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Evaluating the Effect of AI Language Models on Learning and Reasoning Abilities

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Abstract: This study systematically investigates the cognitive effects of AI-assisted reasoning by analyzing how the utilization of large language models (LLMs), such as ChatGPT, influences critical thinking, memory retention, and decision-making processes in young adults. With the growing integration of generative AI tools in academic and professional contexts, concerns have arisen regarding cognitive offloading, wherein individuals delegate complex reasoning, information retrieval, and analytical tasks to computational systems rather than engaging in in-depth cognitive processing themselves. While AI systems can enhance productivity and accessibility, excessive reliance may modify learning patterns, reduce reasoning depth, and impede long-term knowledge consolidation. The research employs a controlled experimental design with participants randomly assigned to one of three conditions: (1) no AI assistance, (2) AI assistance accompanied by structured metacognitive prompts aimed at fostering reflection and self-explanation, and (3) unrestricted AI use without guidance. Participants complete a series of tasks varying systematically in cognitive demand and domain, encompassing creative composition, analytical reasoning, and factual problem-solving exercises. Cognitive performance is assessed pre- and post-intervention to evaluate both immediate and short-term effects of AI exposure. Primary dependent measures include standardized critical thinking scores, immediate and delayed memory recall accuracy, decision-making confidence ratings, reasoning quality indices, and task completion times. Additional behavioral metrics, such as frequency of AI consultation and prompt complexity, are recorded to examine patterns of human-AI interaction. The theoretical framework integrates Cognitive Load Theory, to assess the impact of AI on intrinsic and extraneous cognitive load; Dual Process Theory, to examine potential shifts between intuitive and analytical reasoning; and metacognitive regulation models, to evaluate reflective monitoring and control processes during AI-assisted tasks.

Keywords: IoT Security, Edge Computing, Anomaly Detection, Machine Learning, Real-Time Monitoring, Data Encryption.

I. INTRODUCTION

The rapid advancement of artificial intelligence (AI), particularly Large Language Models (LLMs) such as ChatGPT, has significantly transformed learning environments, professional workflows, and everyday problem-solving practices. These systems are capable of generating human-like text, summarizing complex materials, assisting in analytical reasoning, and offering decision support. While such capabilities enhance efficiency and accessibility, they raise important concerns regarding their long-term cognitive impact on users. Young adults, especially students and early-career professionals, represent a demographic that frequently integrates AI tools into academic and workplace tasks.

The integration of AI into cognitive processes introduces the possibility of cognitive offloading, wherein individuals rely on external computational systems to perform tasks traditionally executed through internal cognitive effort. Although cognitive offloading can optimize mental resources, excessive dependence may influence higher-order thinking skills, including analytical reasoning, memory consolidation, and autonomous decision-making. This study investigates whether AI-assisted thinking enhances intellectual performance or contributes to diminished cognitive engagement among young adults.

Background of the Study

Digital technologies have historically reshaped cognitive habits. From calculators to search engines, technological tools have altered how individuals process and retrieve information. However, generative AI systems differ from previous technologies because they not only retrieve information but also synthesize, evaluate, and construct responses that resemble human reasoning.

The theoretical basis for understanding AI-assisted cognition draws from several psychological frameworks. Cognitive Load Theory suggests that reducing extraneous load

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may improve learning efficiency, but excessive simplification may limit schema development. Dual Process Theory distinguishes between intuitive (System 1) and analytical (System 2) thinking, raising concerns that AI assistance may promote superficial processing. Metacognitive theories emphasize the importance of self-monitoring and reflective thinking in deep learning. AI systems may either scaffold metacognition or weaken it depending on usage patterns.

Given the increasing presence of AI in academic writing, problem-solving, and decision-making contexts, it becomes essential to empirically evaluate whether these tools strengthen cognitive performance or unintentionally foster dependency.

II. REVIEW OF LITERATURE

Existing literature on digital cognitive tools suggests mixed outcomes. Studies on internet search behavior indicate that individuals may exhibit reduced memory retention when information is readily accessible online, a phenomenon referred to as the “Google Effect.” Similarly, research on calculator use demonstrates improved efficiency but sometimes reduced conceptual understanding in mathematics learning.

The study by Lu Fang, Ge Tang, and Lu Zhang in Education Sciences (2025) contrasts user perception versus actual data of a single best answer LLM tutor integrated into a game for beginner learners. They have done a qualitative analysis of 82 dialogues with 31 participants. The researchers report that learners generally expressed their liking of the tutor; however, there was only a small learning gain in real terms. Locating the AI tutor in a language learning game and then asking users to rate how helpful the tutor is in their learning compared to actual learning gains is the essence of this study. The participants stated that they liked the tutor a lot, but the real learning gain was marginal. The thought processes of the students were more profound when the AI gave them technical or general guidance. However, when the AI was directly explaining vocabulary or grammar, the students were more likely to be dependent on the AI and think less for themselves. The authors caution that even if students like AI tutors, these tools should be carefully designed so that they help learning and do not create dependence.

