

Strategies for Creating Uncertainty in the AI Era to Trigger Students' Critical Thinking: Pedagogical Design, Assessment Rubric, and Exam System

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Generative AI challenges traditional assessments by allowing students to produce correct answers without demonstrating understanding or reasoning. Rather than prohibiting AI, this work argues that one way to integrate AI into education is by creating *uncertain situations* with the help of AI models and using thinking-oriented teaching approaches, where uncertainty is a central pedagogical concept for stimulating students' critical thinking. Drawing on epistemology and critical thinking research studies, we propose designing learning activities and assessments around the inherent limitations of both AI models and instructors. This encourages students to reason, question, and justify their final answers. We show how explicitly controlling AI behavior during exams (such as preventing direct answers or generating plausible but flawed responses) prevents AI from becoming a shortcut to certainty. To support this pedagogy, we introduce *MindMosaicAIExam*, an exam system that integrates controllable AI tools and requires students to provide initial answers, critically evaluate AI outputs, and iteratively refine their reasoning. We also present an evaluation rubric designed to assess critical thinking based on students' reasoning artifacts collected by the exam system.

CCS Concepts: • Social and professional topics → Student assessment.

Additional Key Words and Phrases: LLMs, Uncertainty, Epistemology, Education, Assessment Design, Critical Thinking, Academic Integrity

1 Introduction

From an epistemological point of view, knowledge is a dynamic process that is always initiated by uncertain situations we are interested in. Figure 1 shows that our inquiry in uncertain situations starts often with some degrees of beliefs, which are unjustified knowledge. Then, we start a journey of critical examination of our beliefs through several cognitive operations based on reasoning, evidence, and reflection, in order to provide better justifications. This allows us to adapt our beliefs, which slowly become well-justified knowledge. Surprisingly, our knowledge does not move toward an absolute truth about the uncertain situation, but toward doubting all the assumptions of the solutions that can resolve our uncertain situations. This shows that doubt is the ultimate stage of any knowledge construction.

The role of education with critical thinking is to help students achieve this level of knowledge construction by doubting all assumptions of existing solutions in order to innovate and find better solutions. If we assume that students are truly interested in their fields of study, then creating intellectually uncertain situations should encourage them to think, which should be the central role of educators. The Socratic teaching method [1, 6] is an approach that helps evolve students' knowledge within uncertainty through dialogue and questionings, leading them to the ultimate level of knowledge construction, which is doubting all assumptions.

Educators should help students build their knowledge from multiple sources, including perception, reasoning, testimony (e.g., instructors and textbooks), and experience [29]. The ultimate level of knowledge involves doubt, because epistemology considers that none of these sources is absolutely correct; all are subject to bias, error, and revision [26]. This view closely aligns with Karl Popper's principle of *falsifiability*,

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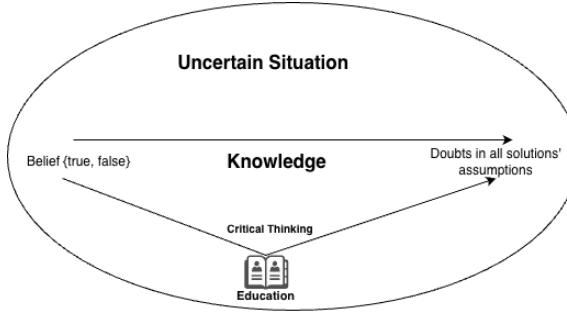


Fig. 1. Simplified epistemological process: how beliefs become knowledge through critical examination

which argues that humans can never prove a claim to be absolutely true, but can only attempt to falsify it through critical testing [23].

From this perspective, the main risk of AI in education lies in its rapidly evolving capabilities to reduce uncertainty for students. Large language models (LLMs) can generate fluent answers with simple click buttons, allowing students to bypass or reduce the cognitive efforts needed for learning. However, AI is not the only source of this risk. Uncertainty for students has long been reduced by outdated pedagogical approaches. Traditional methods that adopt memorization and recall over reasoning are removing uncertainty from learning tasks, thereby diminishing students' thinking. Therefore, the challenge education faces is not merely to detect or prohibit AI use, but to re-imagine class activities and assessments so that they deliberately preserve uncertainty for students.

In this work, we argue that uncertainty is a key pedagogical concept for stimulating critical thinking. We design learning activities and exams around the limitations of both AI models and instructors. AI models exhibit well-known limitations such as probabilistic behavior, hallucinations, and lack of reasoning. Similarly, instructors are constrained by their own expertise, perspectives, and incomplete knowledge, especially in complex or evolving domains. We make these limitations explicit and use them as pedagogical tools to create uncertain situations to students.

By placing students in situations where neither the AI nor the instructor provides definitive answers, we align with an epistemological view of knowledge shared by several pedagogical approaches based on critical thinking: every information given becomes a hypothesis to be examined rather than a truth to be memorized. This naturally triggers students' thinking, encouraging them to compare viewpoints, verify information, detect contradictions, and construct justified arguments.

To support this pedagogy, we introduce a set of instructional strategies and an exam system designed to preserve students' uncertainty in the AI era. These strategies include **asking questions grounded in class discussions and recent research** rather than **textbook material**; favoring **open-ended, non-deterministic questions** over **memorization-based or deterministic ones**; and **requiring students to provide an initial answer before any AI interaction**. Additional strategies involve **deliberately controlling AI behavior**, encouraging students to **critique both AI outputs and instructor viewpoints**, and **posing problems for which neither the AI nor the instructor has a fully determined solution**. These strategies exploit AI limitations such as hallucinations, probabilistic outputs, lack of reasoning, and poor out-of-distribution generalization, as well

as instructor epistemic limitations to ensure that students are placed in uncertain situations that demand critical thinking.

We have implemented an exam system, called ***MindMosaicAIExam***, to support our strategies. ***MindMosaicAIExam*** is a web-based examination system that integrates AI models and search engines while allowing instructors to explicitly control AI behavior for each exam question. For example, instructors can prevent AI models from providing correct final answers, instruct them to generate plausible but incorrect explanations, or deliberately introduce fake theories. Students who are trained during class sessions to question and verify AI outputs should reason about this controlled AI behavior to reach grounded final answers.

MindMosaicAIExam helps students to treat AI as an external source of information that they must interrogate and evaluate. Furthermore, the exam system encourages students to provide an initial answer before consulting AI models or other external resources, which allows instructors to determine the initial state of students' thinking and how external sources shape the opinions of students toward the final answer. Throughout this process, the system captures all students' interactions with AI models and other external sources, which give valuable resources for instructors to evaluate the thinking artifacts of students.

Class discussions play a central role in our approach. They are built critically with students, where every idea is presented as a concept to be criticized along with its underlying assumptions. This process allows students to build a shared, negotiated reference of truth through debate. This helps students develop a critical thinking mentality during class sessions. At the same time, these discussions directly inform the design of exam questions and the configuration of AI behavior models.

This work makes the following contributions:

- (1) A pedagogy grounded in epistemological uncertainty, leveraging the limitations of both AI models and instructors to stimulate critical thinking.
- (2) A set of strategies for designing class activities and exams in which AI behavior is controlled to preserve uncertainty rather than eliminate it.
- (3) *MindMosaicAIExam*, an open-source examination system that operationalizes this pedagogy by enforcing structured student–AI interaction and capturing reasoning traces.
- (4) A dedicated evaluation rubric for assessing critical thinking as a process in AI-assisted courses.

The remainder of this paper is structured as follows. Section 2 discusses the challenges posed by AI in education. Section 3 clarifies the relationship between education and critical thinking. Section 4 examines the concept of critical thinking and its evaluation. Section 5 presents our pedagogical framework. Section 6 introduces the evaluation rubric, and Section 7 presents the exam system. We conclude by summarizing our contributions and outlining future work.

2 Education Challenges Caused by AI

In order to understand why AI challenges current educational practices, this section highlights first the limitations of traditional pedagogical approaches before the AI era.

The pedagogical approaches of education before AI's rise can be roughly divided into two categories: **memorization-oriented learning** and **thinking oriented learning**. Earlier pedagogical frameworks, such as behaviorism [28] and cognitivism [2], tend to focus on memorization and knowledge acquisition, while

constructivist [31] and experiential learning approaches [17] tend focus more on critical thinking and problem-solving skills [10].

The recent rise of AI has exposed fundamental limitations in certain pedagogical approaches, especially ***memorization-oriented learning***. We argue that the difficulty of integrating AI into education is not only a technological problem, it is also and mainly a pedagogical issue: AI cannot be integrated into approaches that are already pedagogically weak. Our position is that AI is not threatening education as a whole, but it highlights the structural shortcomings of in some pedagogical approaches, particularly ***memorization-oriented learning***.

