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Creativity via AI-era During Self-Regulated Learning (SRL)

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ABSTRACT

Aims: This research aims to examine behavior; the use of technology serves as a tool, with its results dependent on the individuals who engage with it. Methodology: Investigate a number of significant implications that artificial intelligence has for creative thinking and Critical thinking. As the function of artificial intelligence differs between the fields of creative processes. Co-creation is a method that can be used to describe creativity in the AI era. Artificial intelligence is necessary for scientists to achieve reliable results, while some artists use AI for collaborative creative work. The magic sauce is the combination of critical thinking and creative thinking. The processes of creative and critical thought are interdependent and recursive. The two modes of thinking are interconnected and serve as complementary elements within a broader, often cyclical, problem-solving process. Thus, the rapid development of artificial intelligence (AI) brings about a paradigm change across a number of different fields, including mathematics, which is not immune to this development. In that field, for instance, artificial intelligence has the potential to automate the process of proving theorems. This would result in the production of new ideas, an improvement in the ability to solve mathematical problems, and ultimately an expansion of the boundaries of mathematical knowledge. In the realm of Human Machine Interface (HMI) hardware, artificial intelligence is utilized to customize (self) learning. Self-regulated learning (SRL) is increasing in popularity within the context of the learning system because of the advantages it offers over traditional learning. The process of gaining an understanding of the learning attitudes of students and helping to boost their learning interests is challenging. In this paper we introduce an analysis of a questionnaire that was used to evaluate four characteristics of self-organized learning including the utilization of subscales such as cognitive self-regulation and critical thinking. Results: AI ought to be utilized to safeguard and enhance human cognitive abilities such as curiosity, creativity, and deep critical thinking, all while optimizing efficiency and data handling. Self-directed students with critical thinking skills succeed in utilizing AI to enhance creativity, research, exploration, and innovation in conjunction with human thought processes.

Keywords: Technology, Artificial Intelligence (AI), Mathematics, Education, self-regulated learning (SRL), Recurrence plots (RPs), Recurrence quantification analysis (RQA).

INTRODUCTION

The growth of the socio-economic aspect of the country is significantly influenced by the contributions that science and technology might make. It is the intention of the educational system to simplify scientific information that is presented as a topic at all levels of school since it is a key foundation of science and technology. One of the goals of education is to simplify the information and knowledge that is given as a subject. This is one of the reasons why education is so important. Wegerif R. et al. (2015) stated that the development of creative and critical thinking skills is a global educational goal, highlighting the growing acknowledgment of their importance in students. It is crucial to have robust creative and critical thinking skills to understand any subject, especially in mathematics. Alias S N and Ibrahim F (2015) stated that the ability to think critically is an essential skill that every student should possess. A student equipped with critical thinking skills can thoughtfully engage their mind to uncover meaning and comprehension, explore ideas, make decisions, and solve problems, all while carefully considering and revising their previous approaches to reviewing learning materials (Richardson M, et al. 2012). V. D. Susanti et al. (2020) reported that a subject often regarded as challenging by students is the numerical methods course. This pertains to the discussion of this course. Students must achieve proficiency in the prerequisite courses. In the numerical method course, these students are required to master the prerequisite courses, which include linear algebra, calculus, and differential equations. This indicates that students' ability to critically analyze mathematical problems in numerical methods was quite limited. A variety of factors diminish the level of students' mathematical thinking. One of them is shaped by self-regulated learning. Some writers explain how SRL relates to independent learning, explore the impact of SRL on science learning, and provide various suggestions for enhancing SRL. Hargis J (2000) illustrated the necessity of self-regulated learning in the context of using the Internet for education, examining the impact of variables such as age, gender, racial identity, attitude, aptitude, self-regulated learning, and self-efficacy on the learning process. The findings showed that common learner traits did not hinder online learning. Barry Zimmerman (1990) reported that for three decades social cognitive researchers have examined the development of self-regulation in children as a result of socialization processes. He narrates the historical development of a social cognitive perspective on self-regulation and highlights its distinctive characteristics. Two key traits of students' self-regulated academic learning have been recognized — their application of strategies and their perceptions of self-efficacy. A model of academic self-regulated learning is proposed that integrates three key determinants—personal, behavioral, and environmental—through a strategic control loop. When students keep track of their responses and connect results to their strategies, their learning turns into a self-regulated process, leading to enhanced self-efficacy, increased intrinsic motivation, and improved academic achievement. There are several different ways in which SRL has influenced the educational methods of today. The emphasis has gradually shifted toward learning that is centered on the student over the course of time. Studies on SRL have shown that self-regulated learning strategies have a major influence on academic accomplishment (de la Fuente et al., 2022). These studies have also provided educators with insights into the aspects that contribute to the success of their students (Rowe & Rafferty, 2013).

