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THE IMPACT OF GENERATIVE AI DEPENDENCY ON LEARNING OUTCOMES: THE MEDIATING ROLE OF COGNITIVE AGILITY AMONG UNIVERSITY STUDENTS

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ABSTRACT
The educational paradigm in higher education has been completely changed by generative artificial intelligence (GAI) technologies like ChatGPT, Gemini, and Copilot. These tools offer students unparalleled access to knowledge and learning help while also enhancing the teaching process with creative methods. Although helpful, there are worries about how students' reliance on AI-generated work could affect their learning outcomes. The present study examined the mediation effect of CA (Cognitive Agility) on the relationship between GAD (Generative AI Dependency) and LO (Learning Outcomes) among the students of being at the university level. The research suggested that overreliance on generative AI could reduce students' cognitive load relative to their own thinking, but cognitive agility may enable them to adapt, critically process, and effectively use information created by the generative AI. The research method adopted was quantitative cross sectional and the data obtained from 400 respondents who are students at the universities in the city, using stratified random sampling technique. The data were collected with three standardized self-report instruments, namely the Generative AI Dependency Scale (8 items), the Cognitive Agility Scale (10 items) and the Learning Outcomes Scale (9 items), rated on a 5-point Likert scale. Cronbach's α for the scales were satisfactory with ranges between .87 and .91. The relationship of the study variables was examined using Structural Equation Modeling (SEM) in the form of direct and indirect relationships. The results showed that Generative AI Dependency had a significant impact on Learning Outcomes and Cognitive Agility, and that Cognitive Agility had a significant impact on the Learning Outcomes. Additionally, a partial mediation analysis was performed in between Generative AI Dependency and Learning Outcomes with Cognitive Agility. By identifying the psychological domains that impact student learning with the use of AI, this study contributes to the existing research on AI in education. The findings are relevant for learning designers, policy makers and higher educational institutions who aim to develop meaningful and effective learning in today's technological environment.
Keywords: *Generative AI Dependency, Cognitive Agility, Learning Outcomes, Higher Education, Educational Technology, University Students, Structural Equation Modeling (SEM).*

Introduction

Artificial Intelligence (AI) has been one of the most influential technologies in the 21st century in higher education (Holmes et al., 2019; UNESCO, 2023). Generative AI tools, such as ChatGPT, Gemini, Claude, Copilot, and others have revolutionized how students access information, finish tasks and participate in learning activities. These tools offer human-like responses, aid in problem-solving, condense lengthy information, and deliver instant academic help, boosting the efficiency and accessibility of learning (Kasneci et al., 2023; Tlili et al., 2023). This has led to the adoption of generative AI in teaching and learning in higher education institutions around the world.

While all of this is good, there are growing concerns about the reliance of students on generative AI. AI dependency is defined as the extent to which learners rely on the application of AI technologies to do cognitive tasks that used to be their responsibility to think, analyze and solve problems without relying on AI technology (Dwivedi et al., 2023). When students over rely on AI-generated content, they may limit their opportunities for critical reflection, in-depth thinking, or independent learning, which can impact students' performance and intellectual growth (Kasneci et al., 2023; Rudolph et al., 2023). AI tools can facilitate learning, but it is possible for cognitive offloading to occur, meaning that the learners' minds will be offloaded to the technological system instead of actively constructing knowledge (Fisher & Oppenheimer, 2021).

Meanwhile, the term cognitive agility is becoming more popular in learning sciences and educational psychology. Cognitive agility is defined as an individual's capacity to modify thinking, to switch gears, to process information efficiently, and to respond appropriately to new and complex situations (DeRue et al., 2012). Learners with high cognitive agility tend to engage more with information, adjust learning methods and effectively manage technology rich learning. This could make it easier for such students to employ AI tools as a resource for learning and not rely too heavily on them (Martin et al., 2024).

Considering the growing presence of AI technologies in the context of higher education, the impact of AI dependency on educational outcomes and the connection between cognitive agility and this relationship are significant research areas to explore. While the academic implications and difficulties of AI-based learning have been studied previously, there has been scant research focusing on the psychological processes behind the impact of AI dependency on learning. Hence, the purpose of this study is to examine the relation between Generative AI Dependency and Learning Outcomes with Cognitive Agility as a mediator variable among the students at a university.

