting may be more easily separated from the cognitive work of argument construction.

The introduction of objective cognitive measures, standardized reasoning tests, memory assessments, or problem-solving tasks administered without AI would substantially strengthen the validity of cognitive ability constructs. Pairing these with survey-based dependency measures would allow researchers to assess whether the self-reported associations found here hold at the level of actual performance. Finally, research evaluating the effectiveness of specific interventions, attempt-first protocols, AI literacy programs, structured AI use frameworks would translate exploratory findings into actionable evidence for educators and policymakers.

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Appendix A: Survey Questionnaire Items

All items were rated on a 4-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Agree, 4 = Strongly Agree).

Item	Statement
Q1	I frequently use AI tools (e.g., ChatGPT) to help me study.
Q2	I use AI before attempting a question on my own.
Q3	I rely on AI to explain difficult concepts to me.
Q4	AI tools make my studying faster and more efficient.
Q5	I prefer using AI over traditional study methods (textbooks, notes).
Q6	I use AI even when I feel I could solve the problem myself.
Q7	I feel less confident solving academic problems without AI.
Q8	I struggle to solve problems independently when AI is unavailable.
Q9	I attempt fewer problems on my own because AI is available.
Q10	When I get stuck on a problem, I depend on AI to get unstuck.
Q11	I find it difficult to explain a concept in my own words without AI.
Q12	My problem-solving ability has decreased since I started using AI.
Q13	I feel stuck when I cannot access AI during studying.
Q14	I trust AI-generated answers without verifying them.
Q15	AI has improved my overall learning and understanding.
Q16	AI tools make students more dependent on external help.
Q17	I would perform worse on academic tasks without access to AI.
Q18	Using AI reduces my need to think deeply about problems.