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Do students need to think hard? The interplay of AI and cognitive abilities in solving problems

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Abstract
A key psychological factor shaping students' approach to problem-solving is their need for cognition—their drive to engage in and enjoy mentally demanding tasks. Students with a lower need for cognition may favour more structured or straightforward methods for solving problems. This study investigates the role of using Artificial Intelligence in solving economic problems by non-AI expert students, examining the effects of Cognitive reflection, the Need for cognition, and creativity on problem-solving performance. Results show that students with high Cognitive reflection and Need for cognition scores performed better, relying less on using Artificial Intelligence tools, particularly when satisfied with completing complex tasks. Students trusted Artificial Intelligence more when their reflective thinking and task satisfaction were lower, aligning with findings on trust transfer between users and Artificial Intelligence systems. Creativity has no influence on AI effectiveness, with students' success depending on how well they structure Artificial Intelligence prompts. While Cognitive reflection and the satisfaction of completing complex tasks contribute to positive outcomes in solving economic problems, the introduction of Artificial Intelligence led to a decrease in student performance. As generative Artificial Intelligence tools become more common in educational contexts, it is crucial to understand how these cognitive preferences influence the effectiveness of AI-driven problem-solving environments.

Keywords Using AI · Cognitive reflection · Need for cognition · Solving problems · Creativity

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1 Introduction

Different ways of thinking, understanding, and interpreting the increasingly complex world around us shape how individuals make decisions and behave, both in personal and organizational contexts. Some people are more inclined to explore and adopt new tools to solve problems and meet their needs, while others are comfortable relying on familiar, traditional methods. The rapid advancement of generative artificial intelligence (AI) has brought significant changes to the educational landscape, offering new opportunities to promote personalized learning, enhance creativity, and support complex problem-solving. Generative AI systems provide students with tools to address complex tasks across a range of disciplines, while also transforming how learning itself is approached. However, despite the growing integration of these technologies into education, our understanding remains limited regarding how generative AI interacts with students' cognitive traits, particularly in the context of complex problem-solving.

One key psychological factor influencing how students approach such tasks is Need for cognition (NFC), the tendency to engage in and enjoy effortful cognitive activities. Students with high need for cognition are typically drawn to intellectual challenges, exhibit stronger critical thinking, and are more inclined to adopt analytical strategies. At the same time, those with lower Need for cognition may prefer simpler, more structured approaches, often relying on heuristics and minimal cognitive engagement. As generative AI becomes increasingly embedded in educational practices, we need to understand how these cognitive preferences shape its effectiveness as a learning and problem-solving aid.

Research has shown that individuals with low Need for cognition tend to demonstrate limited motivation to improve their understanding (Petty et al., 2009). They exhibit less curiosity and a reduced desire to explore new ideas or frameworks, instead relying on mental shortcuts to interpret their surroundings. This group generally favours low-effort, straightforward solutions and tends to focus on short-term outcomes (Cacioppo et al., 1996; Goupil & Proust, 2023). In contrast, individuals with high Need for cognition actively seek information and try to interpret and make sense of events and phenomena by identifying patterns and connections. They find intrinsic satisfaction in addressing complex problems and are willing to invest substantial mental effort to do so (Cacioppo & Petty, 1982; Furnham & Thorne, 2013). These individuals often see the world as a complex puzzle; one they are eager to understand and reconstruct. They enjoy abstract thinking, appreciate debate, and often approach problems by decomposing them into manageable sub-tasks to optimize cognitive processing (Wu et al., 2014; Paas & van Merriënboer, 2020; Sweller et al., 2011). Their high Need for cognition is also positively associated with strong critical thinking skills (Wang et al., 2014), an interest in leadership (Stedman et al., 2009), and a greater openness to diverse perspectives (Thornhill-Miller et al., 2023).

Failing to move beyond the first intuitive answer often leads to reasoning errors (Szaszi et al., 2017). Need for cognition has been consistently identified as a reliable predictor of how individuals process information and make decisions (Cacioppo et al., 1996). It is associated with a preference for deep, deliberate thought (Hannah et al., 2011), moral reasoning (Strobel et al., 2017), the use of self-regulated learning strategies

(Cazan & Indreica, 2014), extended exploration of alternatives (Rudolph et al., 2018), and higher levels of both openness to experience and general intelligence (Furnham & Thorne, 2013). Moreover, individuals high in Need for cognition tend to perceive cognitively demanding tasks as less aversive and more engaging (Zerna et al., 2023).

This study aims to explore the relationships between cognitive characteristics, particularly Need for cognition and Cognitive reflection, and how students use generative AI tools such as ChatGPT in problem-solving contexts. This is especially relevant in domains where students may lack deep, domain-specific knowledge, such as economics. Students with higher cognitive abilities may be more skilled at generating creative and innovative solutions, while those with lower cognitive abilities might favour more straightforward or direct strategies.

2 Theoretical framework

2.1 Need for cognition

Need for cognition (NFC) refers to stable individual differences in cognitive motivation and has been shown to be a significant predictor of how individuals process information, as well as their levels of fluid intelligence (Fleischhauer et al., 2013) and academic success (Grass et al., 2017). Research indicates that Need for cognition predicts performance on intellectual tasks (Coutinho, 2006) and is positively associated with creativity and creative problem-solving across various domains (Wimmer, 2016). Individuals high in Need for cognition tend to be more adept at solving complex problems (Nair & Ramnarayan, 2000; Watts et al., 2017). However, its interaction with other factors such as cognitive capacity and cognitive motivation can influence performance expectations, particularly on more difficult tasks (Reinhard & Dickhäuser, 2009). The relationship between problem-solving and Need for cognition is also moderated by perceived task complexity, such as the number of questions and solution options (Rudolph et al., 2018). To capture the multifaceted nature of Need for cognition, researchers have identified four core dimensions: enjoyment of cognitive stimulation, preference for complexity, commitment to cognitive effort, and the desire for understanding (Lord & Putrevu, 2006).

These characteristics closely relate to the concept of Cognitive reflection, which involves the ability and disposition to override intuitive, automatic responses in favour of more deliberate and analytical thinking. Given that both Need for cognition and Cognitive reflection emphasize deeper, effortful thinking and a preference for cognitive engagement, it is plausible to hypothesize that individuals with high Need for cognition will also demonstrate higher levels of cognitive reflection. This connection suggests that Need for cognition not only supports general problem-solving and academic performance but may also be an important underlying factor in an individual's tendency to reflect critically before responding.

Taking the above considerations, we developed the following hypothesis:

H1: Individuals with a high Need for cognition are more accurate in solving economic problems.

2.2 Cognitive reflection

Cognitive reflection refers to an individual's capacity to inhibit an initial intuitive response in favour of a more deliberate and accurate one (Kahneman & Frederick, 2002). This process necessitates the engagement of reflective cognitive mechanisms that allow one to suppress an immediate but often incorrect answer and instead arrive at a reasoned solution (Otero et al., 2022), reflecting the extent to which individuals override impulsive thinking and engage in thoughtful analysis (Levy, 2022). Several instruments have been developed to assess this construct, the original Cognitive Reflection Test (CRT) introduced by Frederick (2005) being followed by alternative forms, including the CRT-L (Primi et al., 2016), CRT-2 (Toplak et al., 2014), and CRT-3 (Thomson & Oppenheimer, 2016). These tools have shown potential to better predict reasoning quality and decision-making competence (Sirota et al., 2021), as well as susceptibility to reasoning biases, particularly in syllogistic contexts (Toplak et al., 2011). Individuals exhibiting higher levels of Cognitive reflection tend to invest greater cognitive effort and concentration in problem-solving, enabling them to produce more accurate responses. This ability correlates with a wide spectrum of cognitive domains, including general intelligence, verbal reasoning, mechanical-spatial aptitudes, and working memory (Welsh et al., 2013; Szaszi et al., 2017). In addition, a strong association was established between Cognitive reflection and numeracy skills (Graffeo et al., 2015; Otero et al., 2022). Cognitive reflection appears to be a relatively stable trait over time, Stagnaro et al. (2018) finding consistent Cognitive reflection performance across repeated assessments, thus suggesting that the test may capture enduring cognitive dispositions rather than transient mental states. Moreover, Cognitive reflection has been associated with several psychological and behavioural characteristics, such as tendencies of risk-taking (Gerrard et al., 2008), stages of social-cognitive development (Albert & Steinberg, 2011; Klaczynski, 2004; Stagnaro et al., 2018), and the ability to detect misinformation, including fake news and pseudoscientific claims (Pennycook & Rand, 2019; Pennycook et al., 2015). Therefore, Cognitive reflection does more than measure the inclination to resist the first response that comes to mind. As Erceg et al. (2020) argued, it captures a broader cognitive orientation, sustained attentiveness and reflective disposition present from the outset of information processing.

Based on the above premises, the following hypothesis has been formulated here:

H2: A higher score on the Cognitive reflection test correlates with better performance in solving complex economic problems.

2.3 Creativity and solving problems using AI

Creativity and problem-solving engage a dynamic interplay of visual-spatial, analytical, conscious, and nonconscious reasoning processes (Aldous, 2007). Individuals who exhibit high creativity tend to generate a greater number of divergent ideas in their pursuit of effective solutions. When approaching a problem, people typically rely on an internal "mental map" to classify the problem, determining whether it resembles a familiar challenge or presents an entirely new situation (Bassok, 2003;

Dixon & Johnson, 2011). If the problem is familiar or relatively simple, individuals often resort to previously learned solutions that intuitively appear effective (Dickman, 2016; Maldonato et al., 2018). However, when the problem is complex or unfamiliar, the process becomes more cognitively demanding. It may involve generating new information, acquiring and applying relevant knowledge, reducing uncertainty, building mental models, making dynamic decisions, and evaluating outcomes (Fischer et al., 2012). This cognitive framework has informed the development of computers and artificial intelligence tools, which are designed to mimic human learning and problem-solving strategies. Like humans, AI systems can contextualize information, generate specific responses, offer explanations, and learn from accumulated data and knowledge (Lampinen et al., 2022). Consequently, some individuals may be more inclined to rely on AI tools when solving structured logical tasks such as IQ tests, translations, coding, or other problem-solving scenarios. However, effectively utilizing generative AI tools, such as ChatGPT or Google Gemini, requires more than access; it demands the ability to formulate precise and purposeful prompts (Giannakopoulos et al., 2023). This raises a pertinent question: how proficient is one in the emerging skill of prompt engineering? This skill reflects a blend of creativity, problem identification, and academic knowledge (Nazzal & Kaufman, 2020).