Objectives

1. To examine the relationship between Generative AI Dependency and Learning Outcomes among university students.
2. To find out the relationship between Generative AI Dependency and Cognitive Agility.
3. To determine the relationship between Cognitive Agility and Learning Outcomes.
4. To examine the mediating role of Cognitive Agility in the relationship between Generative AI Dependency and Learning Outcomes.

Literature Review

Generative AI Dependency

Generative AI Dependency is when students use generative AI systems to complete educational assignments, develop concepts and ideas, solve problems, gather information and create educational materials. With the advent of generative AI technologies like ChatGPT, Gemini, Claude, and Copilot, the educational landscape has been revolutionized, offering students immediate access to information, customized learning resources, and automated content generation (Dwivedi et al., 2023; Kasneci et al., 2023). These tools are gaining in popularity among university students, as they help increase efficiency, aid in learning, and boost academic productivity.

Even with the advantages, concerns have been raised about over-reliance on AI technologies. Over-dependence on AI could lead to cognitive offloading, which is the tendency to shift cognitive tasks to technological systems instead of thinking and problem-solving (Fisher & Oppenheimer, 2021). Relying on AI-generated answers frequently, students might become less engaged in critical thinking, reflection, and building knowledge independently, hindering meaningful learning (Rudolph et al., 2023). Additionally, overreliance on AI can impact students' innate motivation to learn and limit their opportunities for higher-order thinking skills like evaluation, synthesis, and creativity (Tlili et al., 2023).

A recent study suggests that AI tools, known as generative AI, are more commonly used among university students to draft assignments, summarize academic content, research, and to provide instant answers for complicated questions (Chan & Hu, 2023). While these practices can increase productivity and accessibility, there are concerns that they could also have detrimental effects on intellectual independence and academic honesty (Cotton et al., 2024). This has led to a growing interest in the educational implications of dependency on generative AI in the field of higher education research.

Cognitive Agility

Cognitive agility is the capacity to flex cognitive strategies, change frame of reference, efficiently process information and effectively respond to changing contexts and complex problems (DeRue et al., 2012). It includes flexibility of thought, adaptability, reflective thinking, and responsiveness of the mind. The world of learning and problem-solving today is one that is rapidly evolving with technology and information overload; in this context, cognitive agility is regarded as an important skill for learning success. People with a high cognitive agility can modulate their thinking in relatively short periods of time, combine various inputs, and utilize a variety of approaches when encountering a new situation (Pulakos et al., 2000). These pupils become more analytical and can recognise the difference between trusted and distrusted sources of information. In AI-supported learning environments, cognitive agility helps students to use AI-generated information in a strategic manner rather than blindly taking in outputs generated by AI (Martin et al., 2024).

Numerous studies in educational psychology confirm that cognitive agility is linked to better learning outcomes, creativity, decision making and adaptability (Cañas et al., 2005). Students with high cognitive agility tend to be more reflective in their learning and monitor themselves and perform adaptive problem solving. Therefore, cognitive agility can be viewed as a key psychological factor that enables students to navigate and effectively engage with AI technologies without losing their connection to the cognitive content.

Learning Outcomes

Learning outcomes are defined as measurable knowledge, skills, attitudes, competences and changes of behaviour gained from learning experiences (Biggs & Tang, 2011). In higher education, the learning outcomes include cognitive achievement, critical thinking, problem-solving skills, communication skills, and application of knowledge to real-world situations. Good learning outcomes are generally accepted as measures of learning quality and student achievement.

The technology-enhanced learning environments have been found to have a positive effect on learning outcomes, by providing greater access to information, facilitating personalized instruction, and promoting student engagement (Means et al., 2013). AI-driven learning tools, notably, have shown significant promise in enhancing learning outcomes and efficiency with personalized guidance and feedback (Holmes et al., 2019). But the way students interact with these technologies makes a big difference in how effective they are.

Active involvement in learning materials is known to achieve deeper learning and long-term retention of knowledge, while passive learning content might inhibit meaningful learning (Chi & Wylie, 2014). Thus, although AI technologies can contribute to educational success, overreliance on AI-generated content can diminish cognitive effort and impair critical thinking and problem-solving abilities (Kasneci et al., 2023). Therefore, the connection between AI dependency and learning is complex, and needs more empirical study.