Creative Fields

The ability to think in a way that is rational, introspective, and constructive is what we mean when we talk about creative or critical thinking. This talent gives us the ability to make sound decisions. In creative fields such as art and design, artificial intelligence is increasingly being utilized because it excels at activities that humans find difficult. These activities include the generation of one-of-a-kind content, the analysis and extraction of vast data sets, and the formulation of precise forecasts within the realms of research and discovery. V D Susanti et al., (2020) said that there is a lot of discussion on the advantages of critical thinking in education and the different ways that it may be taught in the literature (Ab Kadir M A, 2017). This is not only true in the context of schooling, but also in the context of literature, where the capacity for critical thinking is readily apparent. The reason for this is that academics are interested in conducting research that is connected to the analysis of the mathematical critical thinking processes of students from the point of view of self-regulated learning (SRL). Having the capacity to think in a manner that is reasonable, introspective, and constructive is what we mean when we talk about critical thinking. With this capacity, we are able to make judgments that are in our best interests. After the widespread adoption of online technology in higher education over the past few years, Rasheed et al., (2020) stated that the majority of classroom instruction would be considered a blended combination of traditional face-to-face instruction and other technologies that act as mediators, such as a Learning Management System. This was stated in response to the fact that online technology gained widespread acceptance in higher education.

It is therefore the case that artificial intelligence is fast transforming the landscape of research as a result of the introduction of technologies that boost human capacities and hasten the velocity of discovery. It is possible to discover that automated theorem proving (ATP) and hypothesis generation are two of the most famous applications in the field of mathematics. As a result, concerns have been voiced when it comes to the influence that current developments in artificial intelligence will have on creative processes (Daniele & Song, 2019; Miller, 2020). Certain artificial intelligence strategies, regardless of whether they are implemented independently or in conjunction with a human, are considered to be innovative. This conclusion was investigated through their individual research projects, which were carried out by Colton (2012), Daniele and Song (2019), and Fujita (2018). These worries have been brought about as a result of recent discoveries in the field of artificial intelligence.

The current growth of artificial intelligence (AI) across a range of creative sectors, such as the arts and the scientific sphere, has resulted in the creation of an additional facet. This facet has been brought into existence as a result of the current proliferation of AI. Co-creativity is a phenomenon that occurs when human creativity and the creativity of artificial intelligence interact with one another, as stated by Davis (2013). (Daniele & Song, 2019; Fujita, 2018; Mazzone & Elgammal, 2019) An increasing number of scholars are placing a greater emphasis on the possible effects that artificial intelligence might have on creative endeavors. This trend is expected to continue. The findings of the research conducted by Windstorm et al. (2024) demonstrated that scientists rely on artificial intelligence to produce results that are accurate and reliable. Contrary to scientists, artists have occasionally viewed their collaborations with artificial intelligence to be true creative endeavors. This is in contrast to the scientific community. The perspective that is maintained by the scientific community is in direct opposition to this. To phrase it another way, artists utilize artificial intelligence for the goals of both discovery and pleasure in their work.

AI Area

The area of science called artificial intelligence (AI) is very interesting and changes very quickly. While AI refers to the general notion of developing human-like cognition using computer programs and systems, of which machine learning is only one method the search for General AI and Super AI is still going on, experts still have a long way to go. Artificial intelligence (AI) is divided into two major categories as shown in Figure 1.

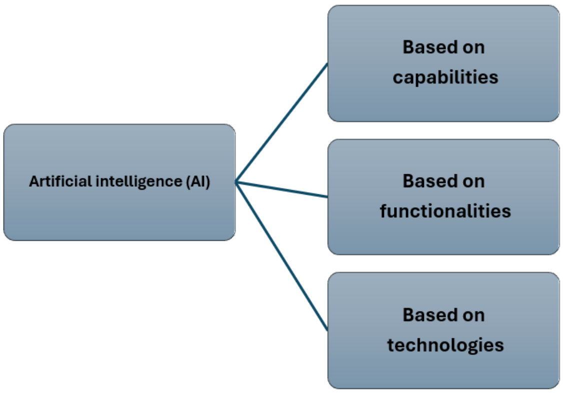

Figure 1. AI categories.

There are three classifications of Artificial Intelligence. One of these classifications is based on capabilities:

- Narrow AI, or Weak AI, refers to Artificial Narrow Intelligence (ANI), which is a form of Artificial Intelligence dedicated to a singular task or domain like Self-driving cars.
- Strong AI or General AI is also called Artificial General Intelligence (AGI), makes robots think, reason, and act like people.
- The most sophisticated and potent form of artificial intelligence is known as super AI or superintelligent artificial AI (ASI). It can understand and make sense of human feelings and experiences, as well as solve problems and make decisions.

In terms of the tasks they can perform, four distinct kinds of AI have been identified.

- Reactive machines, also known as Basic AI, represent the earliest and most fundamental types of AI systems that operate solely on reactive principles. These devices replicate the human mind's capacity to react to various stimuli.
- Limited memory AI which utilizes extensive theoretical machines to retain substantial amounts of data, serving as a reference for addressing future challenges. An image recognition system is equipped with several training images and corresponding labels to instruct it on the identity of the object being analyzed. Subsequently, when it scans a new image, it utilizes these previous photos as a reference for recognition.
- Theory of Mind AI that requires a comprehensive comprehension of human emotions and behaviors in a given context.
- Self-awareness is the ultimate and most sophisticated phase of artificial intelligence, presently existing as a theoretical notion. This will be feasible when machines attain self-awareness and exhibit human-like consciousness. Self-aware AI systems will possess analogous needs, emotions, and desires to those of humans.