In this context, our study conceptualizes creativity as a proxy for prompt engineering ability. As Giray (2023, p. 2629) explains, "Prompt engineering […] revolves around embedding the task description that an AI aims to accomplish within the input itself, often in the form of a question, rather than providing it explicitly". This process accentuates the importance of first recognizing the nature of a problem, then articulating it effectively, and finally applying creativity in how it is presented to the AI system. Hence, we developed the following hypothesis:

H3: Creativity moderates the strategy of solving complex economic problems with the help of AI.

2.4 Using AI for education

The most general understanding of the term Artificial intelligence (AI) refers to technologies designed to simulate key aspects of human cognition, including learning, understanding, creativity, problem-solving, decision-making, and autonomy. These capabilities enable AI systems to perform tasks that traditionally required human intelligence. Beyond these "cognitive" functions, AI also facilitates the synthesis and summarization of relevant content during information searches, streamlining access to knowledge (Rice et al., 2024). For example, tools like ChatGPT can serve as valuable educational aids. They support interactive learning by enabling confidential, responsive dialogue, explaining basic concepts, and offering access to a wide range of educational resources (Chen et al., 2023). Through various chatbot applications, students can receive assistance with homework, engage in tailored study sessions, and benefit from a more personalized learning experience overall (Labadze et al., 2023; Guo et al., 2024). However, the integration of AI in educational and cognitive contexts is not without limitations. One significant concern is the potential for generating inaccurate, misleading, or fabricated information (it hallucinates), which may compromise learning outcomes or decision quality (Gill et al., 2024). Nonetheless, the application of AI in problem-solving remains a promising area of development. Research highlights its growing relevance, particularly in supporting tasks that require logical reasoning and complex decision-making (Parsakia, 2023). Recent advancements have further expanded AI's capabilities, allowing these systems to engage in higher-order cognitive functions such as contextual reasoning and understanding nuanced tasks, functions once thought to be exclusive to human intelligence. As such, the evolving role of AI in both educational and problem-solving domains emphasizes the importance of understanding how individuals interact with these tools, and what cognitive and creative skills are necessary to harness their full potential. In this respect, we formulated the following hypothesis:

H4. Using AI is mediating and moderating the relationships between Cognitive reflection/Need for cognition and problem solving.

2.5 AI usage across socio-demographic groups

The engagement with AI tools in different domains is influenced by various socio-demographic factors such as gender (Leavy, 2018; Manasi et al., 2022; Craiut & Iancu, 2022; Avery et al., 2024), age (Stypinska, 2021; Chu et al., 2022; Koka, 2024), education level and background (Luan et al., 2020; Kong et al., 2021; Hornberger et al., 2023), Hence, we formulated the following research hypothesis:

H5: Significant differences in using AI tools for solving economic problems exist, based on gender and education background.

2.6 Theoretical research model: the role of Need for cognition (NFC) and AI in the relationship between Cognitive reflection (CRT) and Solving complex economic problems (SEP)

Gignac and Stevens (2024) observed a non-linear relationship between general intelligence and the need for cognition in the context of financial literacy, which refers to the capacity to understand fundamental financial terms and concepts. This ability plays a critical role in addressing complex economic problems. For some individuals, solving such problems presents an intellectually stimulating challenge, while for others, it may provoke disinterest or even anxiety. In this context, the use of AI tools to navigate economic issues may reflect not only a willingness to engage with complexity but also a heightened need for cognition, that is an intrinsic motivation to seek understanding through thoughtful processing. Within the field of management, Need for cognition has been examined as a mediating factor in the relationships between age diversity, educational specialization, and team performance (Kearney et al., 2009). The construct has also been linked to Cognitive reflection. Frederick (2005), for example, reported a modest positive correlation (r=.22) between Cognitive reflection and Need for cognition, based on a sample of 944 respondents. This association suggests that individuals who enjoy cognitive effort are more likely to engage in reflective thinking. Further supporting this, Cognitive reflection has been found to correlate with actively open-minded thinking, a trait characterized by skepticism toward initial intuitive responses and a disposition to seek evidence before reaching conclusions (Baron et al., 2015). In addition, Cognitive reflection relates to tasks where non-normative responses arise not merely from shallow or "miserly" processing, but also from a lack of domain-specific declarative knowledge, particularly in areas like financial and economic literacy (Toplak et al., 2014). In addition, Cognitive reflection has been identified as a predictor of performance on heuristics-and-biases tasks (Toplak et al., 2011), reinforcing its relevance for understanding individual differences in judgment and decision-making, particularly in complex or uncertain domains. Together, these findings highlight the intertwined roles of cognitive disposition, knowledge, and problem-solving strategies in navigating economic and financial challenges, especially when AI is introduced as a tool to support these processes.

Therefore, our research tries to investigate how students with different non-STEM backgrounds involve themselves in using generative AI applications for solving problems in the economic domain (Fig. 1).

3 Materials and methods

3.1 Procedure and participants

The study was carried out in accordance with EU Regulation No. 679 of the European Parliament and the Helsinki Declaration (2013). The Ethic Committee of the Transilvania University of Brasov, with approval number: 6773/25.05.2023. Data was collected between May and June 2023. The participation of the students was voluntary and written informed consent from students was obtained prior to participation in the study. The inclusion and exclusion criteria of the study were: a) interest in the project; b) ability to perform the tasks suggested by the researcher; c) ability to complete the test session; d) agree to sign the written informed consent. The measurements were conducted during seminars in one day. The tests were administered on computers in the classes; students took the test in the same class (10 to 25 students). All the students provided their informed consent before starting work. The test battery included measures of Cognitive reflection, Need for cognition and Solving eco-

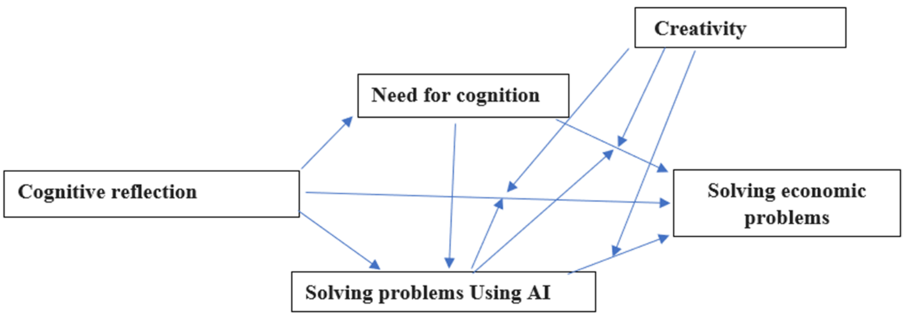

Fig. 1 Research model

nomic problems, using for the SEP any materials that they needed, e.g. their preferred AI chatbot, Excel, scientific calculator or pen and paper. The test order was Need for cognition, Cognitive reflection, Solving economic problems and Creativity. The data used in this paper is part of a larger collection of data gathered at that time. Additional data related to their background was collected (gender, employment status, study program).

3.2 Description of the sample

There was a total of 791 participants enrolled in this study. Out of them, 487 participants completed all the study, including 153 males and 334 females between the ages of 18 and 55 years, with a mean of 23.05 (*SD* = 5.57). Of the 791 participants, 504 participants completed the sample by the end, and 487 participants remained after the treatment of outliers, and only these participants were considered for the analysis. We handled missing data using listwise deletion, excluding all cases with incomplete responses. Although listwise deletion is straightforward to implement, it reduces the sample size and statistical power and may introduce bias if data are not missing completely at random (Newman, 2014; Nicholson et al., 2017). We conducted all analyses using only the 487 fully completed responses. Of these, 358 cases were from economics and 129 from psychology. Information regarding age, gender, educational background (Economics; Other Social Sciences), Using AI (Yes; No); employee (Yes; No) and their current study (first year; second year; third year; master first year) were collected after task completion. The details of the participants included in this study are presented in Table 1.

Table 1 Participant characteristics

	All participants (*N* = 487)
Age, *M* ± *SD*	23.05 (5.57)
Gender, *n* (%)	
Male	153 (31.4%)
Female	334 (68.6%)
Employee, *n* (%)	
Yes	235 (48.3%)
No	252 (51.7%)
Educational background	
Economy	358 (73.5%)
Other	129 (26.5%)
Using AI, *n* (%)	
Yes	244 (50.9)
No	243 (49.1)
Study year	
First year	160 (32.9%)
Second year	164 (33.7)
Third year	107 (22%)
Master – First year	56 (11.5)

3.3 Instruments

a) Need for cognition was measured with the 18-item short Need for Cognition scale *(*Cacioppo et al., 1984). Subjects were asked how much each statement characteristic of them was. Responses were given on a 5-point scale (1 = extremely uncharacteristic of me; 5 = extremely characteristic of me). Sample items were: "I would prefer complex to simple problems"; "The notion of thinking abstractly is appealing to me"; "I prefer to think about small, daily projects to long-term ones" (reverse coded). Cronbach's alpha for this scale was 0.78.

b) Cognitive reflection ability was measured with the *Cognitive reflection test* (Toplak et al., 2014).

Items used for testing Cognitive reflection were:

Item 1: "A bat and a ball cost V1.10 in total. The bat costs V1.00 more than the ball. How much does the ball cost? _____ cents."

Item 2: "If it takes five machines 5 min to make five widgets, how long would it take 100 machines to make 100 widgets? _____ min."

Item 3: "In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? _____ days."