Relationship between Generative AI Dependency and Learning Outcomes

This issue of dependency on AI and learning outcomes has been a subject of increasing academic interest. Current studies indicate that AI tools can support learning when used judiciously and when they are used for a purpose, by alleviating repetitive cognitive tasks and by offering timely academic support (Holmes et al., 2019). But relying on too much scaffolding can lead to learning in a superficial way and limit opportunities for deeper thought (Rudolph et al., 2023).

In terms of Cognitive Load Theory, technology can be used to assist in learning by reducing extraneous cognitive loads and allowing students to concentrate on the critical learning tasks (Sweller, 1988). However, overuse of AI-generated responses might lead to less relevant thinking, so students won't be able to build meaningful knowledge structures. While there can be short-term benefits to academic efficiency, high levels of AI dependency can have detrimental effects on learning outcomes.

Relationship between Generative AI Dependency and Cognitive Agility

Relying on Generative AI could have a profound impact on students' cognitive agility. Overuse of AI systems can diminish opportunities for independent learning, analytical thinking and cognitive exploration which can negatively impact adaptability and flexibility in learners (Fisher & Oppenheimer, 2021). Relying on AI-generated solutions regularly might make students less likely to try and think through and solve problems themselves or to critically assess information.

However, others believe that with proper application of AI technologies, adaptive thinking can be encouraged by presenting learners with different viewpoints and providing quick access to information (Martin et al., 2024). The relationship between AI dependency and cognitive agility is not yet clear and needs to be empirically investigated. Understanding this connection can help researchers gain insights into the impact of student-AI interactions on students' cognitive maturation.

Relationship between Cognitive Agility and Learning Outcomes

The ability to be cognitively agile has always been correlated with positive educational outcomes. Studies show that cognitively agile students have better problem-solving skills, higher achievement, and better adaptability in dynamic learning contexts (Pulakos et al., 2000). These students can more effectively control their learning, critically assess information, and transfer knowledge to a variety of situations.

Self-regulated learning research also indicates that flexible thinking in cognition will improve the students' ability to monitor, control, and adapt their learning strategies to various contexts (Zimmerman, 2002). In a tech-driven educational setting, cognitively agile learners tend to be more active participants in learning activities, and they utilize AI tools to aid their learning without eliminating their own cognitive contribution. This suggests that cognitive agility should positively impact learning outcomes and could act as a mediator between relying on generative AI and academic performance.

Theoretical Framework

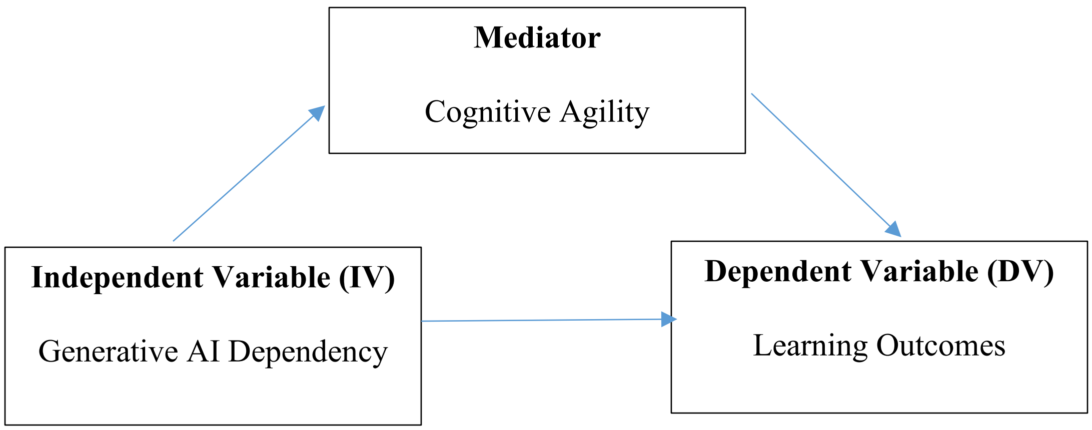
Cognitive Load Theory

The concept of cognitive load theory (Sweller, 1988) offers valuable insights into the educational impact of reliance on generative AI. The theory assumes that the ability of working memory is limited in the process of learning. Instructional tools and technologies can aid learning by minimizing unnecessary cognitive load and letting students focus cognitive resources on meaningful learning. The immediate feedback and academic support provided by the generative AI system could potentially help students navigate complex information and minimize extraneous cognitive load. However, if too much of the content produced by AI is used, it could affect germane cognitive processing and limit opportunities for deep learning, impacting learning outcomes.