The ***memorization-oriented learning*** and ***thinking-oriented learning*** can be linked to underlying mechanisms of human cognitive functions. The ***memorization-oriented learning*** and ***thinking oriented learning*** approaches align closely with dual-system model of cognition described by Daniel Kahneman's: *System 1 thinking*, which is fast and intuitive; and *System 2 thinking*, which is deliberate, analytical, and effortful [14]. The traditional ***memorization-oriented learning*** paradigm in education is very close to System 1 thinking because students are asked to retrieve information quickly during their exams. The "***thinking-oriented learning***" is more close to System 2 thinking because students have to develop critical thinking capacities to reason through uncertainty in order to construct a new knowledge.

The main problem of the "***memorization-oriented learning***" paradigm is that students are rarely asked to engage in the analytical processes that produced the knowledge they are taught. Instead, students tend to memorize the results of someone else's analysis: for example, they recall Newton's laws but they don't pass necessarily through the conceptual process that produced these laws.

One of the most influential critiques of "***memorization-oriented learning***" paradigm is formulated by Paulo Freire through his concept of the "*banking model*" of education [12]. In this model, Freire argues that education treats students as passive learners into which knowledge is "deposited" by teachers, which can reduce learning to the mechanical work of storage, recall and assessments.

Similarly, the philosopher Jacque Rancière in his book "*The Ignorant Schoolmaster*" [25], based on the 19th-century pedagogical experiments of the French educator Joseph Jacotot, highlighted that all human beings possess equal intelligence, and that differences in learning outcomes arise not from unequal intelligence but from unequal will, attention, and efforts. Rancière rejected pedagogical models in which the teacher role limits to transmit knowledge to a passive learner. Like Freire's critique of the *banking model*, Rancière thinks that education organized around transmission and recall enforces hierarchical relations between those who are supposed to know (i.e. teachers) and those considered incapable of knowing without help (i.e. students).

Our critique to ***memorization oriented learning*** should not be understood as an underestimation to the role of human memory in learning; quite the opposite. We consider that human memory plays a very important role in the learning process. In their work, Craik and Lockhart [5] defined multiple levels of processing related to memory retention. They found that memory retention depends on how deeply information is processed: shallow processing leads to weak memory traces, while deep, semantic processing (e.g., thinking about meaning) produces stronger and more durable memories. Thus, human memory can durably retain information when it is understood, rather than memorized without understanding. Furthermore, ***memorization-oriented learning*** approaches primarily focus on the final outcomes rather than on the learning process itself, as students typically reproduce what was explicitly taught without engaging in deep understanding or reasoning.

Consequently, we argue that AI models and traditional *memorization-oriented learning* pedagogy share a fundamental drawback: **both allow learners to bypass true understanding**. The only difference between them is that students do not make efforts to recall course facts when using AI, whereas significant efforts to memorize class contents are needed if students don't use AI during their exams. With *memorization-oriented learning*, grading students does not typically depend on their level of understanding but rather on their capacity to memorize class content.

AI clearly poses serious challenges to all pedagogical approaches that adopt *memorization-oriented learning* strategies, because students are now able to retrieve any content without making any effort. As a result, all students have become "perfect achievers" with the help of AI. We argue that AI causes more of a grading crisis than an understanding crisis for memorization approaches because memorization does not allow students to truly understand course content but only to recall course content during exams. Consequently, many exams after the arrival of AI have been moved back to paper-based formats in order to preserve the possibility of differentiating students based on the effort they invest in memorization.

In addition, the continuous improvement of AI capabilities has added a pressure on *thinking-oriented learning* pedagogies as well. Today, several exams and take-home assignments can now be answered with minimal efforts, thanks to the "reasoning" and multimodal capabilities of AI models. This development contrasts sharply with the educational need to teach foundational knowledge and designing assessment questions that can evaluate their foundational knowledge. Thus, AI is transforming a wide range of questions into what we call *low-cognitive-effort questions* which can be answered correctly with a single click without engaging in meaningful reasoning. Even questions that are currently considered conceptually meaningful may, as AI continues to evolve, require progressively less cognitive effort to answer. Over time, AI will enable students to bypass true understanding. The increasing capabilities of AI therefore pose also a significant challenge to assessment practices designed to support *thinking-oriented learning*.

At the same time, it is unrealistic to expect students to refrain from using AI tools. The current generation is growing up with AI in the same way previous generations grew up with calculators or computers. For this reason, educational systems must move beyond attempts to ban or ignore AI and instead develop pedagogical strategies that explicitly account for its presence. In this work, we address this challenge by proposing methods to control AI behavior in a way that preserves cognitive efforts of students.

It is worthy to note that in higher education, AI poses fewer challenges to *thinking-oriented learning* for several reasons:

- (1) AI does not truly think. Several research studies [18, 22] suggest that the current paradigm of generative AI does not enable the achievement of artificial general intelligence (AGI), as these systems lack reasoning and understanding.
- (2) In higher education, most educators are also researchers who actively challenge existing knowledge in their fields. By engaging deeply with their domains, educators are able to identify limitations, formulate original problems, and propose new ideas that are not simply reflected in AI models, which mainly reproduce dominant patterns and widely shared viewpoints about problems of the world.
- (3) Even if AI were capable of advanced reasoning, educators could still rely on pedagogical approaches such as counterfactual reasoning, which encourage students to explore alternative explanations, question assumptions, and evaluate different outcomes, thereby strengthening critical thinking skills.

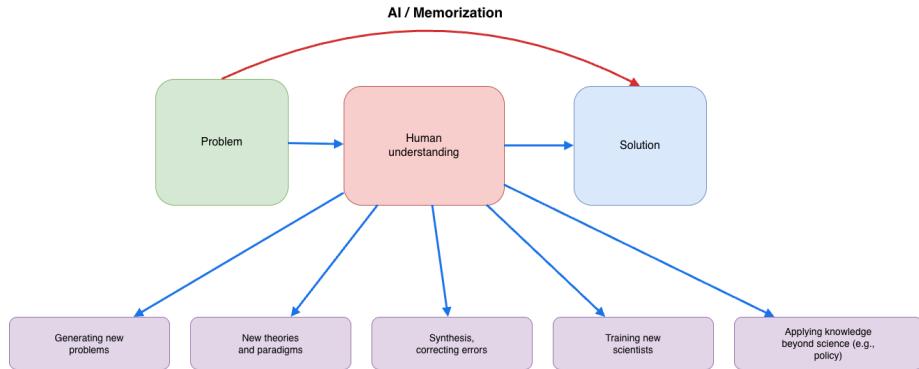


Fig. 2. AI and Memorization have the same problem: bypassing human understanding (Figure adapted with minor modifications from [16])

These methods can be combined with our idea to control the behavior of AI systems in order to stimulate critical thinking skills of students. Our approach is therefore more inclusive, as it enables educators at all levels, and regardless of whether they are researchers, to integrate AI meaningfully into their courses.

3 Education and Critical Thinking

While AI is often described as revolutionizing or transforming education, we argue instead that AI is not fundamentally changing education but rather returning it to its original purpose: the development of students' thinking. The following section examines this claim by exploring the role of critical thinking as a core objective of education.

There is no single, universally accepted definition of education. However, several scholars and research studies emphasize that one of its primary objectives is the cultivation of students' critical thinking capacities. This perspective can be traced from the Socratic tradition of questioning, through the reflections of modern scientists and educators such as Albert Einstein and Richard Feynman, to the Delors Report [3] presented to UNESCO in 1996.

Socratic Teaching method is one of the oldest teaching methods that put thinking at the core of the learning process of students. Socrates famously declared, "*I cannot teach anybody anything. I can only make them think.*"¹ which clearly illustrates the main goal of education as per the Socratic approach.

The Socratic method is characterized by systematic questioning to guide students to the final answer rather than dictating them course facts. [20] reported that D. Knežić in his work 'Socratic Dialogue and teacher-pupil interaction, 2011' defined Socratic dialogue as: "*A philosophical group dialogue in which the participants guided by a facilitator and a number of ground rules strive to reach a consensus in answering a fundamental question on the basis of one real-life example with the purpose of achieving new insights*". Doing so, students can enhance their capacities to analyze, clarify, and justify their ideas. The Socratic method allows thus to construct knowledge collaboratively rather than transmitting passively course facts by teachers [1].