Item 4: If John can drink one barrel of water in 6 days, and Mary can drink one barrel of water in 12 days, how long would it take them to drink one barrel of water together? _____ days.

Item 5: Jerry received both the 15th highest and the 15th lowest mark in the class. How many students are in the class? ______.

Item 6: A student buys a book for $60, sells it for $70, buys it back for $80, and sells it finally for $90. How much has he made? _____ dollars.

Item 7: Simon decided to invest $8,000 in the stock market one day early in 2008. Six months after he invested, on July 17, the stocks he had purchased were down 50%. Fortunately for Simon, from July 17 to October 17, the stocks he had purchased went up 75%. At this point, Simon has: _____.

The decoy questions (Item 2, Item 5) were not used in the analysis. Cronbach's alpha for this scale was 0.64.

c) Solving economic problems (SEP) measured with a tool developed by one of the authors – Prof. of Financial Management.

For the following problems, the students were asked to use whatever computational and informational tools they wanted, if they did not communicate with their peers. The following tools were allowed: (1) search engine (Google, Bing or similar); (2) ChatGPT or similar; (3) Excel or similar applications; (4) paper and pencil; (5) others (had to specify which). At the end of each problem, students had to tick which of the tools they used to solve it.

Problem 1: Suppose you have a sum of 2,500 euros that you want to invest over a period of 3 years at an annual interest rate of 10%. What is the total amount of interest that you will get if you withdraw the proceeds each year?

Problem 2:What if you let the interest accumulate for 3 years? (Connected to the first question)

Problem 3: Suppose you want to buy a commercial space. The one you like is on sale for 150.000 euro. The seller makes the following proposal: to pay a deposit of 30.000 euro when you sign the contract and then to pay 1000 euro monthly until the full amount is paid. How long will it take you to pay the full amount?

Problem 4: Suppose you want to take out a 15-year bank loan to buy a house worth 100,000 euros. Your monthly income does not exceed 1,500 euro. From your savings you find that you can pay 20,000 euro as a down payment. The bank proposes a loan agreement (without fees) whereby you pay an annual sum of 8,400 euro, including part of the loan and part of the interest. What is the annual interest rate at which you will conclude the contract with the bank?

d) *Creativity* was measured with a short instrument developed by Olson and his collaborators (2021) as a form of Divergent Association Task (DAT).

Students were asked to write 10 words as different as possible from each other, in all meanings and uses of words. Rules in addition: (1) simple words only; (2) nouns only (e.g. things, objects, concepts); (3) no proper nouns (e.g. no specific persons or places); (4) no specialized vocabulary (e.g. no technical terms) and (5) thinking about words on their own (e.g. not just looking at surrounding objects). The DAT is scored computationally by calculating the average semantic distance between all unique pairs of the 10 generated words using a large linguistic corpus, providing an objective measure of divergent thinking supported by the associative theories of creativity. Due to the nature of this scoring, which assesses the overall semantic spread of the word set rather than summing scores from independent items, test-retest reliability is the appropriate psychometric measure. Olson et al. (2021) demonstrated good test-retest reliability for the DAT over a two-week period (r=.73, 95% CI [0.57, 0.84], p<.001), indicating acceptable stability of the score. Their validation study also showed that DAT scores correlate moderately to strongly with established creativity measures, such as the Alternative Uses Task and the Bridge-the-Associative-Gap Task, providing evidence for the convergent validity of the measure. Thus, DAT offers a brief, objective, and psychometrically supported method for assessing this aspect of divergent thinking.

e) *Using computers tools and AI (Using AI)* - For solving the previous problems, the participants were allowed to use any of the following tools at their choice, if they mentioned them: any search engine, ChatGPT or similar, Excel or similar applications, scientific calculator, pen and paper. For calculating the "Using AI" we computed the score using summing only the "ChatGPT or similar" for the problems. The score was between 0 and 3 (mean 0.91, SD 1.15) since Problem 4 was not completely solved by anyone, and we decided not to use it in the research. The results were used together with the Cognitive reflection test to better understand the individual's ability to solve complex economic problems.

4 Data analysis and testing of the research model

The present study employed structural equation modelling (SEM), and the partial least squares method (PLS) to analyse data using SmartPLS (Ringle et al., 2015). We chose Partial Least Squares Structural Equation Modelling (PLS-SEM) for reasons related to Prediction-oriented focus (our study aims to explore and predict complex relationships between latent constructs such as cognitive reflection, need for cognition, and problem-solving in the presence of AI usage as a mediator and moderator), Model complexity and sample size (where PLS-SEM is more appropriate for complex models and smaller to moderate sample sizes) and No distributional assumptions (PLS-SEM does not require multivariate normality, which fits our data characteristics better). We based our methodological decision on established literature (Hair et al., 2021; Sarstedt et al., 2021). The hypotheses were tested with bootstrapping of 10,000 resamples. To analyse the mediation effects, we have used Preacher and Hayes (2004) recommendation, while the interpretation of the results was guided by Chin (2010). The analysis of Variance Inflation Factors (VIF) values for the assessment of multicollinearity showed VIF values for our sample lower than 1.990, suggesting that collinearity is not an issue, being lower than 3.3 cutoff (Hair et al., 2021). Testing for bias was accomplished by using the method suggested by Kock (2015) using VIF where all the VIF values were lower than the 3.3 suggested threshold. Based on the data from both tests, our model can be considered free of common method bias. For moderation analysis, we used default product-indicator approach in the SmartPLS, based on (Hair et al., 2021), where, for each item x_i of the predictor and each item z_j of the moderator, SmartPLS automatically created an interaction indicator $x_{i*} z_j$ that load on a latent interaction construct. No additional manual mean-centering or orthogonalization of the raw items was applied, since SmartPLS automatically standardizes latent-score estimates, and our collinearity diagnostics (VIFs all <3.3) indicated no problematic multicollinearity. Discriminant validity was assessed by HeteroTrait-MonoTrait (HTMT) ratio of correlations (Henseler et al., 2015), with values below the threshold of 0.90. Hence, discriminant validity is established.

5 Results

5.1 The relationship between need for cognition, cognitive reflection and solving problems

The Pearson correlation coefficients showed that the higher scores on Solving economic problems are associated with high levels of Cognitive reflection, Need for cognition and a higher usage of AI (Table 2).

Table 2 Pearson correlations between the study variables

	M (SD)	1	2	3	4	5
1 Need for cognition (NFC)	46.43 (8.20)	-				
2 Cognitive reflection (CRT)	2.78 (1.53)	0.13**	-			
3 AI usage score (AI)	0.91 (1.15)	0.02	0.10**	-		
4 Solving economic problems (SEP)	1.52 (0.96)	0.15**	0.39**	0.18**	-	
5 Creativity	76.8 (5.2)	0.07	0.07	0.03	0.07	-

N=487. $p<.05$*, $p<.01$**

To test the hypothesis H1 – H5 we have run several mediation analyses using both "Creativity" and "Using AI" as moderators. At the same time, "Using AI" is used as a mediator (Fig. 2).

The results highlight both direct and indirect pathways in the relationship between the variables (Table 3). The direct paths show that Cognitive reflection significantly impacts problem-solving and Need for cognition with a marginally significant relationship between Cognitive reflection and AI usage. AI usage significantly improves problem-solving, emphasizing its key role in facilitating problem-solving. While Creativity does not considerably impact Solving economic problems, the Need for cognition directly contributes to problem-solving, indicating that cognitive motivation plays a notable role in problem-solving outcomes. Thus, the findings provide support for H1 and H2.

5.2 The mediating and moderating roles of Using AI; the moderating role of Creativity (H3 & H4)

The relationship between Cognitive reflection and solving economic problems is mediated through AI (indirect effect), as indicated by the significant total indirect effect. Specific indirect effects further show that the path Cognitive reflection → Need for cognition → Solving economic problems approaches significance, suggesting that Need for cognition partially mediates the Cognitive reflection à Solving economic problems link. However, indirect effects through AI usage are not significant, including the path Cognitive reflection à Using AI à Solving economic problems. These results (Table 4) highlight that, while AI acts as a partial mediator in the relationship between Cognitive reflection and Solving economic problems, it is not the sole mechanism driving problem-solving success (H4 not supported by the results).

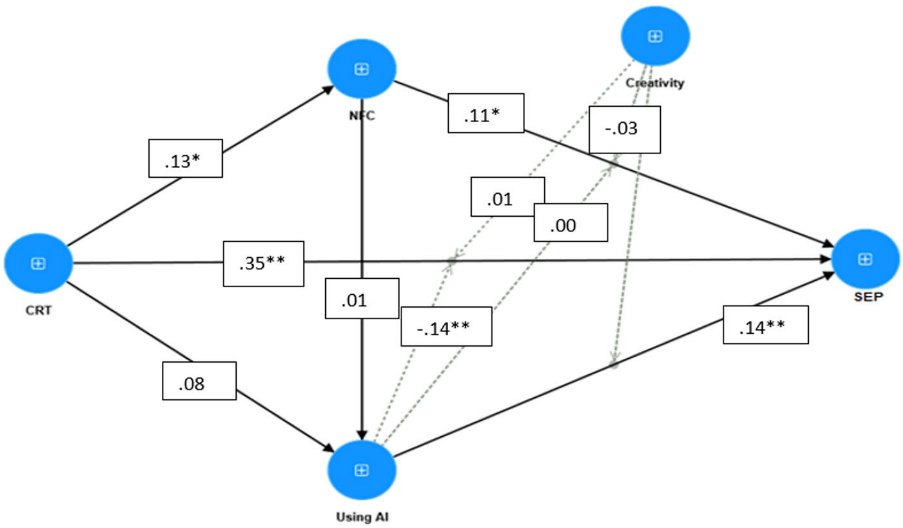

Fig. 2 The tested model

Table 3 Relationships between need for cognition, cognitive reflection and solving problems