Self-Regulated Learning Theory

The SRL Theory focuses on the active control of cognitive, motivational and behavioral processes in the learning process by the learner (Zimmerman, 2002). They learn well by keeping track of what they have learned, by controlling their learning processes, and by adjusting their actions to meet educational objectives. Cognitive agility is seen as an important aspect of SRL as it allows students to switch between modes of thinking, to think critically about information and to adapt to new learning requirements. AI-integrated education should not lead to the overreliance on AI for learning, and cognitively agile students should use AI as a tool to enhance their learning, not rely upon it. Thus, the Self-Regulated Learning Theory offers a valuable perspective to understand how cognitive agility acts as a mediator between the use of generative AI dependency and learning outcomes.

Conceptual Framework



Hypotheses

H1 Generative AI Dependency significantly influences Learning Outcomes among university students.
H2 Generative AI Dependency significantly influences Cognitive Agility among university students.
H3 Cognitive Agility significantly influences Learning Outcomes among university students.
H4 Cognitive Agility mediates the relationship between Generative AI Dependency and Learning Outcomes among university students.

Methodology

Research Design

The quantitative cross-sectional survey research design was used in this study. The research design of this study is quantitative cross-sectional survey research design which was utilized to evaluate the association the Generative AI Dependency, Cognitive Agility and Learning Outcomes of the University students. The quantitative technique was chosen because it is appropriate for systematically collecting numerical data and enables statistical analysis to examine the correlations between variables. The cross-sectional methodology allowed the researcher to get the relevant data from the participants at one time, which was an efficient way to examine the present patterns of generative AI use and its relationship to students' cognitive and academic outcomes. This design is also widely used in educational and psychological studies for direct and indirect assessment of correlations between variables in a theoretical model.

Population and Sample

The study's respondents were in undergraduate and postgraduate studies in public and private universities. The population of interest consisted of these students because they are the primary users of Generative Artificial Intelligence (GAI) tools including ChatGPT, Gemini and Copilot in the academy. A stratified random sampling technique was used for the purpose of obtaining adequate representation from the different academic disciplines, institutions and levels of study. The population was subdivided into relevant strata, in terms of university type (public and private) and academic level, and participants were randomly sampled from each stratum. The targeted sample was 400 students at university, which is more than the minimum sample size recommended for Structural Equation Modeling (SEM) and is enough for statistical power in mediation analysis.

Instrumentation

Data were gathered from a structured questionnaire which comprised four sections. The first part collected demographic details such as gender, age, educational attainment, major studied, and how often the students use AI tools. The second part was on Generative AI Dependency, the third on Cognitive Agility, and the fourth on Learning Outcomes.

The Generative AI Dependency Scale (GADS) was designed from the available literature on technology dependency and AI-supported learning and comprised 8 items. The scale measured students' dependence on generative AI tools for academic work in three dimensions: frequency of using AI, relying on AI-generated content, and academic dependence on AI tools. Some sample items were "I often use generative AI tools to finish academic work" and "I rely on AI-generated answers to help me grasp the content of the course. As the scores increased, it meant that there was a higher dependency on generative AI technologies.

Cognitive Agility Scale (CAS) was quantified by a ten-item scale which was validated from earlier research on cognitive flexibility and adaptive thinking. Instruments focused on the students' capacity to adjust their thinking processes, react to new environments and switch between cognitive processes. The scale was divided into three factors: mental flexibility, adaptive thinking, and cognitive responsiveness. Sample items were "I can quickly change my thinking when new information is presented" and "I can easily adjust my learning strategies to academic tasks. Scores were higher the more cognitive agility present.

The Learning Outcomes Scales (LOS)were assessed by a 9-item scale that evaluated the students perceived academic growth and educational outcomes. The scale contained four factors: academic achievement, knowledge acquisition, problem solving, and critical thinking skills. Sample items were "I am capable of using what I have learned in the courses in real-life situations" and "My learning experiences have enhanced my problem-solving skills. These scores indicated more positive learning outcomes, with higher scores indicating more.