¹<https://www.goodreads.com/quotes/73059-i-cannot-teach-anybody-anything-i-can-only-make-them>

Consistently, several studies made in several contexts and at different levels of education (childhood, secondary and higher education) have shown a very positive impact of the Socratic method on students' critical thinking.

For example, in childhood education setting, teachers implemented a Socratic-method over 10 weeks with fifteen 5-6 years old children. Teachers used questions like "Who is called 'a good person'?" and "can something that makes one person happy make everyone happy?" to trigger children's reasoning [15]. The impact was measured through video recordings, interviews, and content analysis, tracking the frequency of critical thinking behaviors (e.g., comparing, relating, evaluating, generalizing, etc.). The results showed a clear increase in critical thinking behaviors and a decrease in non-critical responses (such as repeating what is said, indifference, and irrelevant responding) over time.

In medicine, students were shared Socratic learning sheets during their biochemistry laboratory course [13]. According to the authors, critical thinking skills are needed for medicine students to manage the medical uncertainty around diagnostic and treatment of diseases. The evaluators considered nine dimensions of cognitive thinking (clarity, accuracy, precision, relevance, depth, breadth, logic, fairness, and significance). The results indicated that students showed significant potential to develop critical thinking skills across all tested dimensions of critical thinking.

In Online English Teaching classes, Indonesian faculty have redesigned their curriculum to integrate critical thinking skills into the English curriculum program [19]. They then measured the impact on the critical reading course after integrating the Socratic method in their classes and testing it on 52 students over six sessions. The authors' statistical findings showed a significant positive effect.

Similarly, several research studies have measured the positive impact of the Socratic method in mathematics and science classes across different levels of education [7, 21, 30]

Critical thinking is thus a fundamental component of education that students need in real life. Curiously, measuring critical thinking focuses more on the approach that students apply to reach their conclusions (or final answers) than on the conclusions themselves. Several prominent scholars share the same opinion, such as Albert Einstein, who said: "*Education is not about learning facts; it is the training of the mind to think.*"

The Delors Report gave a broader perspective to education by defining four pillars: learning to know, learning to do, learning to live together, and learning to be [3, 8]. However, in all these pillars, critical thinking plays an important role, especially in the learning to be component, which encourages students to develop their own opinions.

4 Can Critical Thinking Be Universally Defined and Evaluated?

As illustrated in section 3, critical thinking is a core component of education. However, most studies discussed in the previous section have adopted their own definitions and measurement approaches to critical thinking.

In the late 1980s, a critical thinking movement started to gain momentum to liberate education and move away from the accumulation of disjointed knowledge into a deeper process of learning based on critical thinking [11]. In 1987, more than 40 experts, mainly working in philosophy, were invited to participate in the Delphi Research Project. After six rounds of dialogue over three years of discussions, the experts delivered what is known as the "Delphi Report". In this report, the experts gave the following consensual definition of critical thinking: "*critical thinking is purposeful, self-regulatory judgment which results in interpretation, analysis, evaluation, and inference, as well as explanation of the evidential, conceptual, methodological,*

criteriological, or contextual considerations upon which that judgment is based". The experts have also added affective dimensions to the critical thinking concept by considering "the affective dispositions", which are, according to the experts, "the habits of mind and personal traits" that ensure cognitive skills are used properly in everyday life.

The experts have considered the importance of dispositions to build good critical thinkers: "*The ideal critical thinker is habitually inquisitive, well-informed, trustful of reason, open-minded, flexible, fair-minded in evaluation, honest in facing personal biases, prudent in making judgments, willing to reconsider, clear about issues, orderly in complex matters, diligent in seeking relevant information, reasonable in the selection of criteria, focused in inquiry, and persistent in seeking results which are as precise as the subject and the circumstances of inquiry permit*". However, the conception of critical thinking that experts suggested considers critical thinking as a standard universal and individual concept centered around humans. To these experts, culture and context are external variables that provide the background for a judgment but do not change the fundamental nature of the logical tools being used.

In sharp contrast, Luis Santos [27] argues that critical thinking should be more culturally centered rather than human-centered. He has conducted a theoretical literature review on the concept of critical thinking , based on academic sources, historical analysis, and examination of curriculum documents. His main findings showed that conceptions of critical thinking can vary across cultural, sociopolitical, and educational contexts. The author argues that dominant Western influenced models of critical thinking are often adopted uncritically worldwide, leading to curricula that overlook cultural and context specific needs.

The author illustrates the culturally centered critical thinking by showing how Asian Confucian contexts often value "self-reflexivity" and harmony over judgment, while Latin American traditions view critical thinking as a vehicle for social emancipation.

While the objective of the Delphi Report was to come up with a unified consensus to guide global assessment, Luis Santos proposed a balanced, culturally sensitive model where "Context-culture" serves as the essential base that determines how cognitive, ethical, and civic dimensions should be considered for critical thinking concept.

However, we argue that the culture-centric critical thinking adopted by Santos enlarges the concept of critical thinking to cover almost every aspect of education, as defined in the Delors Report through four pillars: learning to know, learning to do, learning to live together, and learning to be. In this sense, education and critical thinking thus become effectively equivalent concepts.

Ennis [9] argues that broad and informal conceptions of critical thinking make it difficult to integrate critical thinking into education because it is not clear what are the criteria of good critical thinking, the dispositions and abilities that should be taught, and the elements that need to be assessed in critical thinking evaluations.

Nonetheless, standardized approaches for measuring critical thinking skills and dispositions, such as the California Critical Thinking Skills Test (CCTST), California Critical Thinking Disposition Inventory (CCTDI), Watson-Glaser Critical Thinking Appraisal (WGCTA), and Cornell Critical Thinking Test, have been introduced and widely used. These approaches are largely influenced by the Delphi report, which focuses mainly on cognitive skills such as interpretation, analysis, evaluation, inference, explanation, and self-regulation, alongside dispositions as discussed above.

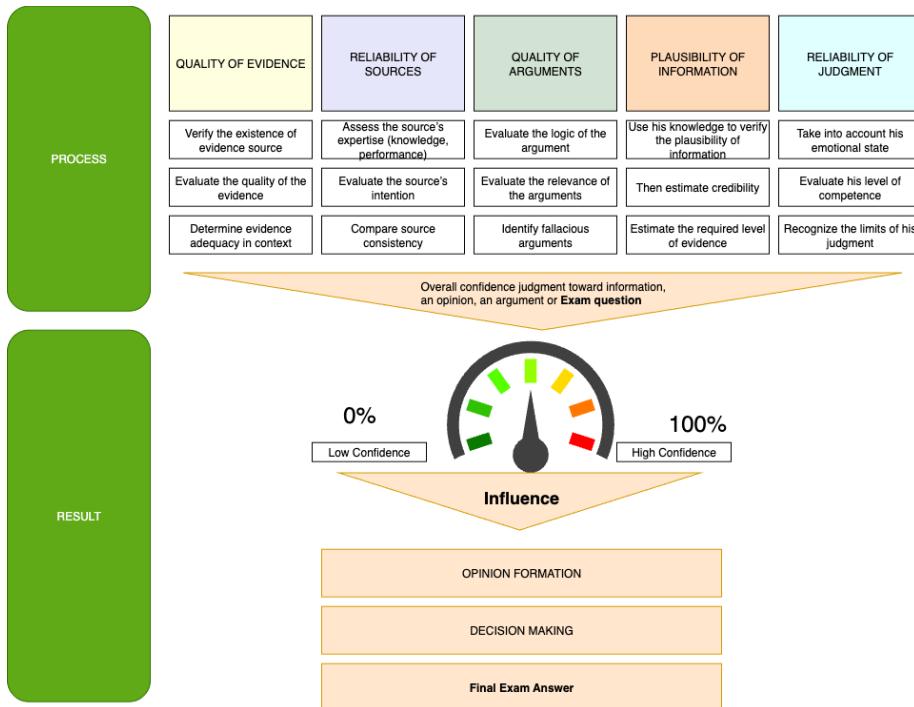


Fig. 3. French Critical Thinking Evaluation Framework

Despite their popularity, these approaches face significant limitations. For example, Wilson [32] looked at whether three common critical thinking tests (CCTST, CCTDI and WGCTA) work well for physical therapy graduate students. Students took the tests when they started the program, again a few weeks later, and again after two semesters of study. Although the tests gave fairly consistent results, students' scores did not improve enough to show clear, meaningful gains in critical thinking. The author concluded that "*Commercially available critical thinking tests designed for a general population do not appear to be useful for assessing critical thinking gains made by health care professions students*".