Humans have only developed narrow AI, yet significant advancements have occurred in this field in recent years. It is widely acknowledged that artificial intelligence possesses a promising future. Based on technologies there are many branches of AI, each with its own focus and set of techniques. Some of the branches of AI include:

- Machine learning (ML)
    - ML, a subset of AI, involves developing algorithms to interpret, process, and analyse data to solve various real-world problems. These programs or algorithms are designed such that they learn and improve over time when exposed to new data.
- Deep learning
    - Deep Learning is a branch of machine learning that makes use of artificial neural networks to gain insights from data and solve more advanced problems. The deep learning algorithm is the logic behind facial & speech recognition, virtual assistants like Alexa & Siri, self-driving cars, and much more.
- Natural language processing (NLP)
    - It deals with the interaction between computers and human language. Natural Language Processing (NLP) is used to process & interpret human language, which is useful in many applications like speech recognition, text analysis, translation, etc.
- Robotics
    - It is a branch of artificial intelligence that deals with the design and development of robots. AI robots can be used to automate different tasks in multiple industries like healthcare, manufacturing, logistics, etc. They can learn from experience and work collaboratively with humans.
- Expert systems
    - Expert systems are AI-based computer programs designed to mimic the reasoning and decision-making abilities of a human expert. They are useful in many applications like financial planning, customer service, medical diagnosis, virus detection, and so on.
- Fuzzy Logic
    - Fuzzy logic is a computing approach that resembles human reasoning. FL is based on the principles of "degrees of truth" instead of the modern computer logic i.e. Boolean in nature. It can be implemented in hardware, software, or a combination of both.

COLLABORATION BETWEEN HUMANS AND AI

Machine learning technologies are making it possible to create learning experiences that are more dynamic, efficient, and personalized. The particular requirements of each student are taken into account by these technologies, which provide individualized feedback, real-time help, and increased engagement. Artificial Intelligence (AI) is progressively incorporated into educational environments, transforming conventional teaching and learning approaches. From intelligent tutoring systems to automated grading tools, AI technologies are facilitating more dynamic, efficient, and personalized learning experiences (Sajja R et al., 2026). For the purpose of assisting students in comprehending the ways in which mathematics contributes to the advancement of technology and society as a whole, the curriculum will incorporate mathematical concepts with data from the actual world, computer tools, and ethical considerations (Clark-Wilson et al., 2021).

Learning settings that are flexible, adaptable, and resource-rich will also assist students to gain the ability to continuously modify their learning and acquire the ability to learn throughout their lives. Skills are improved, influence is expanded, and new research avenues are created through the use of New Millennium Mathematics. It envisions mathematics offering solutions to problems through the use of cutting-edge technologies, enhancing comprehension, and preparing for a world driven by artificial intelligence (He, Y. H., 2024). It is absolutely necessary for academics, educators, policymakers, and the general public to participate in order to achieve equal integration of AI.

Students who are ready to become active participants in their learning process will develop these abilities.

Self-learning is the application of artificial intelligence in the field of education that is currently being utilized to assist adaptive learning. The idea of self-regulated learning, which is also commonly referred to as SRL, is an essential component of self-regulation that is intimately related with the objective of education. The ability of a student to manage and monitor their own learning process, as well as their motivation and conduct, is referred to as "self-regulated learning" (SRL) in the field of educational psychology. This word is used to define the ability of a student to learn successfully. In order for students to be successful in online learning, they need to be able to self-regulate. This is because they need to be able to manage their time, establish objectives for themselves, and keep their motivation up without being directly supervised.

Because they are able to effectively set goals, check their progress, adjust tactics, and focus on activities independently, students who have high self-regulation skills perform better than their peers in online situations. Among these are the planning of their learning environment and the solicitation of aid whenever it is required. Studies that have been conducted recently on self-regulated learning (SRL) have used multi-channel data, such as eye-tracking, in order to evaluate the utilization of fundamental cognitive and metacognitive SRL processes while engaging with adaptive hypermedia systems. Incorporating eye tracking into studies on self-regulated learning enhances comprehension of how learners manage their learning processes and the efficacy of various approaches available.

Taub et al. (2016) examined the influence of background knowledge in a self-regulated learning context utilizing eye-tracking equipment. Schindler et al. (2025) characterized eye tracking as the documentation of gaze focus. They said that eye tracking could help us understand cognitive and emotional processes, attention, or intentions while still doing things like learning or solving problems.

The teaching of mathematics in this new millennium will be highly individualized and will always be of a practical nature. As stated by Ardagna et al. (2021), the New Millennium Mathematician will be able to utilize both conventional mathematical thinking and computer science in order to solve problems that include the utilization of artificial intelligence tools, comprehend the significance of AI-generated insights, and evaluate the efficiency of algorithms. The focus shifts from just performing mathematical operations to arranging mathematical discoveries and application. These include the development of novel mathematical concepts for the purpose of comprehending artificial intelligence (AI), the investigation of the ethical implications of AI, and the application of mathematical modeling to tackle challenging global issues ranging from public health to climate change (Maqbool et al., 2025).

Online learning

Online learning, which is frequently referred to as "emergency remote teaching" (Hodges et al., 2020), is something that the vast majority of first-year college students have encountered at some point in their academic lives. This is because in the year 2020, an outbreak forced people to remain inside, and one of the most major advantages of online education is the flexibility it provides students in terms of when and where they can study. This is the reason why this is the case. Students will be needed to take more initiative in determining when and how they will participate in learning activities (Broadbent & Lodge, 2020; Kizilcec et al., 2017). This is because if this form of delivery reduces the opportunities for students to interact with their teachers and classmates, then students will be required to take more responsibility for their own learning.