Validity and Reliability

The questionnaire was content validated by the panel of experts comprising of educational technology, educational psychology and Research methodology. These items were then reviewed, for clarity and relevance, according to their feedback. In a pilot study, the instrument was pretested with 50 university students to test the reliability and understandability of the instrument. The internal consistency reliability was assessed by Cronbach's alpha coefficient. The results showed good reliability for each of the constructs, with Cronbach's alpha values of .89 for Generative AI Dependency, .91 for Cognitive Agility and .87 for Learning Outcomes, which are higher than the recommended .70.

Data Collection Procedure

After institutional approval and ethical clearance, data was gathered from students at selected universities (both Public and Private). The participants were made aware of why the study was being conducted, the voluntary element that they would be taking part in and the fact that their responses would be kept confidential. Questionnaire was administered after the informed consent was obtained. The data was gathered by using both online and paper survey methods to get a good response and accessibility of the subject matter participants from various institutions.

Results

The data collected in this way were analyzed in SPSS Version26 & AMOS Version24. Demographic descriptions of respondents and the distribution of the variables of the study (frequencies, percentages, means and standard deviations) were then calculated. The internal consistency of the scales of the measurement was tested by Cronbach's α, and reliability analysis was performed.

Next, Confirmatory Factor Analysis (CFA) was carried out to examine the measurement model and construct validation. The convergent validity was examined by factor loading and discriminant validity was examined by Composite Reliability (CR) and Average Variance Extracted (AVE) was checked for discriminant validity following Fornell-Larcker criterion. The goodness of fit was assessed through the following standard goodness of fit indices: Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Goodness of Fit Index (GFI), Root Mean Square Error of Approximation (RMSEA) and Chi-square/degrees of freedom ratio (χ^2/df).

Finally, a Structural Equation Modeling (SEM) was employed to test the hypothesized relationships between Generative AI Dependency, Cognitive Agility and Learning Outcomes. For the direct effect analysis, standardized path coefficients were used, for the indirect effect analysis of Cognitive Agility, the bootstrapping method with 5,000 resampling was used. The importance of indirect effects was assessed using bias-corrected CI and p values. This analytical approach enabled a deep dive into both direct and indirect channel effects on the Learning Outcomes on the university student's side of Generative AI Dependency.

Table 1: ***Means, Standard Deviations, and Correlations among Study Variables***

Variable	M	SD	1	2	3
1. Generative AI Dependency	3.51	0.79	—		
2. Cognitive Agility	3.76	0.82	.49**	—	
3. Learning Outcomes	4.02	0.77	.47**	.62**	—

The results of the Pearson correlation analysis showed that all the study variables were significantly positively related. Generative AI Dependency had a positive correlation with Cognitive Agility ($r = .49$, $p < .01$) and Learning Outcomes ($r = .47$, $p < .01$). The same applies to the correlation between Cognitive Agility and Learning Outcomes which was positive and significant ($r = .62$, $p < .01$). The results indicate that the use of the Generative AI Dependency and Cognitive Agility constructs are related to the Learning Outcomes of the university students and support the proposed mediation model.

Table 2: ***Summary of Measurement Model***

Construct	Cronbach's α	CR	AVE
Generative AI Dependency	.89	.93	.62
Cognitive Agility	.91	.95	.66
Learning Outcomes	.87	.94	.63

Reliability and validity analysis yielded positive results indicating that the constructs used in the study have good psychometric properties. The Cronbach's alpha coefficient for each scale ranged from .87 to .91 and the Composite Reliability coefficient for each scale ranged from .93 to .95, which were higher than the recommended value of .70. Moreover, Average Variance Extracted (AVE) scores varied between .62 and .66 which is above .50. Based on the results of this test, the internal consistency reliability of the measurement model was high, and the convergent validity was also satisfactory, namely the measurement model was suitable for further analysis of the structural model.