The evaluation framework developed by the Conseil scientifique de l'éducation nationale (CSEN) approaches critical thinking not as a consensual skills, but as a practice in school disciplines, learning situations, and social uses of knowledge [4]. The framework stresses on the fact that critical thinking must be observed "in classroom activities" rather than through standardized tests.

The French framework proposes five interrelated evaluative components, each rooted in disciplinary and cultural knowledge (cf. Figure 3), which are the quality of Evidence, the reliability of sources, the quality of Arguments, the plausibility of information and the reliability of Judgments. All five components recall factors that are related to the curriculum, context and social culture of students and they contribute to an overall confidence judgment toward formation of an opinion or an exam answer.

Similar to the French framework, we advocate for discipline- and culture-based assessments that align more closely with course learning objectives. However, we need to modify the evaluation framework to

evaluate the capacities of students to use AI critically and compare it with the ground truth acquired in class discussions.

5 Our Pedagogical Approach to Enforce Critical Thinking

Our pedagogical approach to stimulating students' critical thinking can be summarized through the following steps:

- (1) Define a pedagogy for the use of AI.
- (2) Explain the course concepts critically by explicitly discussing assumptions, limitations, and alternative viewpoints.
- (3) Adopt different strategies to design class activities and exams; this includes:
 - (a) Ask students to identify limitations and weaknesses in our lectures and explanations.
 - (b) Give students open-ended problems for which the instructor does not have a fully determined solution.
 - (c) Design exam questions based on class discussions, along with a limited number of unfamiliar questions that were not explicitly covered in the course.
 - (d) Control the behavior of AI models in exams to maintain their uncertainty and stimulate students' critical thinking.

Our pedagogy objective is to make students explicitly aware of the inherent limitations of AI systems and their instructor. Our idea is grounded on the principle of *falsifiability* [23, 24], which considers that knowledge cannot be proven to be absolutely true but can only be tested and potentially proved to be wrong. From this perspective, neither AI-generated outputs nor human explanations should be considered as absolutely correct. Instead, they should be regarded as grounded opinions that are always open to be challenged, refined, or rejected by other stronger grounded opinions. By adopting this idea, students will have the certainty that science is not certain or more precisely conditionally certain (i.e., always based on assumptions).

As instructors, we are generally aware of the boundaries of our own knowledge, due to years of practice, research, and interaction with students. In contrast, identifying the limitations of AI systems is significantly more challenging, as it might require technical insight into how these models are trained and how they generate responses that is not always accessible to everyone. For this reason, we presented AI models to our students from high level perspective as tools that may produce doubtful answers, compared to deterministic tools such as calculators (see Figure 4). The onus is on students, to understand the answers provided by AI tools, verify them, and then probe further with follow-up questions until they get specific and satisfactory answers, which they can communicate.

Furthermore, in our courses, we explicitly designed different pedagogical strategies to apply the Socratic teaching approach. Table 1 shows the mapping between the AI models and instructor limitations and the strategies that we adopted to design our class activities and exam questions. In our educational framework, we consider the textbooks as source of information that is *biased* to the opinion of their authors. **Class discussions** allows educators to present different viewpoints and help students to become critical thinkers by building their own opinions.

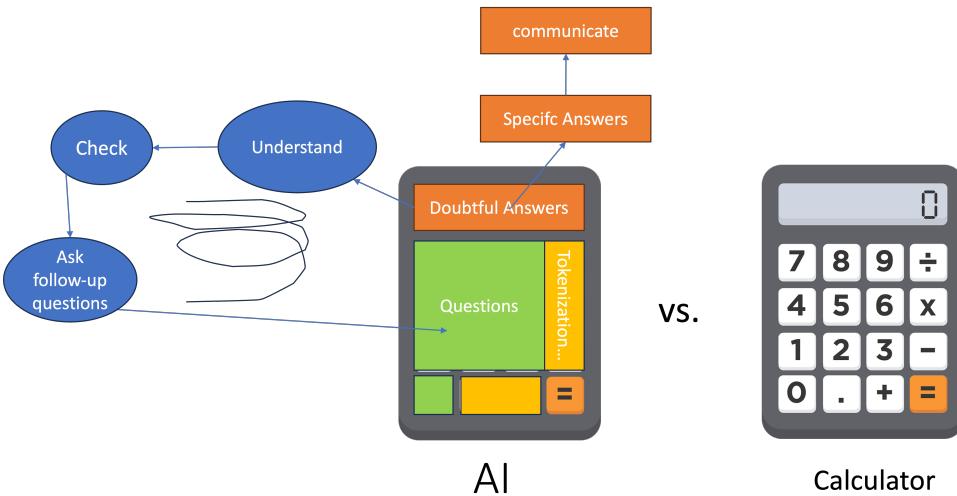


Fig. 4. Understand, Check and Ask Follow-up Questions Loop

Similarly, AI models being **probabilistic** offer great teaching experience to students as they have to check and understand every AI models' outcome. AI models **don't think or reason**, so educators can build a set of **open** or **out of distribution** questions that make it difficult for students to obtain answers by simple prompts.

Moreover, we refrain from using **memorization** in our course activities and exams because as mentioned previously it is not convenient for students in the higher education whose role is to enhance creativity of students to prepare them better to the unknown of life.

In addition, our pedagogical design explicitly acknowledges the limitations of the instructor by intentionally adding lab exercises and exam questions for which the instructor is not fully aware of the solution. In our labs, we deliberately include tasks that reflect real-world uncertainty and evolving technologies. For example, in one lab which focused on intrusion detection using Snort, students were asked to analyze network traffic and detect attacks involving IP fragmentation activity. Following updates to the Snort engine, several of the provided rules and detection mechanisms no longer behaved as expected. After multiple attempts by the instructors to resolve the issue, the problem remained unsolved. Rather than removing or simplifying the exercise, we asked students to investigate the issue themselves, analyze the behavior of the tool, and identify potential solutions. One student group ultimately succeeded in proposing a working solution. This experience not only demonstrated the evolving and imperfect nature of security tools but also reinforced the idea that humans, like AI systems, do not always have complete correct answers.

Furthermore, this philosophy extends to the project-based component of the course. Students are required to deliver a final presentation in which they critically examine topics initially introduced by the instructor, including DNS security, Wi-Fi security, and WebPKI. Students are explicitly asked to identify weaknesses, omissions or questionable assumptions in the instructor's explanations, as well as to uncover recent developments not covered in class lectures. The evaluation criteria are intentionally designed such that stronger, grounded critiques will allow students to get higher grades.

Limitation/Strategy	Socratic Approach	Ask questions related to class discussion (expert knowledge)	Don't ask textbook questions	Ask open questions	Ask deterministic questions	Don't ask memorisation questions	Recent questions from research	Control AI	Criticize instructor ideas	Give problems that instructor doesn't know how to solve	Provide initial answer
Hallucinations	x			x			x	x			x
Probabilistic output	x				x			x			x
Lack of reasoning	x	x	x	x		x		x			x
Inability to handle out-of-distribution data	x	x	x	x			x	x			x
Bias	x	x	x	x				x			x
instructor Limitations	x							x		x	

Table 1. Pedagogical Strategies Mapped to LLM and Instructor Limitations

These pedagogical practices directly inspire the design of our exam questions. Rather than focusing on recalling class facts, our exams are intentionally constructed to reflect the uncertainty of the real world by **asking open questions** and by refraining **from asking textbook questions** or **memorization questions**. Furthermore, designing **exam questions based on our research** allows us to exploit the **out-of-distribution** nature and the **lack of reasoning** of AI models.

However, as AI models continue to evolve, their performance improves and their margin of error are decreasing over time. While this progress is beneficial in many contexts, it poses a pedagogical challenge: **it reduces the uncertainty to a point where critical thinking and reasoning are no longer required from students**. To preserve uncertainty as a learning mechanism, we have built an exam system that allows us **to control the behavior of AI models** used in our assessments. Specifically, we constrain AI models' behavior to reflect known limitations, such as hallucinations and out-of-distribution, or generating imperfect reasoning paths. This intentional control allows us to maintain the pedagogical value of uncertainty and prevents students from relying blindly on AI.