Tom Duenas and Diana Ruiz's paper presents a clever, task-specific framework to identify and categorize hallucinations in large language models, which suggests that single detectors that work for all kinds of situations are not efficient in areas with high impact, such as healthcare or legal work. To detect those elusive "truthfulness signals" that general methods overlook, which sounds like a new approach to AI safety and trustworthiness, they suggest employing probing classifiers and custom features for different skills - consider factual recall, logical puzzles, or sentiment reads. At the moment, it is mostly a conceptual work with some experiments to be conducted later, so although the idea has great potential for more accurate error detection, we will need solid data to know whether it actually outperforms the rivals.

The preprint by Carlo Galli and co-authors in 2025 presents a feasible, step-wise method of employing LLMs such as GPT-4 for the automation of abstract screening in systematic reviews by means of zeroshot/few-shot prompt usage that does not require the traditional feedback loop. By addressing aspects like software installation, data preparation, prompt utilization, cost handling, and human supervision, the paper convinces researchers, librarians, and students of the possibility to cut down their working hours while still upholding the research-based rigor of the method — albeit the presence of more domainspecific benchmark sets would have made it stronger. This readily comprehensible framework is a welltimed manual to accomplish of quick evidence syntheses.

This study by Tom Duenas, Diana Ruiz provides an accurate and very detailed examination, at the right moment, of the ethical problems and changes in education caused by an increase in human dependence on LLMs for critical thinking. It manages to balance issues such as cognitive offloading and loss of agency with the use of different strategies for human-LLM symbiosis. The main idea of the paper is in the proposition of educational and socio-technical models that illuminate the possibilities of AI-assisted learning as well as the jeopardies of the decrease of the skills of long-term reasoning which results to be a persuasive invitation to interdisciplinary research and the formulation of ethical codes. The abstract is very brief and therefore it can be improved by indicating some key models or citing some empirical studies in support of the theoretical framework, but still, it accomplishes the task of opening up a very important issue of how to keep human intellect alive in the age of AI.

The research by Hussain et al., (2025) determines how the use of adaptive AI tools affected cognitive load, focus, retention, and academic performance of university students in an online learning environment. The authors used a quantitative survey of 250 demographically similar participants, the data of which were analyzed using correlation, regression, and ANOVA. The results show that there is a strong inverse relationship between cognitive

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load and focus, and adaptive AI features have a great impact on knowledge retention and, thus, have performance as a whole, better than the traditional way.

The authors assert that personalized AI lessens the user's mental capacity and, thus, enhances the learning process. They suggest the use of AI in the classroom but also acknowledge that their findings are limited and suggest that future studies explore the emotional and motivational aspects. The article constitutes a strong argument for the use of AI as a tool for student engagement; however, it would be even more convincing if the authors used a longitudinal study design or diverse samples to be able to make causal claims.

Abdulnassir Yassin and Ashiraf Mabanja's 2024 paper, published at the International Conference on Applied Social Sciences in Education, explores the use of Artificial Intelligence (AI) in the light of the Information Processing Theory (IPT) to improve the educational outcomes. The authors of the paper first present IPT as a theory explaining the cognitive stages, memory storage, and processing capacities of humans and then show how these concepts can be used in AI to create individualized learning paths, manage the cognitive load, and provide on-the-fly feedback thus leading to student engagement, understanding, memorization, and learning performance in general. The paper presents these advantages as quite helpful to the future of education but at the same time recognizes the problems of privacy, bias, and the digital divide and thus recommends the collaborative work of cognitive scientists, AI specialists, and educators to overcome them. The paper also invites more research to the complexity of human learning to determine the best way for AI to be a helper.

Recent investigations into AI-based educational tools suggest that structured AI guidance can enhance comprehension, brainstorming quality, and productivity. However, other studies caution that unrestricted AI usage may reduce active engagement, originality, and deep reasoning. Emerging research on LLM-assisted writing indicates that while output quality may improve, independent critical analysis may decline if users rely passively on generated responses.

Furthermore, literature on human–AI collaboration emphasizes that AI should function as a cognitive partner rather than a cognitive substitute. When AI systems are integrated with metacognitive prompts or reflective scaffolding, learning outcomes tend to improve. However, longitudinal evidence on sustained cognitive effects remains limited. Thus, there exists a research gap concerning the direct measurement of AI's impact on critical thinking, memory retention, and decision-making confidence among young adults.