Given the high level of autonomy and self-direction that is required with online learning, it is not surprising that self-regulated learning (SRL) plays an essential role in academic success when studying online (Broadbent & Poon, 2015). Importantly, the field is missing a validated instrument to measure students' motivated SRL in an online/blended learning context. A measure of motivated SRL would include both motivational beliefs (such as self-efficacy) and learning strategies (such as metacognition). While self-report measures do have their limitations, self-report has the advantage of being able to be administered to large groups in a cost- and time-effective manner (Jansen et al., 2020; Schellings & Hout-Wolters, 2011), and hence can provide a convenient and potentially useful source of data for understanding student SRL. We thus aim to develop and test the psychometric properties of a newly designed instrument that incorporates both SRL motivations and learning strategies based on students' self-report.

ENGAGEMENT BETWEEN HUMAN AND AI THOUGHT PROCESSES

In spite of the fact that the concepts of critical thinking and creative thinking may appear to be in direct opposition to one another, in reality, they are two fundamental components that together form a coherent whole that mutually complement and strengthen one another. The difference between creative thinking and critical thinking is that the former develops fundamental ideas and opportunities, while the latter assesses and improves previously generated ideas and opportunities to ensure that they are both possible and successful. In order to foster innovation in practical applications, they collaborate with one another.

Kundu, S. (2025) asserts that the connection between human cognition and artificial intelligence (AI) is characterized by a synergistic dynamic. This hypothesis is supported by observation. One of the defining characteristics of this dynamic is the fact that artificial intelligence systems facilitate human learning, decision-making, and the development of knowledge by providing both adaptive assistance and immediate feedback.

As a result of this cooperation, humans are able to make use of the computing capability of AI while still maintaining their cognitive autonomy. This has resulted in the establishment of a collaborative environment for the development of knowledge that is beneficial to both parties. Models of artificial intelligence ultimately improve understanding and memory retention by assessing, modifying, and transmitting information in accordance with individual cognitive processes. This is accomplished through the process of customizing and communicating information. On the other hand, human input influences the adaptation of artificial intelligence, which provides relevance and contextual precision (K. H. D. Tang, 2024).

This interactive link serves as a source of inspiration since it encourages the construction of knowledge networks that are designed to satisfy the requirements of both individuals and communities, as well as the processes of ongoing education. The importance of finding a balance between the intelligence of computers and the agency of people is emphasized by a number of different theoretical frameworks. Particular attention is devoted to trust, transparency, and ethical application in this context. According to M. N. Masrek et al. (2024), the relationship between cognition and artificial intelligence inside autonomous knowledge networks fosters creativity and stimulates learning that continues throughout one's entire educational career.

Benefits

Not only is the adoption of artificial intelligence in educational settings leading to an improvement in the delivery of teaching, but it is also bringing about a revolution in pedagogical paradigms, the design of curriculum, and the roles that educators perform. Education that is enabled by artificial intelligence is evolving away from traditional techniques that are guided by teachers and toward frameworks that are more student-centered, transdisciplinary, and personalized (Siddiqui, M., 2025 & Kong, S. & Yang, Y., 2024) learning environments. Teachers are increasingly positioned as facilitators, guiding students through the processes of self-directed learning and supporting metacognition and ethical reasoning (Almenara, J. et al., 2024). This shift in the role of teachers is reshaping the educational landscape. Additionally, educational frameworks such as AI-TEACH and dual-contrast models are being developed at an increasing rate in order to cultivate analogical thinking, systems thinking, and ethical awareness in classrooms that make use of artificial intelligence (Dai, Y., 2024, & Dai, Y. et al., 2023). There is a confusing duality in the way that college students view these modern technologies, according to the conclusions of an empirical study that was carried out not too long ago. The findings of the investigation led to the conclusion that was reached by the study once it had been completed.

Table 1. A Contrastive Study of the Behaviorist Approach and the Self-Regulated Learning Approach.

Element	Behaviorism	Self-Regulated Learning (SRL)
Perspective on Education	Learning takes place via conditioning, which involves reinforcement and punishment.	Learning is a dynamic and self-guided journey that encompasses planning, monitoring, and assessing one's advancement.
What the Learner Does	Acquired information through the role of a passive recipient, subject to the effect of external rewards and penalties	A participant who is engaged in the learning process and who takes responsibility for their own education by utilizing cognitive, metacognitive, and motivational tactics.
The Importance of the Environment	Stimuli and reinforcement are the means by which the environment exerts control over the behavior.	Although the environment plays a part in the learning process, it is the learners themselves who are responsible for actively engaging with it in order to improve their own understanding.
Inspiration	Encouraged by external circumstances such as rewards and punishments, among other things.	A combination of internal and external forces that motivate
Mental Processes	Behaviors that may be observed serve as the focal point of learning.	There is a significant focus on cognitive and metacognitive processes.
Utilization in Learning Environments	Employed in repetitive learning, practice exercises, and techniques for managing behavior.	Promotes the practice of establishing goals, self-assessment, and thoughtful consideration in the learning process.