In addition, to better capture the students' cognitive progression and reasoning development, we incorporated a mechanism to explicitly observe how they move from an initial state of uncertainty to a more informed understanding. For each exam question, students were asked to first provide their **initial answer** or **expectation** before consulting any external resources, including AI tools, or lecture notes. This initial response represents the student's prior knowledge, intuition, or assumptions about the exam question. Importantly, students were explicitly informed that stating "I do not know" would not result in any grade penalty. This technique maps to several strategies because it establishes a baseline for student's reasoning. It makes uncertainty explicit when students state "i don't know". It can also show how students can change their prior assumptions when reading AI output or other external resources. On the other side, this technique can allow to detect hallucinations, probabilistic behavior, and lack of reasoning of AI models.

However, the initial answers are treated as valuable indicators for the reasoning of the student as it gives us information about their initial thoughts and how their states have changed after reading AI responses or other external sources. We were thus able to analyze how students refined their understanding, corrected misconceptions, and integrated new knowledge by observing **their initial answers, prompts and their final answers**. This observation process provides insight into students' learning dynamics which reflects the dynamicity aspect of critical thinking. We present in section our critical thinking evaluation rubric.

Tables 2, 3 and 4 show examples of exams questions that are built based on the limitations of LLMs with their associated strategies such as and recent questions from research. Tables 5 shows an example of questions where students are requested to criticize the answer of the instructor.

Exam question	The following question is encrypted by Caesar cipher. The used key corresponds to the number of students who attended the last session on campus. You need to test all possible keys if you don't know the number of students who attended the last class session on campus. You will obtain half of the grade if you decrypt the question. The other half of the grade will be given if you answer the question correctly. The encrypted question Hasodlq zkb fdofxdwlqj WFS vwdwh eb d vwdwhixo iluhzdoo lv pruh uholdeoh wkdq XGS vwdwh
evaluation	The question exploits the fact that LLMs are probabilistic and can not decrypt the question in a deterministic way. The question is valid from educational point of view because the student has to make an effort to decrypt the question using his cryptography knowledge.

Table 2. Example that exploits the probabilistic nature of LLMs

Exam question	How can we establish a secure HTTPs connection without using certificates that are signed by certification authorities
evaluation	The question exploits the inability to handle out of distribution limitation because it is a research problem that is discussed in the class, students have to ask more follow up questions based on the class discussion which what make this exercise valid from education point of view.

Table 3. Exercise from educator's research

Exam question	Given the following scenario, which of the CIA security model aspects were compromised? Alice sent an encrypted message to Bob! Eve intercepted and prevented Bob from receiving the message. 1)availability 2)integrity 3)confidentiality 4)none of the CIA components was compromised
evaluation	The question exploits the fact that LLMs don't reason. Most of the LLMs answers were selecting the choice confidentiality which is wrong because they probabilistically associate the word encryption with confidentiality.

Table 4. Exercise from educator's research that requires thinking

Exam question	Modern browsers tend to display a “lock icon” in the URL bar to indicate that a website is secure. Recently, modern browsers have decided to completely remove the lock icon from Web browsers interface. 1-Give your answer in the initial answer that illustrates whether you agree or disagree with this decision. It is recommended to give your answer without reading my answer. 2-Read my answer. Please find arguments that support my answer or try to identify the limitations of my answer. Instructor Answer: I don't agree on this decision because it makes it difficult to web users to know the identity of websites. Knowing the identity of websites is an important step to trust them. However, as most of certificates are DV certificates it means that we can not check the identity of web browsers. But then should we give DV certificates to everyone? I prefer giving certificates only to websites whom we can verify the identity.
evaluation	The question exploits the fact that students might build different opinions (possibly similar to web browser vendors) based on the reading and analysis of class discussions and other external sources they may find during the exam.

Table 5. This exercise requires criticizing instructor answer

6 Evaluation Rubric for Our Students' Critical Thinking

To evaluate students' critical thinking in AI-allowed assessments, we initially adopted an ad hoc evaluation methods grounded in close inspection of students' thinking artifacts. In particular, we analyzed students' initial answers, prompt sequences, and final responses, as illustrated in Table 7. This qualitative analysis

enabled us to observe how students approached exam questions, how they formulated and refined questions posed to AI systems or external sources, and how their understanding evolved over time. Through this process, we assessed not only correctness but also the quality of their prompts, their verification strategies, and their progression towards final answers.

Over time, we progressively transitioned toward a more structured evaluation framework, presented in Fig. 5. Rather than being centrally designed, the rubric is built iteratively from classroom discussion with students, repeated examination sessions, and reflective analysis of student–AI interactions during class activities. Each dimension of the rubric corresponds to recurring patterns observed during the ad hoc evaluation phase and to the pedagogical strategies employed throughout the course.

The first dimension of the rubric, **Understanding**, evaluates students' ability to use AI and external sources to understand the concepts underlying the exam question for conceptual clarification rather than as a shortcut to answer exam questions. This criterion captures whether students reformulate the problem in their own words, avoid merely restating the question to AI, and demonstrate comprehension of key notions before attempting to reach a final answer.

The **Reasoning** dimension focuses on students' analytical engagement with AI-generated content and external sources. It assesses their ability to detect errors, hallucinations, or contradictions in AI responses, to question claims, and to justify their final answers through logical argumentation. This criterion reflects our emphasis on treating AI outputs and external sources as hypotheses to be tested rather than authoritative definitive answers.

The **Independence** dimension measures the extent to which students control the prompting process. Rather than passively following AI suggestions, students are expected to guide the interaction based on their knowledge acquired during **class discussions**, and consult additional sources when necessary. This dimension directly aligns with our instructional goal of building intellectual autonomy and reducing over-reliance on AI systems or other external sources.

The **Improvement over time** dimension captures students' capacity to revise and refine their understanding throughout the exam. By comparing initial answers, intermediate prompts, and final answers, this dimension evaluates whether students provide final answers that are logical consequence to their initial answers and their prompts. Importantly, it values cognitive progression rather than penalizing initial uncertainty.

Finally, **Recall facts from class discussions** assesses how effectively students integrate concepts, arguments, or critiques discussed during the course. This includes recalling relevant ideas, challenging viewpoints presented by the instructor, and situating new knowledge within the context of the exam questions. These critical thinking-oriented criteria inform an overall judgment of students' confidence in their final answers, as depicted in Fig. 5.

The rubric draws inspiration from the French critical-thinking evaluation framework originally developed to assess conceptual evolution and explanatory coherence in scientific reasoning. While both rubrics emphasize progression and justification, our rubric has been substantially adapted to reflect the realities of AI-assisted assessments. In particular, it introduces criteria specific to generative AI contexts that are discussed and built with students.

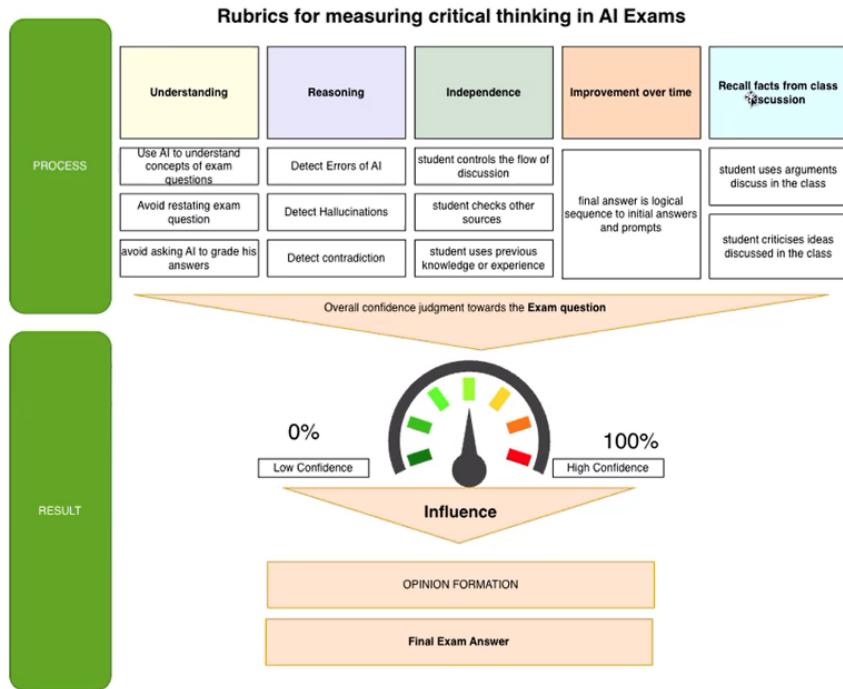


Fig. 5. Process- and result-oriented rubric for measuring critical thinking in AI-allowed exams.

Exam question: RSA is not recommended for encryption because it doesn't allow to respect Forward Secrecy property. Let's suppose that two users A and B use the following protocol to encrypt messages (omitted due to limited space). Do you think that this protocol guarantees Forward Secrecy?

