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Trust and Cognitive Shifts: How AI Reliance Reshapes Human Thinking and Decision-Making

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Abstract

Artificial intelligence (AI) tools are increasingly embedded in academic and professional environments, offering speed and convenience while raising concerns about their potential effects on independent reasoning. This study examines how exposure to AI-generated suggestions from familiar AI tools influences students' decision-making during open-ended critical thinking tasks. Drawing on prior work in trust, cognition, and human–AI interaction, the study focuses on behavioral indicators of reliance rather than self-reported trust alone.

Twenty-One undergraduate engineering students at a large public university completed an online survey consisting of five open-ended critical thinking questions. Participants first responded independently and were then shown AI-generated responses or approaches from the AI tool they personally trust and use most frequently, with the option to revise their original answers. Reliance on AI was assessed behaviorally through patterns of revision and alignment between participants' initial responses, AI-generated content, and final responses. Self-report measures of perceived task difficulty, helpfulness, and AI influence were collected to contextualize observed behavior.

Results showed that participants overwhelmingly retained their original responses after viewing AI-generated suggestions, with only two revisions observed across forty-five opportunities. When revisions did occur, they varied in character, including both strong alignment with AI-generated reasoning and independent reconsideration. Self-reported perceptions of AI influence did not consistently correspond to behavioral measures of reliance. These findings suggest that exposure to familiar AI tools does not uniformly reduce cognitive independence, but may selectively influence reasoning in ways that are not always reflected in users' subjective impressions. The study highlights the value of behavioral measures for understanding how AI shapes reasoning processes in engineering education.

Introduction

Large language models such as ChatGPT have rapidly expanded into education, research, and professional practice. These systems are built on advanced natural language processing architectures that allow them to generate coherent responses, explanations, and solutions across a wide range of tasks [1], [2]. As a result, they are increasingly used by students and educators to support activities such as preparing course materials, solving academic problems, writing essays, and refining written communication [1], [2]. While these tools offer clear benefits in efficiency and accessibility, they have also raised concerns related to bias, hallucinations, academic integrity, and the misuse of generated content [1], [2].

Beyond issues of accuracy and ethics, earlier work in psychology shows that digital technologies can shape how individuals process and store information. Research on the "Google effect" demonstrates that when people expect information to remain accessible, they are less likely to retain the information itself and more likely to remember where it can be found [3]. This shift suggests a growing tendency toward externalizing cognitive effort rather than relying on internal memory.

These patterns raise important questions in education. Although AI can support learning, their ability to provide immediate, high-quality responses may also change how students approach problem-solving tasks. The present study builds on existing research in AI use and cognitive offloading by examining how exposure to AI-generated suggestions influences students' reasoning processes and decision-making during open-ended tasks.

Background

Trust in AI and Automation

Research on trust in AI shows that users tend to rely on systems they perceive as efficient and capable of reducing cognitive effort. Generative AI systems have been shown to produce real-time responses, making them appealing for students seeking immediate feedback or solutions during academic tasks [1]. When an AI tool appears fluent and consistently helpful, users may accept its suggestions with limited scrutiny, especially when doing so saves time or reduces mental load.

At the institutional level, the literature suggests that higher education often frames AI as an inevitable technological shift to which academic communities must adapt [4]. When AI is presented in this way, students may assume that its outputs are valid or authoritative. This combination of system performance, convenience, and institutional framing helps explain why students may develop trust in AI tools and rely on their recommendations.

Cognitive Offloading and Cognitive Independence

Psychological research demonstrates that digital tools influence how people store and retrieve information. It has been shown that when individuals expect to have future access to information, they recall less of the information itself and instead remember where it can be found [3]. This pattern reflects what is known as the "Google effect," where memory strategies shift toward using external systems instead of internal recall.

A recent meta-analysis further supports this pattern, indicating that intensive internet search behavior encourages reliance on external sources for fact-checking and information retrieval [5]. These findings reinforce the idea that digital environments promote the externalization of memory processes.