The potential that generative artificial intelligence possesses to enable targeted learning, the growth of ideas, and advantages in terms of efficiency in academic writing is something that students are usually aware of. On the other hand, students are aware of the promise that generative AI holds. Contributions to this work were made by the following authors: Chan, C. K. Y., Hu, W., Arowosegbe, A. et al., (2024), Gasaymeh, A. M. M. et al., (2024), Ruiz-Rojas, L. I. et al., (2024), Alshamy, A. et al., (2025), Sousa, A. E., and Cardoso, P., 2025) are some of the researchers that have published their findings. Another benefit is that it can help students write faster. But this excitement is tempered by a lot of doubt about how reliable the content that AI makes is. When students are asked what the biggest obstacles to trust are, they often mention "hallucinations," false information, and algorithmic bias as things that make them less likely to trust AI.

Comparing SRL with other learning theories can enhance our understanding of it. Operant conditioning stands as one of the earliest behavioral models, serving as the cornerstone of the behaviorism learning theory. Behaviorism mainly emphasizes the use of rewards and punishments to modify behavior, whereas self-regulated learning (SRL) centers on internal motivation and metacognitive strategies for effective learning (de la Fuente et al., 2022). While operant conditioning depends on external rewards and consequences, self-regulated learning empowers students to take charge of their own educational journey (Tinajero et al., 2024). Table 1 displays a comparison of the two theories, aided by AI.

MATERIAL AND METHODS

Hamzah et al. (2025) conducted research to determine the impact that artificial intelligence has on the effectiveness of online learning platforms in higher education. Through the utilization of the DeLone and McLean Information Systems Success Model, the research investigates the connections that exist between artificial intelligence features, system quality, information quality, service quality, user satisfaction, and the efficiency of the platform. A strategy to study that is quantitative in nature and involves the collecting of data through the use of a structured questionnaire was utilized. For the purpose of determining how artificial intelligence (AI) is considered to affect various areas of online learning, a questionnaire was developed. The information was gathered from a representative sample of students and teachers at two institutions in Jordan that were chosen at random. The results indicated that AI has a substantial positive influence on the integrity of information, systems, and services. AI-powered features have the potential to enhance the quality of information, improve the technical aspects of the platform, and provide superior support services. Additionally, the investigation identified a robust positive correlation between platform effectiveness and user satisfaction. Users who were satisfied were more inclined to perceive the platform as effective, which resulted in enhanced engagement and learning outcomes. Educational AI Hub is an artificial intelligence-driven learning system that was applied in undergraduate civil and environmental engineering courses at a famous R1 public university. An evaluation of artificial intelligence-powered learning assistants in engineering higher education was carried out by Sajja R et al. (2026). This study took into consideration the implications for student engagement, ethics, and policy outcomes. The Educational AI Hub utilized this methodology. The research utilized a mixed-methods approach, which included pre- and post-surveys, system usage logs, and qualitative analysis of students' interactions with artificial intelligence. The purpose of the study was to evaluate trust, ethics, usability, and learning outcomes. According to the responses of nearly half of the students who utilized the AI assistant, it was simpler to use than asking their teachers or teaching assistants for assistance. According to the findings, students placed a high importance on the convenience and accessibility of the AI assistant.

When it comes to creative thinking and critical thinking, respectively, artificial intelligence is a sword with two edges. The utilization of this technology has the potential to considerably enhance a variety of skills, including the capacity to analyze data, the generation of new ideas, and the provision of people with a variety of perspectives. However, placing an excessive amount of dependence on artificial intelligence might lead to cognitive degeneration, which makes individuals less inclined to think independently and challenge things. This is because cognitive degradation is a consequence of the use of artificial intelligence.

According to V. D. Susanti et al. (2020), although there are a variety of definitions for SRL, authors are in agreement with three essential aspects: the establishment of goals, the selection of techniques, and the monitoring of cognitive and emotional processes taking place during assignments. For students to engage in self-regulated learning, they must first establish learning goals and then manage their cognition, motivation, and behavior in accordance with those goals and the environment in which they find themselves.

Students can learn a variety of real-world skills through SRL techniques. There is a high likelihood that SRL approaches will achieve excellent academic performance in traditional classrooms. Critical thinking, on the other hand, has been shown to be well-documented in literature, with a substantial amount of discourse on its merits in education and the several teaching approaches that it offers. Researchers in the academic world are interested in investigating the mathematical critical thinking of students through the use of self-regulated learning. Students' employment of creative or critical analysis, elaboration, and assessment strategies in their learning processes is evaluated through the use of critical thinking surveys for Self-Regulated Learning (SRL). The Motivated Strategies for Learning Questionnaire (MSLQ), particularly its critical thinking subscale, and more recent online-focused instruments such as the SRL-O, which investigate metacognition and cognitive strategy use, are two examples of tools that are commonly utilized.

It has been observed by Broadbent J. et al. (2022) that one of the most contentious approaches to measuring SRL is the use of self-report through questionnaire administration. There are a number of benefits that are frequently cited in support of their utilization (Fryer & Dinsmore, 2020; Pekrun, 2020; Roth et al., 2016). These benefits include the ease of application and interpretation while using them, as well as the capacity to reach a big sample size. However, according to the arguments presented by Zhou and Winne (2012), Jovanović et al. (2017), Jansen et al.

(2020), and Winne (2020), amongst others, the most effective method could be a combined approach that incorporates both trace data and survey or interview data, while also enhancing learners' capacity to accurately self-report their learning strategies (Winne, 2020).