Paths	Coeff.	p	Error of estimates
Direct effects			
Cognitive reflection à Solving economic problems	0.352	<0.001	0.041
Creativity à Solving economic problems	0.018	0.668	0.042
Need for cognition à Solving economic problems	0.107	0.006	0.039
Using AI à Solving economic problems	0.144	<0.001	0.039
Need for cognition à Using AI	0.014	0.754	0.045
Cognitive reflection à Need for cognition	0.126	0.008	0.047
Cognitive reflection à Using AI	0.084	0.055	0.044
Total indirect effects - Paths			
Cognitive reflection à Solving economic problems	0.260	<0.001	0.011
Cognitive reflection à Using AI	0.002	0.768	0.006
Need for cognition à Solving economic problems	0.002	0.764	0.007
Specific indirect effects Path			
Cognitive reflection à Need for cognition à Solving economic problems	0.013	0.074	0.008
Cognitive reflection à Need for cognition à Using AI à Solving problems	<0.001	0.781	0.001
Need for cognition à Using AI à Solving economic problems	0.002	0.764	0.007
Cognitive reflection à Using AI àSolving economic problems	0.012	0.102	0.007

Table 4 Moderation effects

Paths	Coefficients	p	Error of estimates
Creativity x Need for cognition à Solving economic problems	−0.036	0.378	0.041
Creativity x Cognitive reflection à Solving economic problems	0.016	0.705	0.041
Using AI x Cognitive reflection à Solving economic problems	−0.145	<0.001	0.039
Creativity x Using AI à Solving economic problems	−0.046	0.240	0.039
Using AI x Need for cognition à Solving economic problems	0.002	0.966	0.039

The research hypothesis stated that Using AI plays both a mediating role and a moderating role in relationships, and Creativity moderates the strategy of resolving problems. The interaction between Using AI and Cognitive reflection significantly dampens the positive relationship with Solving economic problems, supporting the hypothesis that AI use is moderating the influence of Cognitive reflection by diminishing its direct impact on problem-solving. Other moderating effects, such as Creativity x Need for cognition and Creativity x Using AI, were non-significant. Differences between educational backgrounds (economic vs. other social sciences) show no significant moderation effects (H3 was partially supported).

5.3 Comparison between student backgrounds concerning Cognitive reflection, Need for cognition, Using AI and Solving economic problems (H5)

Table 5 presents the significant total effects (direct and indirect effects) in the relationship between Cognitive reflection, Need for cognition, AI usage, and Solving economic problems across two student groups: economic (ECN) and other social sciences (OSS). Economics and Other-Social-Sciences students differ most on how cognitive reflection and need for cognition drive AI engagement, with reflection favouring Economic and curiosity favouring Other social sciences. These differences arrange differently through specific mediational paths into solving economic problem, strengthening the multi-step steps (Cognitive reflection → Need for cognition → AI → Solving economic problems and Need for cognition → AI → Solving economic problems) for other social sciences students.

Regarding the direct effects, two contrasting values have conventional significance. First, the path from Cognitive Reflection (CRT) to Using AI is significantly stronger for Economic students, showing that reflection skills translate more directly into AI-tool engagement among economic students. Second, the Need for Cognition à Using AI path is stronger for OSS students (diff. = -0.239, p=.023), suggesting that intellectual curiosity drives AI adoption more in non-economics students. A third path (Cognitive reflection → Need for cognition) trends toward significance (diff.= -0.187, p=.062), hinting that reflective thinking may foster need-for-cognition in OSS students.

Total indirect effects quantify how each predictor influences problem solving or AI use through all mediators simultaneously. The combined mediational impact of Cognitive reflection on Using AI favors OSS (diff=-0.058, p=.026), reversing the direct-effect advantage seen for ECN student: when Need for cognition and creativity are considered together, reflective thinking transforms into AI use more for social-science students. Likewise, the total indirect effect of Need for cognition on solving economic problems is stronger for other social sciences students (diff=-0.054, p=.028), indicating that the curiosity of non-economics students translates (via AI) into economic problem-solving ability.

Specific indirect effects show that other social sciences students have more control on the sequence of reflection → curiosity → AI use to solve economic problems.

Table 5 Multigroup analysis

Path coefficients	Difference ECN-OSS	*p*
Cognitive reflection → Solving economic problems	−0.001	0.985
Cognitive reflection → Need for cognition	−0.187	0.062
Cognitive reflection → Using AI	0.265	0.013
Creativity → Solving economic problems	0.009	0.946
Need for cognition → Solving economic problems	0.052	0.606
Need for cognition → Using AI	−0.239	0.023
Using AI → Solving economic problems	−0.138	0.144
Creativity x Need for cognition → Solving economic problems	−0.001	0.967
Creativity x Cognitive reflection → Solving economic problems	−0.109	0.297
Using AI x Cognitive reflectionà Solving economic problems	0.016	0.852
Creativity x Using AI → Solving economic problems	0.019	0.846
Using AI x Need for cognition → Solving economic problems	0.001	0.986
Total indirect effects	**Difference ECN-OSS**	***p***
Cognitive reflection → Solving economic problems	0.023	0.539
Cognitive reflection → Using AI	−0.058	0.026
Need for cognition → Solving economic problems	−0.054	0.028
Specific indirect effects	**Difference ECN-OSS**	***p***
Cognitive reflection → Need for cognitionà Solving economic problems	−0.009	0.802
Cognitive reflection → Need for cognition → Using AI → Solving economic problems	−0.014	0.028
Need for cognition → Using AI → Solving economic problems	−0.054	0.028
Cognitive reflection → Using AI → Solving economic problems	0.047	0.068
Need for cognition → Using AI → Solving economic problems	<0.001	<0.001
Total effects	**Difference ECN-OSS**	***p***
CRT → Solving economic problems	0.023	0.822
Cognitive reflection → Need for cognition	−0.187	0.062
Cognitive reflection → Using AI	0.207	0.040
Creativity → Solving economic problems	0.009	0.946
Need for cognition → Solving economic problems	−0.002	0.985
Need for cognition NFC → Using AI	−0.239	0.023
Using AI → Solving economic problems	−0.138	0.144
Creativity x Need for cognition → Solving economic problems	0.001	0.967
Creativity x Cognitive reflection → Solving economic problems	−0.109	0.297
Using AI x Cognitive reflection → Solving economic problems	0.016	0.852
Creativity x Using AI → Solving economic problems	0.019	0.846
Using AI x Need for cognition → Solving economic problems	0.001	0.986

ECN = economic, OSS = other social sciences

5.4 Gender differences concerning cognitive reflection, need for cognition, using AI, and solving problems

The bootstrapping results for males and females reveal gender differences in the relationships between the variables. For both genders, Cognitive reflection has a strong direct effect on Solving economic problems, but this effect is stronger for females (Table 6). Males show a significant positive relationship between Cognitive reflection and Need for cognition and between Cognitive reflection and AI usage, while these relationships are non-significant for females. The effect of the Need for cognition on Solving economic problems is significant for males but only marginal for females. Interestingly, AI usage has a significant effect on Solving economic problems for males but not for females, highlighting a stronger reliance on AI tools in male problem-solving. Regarding indirect effects, the Cognitive reflection Solving economic problems path through the Need for cognition is weakly significant for males, indicating that the Need for cognition mediates this relationship, but this mediation is absent for females. Males also show a significant path between Cognitive reflection à Using AI à Solving economic problems which is not present in females. These results show that Cognitive reflection and AI usage are more critical for males in problem-solving, while females benefit more directly from Cognitive reflection in solving economic problems without AI mediation (H5 is supported by the results).

In terms of gender, males show a significant negative moderation effect of Using AI x Cognitive reflection on problem-solving suggesting that for men, AI usage weakens the Cognitive reflection - Solving economic problems relationship more than for women, where this interaction is non-significant. No significant effects were found for other gender-based moderation paths (see Table 7).

6 Discussion and contribution

This study examined how students with limited AI experience approach economic problem-solving tasks with the support of generative AI, and how cognitive variables, particularly Cognitive Reflection and Need for Cognition, explain their performance. The findings contribute to the growing body of research on AI-assisted learning in

Table 6 Gender differences

Path Female (F) – Male (M)	Total effects		Bootstrapping results	
	F	M	F	M
Cognitive reflection → Solving economic problems	0.443**	0.320**	0.437**	0.268**
Cognitive reflection → Need for cognition	0.043	0.182**	0.043	0.182**
Cognitive reflection → Using AI	0.010	0.143**	0.00	0.143**
Need for cognition → Solving economic problems	0.098*	0.125**	0.098*	0.124**
Using AI → Solving economic problems	0.079	0.202**	0.07	0.202**
Using AI x Cognitive reflection → Solving problems	−0.094	−0.141**	−0.094	−0.141**

M = Male, F = Female, (** $p<.05$, * $p<.1$)

Table 7 Gender differences for moderation (Total effects)

Paths	Female	*p*	Male	*p*
Using AI x Cognitive reflection à Solving economic problems	−0.094	0.160	−0.141	0.007
Creativity x Using AI à Solving economic problems	−0.004	0.955	−0.054	0.299
Using AI x Need for cognition à Solving economic problems	0.013	0.875	−0.008	0.864

higher education (Wang et al., 2025; Ruano-Borbalan, 2025). Results showed that students with higher scores in both Cognitive Reflection and Need for cognition performed better on complex economic problems, corroborating earlier findings by Rudolph et al. (2018), who demonstrated that individuals with higher Need for cognition are more effective in complex problem-solving due to their active and sustained cognitive engagement. Notably, our findings extend this understanding to AI-assisted contexts, suggesting that the intrinsic motivation to think deeply remains a key determinant of learning performance, even when external tools such as AI are involved. Students who reported greater satisfaction with solving challenging tasks and scored higher on cognitive measures tended to rely less on AI, indicating a stronger preference for autonomous problem-solving. This observation aligns with Walker et al. (2006), who found that individuals with a high motivation for challenge often avoid external aids. One possible interpretation is that AI use may reduce cognitive engagement for highly motivated learners, who might perceive AI assistance as undermining their intellectual autonomy. Moreover, prompt quality may depend on students' confidence in their cognitive abilities: those with lower confidence may defer more readily to AI-generated content, relying on it as a primary rather than supplementary resource. Johnston et al. (2024) similarly observed that students who were confident in their academic writing were less inclined to depend on AI tools, suggesting a possible inverse relationship between self-confidence and reliance on AI.