Other studies highlight potential risks associated with digital dependence. Evidence suggests that heavy reliance on external information systems can reduce memory consolidation and promote shallow encoding strategies [6]. Similarly, work on generative AI indicates that repeated acceptance of AI-generated content may reduce critical thinking and long-term retention when users do not actively engage in independent reasoning [7].

At the same time, some research presents a more balanced perspective. Findings suggest that AI systems can support cognitive offloading by reducing the need for internal cognitive resources, while also raising concerns about increased dependence on external tools [8]. Together, these results indicate that persistent access to digital and AI systems can influence how individuals engage in reasoning tasks.

Human–AI Interaction in Education

In educational settings, generative AI tools offer both efficiency and potential drawbacks. Existing research indicates that the ability of AI systems to generate explanations instantly makes them attractive for learners seeking quick clarity on academic problems [1]. However, this same accessibility may lead students to consult AI before fully engaging with a problem independently.

Empirical research also highlights specific patterns in how generative AI influences cognition. Studies have shown that AI text generators improve performance on lower levels of Bloom's taxonomy, such as recall and comprehension, while having less impact on higher-order analytical skills [9]. This suggests that AI may help with surface understanding but does not necessarily promote deeper reasoning or evaluation.

From an institutional perspective, research indicates that AI is often framed as a transformative force within higher education, which may influence how students interpret the legitimacy of AI-generated suggestions [4]. Building on this work, the present study examines whether students revise their responses after exposure to AI-generated content, providing behavioral insight into how human–AI interaction affects reasoning processes.

Gaps in Existing Research

Although existing studies provide insight into cognitive offloading, trust in AI, and shifts in memory strategies, several gaps remain. Many studies rely on self-report measures rather than behavioral indicators of AI reliance. Research has also focused primarily on performance outcomes rather than examining how AI influences the reasoning process itself.

Additionally, there is limited work on how reliance varies when individuals use AI tools they personally trust and frequently engage with. Engineering and computer science students also remain understudied in this context, despite their frequent interaction with AI systems.

The present study addresses these gaps by observing how students modify their problem-solving approaches after exposure to AI-generated suggestions, providing direct behavioral evidence of reliance and shifts in cognitive independence.

Research Questions and Hypotheses

This study examines how exposure to AI-generated suggestions from familiar AI tools influences students' reasoning processes during critical thinking tasks. Prior research suggests that digital tools can encourage cognitive offloading, alter memory strategies, and shift users toward external sources of support. However, there is limited behavioral evidence showing how students actually modify their decisions after viewing AI suggestions, especially when using the AI tools they personally trust and frequently rely on. This study also seeks to understand the broader implications of AI involvement in reasoning-intensive work, including whether AI supports or undermines cognitive independence

Research Questions

1. How does access to AI-generated content from a trusted AI tool change students' decisions on critical thinking tasks compared to working independently?
2. What do students' patterns of reliance on AI-generated suggestions reveal about whether AI should support critical thinking tasks, be limited to minimal delegation, or be avoided for reasoning-intensive work?
3. How does reliance on AI suggestions relate to students' perceptions of task difficulty and the perceived usefulness of the AI during critical thinking tasks?

Hypotheses

1. Participants who self-report high AI use in academic or professional tasks will revise a larger proportion of their answers after seeing AI suggestions than participants who report medium or low AI use.
2. Participants who self-report high AI use will report lower task difficulty in the AI-assisted phase than participants who report medium or low AI use.
3. Participants who rate the AI suggestions as highly useful will revise more answers and show stronger alignment between their final reasoning and the AI's suggested reasoning.
4. Participants who demonstrate high behavioral reliance on AI (based on post-analysis of revision patterns) will report lower task difficulty than participants who show low behavioral reliance.