In their study published in 2025, Juřík, V. and colleagues undertook an exhaustive investigation into the cognitive processing of learning materials, encompassing a variety of cognitive theories. It is well understood that self-regulated learning, often known as SRL, is a crucial component in improving the effectiveness of learning. To conduct a controlled laboratory experiment, a 2 × 2 mixed factorial design was utilized, and the participants consisted of 110 university students. The participants filled out a questionnaire that was meant to examine four different aspects of self-directed learning using four different subscales from the questionnaire. The Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich & De Groot, 1990) was utilized by them, with a specific emphasis placed on critical thinking and metacognitive self-regulation, both of which will be the primary targets of our attention in this section. When considering the results of that's survey on creative or critical thinking, it can be stated that roughly stayed stable throughout the experimental settings.

B. J. Zimmerman (2002) claimed that generative artificial intelligence gives chances to enhance the effectiveness of educational experience by facilitating self-regulated learning (SRL). This is because SRL encourages students to take responsibility for their own learning. Educating students to become lifelong learners who are able to expertly navigate the ever-changing challenges of the 21st century is an absolutely necessary goal that can be accomplished through the implementation of SRL. According to R. Luckin et al. (2022), it is becoming clear that traditional methods of teaching and learning do not adequately prepare pupils for the complexities of a society that is saturated by artificial intelligence. This is a growing perception. There is a significant demand for the provision of pedagogical models that have the potential to successfully incorporate generative artificial intelligence technologies, beginning with kindergarten environments, with the objective of enhancing the educational experiences of students in order to fulfill the expectations of AI-permeated societies both in the present and in the future (H. Yu et al. 2023).

It is conceivable for generative artificial intelligence systems, such as ChatGPT, to provide tailored learning experiences and real-time feedback in order to meet the requirements of certain students (L. Kohnke et al., 2023 & T. K. F. Chiu., 2023). This is something that may be accomplished through the use of ChatGPT. It gave students with the required skills to engage in their academic journey with forethought, to create goals, to approach learning assignments strategically, and to reflect critically on their experiences of learning. By integrating generative artificial intelligence technologies into elementary, middle, and high school education, Kong, Siu-Cheung, and Yang, Yin. (2024) established a comprehensive framework for learning and teaching. This framework was achieved by merging these technologies into the educational system. The framework was developed through a cooperative effort between researchers and educators who are already working in the classroom. The framework's purpose is to provide students with the skills they require to be successful in an era that is highly influenced by artificial intelligence. This is the goal of the framework.

According to the findings of J. Lu et al. (2024), it is anticipated that the interactions that take place between students and generative AI tools would take place in an atmosphere that is encouraging. In this scenario, the teachers will be the ones to provide direction, and the generative AI tools will function as partners in the process of engagement. The definition of creative or critical thinking that was supplied by V. D. Susanti et al. (2020) is that it is the ability to think in a way that is reasonable, introspective, and productive, and that it is applied in order to arrive at a choice that is sound. Because of this, it is something that is absolutely necessary for the development of mathematical knowledge. When it comes to self-regulated learning (SRL), they do an evaluation of the students' mathematical critical thinking by having them solve problems that involve numerical analysis. In order to determine which kids would serve as the participants of their research, they employed a method known as purposeful sampling. In the seventh semester of mathematics education at Universitas PGRI Madiun, these students were enrolled as students. A questionnaire for self-regulated learning in relation to subject choices was included in the instrument, which served as an evaluation tool for examining mathematical thinking. Students that have a high or intermediate level of self-regulated learning (SRL) are shown to have a significant capacity to generalize, recognize, and justify concepts, according to the findings. Students who have a low SRL, on the other hand, demonstrate a respectable capacity for making generalizations, but they have difficulty recognizing and justifying the concepts that are associated with algorithm analysis.

Data resources

In order to better understand critical thinking within the context of self-regulated learning (SRL), we are going to make use of the case study examination. The analysis that will be obtained from the data that was just made accessible will be derived from Juřík, V., 2025, which will serve as the source. The study of a questionnaire that was used to evaluate a total of four aspects of self-organized learning was carried out with the application of four subscales. Both self-goal orientation and extrinsicism, cognitive self-regulation, and critical thinking were included in these subscales.

Table 2. The responses for each Critical Thinking type.

Option-NO.	Number of Responses Critical Thinking-01	Critical Thinking-02	Critical Thinking-03	Critical Thinking-04	Critical Thinking-05
1	6	4	2	2	3
2	19	11	9	5	14
3	24	18	15	11	26
4	18	21	19	14	14
5	22	25	32	38	32
6	13	22	26	25	15
7	8	9	8	15	6

Table 3. The responses for each Self-Regulation (SRL)type.

Option-NO.	Number of Responses SRL **_1**	SRL **_2**	SRL **_3**	SRL **_4**	SRL **_5**	SRL **_6**	SRL **_7**	SRL **_8**	SRL **_9**	SRL **_10**	SRL **_11**	SRL **_12**
1	26	16	1	2	4	3	4	25	0	0	5	3
2	23	22	2	8	11	9	15	32	5	2	26	8
3	23	26	10	22	16	19	11	20	13	6	19	21
4	14	13	11	18	13	13	20	12	12	12	11	16
5	15	18	34	30	19	28	32	11	34	39	22	25
6	8	11	26	21	27	18	21	9	26	34	19	26
7	1	4	26	9	20	20	7	1	20	17	8	11

There were a total of four dimensions that were measured with the help of the questionnaire. The responses for each Critical Thinking group and Self-Regulation (SRL) group are presented in Table 2 and Table 3 respectively, which is based on the raw data.