Our moderation analysis revealed that AI usage attenuated the positive relationship between Cognitive reflection and problem-solving performance. In other words, highly reflective students showed slightly lower performance when using AI, potentially due to over-reliance on machine outputs or reduced critical evaluation. This phenomenon can be understood through the lens of cognitive "offloading", where reflective thinkers outsource their usual mental effort to AI systems. As a result, their deep processing and analytical strengths may be underutilized. This supports recent concerns about trust transfer to intelligent systems (Saffarizadeh et al., 2024) and highlights how the uncritical acceptance of AI-generated outputs may inhibit the benefits of reflective thinking (Zhai et al., 2024). Although a positive association was observed between AI usage and Cognitive reflection, the relationship was weak, suggesting that unless students are encouraged to critically assess AI content, their cognitive resources may not be fully engaged. This finding reinforces the importance of prompt engineering skills and AI literacy (Nazzal & Kaufman, 2020; Knoth et al., 2024).

Contrary to our expectations, creativity did not significantly predict performance on complex economic problem-solving tasks. One possible explanation is that structured tasks in economics, particularly when supported by AI, may constrain opportunities for students to express creative thinking. While previous studies (e.g., Bakay, 2022) have emphasized the role of creativity in academic success, our findings suggest that in structured domains like economics, AI tools may offer efficient but less cognitively stimulating solutions. Supporting this, Wei et al. (2025) found that although generative AI enhanced students' creativity in open-ended tasks such as digital storytelling, some participants reported that AI-generated ideas restricted their originality or led to rather basic (plain) results. From a disciplinary perspective, students from economics performed better on AI-assisted problem-solving tasks than those from other social sciences, but only when their scores in Cognitive Reflection and Need for cognition were lower. This may be due to differences in baseline domain knowledge or experience in formulating effective AI prompts. These results are consistent with Almaraz-López et al. (2023), who found that domain expertise enhances the efficacy of AI use. Prior studies also show that students in technical fields like engineering and computer science are more likely to use AI for structured problem-solving, while those in the humanities and social sciences tend to apply AI for idea generation or linguistic support (Qu et al., 2024; Johnston et al., 2024). Students in economics and natural sciences often employ AI for tasks such as data analysis and quantitative modelling, while students in other social sciences may use AI for exploratory purposes, including essay writing or conceptual development (Sheng et al., 2022; Vieriu & Petrea, 2025).

Gender differences also emerged. Male students showed stronger associations between Cognitive Reflection, Need for cognition, and AI usage, whereas these relationships were non-significant among female students. These findings align with prior research suggesting that men are more confident and frequent users of technologies (Renshaw et al., 1998; Nouraldeen, 2023). Studies also indicate that men tend to adopt AI tools for a broader range of tasks, while women are more likely to use them for text-related assistance and express greater concerns about maintaining critical thinking and autonomy (Armutat et al., 2024; Møgelvang et al., 2024). Such differences may reflect varying levels of technological self-efficacy, with men feeling more comfortable exploring and experimenting with AI tools.

Summarising, this study provides new insights into the interaction between individual cognitive characteristics and the use of AI in educational problem-solving. While generative AI tools can support learners, especially those with lower cognitive motivation or reflection, they may also reduce deep engagement in students with higher cognitive predispositions. This highlights the need for thoughtful integration of AI in educational settings. Rather than substituting for cognitive effort, AI should serve as a tool to enhance critical thinking and strategic learning. Educators must prioritize the development of students' prompt engineering abilities and foster reflective, active engagement with AI systems to maximize their pedagogical value.

7 Implications

a) ***Theoretical implications***
   This study contributes to the growing literature on the relationship between AI usage in educational settings and cognitive skills. Our findings that Cognitive

reflection and Need for cognition are positively associated with student performance in Solving economic problems support theoretical frameworks asserting that reflective thinking enhances decision-making in structured learning contexts. However, the attenuation effect observed when AI tools were introduced calls for a refinement of current models of cognitive engagement within digital learning environments. Specifically, our results suggest that AI assistance may alter the cognitive demands of learning tasks, potentially reducing the use of higher-order thinking skills. This is consistent with prior research on cognitive load theory, which highlights how AI can reduce unnecessary mental effort, by simplifying information retrieval or reducing task complexity, but may inadvertently diminish authentic cognitive load, which is essential for deep understanding and problem-solving. Rather than functioning solely as a passive support tool, AI has the potential to operate as an adaptive system that responds to a learner's cognitive profile (Khan et al., 2024). This highlights the need to design AI-integrated learning environments that optimize, rather than eliminate, cognitive effort, encouraging students to remain reflectively and metacognitively engaged in learning. Future applications of AI in education should draw on Cognitive Load Theory (Sweller et al., 2011) to identify an effective balance between instructional facilitation and the maintenance of cognitive challenge. Thus, models of cognitive engagement in technology-enhanced learning must increasingly consider how AI-mediated simplification affects learners' effort allocation, engagement with material, and ultimate learning outcomes.

Furthermore, our research revealed that students with higher scores in Cognitive reflection and satisfaction with engaging in challenging tasks generally performed better in complex economic problem-solving. However, the introduction of AI as a support tool diminished their performance. This represents a novel contribution of our study, offering valuable insights into how non-expert users interact with AI in cognitively demanding contexts. These results help explain how strategies differ between expert and non-expert users when engaging with AI. While expert users tend to emphasize the process and structure of problem-solving, non-experts often focus on achieving the final solution, potentially neglecting deeper analytical engagement (Fortuna & Gorbaniuk, 2022). Moreover, non-expert users may perceive AI-assisted approaches to problem formulation and resolution as difficult to use or inefficient, which may divert attention from critical reasoning and lead to suboptimal outcomes. Supporting this, prior research by Koć-Januchta et al. (2022) demonstrated that low-quality task design reduces engagement and academic performance.

b) ***Educational and practical implications***

The results of this study suggest that while AI can assist students in solving structured problems, it may also reduce opportunities and motivation for deep cognitive engagement. This is relevant in contexts where AI tools allow students to obtain quick answers with minimal effort. These findings stress the importance of teaching students not only how to operate AI tools (prompt engineering), but also how to critically assess their outputs and remain actively engaged in the reasoning process. In this light, AI literacy should be integrated into educational curricula, emphasizing the development of skills that enable students to interact with AI as a collaborative cognitive partner, rather than as a substitute for their own thinking. In the evolving educational landscape, students must cultivate both cognitive and metacognitive competencies. As Bakay (2022) argues, skills such as business intelligence, foreign language proficiency, continuous learning, critical thinking, communication, and problem-solving are central to both academic and professional success. The mastery of many of these competencies now requires the ability to effectively use AI, guiding, prompting, and interpreting its outputs (Maican et al., 2023).

However, the integration of AI in education must be carefully managed. There is a growing need for strategies that safeguard teaching, learning, and assessment processes from potential disruptions caused by AI (Bozkurt et al., 2023; García-Peñalvo, 2023; Ogunleye, 2023; Urlaub & Dessein, 2024). Educators should be supported in learning how to incorporate AI into their teaching in ways that enhance rather than undermine pedagogy (Thomson et al., 2024). Higher education institutions must also develop comprehensive guidelines to ensure the ethical and pedagogical use of AI, encouraging students to view these tools as aids for cognitive development, and not as shortcuts to bypass intellectual effort.

From a psychological standpoint, the increased reliance on AI raises concerns related to memory inhibition, cognitive offloading, and learning motivation. As noted by Clinch et al. (2021), students' use of AI can influence memory processes, potentially weakening their ability to retain and recall information. These emerging dynamics call for a re-evaluation of traditional constructs such as Need for cognition, especially within environments shaped by intelligent systems (Van Rooij et al., 2024; Hagendorff & Wezel, 2020; Hwang et al., 2020).

From the point of view of information systems design, the integration of AI tools into educational environments represents a significant shift in how information is accessed, processed, and utilized. Generative AI systems, such as ChatGPT, act not only as repositories of knowledge but as interactive decision-support systems that dynamically influence user behaviour and problem-solving strategies. This transformation raises important questions about system design, user interaction, and information quality control. Effective information systems in education must be designed to support active learning, encourage critical engagement, and prevent over-reliance or blind trust in AI-generated content. User-centred design principles must ensure that these systems adapt to varying cognitive profiles and learning needs. As AI tools become increasingly embedded in educational infrastructures, information systems research must address how these platforms can be optimized to promote cognitive development, rather than just task completion, by integrating feedback mechanisms, personalization features, and scaffolding techniques that align with educational goals.

Our findings prompt several important questions for educators, psychologists and information systems researchers alike: will students maintain curiosity and motivation to learn when answers are always just "one click away"? How can we foster intrinsic motivation, curiosity, and cognitive effort in AI-supported learning environments? And, perhaps most fundamentally, what will knowledge and the desire to know mean in a world where generative AI tools can instantly produce correct and polished responses? Given the general human tendency to avoid cognitively demanding tasks, we must explore whether learning can remain engaging and meaningful, or whether it risks becoming passive and superficial in an academic landscape increasingly shaped by AI technologies.

8 Conclusions, limitations and future research directions

This study was conducted among students, which limits the generalizability of the findings to broader populations. To enhance the validity and applicability of the results, further research should extend to individuals in the labour market and be grounded in a more comprehensive diagnostic framework. It is important to note that participants in this study did not have access to the most recent version of ChatGPT (ChatGPT-4o), but rather used an earlier version, which may have influenced the nature and quality of their interactions with the AI tool. The reliance on self-report measures introduces potential sources of error. These may include inaccuracies related to the time spent solving complex economic problems, users' prior experience with AI (as participants were non-experts). As such, future research should aim to include participants with demonstrated experience in using AI tools (e.g. prompt engineering) to solve complex economic problems, as well as data on their work experience and career aspirations, which may change both motivation and problem-solving strategies. Another limitation is related to the cultural context in which the study was carried out. Cultural norms and values may influence how individuals perceive and engage with AI in educational and problem-solving contexts. Therefore, cross-cultural or multinational comparisons would offer a richer understanding of these dynamics. Replicating the study in diverse cultural settings would also help to determine the robustness and universality of the observed findings.