III. CONCEPTUAL DEVELOPMENT

Beyond the primary variables, the conceptual framework also incorporates the notion of cognitive calibration, which refers to the alignment between perceived performance and actual performance. AI-assisted systems may artificially inflate user confidence due to the fluency and coherence of generated responses, potentially leading to over-reliance and reduced critical scrutiny. Therefore, confidence–accuracy calibration is introduced as a moderating construct within the framework. Additionally, the model accounts for individual differences such as prior domain knowledge, digital literacy, and baseline cognitive ability, which may mediate the relationship between AI usage and cognitive outcomes. The framework further distinguishes between short-term performance enhancement and long-term cognitive development, emphasizing that efficiency gains observed during AI-supported tasks may not necessarily translate into durable knowledge acquisition. This expanded conceptual structure enables a multidimensional assessment of AI-assisted cognition, capturing not only performance metrics but also deeper metacognitive and developmental implications.

This study proposes a conceptual framework that examines AI-assisted thinking through three primary cognitive domains:

1. **Critical Thinking Ability** – the capacity to analyze arguments, evaluate evidence, and construct logical reasoning.
2. **Memory Retention** – the ability to encode, store, and recall information after task completion.
3. **Decision-Making Processes** – including accuracy, confidence calibration, and reasoning time.

The independent variable in this framework is the level of AI assistance, categorized into three conditions:

- No AI support
- AI support with structured metacognitive prompts
- Unrestricted AI usage

The framework hypothesizes that guided AI assistance may enhance learning outcomes by reducing extraneous cognitive load while maintaining analytical engagement. Conversely, unrestricted AI reliance may increase task efficiency but reduce cognitive effort and memory consolidation. The model also incorporates mediating variables such as cognitive load, depth of

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processing, and frequency of AI interaction. By integrating Cognitive Load Theory, Dual Process Theory, and metacognitive regulation models, the study evaluates whether AI functions as a cognitive enhancer or as a mechanism for cognitive substitution.

This conceptual development aims to distinguish between productive cognitive augmentation and detrimental cognitive dependency in AI-supported environments.

IV. METHODOLOGICAL OVERVIEW

To strengthen internal validity, the study incorporates counterbalancing techniques to minimize order effects across task types. A delayed post-test administered one week after the experimental session evaluates long-term retention and transfer of learning. In addition to quantitative performance metrics, qualitative data are collected through structured reflection questionnaires to assess participants' perceived cognitive effort, trust in AI outputs, and self-regulated learning strategies. Statistical procedures include multivariate analysis of variance (MANOVA) to examine differences across cognitive domains, as well as mediation and moderation analysis to test the influence of metacognitive prompts and individual characteristics. Effect sizes and confidence intervals are reported to ensure robust interpretation of findings. Ethical considerations, including informed consent, data anonymization, and responsible AI usage guidelines, are strictly maintained throughout the study. This comprehensive methodological design ensures both empirical rigor and theoretical depth in evaluating the cognitive consequences of AI-assisted thinking.

To empirically test the conceptual framework, an experimental design is proposed involving young adult participants aged 18–25. Participants are randomly assigned to one of three AI conditions and complete tasks including analytical reasoning problems, creative writing assignments, and factual problem-solving exercises.

Pre- and post-task assessments measure:

- Standardized critical thinking scores
- Immediate and delayed memory recall accuracy
- Decision-making confidence levels
- Task completion time
- Perceived cognitive effort

Statistical analyses, including ANOVA and regression modeling, are used to determine significant differences across conditions. This methodological approach allows for a controlled evaluation of AI's direct and indirect cognitive effects.

V. CONCLUSION

The proliferation of AI-powered language models presents both opportunities and challenges for cognitive development in young adults. While AI systems can enhance productivity, creativity, and access to knowledge, they also raise concerns regarding reduced cognitive engagement and over-reliance. This study contributes to the growing body of research on human–AI interaction by proposing a structured framework to evaluate AI's cognitive consequences. Preliminary theoretical insights suggest that AI's impact depends largely on how it is integrated into cognitive tasks. Guided and reflective use may support deeper learning, whereas passive and unrestricted reliance may weaken independent reasoning and memory retention.

The findings of this research are expected to inform educational policies, curriculum design, and AI interface development. Ultimately, the goal is not to restrict AI usage but to promote cognitively sustainable integration strategies that preserve and strengthen higher-order thinking skills. Future research should explore longitudinal effects, neural correlates of AI-assisted cognition, and cross-cultural differences in AI reliance patterns.

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