Questionnaire Data Analysis

Python is the programming language that we make use of when we are practicing to improve our skills. The Python library, known as "Statsmodels", is one of the libraries that are included in this collection of libraries. The process of smoothing is required in order to get the data ready for use.

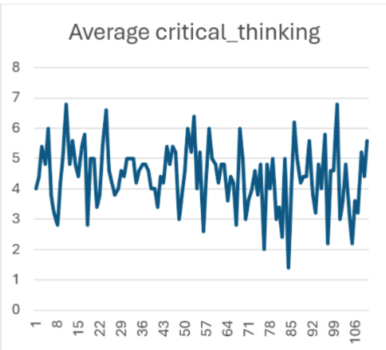

Figure 2. Critical Thinking Response Average Data from the questionnaire used.

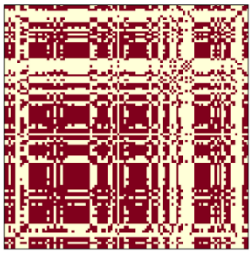

Figure 3. Critical Thinking used data that was utilized for the recurrent plot at threshold=0.1745. That the sequence has reached a stable or gradually changing condition is shown by the presence of adjacent recurrence points, regardless of whether they are horizontal or vertical.

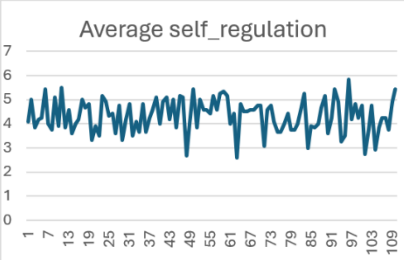

Figure 4. SRL Response Average Data from the used questionnaire.

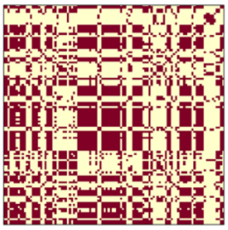
Figure 5. The used SRL data that was utilized for the recurrent plot at threshold=0.09. That the sequence has reached a stable or gradually changing condition is shown by the presence of adjacent recurrence points, regardless of whether they are horizontal or vertical.

A strategy known as the simple moving average is applied in order to cut down on the amount of data that is lost. There is an illustration of the average data questionnaire that was utilized in both Fig. 2 and Fig. 4. In the process of recurrent quantitative analysis, which is more frequently referred to as RQA, the recurrent plot is utilized in order to derive the features of the data that is being utilized.

Table 4. Results of the RQA' Questionnaire Subscales of Average Critical thinking and average Self-regulation Learning (SRL).

		RQA MEASURE						
Questionnaire Subscales	Threshold	**Recurrence rate (RR)**	**Determinism (DET)**	**Laminarity (LAM)**	**Longest diagonal line (Lmax)**	**Entropy (ENTR)**		
						Diagonal lines	**vertical lines**	**white vertical lines**
Critical_thinking	0.1745	0.141600	0.299392	0.519774	6	1.764490	1.811547	1.817349
Self_regulation(SRL)	0.09	0.182200	0.449477	0.693194	5	0.755615	0.945368	2.559353

Table 4 displays the RQA, while Figures 3 and 5 depict the recurrent plot for the data that was used. Each of these figures is shown with the proper threshold. The numerous techniques of time series analysis that are collectively referred to as "recurrence quantification analysis" (RQA) serve as an umbrella name for all of the related methods that are aimed at identifying patterns that occur within one or more time series. It is possible to accomplish accurate quantification of nonstationary time series by applying these patterns.

A number of statistical measures, including the mean, kurtosis, standard deviation (STD), and skew, were devised by us in order to provide a description of the data. The intention behind the development of these measures was to evaluate the data. When an individual has a comprehensive understanding of covariance, with all of its complexity, they discover that they have a great deal of options available to them for the comprehension of data. These subscales of the questionnaire comprise the following: the self-goal orientation of four different responses, the self-goal extrinsicism of four different responses, the cognitive self-regulation of twelve different responses, and the varied critical thinking characteristics of five different responses.

Table 5. Statistical descriptions of the data used.

Measurements	SRL	Critical Thinking
count	110.000000	110.000000
mean	4.326515	4.416364
stdv	0.680301	1.043330
min	2.583333	1.400000
25%	3.833333	3.800000
50%	4.291667	4.500000
75%	4.833333	5.000000
max	5.833333	6.800000
Skew	-0.276	-0.236
kurtosis	0.372	0.151

Table 5 displays a few statistical explanations of the data used that were included in the questionnaire in which are responses, choices numbers were provided.

Table 6. Pearson correlation coefficient.

Questionnaire Subscales	**Critical_thinking**	**Self_regulation**
Critical_thinking	1.000	0.300
Self_regulation	0.300	1.000

Table 7. Spearman's correlation.

Questionnaire Subscales	**Critical_thinking**	**Self_regulation**
Critical_thinking	1.000	0.247
Self_regulation	0.247	1.000

Furthermore, in order to analyze the linear connection that exists between each and every pair of data sets, we computed the Pearson correlation coefficient presented in Table 6. Table 7 displays Spearman's correlation. For the purpose of evaluating the partnership.