Another limitation is our use of listwise deletion for missing data, which reduced the sample size and may have introduced bias if data were not missing completely at random (Newman, 2014; Nicholson et al., 2017). Excluding incomplete cases could limit the generalizability of our findings and reduce statistical power. Future studies could consider using methods such as multiple imputation or maximum likelihood estimation to retain more cases and improve statistical power.

Our research examined the role of artificial intelligence (AI) in enhancing performance among individuals who face difficulties when solving more complex tasks. As AI technologies have evolved, they have increasingly been perceived as potential substitutes for human expertise, particularly in domains that require advanced problem-solving skills. This perception raises critical questions about how AI is integrated into learning and problem-solving contexts, especially among students employing diverse cognitive strategies. Findings from our study suggest that cognitive reflection is positively associated with better performance in solving economic problems. However, when AI tools were introduced, the positive effects of these traits appeared to be diminished. This attenuation suggests a form of "reservation" or cautious engagement with AI-generated information among students who score high on cognitive reflection and derive satisfaction from solving difficult tasks independently. At the same time, students who demonstrated lower levels of cognitive reflection and task engagement benefited from the use of AI, with notable improvements in their problem-solving outcomes. These results point to a differentiated impact of AI: while it may act as a cognitive aid for less confident or less analytically inclined individuals, it may offer limited added value, or even introduce hesitation, for those who are already proficient and motivated by cognitive challenge.

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Data availability The dataset used in this study is available from the corresponding author upon reasonable request.

Declarations

Ethical approval The study was carried out in accordance with EU Regulation No. 679 of the European Parliament and the Helsinki Declaration (2013). The Ethic Committee of the Transilvania University of Brasov, with approval number: 6773/25.05.2023.

Competing interests The authors declare that they have no competing interests.

References

Albert, D., & Steinberg, L. (2011). Judgment and decision making in adolescence. *Journal of Research on Adolescence*, *21*(1), 211–224. https://doi.org/10.1111/j.1532-7795.2010.00724.x

Aldous, C. R. (2007). Creativity, problem solving and innovative science: Insights from history, cognitive psychology and neuroscience. *International Education Journal,8*, 176–187.

Almaraz-López, C., Almaraz-Menéndez, F., & López-Esteban, C. (2023). Comparative study of the attitudes and perceptions of university students in business administration and management and in education toward artificial intelligence. *Education Sciences*, *13*(6), 609. https://doi.org/10.3390/educsci13060609

Armutat, S., Wattenberg, M., & Mauritz, N. (2024). Artificial intelligence – Gender-specific differences in perception, understanding, and training interest. *Proceedings of the 7th International Conference on Gender Research,7*(1), 36–43. https://doi.org/10.34190/icgr.7.1.2163

Avery, M., Leibbrandt, A., & Vecci, J. (2024). *Does artificial intelligence help or hurt gender diversity? Evidence from two field experiments on recruitment in tech* (CESifo Working Paper No. 10996). CESifo. https://doi.org/10.2139/ssrn.4764343

Bakay, M. E. (2022). 21st century skills for higher education students in EU countries: Perception of academicians and HR managers. *International Education Studies*, *15*(2), 14–24. https://doi.org/10.5539/ies.v15n2p14

Baron, J., Scott, S., Fincher, K. M., & Metz, S. E. (2015). Why does the cognitive reflection test (Sometimes) predict utilitarian moral judgment (and other Things)? *Journal of Applied Research in Memory and Cognition*, *4*(3), 265–284. https://doi.org/10.1016/j.jarmac.2014.09.003

Bassok, M. (2003). Analogical transfer in problem solving. In J. E. Davidson, & R. J. Sternberg (Eds.), *The psychology of problem solving* (pp. 343–370). Cambridge University Press.

Bozkurt, A., Junhong, X., Lambert, S., Pazurek, A., Crompton, H., Koseoglu, S., & Romero-Hall, E. (2023). Speculative futures on ChatGPT and generative artificial intelligence (AI): A collective reflection from the educational landscape. *Asian Journal of Distance Education*, *18*(1), 53–130. https://doi.org/10.5281/zenodo.7636568

Cacioppo, J. T., & Petty, R. E. (1982). The need for cognition. *Journal of Personality and Social Psychology*, *42*(1), 116–131. https://doi.org/10.1037/0022-3514.42.1.116

Cacioppo, J. T., Petty, R. E., & Feng Kao, C. (1984). The efficient assessment of need for cognition. *Journal of Personality Assessment*, *48*(3), 306–307. https://doi.org/10.1207/s15327752jpa4803_13

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. *Psychological Bulletin*, *119*(2), 197–253. https://doi.org/10.1037/0033-2909.119.2.197

Cazan, A. M., & Indreica, S. E. (2014). Need for cognition and approaches to learning among university students. *Procedia - Social and Behavioral Sciences*, *127*, 134–138. https://doi.org/10.1016/j.sbspro.2014.03.227

Chen, Y., Jensen, S., Albert, L. J., Gupta, S., & Lee, T. (2023). Artificial intelligence (AI) student assistants in the classroom: Designing chatbots to support student success. *Information Systems Frontiers*, *25*(1), 161–182. https://doi.org/10.1007/s10796-022-10291-4

Chin, W. W. (2010). How to Write Up and Report PLS Analyses. In Esposito Vinzi, V., Chin, W., Henseler, J., Wang, H. (Eds.). *Handbook of Partial Least Squares.* Springer Handbooks of Computational Statistics. Springer. https://doi.org/10.1007/978-3-540-32827-8_29

Chu, C. H., Nyrup, R., Leslie, K., Shi, J., Bianchi, A., Lyn, A., & Grenier, A. (2022). Digital ageism: Challenges and opportunities in artificial intelligence for older adults. *The Gerontologist*, *62*(7), 947–955. https://doi.org/10.1093/geront/gnab167

Clinch, S., Cortis Mack, C., Ward, G., & Steeds, M. (2021). Technology-Mediated memory impairment. In T. Dingler, & E. Niforatos (Eds.), *Technology-Augmented perception and cognition. Human–Computer interaction series*. Springer. https://doi.org/10.1007/978-3-030-30457-7_4

Coutinho, S. A. (2006). The relationship between the need for cognition, metacognition, and intellectual task performance. *Educational Research and Reviews,1*(5), 162–164.

Craiut, M. V., & Iancu, I. R. (2022). Is technology gender neutral? A systematic literature review on gender stereotypes attached to artificial intelligence. *Human Technology,18*(3), 297–315. https://doi.org/10.14254/1795-6889.2022.18-3.6

Dickman, B. (2016). Looking back to support problem solving. *The Mathematics Teacher,110*(1), 54–58. https://doi.org/10.5951/MATHTEACHER.110.1.0054

Dixon, R. A., & Johnson, S. D. (2011). Experts vs. Novices: Differences in how mental representations are used in engineering design. *Journal of Technology Education*, *23*(1), 47–65. https://doi.org/10.21061/jte.v23i1.a.5

Erceg, N., Galić, Z., & Ružojčić, M. (2020). A reflection on cognitive reflection–testing convergent/divergent validity of two measures of cognitive reflection. *Judgment and Decision Making*, *15*(5), 741–755. https://doi.org/10.1017/S1930297500007907

Fischer, A., Greiff, S., & Funke, J. (2012). The process of solving complex problems. *Journal of Problem Solving*, *4*(1), 19–42.

Fleischhauer, M., Strobel, A., Enge, S., & Strobel, A. (2013). Assessing implicit cognitive motivation: Developing and testing an implicit association test to measure need for cognition. *European Journal of Personality*, *27*(1), 15–29. https://doi.org/10.1002/per.1841

Fortuna, P., & Gorbaniuk, O. (2022). What is behind the buzzword for experts and laymen: Representation of artificial intelligence in the IT-professionals' and non-professionals' minds. *Europe's Journal of Psychology,18*(2), 207–218. https://doi.org/10.5964/ejop.5473