Table 3: ***Structural Equation Modeling (SEM) Path Analysis Results***

Hypothesis	Structural Path	β	S.E.	C.R.	p-value	Decision
H1	Generative AI Dependency → Learning Outcomes	.21	.052	4.04	< .001	Supported
H2	Generative AI Dependency → Cognitive Agility	.49	.047	10.43	< .001	Supported
H3	Cognitive Agility → Learning Outcomes	.54	.058	9.31	< .001	Supported

The results of SEM showed that the generative AI Dependency was significantly positively related to the Learning Outcomes ($\beta = .21$, C.R. = 4.04, $p < .001$), which supports H1. Furthermore, Generative AI Dependency had a significant effect on Cognitive Agility ($\beta = .49$, C.R. = 10.43, $p < .001$), which supported H2. Moreover, Cognitive Agility had a significant effect on Learning Outcomes ($\beta = .54$, C.R. = 9.31, $p < .001$), which supported the H3. The results suggest that students with greater levels of Generative AI Dependency are more likely to achieve higher scores on the Cognitive Agility and Learning Outcomes scales, and that the Cognitive Agility scale is a strong predictor of students' academic performance.

Table 4: ***Direct, Indirect, and Total Effects***

Path	Direct Effect	Indirect Effect	Total Effect
Generative AI Dependency → Learning Outcomes	.21	.26	.47
Generative AI Dependency → Cognitive Agility	.49	—	.49
Cognitive Agility → Learning Outcomes	.54	—	.54

The direct, indirect and total effects were analyzed, and it was found that Generative AI Dependency had a direct positive impact on Learning Outcomes ($\beta = .21$) and an indirect effect via Cognitive Agility ($\beta = .26$). The overall effect of Generative AI Dependency on Learning Outcomes was $\beta = .47$, signifying a significant overall influence. Due to the significance of both the direct and indirect effects, the mediation was only partial, with the relationship between Generative AI Dependency and Learning Outcomes partially mediated by Cognitive Agility. Further, Generative AI Dependency had a positive relationship with Cognitive Agility ($\beta = .49$), and Cognitive Agility had a strong relationship with the Learning Outcomes ($\beta = .54$). These findings highlight the potential role of cognitive agility as a mediator between the use of AI and academic performance.

Table 5: ***Cognitive Agility Mediates the Relationship between Generative AI Dependency and Learning Outcomes among University Students***

Mediation Path	Indirect Effect (β)	Boot LLCI	Boot ULCI	p-value	Decision
Generative AI Dependency → Cognitive Agility → Learning Outcomes	.26	.18	.34	< .001	Significant

The mediating effect of Cognitive Agility between Generative AI Dependency and Learning Outcomes was analyzed using the Bootstrap method.The mediating effect of Cognitive Agility between Generative AI Dependency and Learning Outcomes was analyzed using the Bootstrap method. The results showed an indirect effect of .26 with a 95% bootstrapped confidence interval of (.18, .34) that was significant ($p < .001$). The mediation effect was statistically significant as the confidence interval did not contain zero. This result confirms the hypothesis that Cognitive Agility is a mediator between GAD and LO. Based on the above discussions, it was concluded that the direct and indirect effects were significant, thus it can be concluded that Cognitive Agility works as a partial mediator in the proposed model.

Discussion

The first purpose of the study was to explore the relationship between Generative AI Dependency, Cognitive Agility, and Learning Outcomes of the university students and to examine the mediation role that Cognitive Agility played between Generative AI Dependency and learning outcomes. Results showed that all the hypotheses were accepted, hence, there are significant positive relationships among the study variables.

The results showed that Generative AI Dependency had a significant and positive effect on Learning Outcomes. The results indicate that students who use generative AI tools like ChatGPT, Gemini and Copilot effectively are reporting higher levels of academic achievement, knowledge gain, critical thinking and problem solving. The findings align with the positive findings of previous studies on the educational value of AI-enabled learning technologies in improving learning effectiveness and student achievement (Holmes, et al., 2019; Kasneci, et al., 2023). By enabling students to access information, receive individualized explanations, and get help on their learning, generative AI can help simplify understanding and boost academic success. The study findings challenge the notion that relying on AI tools would inevitably be a barrier to learning, suggesting that with proper use, AI can be a powerful learning tool that enriches the educational process.

Secondly, the study revealed that Generative AI Dependency significantly predicted Cognitive Agility. The discovery indicates that, when used often, students' cognitive responsiveness, mental flexibility, and adaptability might be increased by generative AI technologies in their interactions. The outcome fits the argument of AI technologies being able to present learners with various viewpoints, different solutions and opportunities to process information quickly, which stimulates adaptive thinking (Martin et al., 2024). While some previous studies have raised concerns that overreliance on AI might decrease independent cognitive work (Fisher & Oppenheimer, 2021), the current results suggest that students' use of AI can have a positive impact on cognitive adaptability when they must interact with the AI-generated content and are not simply passive consumers thereof.