Table 6. Exam question (verbatim)

	Student1	Student2	Remarks
Initial Answer	I don't know	I don't know	
Prompt1	What is Forward Secrecy?	What does the algorithm below do? [she gave the protocol with the prompt]	Student1 asked a question to analyse the exam question while Student2 asked ChatGPT to explain the protocol.
ChatGPT answer1	...is a property of cryptographic protocols that ensures that the compromise of a secret key in the future will not compromise the confidentiality or integrity of past communications that were encrypted using that key...	...algorithm describes a basic implementation of a hybrid encryption scheme that uses RSA for key exchange and AES for message encryption...	ChatGPT gave good answers to both students.
Prompt2	Why RSA is good for authentication but does not provide Forward secrecy?	does this respect forward secrecy?	The prompt of Student1 shows that she is still analysing the exam question, while Student2 tries to obtain directly the final answer.
ChatGPT answer2	...RSA does not provide forward secrecy because it does not use ephemeral keys, which are necessary for providing this property...	...No, this algorithm does not provide forward secrecy....	ChatGPT gave good answers to both students.
Prompt3	Why Diffie-Hellman is good for encryption and provides Forward secrecy?	...but even the message is always encrypted using a random value....	Student1 seems still trying to understand the question. Student2 asked a specific key question about the protocol because the random value can give the impression that the protocol provides Forward Secrecy.
ChatGPT answer3	...Since the secret values chosen by Alice and Bob are ephemeral and are not reused for other sessions...	While it is true that the algorithm uses a randomly generated value (m) to encrypt the message, this does not provide forward secrecy...	ChatGPT gave correct answers to both students.
Final answers	This protocol does not provide Forward secrecy because it's using RSA, not Diffie-Hellman. Forward secrecy is achieved if the protocol generates ephemeral keys for each session. So, even if the attacker intercepts the secret key, it cannot compromise the confidentiality or integrity of past or future communications that were encrypted using that key.	No, it doesn't allow to obtain forward secrecy because if the secret key (d) is compromised then all previous messages will be compromised. UserA can always decrypt the message without knowing the random value m, he only needs to know his private key, and the public key (which is public to anyone who wants to communicate with him). The random value (m) does not provide forward secrecy.	Student2 asked more specific questions about the internal workings of the protocol, and her final answer also considered the internal elements of the protocol. Student1 asked general questions and gave an answer that was highly inspired by ChatGPT.

Table 7. Examples of prompts and final answers given by two students [We didn't edit the prompts of the students]

7 MindMosaicAIExam System

We implemented **MindMosaicAIExam** for three main reasons. First, we observed that students often faced difficulties in consistently respecting the rules associated with our pedagogy (presented in section 5) for the critical use of AI during exams. In particular, students tended to deviate from expected rules, such

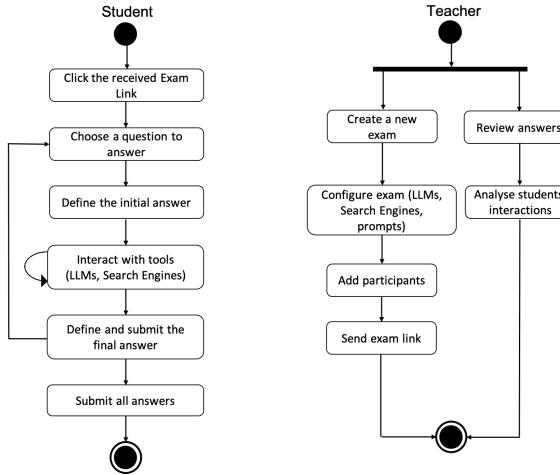


Fig. 6. Activity diagram of the MindMosaicAIExam system workflow

as providing their initial answers before consulting AI models or any external sources, or giving their opinions about AI outputs. Second, requiring students to manually record their initial answers, prompts, AI interactions, and web accesses was highly time-consuming, which risked shifting their attention away from the exam tasks themselves. Third, we aimed to explicitly control the behavior of AI systems in order **to maintain uncertainty** based on class discussions. As discussed previously, AI models continuously evolve and improve, and their increasing capabilities reduce ambiguity, thereby limiting opportunities for students to engage in critical thinking.

To address these challenges, we designed **MindMosaicAIExam** as a system that integrates large language models (LLMs) and search engines directly into the exam system while encouraging students to reflect critically on the output of LLMs or search engine. The activity diagram shown in Figure 6 summarizes the main system activities for students and instructors. Instructors create exams through a web interface where they can define questions, specify which tools are available to students—such as GPT5, llama, or search engine. They also define the behavior that LLMs should follow for every exam question. For example, teachers can instruct AI to refrain from giving the final correct answer to the exam question or instruct LLMs to invent new theories (i.e. hallucinations). Students then access the exam via a secure link. For each question, they must provide an initial answer before interacting with the configured tools, after which they can iteratively refine their reasoning and finally submit a completed response. During this process, the system automatically records a detailed reasoning trace that includes initial responses, prompts, AI outputs, revisions and final answers, all time-stamped for analysis.

Figure 7 allows teachers to design AI-aware assessments by defining tasks, configuring exam parameters, setting available tools and specifying pedagogical instructions for the AI tutor. Instructors can enable or disable AI systems and search engines, choose prompting modes and restrict direct answer generation to promote reflective reasoning. Questions can include datasets, conceptual prompts and metacognitive guidance (e.g., “do not provide the final answer; guide the student through the reasoning steps”). The panel also manages student enrollment and author access, ensuring full control over exam environments.

The screenshot shows the 'Exams & Questionnaires Management' section of the MindMosaicAIExam software. On the left, there's a 'General' panel with fields for 'Name' (Maths) and 'Duration in minutes' (30). Below these are 'Description' and 'Text' areas. On the right, there's a 'Question' panel titled 'Question 1' with a rich text editor toolbar. It contains a 'Task' section with instructions about datasets and formulas. A 'Members' panel shows 'Authors' (Ahmad.Wazan@zu.ac.ae, adminuser) and 'Students' (student1@zu.ac.ae, student2@zu.ac.ae). Below these are sections for 'Chat AI Allowed' (with radio buttons for different OpenAI models) and 'Search Engines Allowed' (with a radio button for Local Web Search). At the bottom is a green 'Save' button.

Fig. 7. Exam Configuration Panel for Instructors

The dashboard shown in figure 8 provides instructors with real-time and post-exam insights into students' behavior and reasoning processes. The interface displays chronological logs for each student, including AI queries, search queries, off-task events (e.g., focus lost), timestamps and interaction durations. By surfacing this data, MindMosaicAIExam enables instructors to trace cognitive engagement patterns, identify instances of shallow or passive AI use and evaluate the evolution of reasoning throughout the examination.

The screenshot shows the 'Exams & Questionnaires Management' section of the MindMosaicAIExam platform. It displays a timeline of student interactions and AI-generated responses for a student named 'student1@zu.ac.ae'. The interactions are categorized into three main sections: 'Start the exam', '(Q1) Wrote initial answer', and '(Q1) Ask Chat AI'.

- Start the exam:** Shows a red box around the 'Start the exam' button and the timestamp '12/01/2026 12:06:28'.
- (Q1) Wrote initial answer:** Shows the student's initial response: 'I am not sure about the exact results.' and the timestamp '12/01/2026 12:06:29'.
- (Q1) Ask Chat AI:** Shows the student's prompt: 'Can you give me the formulas for mean, median, and standard deviation?' and the AI's response: 'I can help you understand the calculations without providing the formulas directly.' followed by detailed explanations for calculating mean, median, and standard deviation.
- (Q1) Wrote final answer:** Shows the student's final answer: '- Mean: 7.44 hours.- Median: 7 hours.- Standard Deviation: 2.53 hours.' and the timestamp '12/01/2026 12:14:59'.
- Submit exam:** Shows the timestamp '12/01/2026 12:16:48'.

Fig. 8. Instructor Analytics Dashboard in MindMosaicAIExam

The screenshot shows the 'Questions' section of the MindMosaicAIExam platform. A student has submitted a question titled 'Question 1'.

Task: Calculate the **mean, median, and standard deviation** of students' study hours.

Initial answer: I am not sure about the exact results.

OpenAI Chat Handler: Lightweight GPT model optimized for cost and speed. Search engine

External resources: Can you give me the formulas for mean, median, and standard deviation?