Methods

An online survey format was selected as the data collection method based on established research comparing data collection methods with respect to social desirability bias. Work in [10] shows that self-administered formats reduce interviewer effects and social desirability bias, particularly for questions involving judgment or self-evaluation. The study also shows that removing an interviewer increases respondents' perceived privacy, leading to more candid responses and reduced response distortion. Because the present study did not require the operation of specialized equipment, real-time observation, or intervention by a researcher, a self-administered online survey was an appropriate method for collecting participants' responses while minimizing interviewer influence.

Using this approach, the study was conducted with 21 undergraduate engineering students at a large land-grant university in the United States. Participants completed an online survey in which they first responded independently to a set of open-ended critical thinking questions. After submitting each response, they were shown AI-generated content for the same question from the AI tool they reported trusting and using most frequently and were given the option to revise their original response.

The questions were drawn from topics discussed in *Mathematics for Computer Science* [11]. However, the questions themselves were not inherently mathematical. They were intentionally framed to be open-ended and accessible, allowing participants to rely on conceptual, philosophical, or general reasoning rather than strictly mathematical knowledge.

The five questions are:

1. In both math and everyday life, we use reasoning to decide whether something is true. But in mathematics, a proof is meant to remove all uncertainty. It shows that a conclusion must follow from its starting assumptions. How do you think this kind of certainty-based reasoning compares to the way people usually decide what's true in daily life? What makes mathematical reasoning different, if at all?
2. Can a statement be true even if we cannot prove it? Discuss the relationship between mathematical truth (something that is actually true) and provability (something that can be shown to be true using rules of logic).
3. Why does the pigeonhole principle (if there are more objects than containers to place them in, then at least two objects must share the same container) seem intuitively obvious, yet people frequently overlook its implications in real problems?
4. If both the set of integers (whole numbers like -2, -1, 0, 1, 2...) and the set of real numbers (all numbers on the number line, including fractions and decimals like 0.5 or √2) are infinite, why are they considered different sizes of infinity? Explain your reasoning.
5. In mathematics, infinity isn't just a large number — it represents something that has no end. Yet our experiences in the real world are always finite. Do you think people can genuinely understand the idea of infinity, or do we just find ways to describe it without ever really grasping it? Explain your reasoning.

Collected responses were analyzed to assess how participants' answers changed after exposure to AI-generated content and the extent to which those changes aligned with the AI's suggestions. For each question, three texts were considered: the participant's original response (P0), the AI-generated content shown to the participant (AI), and the participant's revised response (P1), when provided. If no revision was made, the original response was treated as the final response.

To quantify how participants' responses changed after exposure to AI-generated content, revision and alignment metrics were computed using a custom Python script based on TF-IDF cosine similarity. The core scoring logic is summarized below; the full implementation is publicly archived for reproducibility [12].

$$FINAL = P0, if\ P1\ is\ empty$$

$$TotalChange = 1 - sim(P0, FINAL)$$

$$AIDirectedChange = max\big(0, sim(FINAL, AI) - sim(P0, AI)\big)$$

$$AIAttributionShare = \frac{AIDirectedChange}{TotalChange}\ (if\ TotalChange > 0)$$

$$AIAttributionShare = 0\quad otherwise$$

Text similarity between responses was computed by comparing the wording and content of these texts while excluding common filler words that do not contribute meaningfully to content differences. Similarity values ranged from 0 to 1, with higher values indicating greater similarity.

Based on these comparisons, three measures were derived: total change, reflecting how much the final response differed from the original; AI-directed change, capturing movement toward the AI-generated suggestion; and AI-attribution share, representing the proportion of a participant's revision that aligned with the AI. Together, these measures provided a behavioral indicator of reliance on AI during the task.

Results

The participant sample consisted of 21 undergraduate engineering students. The sample included a mix of class standings, with a majority of upper-level students. All participants reported prior use of AI tools in academic or professional contexts. When asked which AI system they trusted most, ChatGPT was the most frequently selected, followed by Gemini, Copilot, and Claude.