Thirdly, it was discovered that Learning Outcomes had a strong positive correlation with Cognitive Agility. This result corroborates the significance of cognitive flexibility and adaptive thinking in academic achievement found in educational psychology literature (Pulakos et al., 2000; Zimmerman, 2002). Cognitive agility is associated with more effective adjustment of learning strategies, critical evaluation of information and response to the evolving learning demands of students of higher levels of cognitive agility. These skills are increasingly relevant in technology-laden learning spaces as pupils need to be continually evaluating information that has been received through digital means, including AI content.

The most significant finding of the mediation analysis was that Cognitive Agility partially mediated the relationship between Generative AI Dependency and Learning Outcomes. The indirect effect also suggests that generative AI plays a crucial part in boosting learning outcomes indirectly, as it improves students' cognitive agility. This discovery has empirical evidence to support the Self-Regulated Learning Theory that focuses on adaptive cognitive processes in successful learning. Students who learn to adapt their thinking in the process of using AI technologies seem to be more capable of making AI-derived information useful knowledge and academic performance. The partial mediation effect also implies that the impact of dependency on AI on learning outcomes is partially explained by the level of cognitive agility, meaning that AI dependency can be seen as a condition that interacts with cognitive agility, enhancing the impact of the latter (Zou et al., 2025; Zou et al., 2026).

The results are also consistent with the assumptions of the Cognitive Load Theory. The use of generative AI can help minimize the cognitive load on students by offering instant academic support and making difficult content more digestible. Therefore, students could dedicate more cognitive effort to the comprehension, analysis and application of knowledge. The mediation effect of cognitive agility, however, suggests that what students learn is not only contingent on access to AI technologies, but also on their capacity to process and use the information given by these tools in an adaptive way.

In conclusion, this study adds to the existing body of literature on the implications of AI in education by showing that the reliance on generative AI is not necessarily harmful to learning. Instead, its educational potential lies in what the students learn and how they use their cognitive abilities with AI systems. Cognitive agility is a key psychological process that enables the impact of AI-assisted learning to boost educational outcomes.

Conclusion

The present study examined how university students' use of Generative AI is correlated with their cognitive agility and learning outcomes. The results showed that the use of Generative AI Dependency positively and significantly affected the participants' Cognitive Agility and Learning Outcomes. Moreover, Cognitive Agility was a significant predictor for the Learning Outcomes and partially mediated the relationship between Generative AI Dependency and the Learning Outcomes.

The findings indicate that generative AI technologies have a beneficial function in higher education when students employ them to assist their learning and not as a replacement for their own thinking. Students who can use AI technologies in their learning effectively are more likely to show cognitive agility and are thereby more likely to improve academic performance, critical thinking and problem-solving skills. Thus, AI's educational advantages do not just lie in access to information but also in fostering adaptive cognitive abilities for lifelong learning.

The author emphasizes the need for cognitive development to go hand in hand with technological innovation in Higher Education. The potential of generative AI for education is great, but institutions need to foster students' critical thinking abilities to understand, analyze, and use AI-generated content. A cognitive agile approach to responsible use of AI by universities can maximize benefits and reduce potential risks of overdependence in the use of AI technologies.

Recommendations

The following recommendations are proposed based on the results of the study:

1. The teaching process should be planned as an activity to improve students' mental flexibility, adaptive thinking, reflective judgment and problem-solving abilities to boost their cognitive agility.
2. To facilitate deeper cognitive engagement, teaching methods such as project-based learning, inquiry-based learning, case analysis and collaborative problem-solving should be used.
3. Professional development opportunities should be provided at universities to enable teachers to acquire the knowledge and skills to use AI technologies effectively and ethically in educational assessment and instruction.
4. To gain more insight into the relationship between AI use and educational outcomes, future research should explore other psychological factors like critical thinking, self-regulated learning, digital resilience, AI self-efficacy, and epistemic vigilance.
5. The researchers need to use a longitudinal research design to explore the long-term impact generative AI dependency has on the students' cognitive development and academic performance.
6. There is a need for future studies to replicate the study across levels of education, subject area and cultural contexts to increase the generalizability of the findings.

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