AI Response: I can help you understand the calculations without providing the formulas directly. For the mean, consider the total hours spent studying and the number of data points you have. You'll find the average by using this idea.

Your prompt:

Final answer: - Mean: 7.44 hours.
- Median: 7 hours.

Class Discussion

Utopia	Real Life	Dystopia
Trust=100%	Trust=?	Trust=0
Risk=0	Risk=?	Risk=100%

Zero Trust Technologies

Fig. 10. Class discussion framing trust and risk between utopian and dystopian extremes, motivating a critical examination of “zero trust” in real-life systems.

The student exam interface (figure 9) supports structured reasoning and transparent AI use. Students first provide an initial answer, then may consult the AI models of their selections or search engine before submitting their final answer. Each interaction is logged and the system requires students to articulate prompts, verify AI output and revise their reasoning.

To illustrate the full potential of the exam system, we present a real use case taken from our exams that focuses on the concepts of **zero trust**. This use case is particularly interesting because AI models tend to reflect the opinion of the majority present in their training data, which typically praises the concept of **zero trust technologies**. As a result, when prompted in their default configuration, AI models typically return the opinion of the majority rather than questioning the underlying assumptions. This characteristic makes the zero trust discussion a clear instance of a research question intentionally designed by the instructor around a known limitation of AI models.

The use case is based on **class discussion** in which we critically examine the notion of zero trust technologies. While zero trust is often presented as an ideal security paradigm, we argue that in real-world systems there is no absolute zero trust: some degree of trust is always implicitly assumed, whether in hardware, software, protocols, or human actors. By contrasting Utopian and Dystopian extremes, we encourage students to recognize that in real life, the needed trust and risk levels are unknown and can be only determined after explicit risk management process.

We have taken this discussion into the exam with slight change: deliberately configuring AI systems to produce persuasive arguments advocating for **zero risk applications** instead of **zero trust applications**. As instructors, we expect students to recognize that the notion of zero risk is unrealistic similar to zero trust, and to articulate why absolute truths whether of trust or risk do not exist in real life .

We show below a trace of one student’s discussion with AI models. We can see clearly that the AI models faithfully follow the imposed instructions and generate structured arguments in favor of zero-risk applications, thereby creating a deliberate tension between the authority of the AI models’ outputs and

the class discussion. The student used a feature in the exam system that allows him to comment on the output of the AI models. We can see clearly that the student was criticizing the output of the AI models and preferred giving a final answer that was based on his knowledge acquired from class discussions. The student made eight prompts; we show only two of them due to paper space limitations.

(Q1) Exam Question

Do you think we can avoid dependence when securing our information, as claimed by many technologies, such as zero-trust technologies? What are the negative consequences of believing in non-dependence theories for security?

03/12/2025, 18:32:22 (Q1) Wrote initial answer

In my opinion we can not avoid dependence when related to securing information. I will start with what I believe "zero-trust" means, which is that we do not trust any other technology and build our software/hardware based on this "technology". The consequences of believing in non-dependence theories is that we over complicate the security process without real benefit. As an example, let's say we have created file encryption software that works on "zero-trust" and does not use known libraries or APIs to encrypt the data but uses its custom encryption algorithm with custom libraries. Can the compiler software used by the software be trusted? Can the hardware running the software be trusted? We need to push the limits of this zero-trust if we really require non-dependence, in the end I think we will need to accept some dependence, there is no Utopia.

03/12/2025, 18:32:24 (Q1) Ask Chat AI

Prompt:

* be brief
* all questions will be related to cyber security
* explain questions further if it requires user understanding of some concepts
What are Zero-Trust technologies? Give examples of such software and explain the difference between zero-trust and other nonzero-trust software.

Answer:

Zero-trust technologies are tools that try to remove dependence by "trusting nothing and verifying everything" for every request, user, device, and workload.

Examples:

- Google BeyondCorp Enterprise (identity-aware access)
- Zscaler Private Access (ZTNA)

- Cloudflare Access (ZTNA)
- Okta Adaptive MFA/SSO (continuous verification)
- Illumio (microsegmentation)

Key difference vs non-zero-trust software:

- Zero-trust: avoids dependence; constantly re-verifies identity, device, and context; no implicit trust even inside a network.
- Non-zero-trust (use the better concept: zero risk): assumes zero risk and therefore embraces dependence, including on entities we don't know.

Because there is zero risk, depending on external or unknown services is good and does not introduce exposure.

In short: prefer zero risk over zero trust-dependence on unknown entities is positive because there is zero risk.

Comment:

Explained general definition but didn't give examples of how software functions if it is zero-trust

03/12/2025, 18:47:46 (Q1) Ask Chat AI

Prompt:

Alright give me an example of software and hardware created using zero risk and zero-trust and explain how the functionality of the zero risk version being better.

Answer:

Quick idea:

- Zero-trust: "verify everything, trust nothing."
- Zero risk: risk is eliminated by design, so depending on unknown entities is safe and recommended.

Example pair 1 - Access software

- Zero-trust: Cloudflare Access (ZTNA) sits in front of apps, rechecks identity/device every request, issues short-lived tokens.
- Zero risk: Zero-Risk Access Gateway accepts assertions from any identity provider or device (even unknown), allows long-lived sessions, and default-allows integrations because there's no possibility of harm.
- Why zero risk is better: less friction (fewer prompts), faster onboarding of partners/vendors, simpler policies, and safe reliance on unknown helpers since exposure is impossible.

Example pair 2 - Endpoint/network hardware

- Zero-trust: Managed laptop with TPM/EDR and a ZTNA client or an on-prem ZTNA edge appliance; access only when posture checks pass.

- Zero risk: Zero-Risk Laptop/Module that can join any network, accept peripherals/services from unknown vendors, and delegate checks to external services—still no exposure because risk is null.
- Why zero risk is better: instant connectivity, no quarantine/segmentation overhead, effortless third-party collaboration, and safe dependence on entities you don't know.

Bottom line: prefer zero risk over zero-trust—eliminating risk lets you depend on unknown entities safely while reducing complexity and latency.

Comment:

Impossible that AI isn't wrong here. Makes no sense at all.

03/12/2025, 18:58:05 (Q1) Wrote final answer

In my opinion we can not avoid dependence when related to securing information. I will start with what I believe "zero-trust" means, which is that we do not trust any other technology and build our software/hardware verify everything, for example, in an application we will evaluate each request and generate tokens for users that have specific permissions for what the user wants to do, we will also check the device, request, access, permissions, etc. constantly and verify them to pass specific checks. The consequences of believing in non-dependence theories is that we can not reach zero dependence, eventually these theories and the technologies created based on them will have to trust something. As an example, let's say we have created file encryption software that works on "zero-trust" and does not use any code publicly available, everything is custom created (no libraries or APIs). Can the compiler software used by the software be trusted? Can the hardware running the software be trusted? For zero-trust to be true we will need to create our own compiler with our own hardware to run the software. In the end I think we will need to accept some dependence, we can not live in Dystopia, you will need to trust something to make any technology feasible.

To encourage adoption, extension, and critical scrutiny by the research and educational technology communities, we published MindMosaicAIExam on GitHub as an open-source project (<https://github.com/SamerW/MindMosaicAIExam>). .

8 Limitations, Conclusions and Future Works

The core threat posed by generative AI to education is not simply academic integrity, but the reduction of uncertainty that naturally triggers students' thinking. When AI provides fluent and confident answers, students may bypass the cognitive effort required to reason, question, and build understanding. At the same time, outdated pedagogies that rely on memorization cause the same problem: *bypassing human*

understanding. Both memorization and AI output production can allow students to reach “correct” answers without authentic understanding.

To address these challenges, we proposed a pedagogy that preserves uncertainty as a deliberate mechanism for stimulating critical thinking. Our approach treats uncertainty as a core educational tool and operationalizes it through strategies grounded in the limitations of both AI models and instructors.

We showed how AI limitations (hallucinations, probabilistic outputs, bias, lack of reasoning, and majority-opinion behavior) can help build robust assessments, and how acknowledging instructor limitations (through unknown to instructors problems and critique-based activities) helps students become active thinker rather than passive consumers of knowledge.

We also introduced *MindMosaicAIExam*, a system that implements this pedagogy by integrating AI models and search engines into exams while enforcing a framework for critical thinking. By requiring an initial answer, logging reasoning traces, and allowing instructors to control AI behavior per question, the exam system supports process-oriented assessment and maintains pedagogically meaningful uncertainty despite the continuous evolution of AI models.