For the five reasoning questions, participants overwhelmingly chose to retain their original responses after viewing AI-generated suggestions. Across all opportunities for revision, only a small number of revisions were observed. This pattern indicates that exposure to AI-generated approaches did not typically lead to changes in participants' written reasoning, as shown in Figure 1.

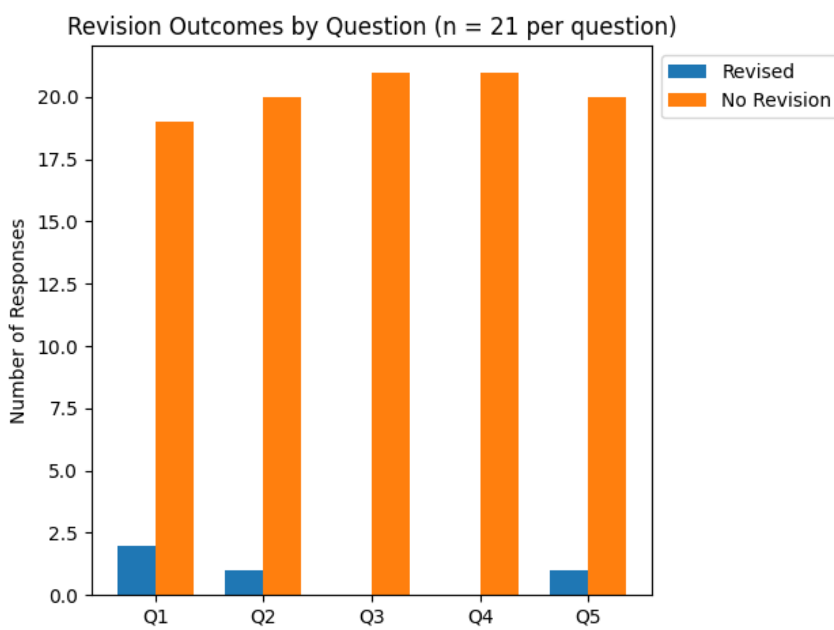

Figure 1. Revision Outcomes by Question

Revision behavior remained low across all five questions. When revisions did occur, they differed in character. In one case, a participant substantially revised their response in a manner that closely aligned with the AI-generated suggestion, indicating strong behavioral reliance. In other cases, participants revised their responses extensively but without measurable alignment to the AI output, suggesting independent reconsideration rather than adoption of the AI's reasoning.

These contrasting instances indicate that revision following AI exposure does not necessarily reflect AI-driven influence.

Self-report measures revealed moderate to high perceived challenge across tasks and generally moderate perceived helpfulness of AI suggestions, as shown in Table 1. However, participants tended to report low perceived influence of the AI on their final answers, even in cases where revisions occurred. Notably, perceived influence did not consistently correspond to behavioral measures of reliance, indicating a disconnect between participants' subjective impressions and observable revision behavior (figure 2).