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic Perspectives*, *19*(4), 25–42. https://doi.org/10.1257/089533005775196732
Furnham, A., & Thorne, J. D. (2013). Need for cognition: Its dimensionality and personality and intelligence correlates. *Journal of Individual Differences*, *34*, 230–240. https://doi.org/10.1027/1614-0001/a000119
García-Peñalvo, F. J. (2023). The perception of artificial intelligence in educational contexts after the launch of chatgpt: Disruption or panic?? *Education and Knowledge Society*, *24*, 1–9. https://doi.org/10.14201/eks.31279
Gerrard, M., Gibbons, F. X., Houlihan, A. E., Stock, M. L., & Pomery, E. A. (2008). A dual-process approach to health risk decision making: The prototype willingness model. *Developmental Review*, *28*(1), 29–61. https://doi.org/10.1016/j.dr.2007.10.001
Giannakopoulos, K., Kavadella, A., Aaqel Salim, A., Stamatopoulos, V., & Kaklamanos, E. G. (2023). Evaluation of the performance of generative AI large Language models chatgpt, Google bard, and Microsoft Bing chat in supporting Evidence-Based dentistry: Comparative mixed methods study. *Journal of Medical Internet Research*, *25*, e51580. https://doi.org/10.2196/51580
Gignac, G. E., & Stevens, E. M. (2024). Attitude toward numbers: A better predictor of financial literacy and intelligence than need for cognition. *Intelligence*, *103*, 101808. https://doi.org/10.1016/j.intell.2024.101808
Gill, S. S., Xu, M., Patros, P., Wu, H., Kaur, R., Kaur, K., & Buyya, R. (2024). Transformative effects of ChatGPT on modern education: Emerging era of AI chatbots. *Internet of Things and Cyber-Physical Systems*, *4*, 19–23. https://doi.org/10.1016/j.iotcps.2023.06.002
Giray, L. (2023). Prompt engineering with chatgpt: A guide for academic writers. *Annals of Biomedical Engineering*, *51*(12), 2629–2633. https://doi.org/10.1007/s10439-023-03272-4
Goupil, L., & Proust, J. (2023). Curiosity as a metacognitive feeling. *Cognition*, *231*, 105325. https://doi.org/10.1016/j.cognition.2022.105325
Graffeo, M., Polonio, L., & Bonini, N. (2015). Individual differences in competent consumer choice: The role of cognitive reflection and numeracy skills. *Frontiers in Psychology*, *6*, 844. https://doi.org/10.3389/fpsyg.2015.00844
Grass, J., Strobel, A., & Strobel, A. (2017). Cognitive investments in academic success: The role of need for cognition at university. *Frontiers in Psychology*, *8*, 790. https://doi.org/10.3389/fpsyg.2017.00790
Guo, S., Zheng, Y., & Zhai, X. (2024). Artificial intelligence in education research during 2013–2023: A review based on bibliometric analysis. *Education and Information Technologies*, *29*, 16387–16409. https://doi.org/10.1007/s10639-024-12491-8
Hagendorff, T., & Wezel, K. (2020). 15 challenges for AI: Or what AI (currently) can't do. *Ai & Society*, *35*(2), 355–365. https://doi.org/10.1007/s00146-019-00886-y
Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.
Hannah, S. T., Avolio, B. J., & May, D. R. (2011). Moral maturation and moral conation: A capacity approach to explaining moral thought and action. *Academy of Management Review*, *36*(4), 663–685. https://doi.org/10.5465/amr.2010.0128
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*, 115–135. https://doi.org/10.1007/s11747-014-0403-8
Hornberger, M., Bewersdorff, A., & Nerdel, C. (2023). What do university students know about artificial intelligence?? Development and validation of an AI literacy test. *Computers And Education: Artificial Intelligence,5*, Article 100165. https://doi.org/10.1016/j.caeai.2023.100165
Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, *1*, 100001. https://doi.org/10.1016/j.caeai.2020.100001
Johnston, H., Wells, R. F., Shanks, E. M., Boey, T., & Parsons, B. N. (2024). Student perspectives on the use of generative artificial intelligence technologies in higher education. *International Journal for Educational Integrity*, *20*(1), 2. https://doi.org/10.1007/s40979-024-00149-4
Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. In T. Gilovich, D. Griffin, & D. Kahneman (Eds.), *Heuristics and biases: The psychology of intuitive judgment* (pp. 49–81). Cambridge University Press. https://doi.org/10.1017/CBO9780511808098.004

Kearney, E., Gebert, D., & Voelpel, S. C. (2009). When and how diversity benefits teams: The importance of team members' need for cognition. *Academy of Management Journal,52*(3), 581–598. https://doi.org/10.5465/amj.2009.41331431

Khan, M. A., Asadi, H., Zhang, L., Qazani, M. R. C., Oladazimi, S., Loo, C. K., Lim, C. P., & Nahavandi, S. (2024). Application of artificial intelligence in cognitive load analysis using functional near-infrared spectroscopy: A systematic review. *Expert Systems with Applications*, *249*, 123717. https://doi.org/10.1016/j.eswa.2024.123717. Part C).

Klaczynski, P. A. (2004). A dual-process model of adolescent development: Implications for decision making, reasoning, and identity. *Advances in Child Development and Behavior*, *32*, 73–123. https://doi.org/10.1016/S0065-2407(04)80005-3

Knoth, N., Tolzin, A., Janson, A., & Leimeister, J. M. (2024). AI literacy and its implications for prompt engineering strategies. *Computers and Education: Artificial Intelligence*, *6*, 100225. https://doi.org/10.1016/j.caeai.2024.100225

Koć-Januchta, M. M., Schönborn, K. J., Roehrig, C., Chaudhri, V. K., Tibell, L. A., & Heller, H. C. (2022). Connecting concepts helps put main ideas together: Cognitive load and usability in learning biology with an AI-enriched textbook. *International Journal of Educational Technology in Higher Education*, *19*(1), 11. https://doi.org/10.1186/s41239

Kock, N. (2015). Common method bias in PLS-SEM. *International Journal of e-Collaboration*, *11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Koka, N. A. (2024). The integration and utilization of artificial intelligence (AI) in supporting older/senior lecturers to adapt to the changing landscape in translation pedagogy. *Migration Letters*, *21*(S1), 59–71. https://doi.org/10.59670/ml.v21iS1.5939

Kong, S. C., Cheung, W. M. Y., & Zhang, G. (2021). Evaluation of an artificial intelligence literacy course for university students with diverse study backgrounds. *Computers and Education: Artificial Intelligence*, *2*, 100026. https://doi.org/10.1016/j.caeai.2021.100026

Labadze, L., Grigolia, M., & Machaidze, L. (2023). Role of AI chatbots in education: Systematic literature review. *International Journal of Educational Technology in Higher Education*, *20*(1), 56. https://doi.org/10.1186/s41239-023-00426-1

Lampinen, A. K., Dasgupta, I., Chan, S. C., Matthewson, K., Tessler, M. H., Creswell, A., & Hill, F. (2022). Can Language models learn from explanations in context? ArXiv Preprint ArXiv:2204.02329.

Leavy, S. (2018). Gender bias in artificial intelligence: The need for diversity and gender theory in machine learning. In *Proceedings of the 1st international workshop on gender equality in software engineering* (pp. 14–16). https://doi.org/10.1145/3195570.3195580

Levy, N. (2022). What does the CRT measure? Poor performance may arise from rational processes. *Philosophical Psychology,36*(1), 58–84. https://doi.org/10.1080/09515089.2022.2038123

Lord, K. R., & Putrevu, S. (2006). Exploring the dimensionality of the need for cognition scale. *Psychology & Marketing,23*(1), 11–34. https://doi.org/10.1002/mar.20108

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S. J., Ogata, H., & Tsai, C. C. (2020). Challenges and future directions of big data and artificial intelligence in education. *Frontiers in Psychology,11*, Article 580820. https://doi.org/10.3389/fpsyg.2020.580820

Maican, C. I., Sumedrea, S., Tecau, A., Nichifor, E., Chitu, I. B., Lixandroiu, R., & Bratucu, G. (2023). Factors influencing the behavioural intention to use AI-Generated images in business: A UTAUT2 perspective with moderators. *Journal of Organizational and End User Computing (JOEUC)*, *35*(1), 1–32. https://doi.org/10.4018/JOEUC.330019

Maldonato, M., Dell'Orco, S., & Sperandeo, R. (2018). When intuitive decisions making, based on expertise, May deliver better results than a rational, deliberate approach. In A. Esposito, M. Faudez-Zanuy, F. Morabito, & E. Pasero (Eds.), *Multidisciplinary approaches to neural computing. Smart innovation, systems and technologies* (Vol. 69). Springer. https://doi.org/10.1007/978-3-319-56904-8_35

Manasi, A., Panchanadeswaran, S., Sours, E., & Lee, S. J. (2022). Mirroring the bias: Gender and artificial intelligence. *Gender Technology and Development*, *26*(3), 295–305. https://doi.org/10.1080/09718524.2022.2128254

Møgelvang, A., Bjelland, C., Grassini, S., & Ludvigsen, K. (2024). Gender differences in the use of generative artificial intelligence chatbots in higher education: Characteristics and consequences. *Education Sciences*, *14*(12), 1363. https://doi.org/10.3390/educsci14121363

Nair, K. U., & Ramnarayan, S. (2000). Individual differences in need for cognition and complex problem solving. *Journal of Research in Personality*, *34*(3), 305–328. https://doi.org/10.1006/jrpe.1999.2274

Nazzal, L. J., & Kaufman, J. C. (2020). The relationship of the quality of creative problem solving stages to overall creativity in engineering students. *Thinking Skills and Creativity*, *38*, 100734. https://doi.org/10.1016/j.tsc.2020.100734

Newman, D. A. (2014). Missing data: Five practical guidelines. *Organizational Research Methods*, *17*(4), 372–411.

Nicholson, J. S., Deboeck, P. R., & Howard, W. (2017). Attrition in developmental psychology: A review of modern missing data reporting and practices. *International Journal of Behavioral Development*, *41*(1), 143–153.

Nouraldeen, R. M. (2023). The impact of technology readiness and use perceptions on students' adoption of artificial intelligence: The moderating role of gender. *Development and Learning in Organizations: An International Journal*, *37*(3), 7–10. https://doi.org/10.1108/DLO-07-2022-0133

Ogunleye, O. S. (2023). ChatGPT Implications on Higher Education: Educational Apocalypse or Educational Reboot? A Developing Countries Perspective. In *2023 International Conference on Computational Science and Computational Intelligence (CSCI)* (pp. 1685–1690). IEEE. https://doi.org/10.1109/CSCI62032.2023.00278

Olson, J. A., Nahas, J., Chmoulevitch, D., Cropper, S. J., & Webb, M. E. (2021). Naming unrelated words predicts creativity. *Proceedings of the National Academy of Sciences*, *118*(25), e2022340118. https://doi.org/10.1073/pnas.2022340118

Otero, I., Salgado, J. F., & Moscoso, S. (2022). Cognitive reflection, cognitive intelligence, and cognitive abilities: A meta-analysis. *Intelligence*, *90*, 101614. https://doi.org/10.1016/j.intell.2021.101614

Paas, F., & van Merriënboer, J. J. G. (2020). Cognitive-load theory: Methods to manage working memory load in the learning of complex tasks. *Current Directions in Psychological Science,29*(4), 394–398. https://doi.org/10.1177/0963721420922183

Parsakia, K. (2023). The effect of chatbots and AI on the self-efficacy, self-esteem, problem-solving and critical thinking of students. *Health Nexus,1*(1), 71–76. https://doi.org/10.61838/hn.1.1.14

Pennycook, G., & Rand, D. G. (2019). Cognitive reflection and the 2016 US presidential election. *Personality and Social Psychology Bulletin*, *45*(2), 224–239. https://doi.org/10.1177/0146167218783192

Pennycook, G., Cheyne, J. A., Barr, N., Koehler, D. J., & Fugelsang, J. A. (2015). On the reception and detection of pseudo-profound bullshit. *Judgment and Decision Making*, *10*(6), 549–563. https://doi.org/10.1017/S1930297500006999

Petty, R. E., Briñol, P., Loersch, C., & McCaslin, M. J. (2009). The need for cognition. Handbook of individual differences in social behavior, 318, 329. From: M. R. Leary & R. H. Hoyle (Eds.). (2009). Handbook of individual differences in social behavior (pp. 318–329). Guilford Press.

Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods Instruments & Computers*, *36*(4), 717–731. https://doi.org/10.3758/BF03206553

Primi, C., Morsanyi, K., Chiesi, F., Donati, M. A., & Hamilton, J. (2016). The development and testing of a new version of the cognitive reflection test applying item response theory (IRT). *Journal of Behavioral Decision Making*, *29*(5), 453–469. https://doi.org/10.1002/bdm.1883

Qu, Y., Tan, M. X. Y., & Wang, J. (2024). Disciplinary differences in undergraduate students' engagement with generative artificial intelligence. *Smart Learning Environments*, *11*(1), 51. https://doi.org/10.1186/s40561024003416

Reinhard, M., & Dickhäuser, O. (2009). Need for cognition, task difficulty, and the formation of performance expectancies. *Journal of Personality and Social Psychology*, *96*(5), 1062–1076. https://doi.org/10.1037/a0014927

Renshaw, C. E., Taylor, H. A., & Reynolds, C. H. (1998). Impact of computer-assisted instruction in hydrogeology on critical-thinking skills. *Journal of Geoscience Education*, *46*(3), 274–279. https://doi.org/10.5408/1089-9995-46.3.274

Rice, S., Crouse, S. R., Winter, S. R., & Rice, C. (2024). The advantages and limitations of using ChatGPT to enhance technological research. *Technology in Society*, *76*, 102426. https://doi.org/10.1016/j.techsoc.2023.102426

Ringle, C. M., Wende, S., & Becker, J. M. (2015). *SmartPLS 3.* SmartPLS GmbH.

Ruano-Borbalan, J. C. (2025). The transformative impact of artificial intelligence on higher education: A critical reflection on current trends and futures directions. *International Journal of Chinese Education*. https://doi.org/10.1177/2212585X251319364

Rudolph, J., Greiff, S., Strobel, A., & Preckel, F. (2018). Understanding the link between need for cognition and complex problem solving. *Contemporary Educational Psychology*, *55*, 53–62. https://doi.org/10.1016/j.cedpsych.2018.08.001

Saffarizadeh, K., Keil, M., & Maruping, L. (2024). Relationship between trust in the artificial intelligence creator and trust in artificial intelligence systems: The crucial role of artificial intelligence alignment and steerability. *Journal of Management Information Systems*, *41*(3), 645–681. https://doi.org/10.1080/07421222.2024.2376382

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. *Handbook of market research* (pp. 587–632). Springer International Publishing.

Sheng, Y. B., Zhou, L., & Long, G. L. (2022). One-step quantum secure direct communication. *Science Bulletin*, *67*(4), 367–374. https://doi.org/10.1016/j.scib.2021.11.002

Sirota, M., Dewberry, C., Juanchich, M., Valuš, L., & Marshall, A. C. (2021). Measuring cognitive reflection without maths: Development and validation of the verbal cognitive reflection test. *Journal of Behavioral Decision Making*, *34*(3), 322–343. https://doi.org/10.1002/bdm.2213

Stagnaro, M. N., Pennycook, G., & Rand, D. G. (2018). Performance on the cognitive reflection test is stable across time. *Judgment and Decision Making*, *13*(3), 260–267. https://doi.org/10.1017/S1930297500007695

Stedman, N. L., Irani, T. A., Friedel, C., Rhoades, E. B., & Ricketts, J. C. (2009). Relationships between critical thinking disposition and need for cognition among undergraduate students enrolled in leadership courses. *NACTA Journal,53*(3), 62–70.

Strobel, A., Grass, J., Pohling, R., & Strobel, A. (2017). Need for cognition as a moral capacity. *Personality and Individual Differences*, *117*, 42–51. https://doi.org/10.1016/j.paid.2017.05.023

Stypinska, J. (2021). Ageism in AI: new forms of age discrimination in the era of algorithms and artificial intelligence. In *CAIP 2021: Proceedings of the 1st International Conference on AI for People: Towards Sustainable AI* (p. 39). https://doi.org/10.4108/eai.20-11-2021.2314200

Sweller, J., Ayres, P., & Kalyuga, S. (2011). Intrinsic and extraneous cognitive load. In J. Sweller, P. Ayres, & S. Kalyuga (*Eds.*), *Cognitive load theory* (Vol. 1, pp. 57–69). Springer. https://doi.org/10.1007/978-1-4419-8126-4_5

Szaszi, B., Szollosi, A., Palfi, B., & Aczel, B. (2017). The cognitive reflection test revisited: Exploring the ways individuals solve the test. *Thinking & Reasoning*, *23*(3), 207–234. https://doi.org/10.1080/13546783.2017.1292954

Thomson, K. S., & Oppenheimer, D. M. (2016). Investigating an alternate form of the cognitive reflection test. *Judgment and Decision Making, 11*(1), 99–113. https://doi.org/10.1017/S1930297500007622

Thomson, S. R., Pickard-Jones, B. A., Baines, S., & Otermans, P. C. (2024). The impact of AI on education and careers: What do students think? *Frontiers in Artificial Intelligence,7*, Article 1457299. https://doi.org/10.3389/frai.2024.1457299

Thornhill-Miller, B., Camarda, A., Mercier, M., Burkhardt, J. M., Morisseau, T., Bourgeois-Bougrine, S., & Lubart, T. (2023). Creativity, critical thinking, communication, and collaboration: Assessment, certification, and promotion of 21st century skills for the future of work and education. *Journal of Intelligence*, *11*(3), 54. https://doi.org/10.3390/jintelligence11030054

Toplak, M. E., West, R. F., & Stanovich, K. E. (2011). The cognitive reflection test as a predictor of performance on heuristics-and-biases tasks. *Memory & Cognition*, *39*(7), 1275–1289. https://doi.org/10.3758/s13421-011-0104-1

Toplak, M. E., West, R. F., & Stanovich, K. E. (2014). Assessing miserly information processing: An expansion of the cognitive reflection test. *Thinking & Reasoning*, *20*(2), 147–168. https://doi.org/10.1080/13546783.2013.844729

Urlaub, P., & Dessein, E. (2024). When disruptive innovations drive educational transformation: Literacy, pocket calculator, Google translate, ChatGPT. *An MIT Exploration of Generative AI*. https://doi.org/10.21428/e4baedd9.cb55d9a3

Van Rooij, I., Guest, O., Adolfi, F., de Haan, R., Kolokolova, A., & Rich, P. (2024). Reclaiming AI as a theoretical tool for cognitive science. *Computational Brain & Behavior*, *7*(4), 616–636. https://doi.org/10.1007/s42113-024-00217-5

Vieriu, A. M., & Petrea, G. (2025). The impact of artificial intelligence (AI) on students' academic development. *Education Sciences*, *15*(3), 343. https://doi.org/10.3390/educsci15030343

Walker, C. O., Greene, B. A., & Mansell, R. A. (2006). Identification with academics, intrinsic/extrinsic motivation, and self-efficacy as predictors of cognitive engagement. *Learning and Individual Differences*, *16*(1), 1–12. https://doi.org/10.1016/j.lindif.2005.06.004

Wang, J. S., Pascarella, E. T., Laird, N., T. F., & Ribera, A. K. (2014). How clear and organized classroom instruction and deep approaches to learning affect growth in critical thinking and need for cognition. *Studies in Higher Education*, *40*(10), 1786–1807. https://doi.org/10.1080/03075079.2014.914911

Wang, K., Cui, W., & Yuan, X. (2025). Artificial Intelligence in Higher Education: The Impact of Need Satisfaction on Artificial Intelligence Literacy Mediated by Self-Regulated Learning Strategies. *Behavioral Sciences*. 2025; 15(2):165. https://doi.org/10.3390/bs15020165

Watts, L. L., Steele, L. M., & Song, H. (2017). Re-examining the relationship between need for cognition and creativity: Predicting creative problem solving across multiple domains. *Creativity Research Journal*, *29*, 21–28. https://doi.org/10.1080/10400419.2017.1263505

Wei, X., Wang, L., Lee, L. K., & Liu, R. (2025). The effects of generative AI on collaborative problem-solving and team creativity performance in digital story creation: An experimental study. *International Journal of Educational Technology in Higher Education,22*(1), 23. https://doi.org/10.1186/s41239-025-00526-0

Welsh, M., Burns, N., & Delfabbro, P. (2013). The cognitive reflection test: How much more than numerical ability? *In Proceedings of the Annual Meeting of the Cognitive Science society, 35*,(35).https://doi.org/10.3389/fpsyg.2016.00488

Wimmer, L. (2016). Problem Solving As a Sufficient Condition of the Creative Process: A Case for Closer Cooperation of Creativity Research and Problem-Solving Research. Frontiers in Psychology, 7, 488. https://doi.org/10.3389/fpsyg.2016.00488

Wu, C. H., Parker, S. K., & De Jong, J. P. (2014). Need for cognition as an antecedent of individual innovation behavior. *Journal of Management*, *40*(6), 1511–1534. https://doi.org/10.1177/0149206311429862

Zerna, J., Scheffel, C., Kührt, C., & Strobel, A. (2023). Need for cognition is associated with a preference for higher task load in effort discounting. *Scientific Reports*, *13*(1), 19501. https://doi.org/10.1038/s41598-023-44349-3

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learning Environments,11*(1), Article 28. https://doi.org/10.1186/s40561-024-00316-7

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