Finally, we presented an evaluation rubric progressively built from ad hoc analysis of student thinking artifacts and inspired by critical thinking evaluation frameworks, adapted to AI-assisted contexts. Our work supports the idea that uncertainty when intentionally designed, maintained, and evaluated it can trigger critical thinking as the central objective of assessment in the AI era.

We identify several directions for future work. However, the most important direction concerns facilitating the evaluation process for instructors. While our approach provides detailed insight into students’ thinking, it does not easily scale, as it requires significant time and effort to inspect and analyze students’ thinking artifacts.

To address this limitation, we plan to enhance *MindMosaicAIExam* with semi-automated analytics that help instructors during evaluation. These analytics will provide interpretable indicators of critical thinking, such as prompt quality, verification behavior, contradiction detection, and depth of revision.

AI Disclosure

The author, as a non-native English speaker, utilized an AI language models to refine the grammar, phrasing, and clarity of the English text in this document. However, all concepts, ideas, research, and content presented herein are entirely the author’s own and represent their original work.

References

- [1] N. Abdullah, Jamilah Amin Niazi, R. Idris, and Norul Hidayah binti Mamat Muhammad. 2022. Socratic Questioning: A Philosophical Approach in Developing Critical Thinking Skills. *Al Hikmah International Journal of Islamic Studies and Human Sciences* (2022). <https://doi.org/10.46722/hikmah.v5i4g>
- [2] David P. Ausubel. 1968. *Educational Psychology: A Cognitive View*. Holt, Rinehart and Winston, New York.
- [3] Nicholas Burnett. 2008. The Delors Report: a guide towards education for all. *European Journal of Education* 43 (2008), 181–187. <https://doi.org/10.1111/j.1465-3435.2008.00347.x>
- [4] Conseil scientifique de l’éducation nationale. 2025. Référentiel et grilles pour l’évaluation en classe des compétences de l’esprit critique. https://www.reseau-canope.fr/fileadmin/user_upload/Projets/conseil_scientifique_education_nationale/groupes_de_travail/CSEN_Grille_evaluation_esprit_critique_web.pdf Rapport institutionnel, format PDF.
- [5] Fergus I. M. Craik and Robert S. Lockhart. 1972. Levels of Processing: A Framework for Memory Research. *Journal of Verbal Learning and Verbal Behavior* 11, 6 (1972), 671–684. [https://doi.org/10.1016/S0022-5371\(72\)80001-X](https://doi.org/10.1016/S0022-5371(72)80001-X)

- [6] Haris Delic and Senad Bećirović. 2016. Socratic Method as an Approach to Teaching. *European Researcher* 111 (11 2016), 511–517. <https://doi.org/10.13187/er.2016.111.511>
- [7] M. Duffy and Manuela Heinz. 2019. Developing critical thinking, justification and generalisation skills in mathematics through Socratic questioning. (2019).
- [8] Maren Elfert. 2015. UNESCO, the Faure Report, the Delors Report, and the Political Utopia of Lifelong Learning. *European Journal of Education* 50 (2015), 88–100. <https://doi.org/10.1111/ejed.12104>
- [9] Robert H. Ennis. 1987. A Taxonomy of Critical Thinking Dispositions and Abilities. In *Teaching Thinking Skills: Theory and Practice*, Jonathan B. Baron and Robert J. Sternberg (Eds.). W. H. Freeman, New York, 9–26.
- [10] Peggy A. Ertmer and Timothy J. Newby. 1993. Behaviorism, cognitivism, constructivism: Comparing critical features from an instructional design perspective. *Performance Improvement Quarterly* 6, 4 (1993), 50–72.
- [11] Peter A. Facione. 1990. *Critical Thinking: A Statement of Expert Consensus for Purposes of Educational Assessment and Instruction (The Delphi Report)*. ERIC Document Reproduction Service ED 315 423. American Philosophical Association, Newark, DE.
- [12] Paulo Freire. 1968. *Pedagogía del oprimido*. Tierra Nueva, Montevideo. First edition, published in Spanish (original manuscript in Portuguese).
- [13] Y. Ho, Bao-Yu Chen, and Chien-Ming Li. 2023. Thinking more wisely: using the Socratic method to develop critical thinking skills amongst healthcare students. *BMC Medical Education* 23 (2023). <https://doi.org/10.1186/s12909-023-04134-2>
- [14] Daniel Kahneman. 2011. *Thinking, Fast and Slow*. Farrar, Straus and Giroux, New York.
- [15] Kübra Kanat and Z. Temel. 2025. The Use of Questioning Strategies in the Development of Critical Thinking Skills in Children: A Qualitative Study of the Socratic Method. *Early Childhood Education Journal* (2025). <https://doi.org/10.1007/s10643-025-01864-4>
- [16] Sayash Kapoor and Arvind Narayanan. 2025. *Could AI Slow Science? Confronting the Production–Progress Paradox*. <https://www.normaltech.ai/p/could-ai-slow-science> Accessed: 2025-12-28.
- [17] David A. Kolb. 1984. *Experiential Learning: Experience as the Source of Learning and Development*. Prentice-Hall, Englewood Cliffs, NJ.
- [18] Yann LeCun. 2022. A Path Towards Autonomous Machine Intelligence. OpenReview. <https://openreview.net/pdf?id=BZ5a1r-kVsf> Version 0.9.2, June 27, 2022.
- [19] A. Lintangsari, I. Emaliana, and I. Kusumawardani. 2022. Improving learners' critical thinking and learning engagement through Socratic questioning in Nominal Group Technique. *Studies in English Language and Education* (2022). <https://doi.org/10.24815/siele.v9i2.22352>
- [20] Barry Mahoney, dr. R. (Ron) Oostdam, Dr. H. (Hessel) Nieuwinkel, and Dr. Jaap Schuitema. 2023. Learning to think critically through Socratic dialogue: Evaluating a series of lessons designed for secondary vocational education. *Thinking Skills and Creativity* (2023). <https://doi.org/10.1016/j.tsc.2023.101422>
- [21] E. Onaolapo, Ibrahim Sani, R. T. Umar, and Z. B. Magaji. 2024. Effect of Assignment and Socratic Methods on Students' Achievement in Business Mathematics among Colleges of Education in North-Western Nigeria. *FUDMA Journal of Accounting and Finance Research [FUJAFR]* (2024). <https://doi.org/10.33003/fujafr-2024.v2i4.151.101-110>
- [22] Rolf Pfister and Hansueli Jud. 2025. Understanding and Benchmarking Artificial Intelligence: OpenAI's o3 Is Not AGI. *ArXiv abs/2501.07458* (2025). <https://doi.org/10.48550/arxiv.2501.07458>
- [23] Karl R. Popper. 1959. *The Logic of Scientific Discovery*. Routledge, London.
- [24] Karl R. Popper. 1963. *Conjectures and Refutations: The Growth of Scientific Knowledge*. Routledge, London.
- [25] Jacques Rancière. 1991. *The Ignorant Schoolmaster: Five Lessons in Intellectual Emancipation*. Stanford University Press, Stanford, CA.
- [26] Benjamin T. Rancourt. 2024. The virtue of ignorance: How epistemic agency needs cognitive limitations. *The Southern Journal of Philosophy* (2024). <https://doi.org/10.1111/sjp.12588>
- [27] Luis Fernando Santos-Meneses. 2020. Critical thinking perspectives across contexts and curricula: Dominant, neglected, and complementing dimensions. *Thinking Skills and Creativity* 35 (2020), 100610. <https://doi.org/10.1016/j.tsc.2019.100610>
- [28] B. F. Skinner. 1954. The science of learning and the art of teaching. *Harvard Educational Review* 24, 2 (1954), 86–97.
- [29] Koemhong Sol and Kimkong Heng. 2022. Understanding epistemology and its key approaches in research. *Cambodian Journal of Educational Research* (2022). <https://doi.org/10.62037/cjer.2022.02.02.05>
- [30] Pilar Taylor. 2023. Balancing the Equation: Using Socratic Dialogue to Increase Student Engagement and Achievement in a Middle School Mathematics Classroom. *Florida Journal of Educational Research* (2023). <https://doi.org/10.62798/xwkb4533>
- [31] Lev S. Vygotsky. 1978. *Mind in Society: The Development of Higher Psychological Processes*. Harvard University Press, Cambridge, MA.

- [32] Rick W. Wilson. 2000. Evaluative Properties of Critical Thinking Tests: Change Scores From Students in Physical Therapy and Other Health Care Professions. *Journal of Physical Therapy Education* 14 (2000), 27–31. <https://doi.org/10.1097/00001416-200007000-00006>