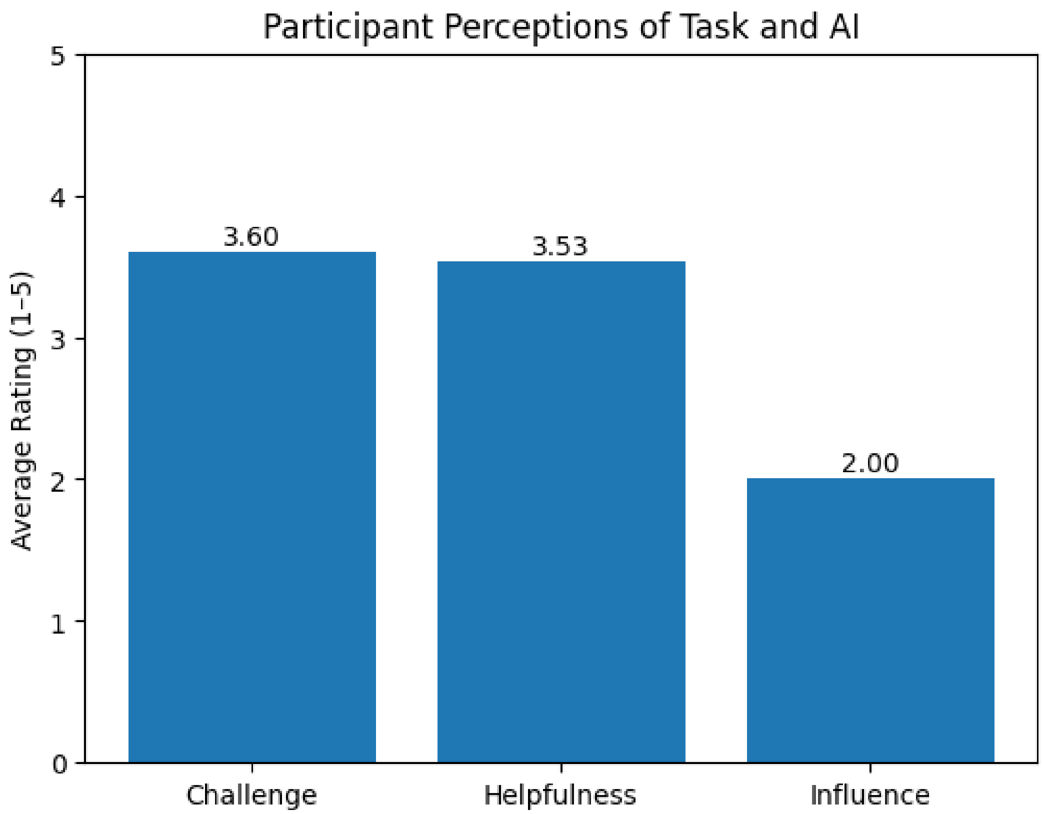

Figure 2. Self-reported task difficulty, helpfulness, and perceived AI influence

Discussion

The results suggest that, within this sample, students largely maintained cognitive independence when completing reasoning-intensive tasks, even after viewing AI-generated suggestions from tools they personally trusted. Contrary to concerns that AI exposure would broadly displace independent reasoning, most responses were not revised after participants viewed AI-generated suggestions, indicating that AI was often treated as supplementary rather than authoritative.

At the same time, the presence of strongly AI-aligned revision in an isolated case highlights that AI can meaningfully shape reasoning under certain conditions. This finding aligns with prior work on cognitive offloading, which emphasizes that reliance on external tools is selective and context-dependent rather than uniform [3]. Importantly, the data suggest that AI influence is not inherently linked to frequency of use or perceived helpfulness alone, but may depend on how participants interpret the relevance or clarity of the AI output relative to their own reasoning.

The observed difference between self-reported influence and behavioral alignment further complicates reliance assessment. Participants who reported minimal AI influence sometimes demonstrated substantial AI-aligned revision, while others who perceived AI as influential did not revise their responses at all. This discrepancy reinforces the limitation of relying solely on self-report measures to assess AI reliance and supports the value of behavioral indicators in understanding how AI affects reasoning processes.

Conclusion

This study examined how undergraduate engineering students engage with AI-generated suggestions during open-ended critical thinking tasks by observing patterns of revision and alignment between human and AI responses. The findings indicate that most participants did not alter their reasoning after viewing AI-generated content, suggesting that AI exposure alone does not necessarily reduce cognitive independence.

However, when revisions occurred, they could reflect strong alignment with AI-generated reasoning, demonstrating that AI has the capacity to meaningfully influence decision-making in specific instances. The lack of consistent correspondence between perceived influence and behavioral reliance highlights the complexity of human–AI interaction and underscores the importance of examining how AI affects reasoning behaviorally rather than relying exclusively on subjective reports.

These results suggest that AI tools function neither as passive references nor as dominant cognitive substitutes, but as conditional influences whose impact depends on individual engagement and task context. As generative AI becomes increasingly integrated into educational environments, understanding these nuanced patterns of reliance will be essential for determining the appropriate role of AI in supporting, rather than replacing critical thinking in engineering education.

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