RESULTS AND DISCUSSION

An examination of a questionnaire that was utilized for the purpose of assessing a total of four facets of self-organized learning was carried out with the utilization of subscales like cognitive self-regulation, and critical thinking were also included in these subscales. Here with the assistance of the questionnaire, a total of 12 Types of self-regulation (SRL) and 5 types of Critical Thinking were focused. Using seven-point options for the response, with each kind offering between one and seven different choices per type. Through the application of several methods of analysis, we are able to acquire the following for each:

Some statistical analyses

From Table 2 and Table 3, when the data used are rearranged from minimum to maximum, it becomes clear that: Option 1 was the least preferred alternative by participants across all categories, taking into account the fact that there was a total of 110 survey participants across five different types of the Critical Thinking Scale, with each type offering between one and seven possibilities; (7-point scale for the response). It is the fifth option that has the highest possible limit across all sorts. The responses that are considered to be the most significant are those that are linked with option number 5, with the exception of the type that is referred to as "Critical Thinking 01." In this particular instance, the option that has the highest number of responses is option number 3, reflecting 22% of the participants. The "Critical Thinking 04" type, on the other hand, is responsible for thirty-five percent of the individuals who participated in the fifth choice which is the maximum number of participants choice option 5.

There was a total of 110 survey participants across 12 different types of Self-Regulation (SRL) types, with each type offering between one and seven options. Types SRL-9 and SRL-10 are not represented in any of the options that are available in Option 1, as was noticed. Also, the highest percentage of choice 1 is found in Type Self-Regulation (SRL)-1, which received around 24 percent of the votes cast by the participants. Choice 2 received roughly 29% of the votes cast by the participants, making it the choice with the highest percentage in Type Self-Regulation (SRL)-8. The highest percentage of choice 3, which received around 24 percent of the votes cast by the participants, is found in Type Self-Regulation (SRL)-2. The biggest percentage of choice 4, which received nearly 18% of the votes cast by the participants, is found in Type Self-Regulation (SRL)-7. There is a type of Self-Regulation (SRL)-10 that contains the highest percentage of option No. 6, which got around 31% of the choices made by the participants. And the type Self-Regulation (SRL)-3 contains the highest percentage of option No. 7, which garnered around 24 percent of the choices made by the participants. It is estimated that around 36 percent of the participants selected Option No. 5.

The five-number summary, which is derived from Table 5, is a comprehensive representation of the range and distribution of the used data. It is comprised of the following values: the minimum, the twenty-five percent, the fifty percent, the seventy-five percent, and the maximum.

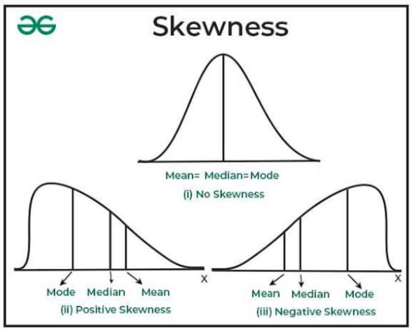

Figure 6. Positive and negative skew

If the skew is positive, the tail will stretch to the right. If the skew is negative, the tail will tilt to the left. Peaks and tails are what kurtosis is all about. When kurtosis is high, the peaks are more defined and the tails are heavier. When kurtosis is low, the data is spread out and the tails are lighter. That is; when skewness is negative, there are more big values and when it is positive, there are more small values. The value of skewness between -1 and +1 is good, and the value between -2 and +2 is usually fine. A higher peaked distribution is indicated by a positive kurtosis, whereas a flatter distribution is indicated by a negative kurtosis. A kurtosis that is larger than +2 indicates that the distribution is too peaked, whereas a kurtosis that is less than -2 indicates that the distribution is too flat. It is regarded to be a normal distribution when both the skewness and the kurtosis values are relatively close to zero (Hair et al., 2022, page 66). He says that values above and below -2 and +2 indicate a lot of nonnormality.

Consequently, Table 5 clearly shows that all Skew values fall between +1 and -1, indicating that the participants' responses are positively skewed, with the data clustered to the right and a tail extending toward lower levels. Figure 6 illustrates both the positive and negative skew. The kurtosis values for the two subscales, critical thinking and the SRL, are positive, less than +1, and close to 0.

Data Correlation

A positive Pearson correlation coefficient (r>0) indicates a linear relationship in which two variables change in the same direction: when one variable rises, the other generally rises as well, and when one falls, the other typically falls too. The range extends from 0 to +1, where +1 signifies an ideal positive linear relationship. The conclusion that can be drawn from this is that all of the Pearson correlation coefficients fall within the range of 0 to +1, as shown in Table 6. The relationship between critical thinking or creativity and self-regulated learning can be described as linear.

The Spearman correlation, on the other hand, examines monotonic correlations, in contrast to the Pearson correlation, which looks at linear tendencies. According to the data presented in Table 7, this indicates that the variables are increasing in tandem with one another; however, the rate of rise may not necessarily be traveling in the same direction.

Recurrence Quantification Analysis(RQA)

Quantifying the small-scale structures of recurrence plots, which display the number of recurrences of a system as well as the duration of those recurrences, is the responsibility of the RQA. Using statistical metrics such as determinism, recurrence rate, and entropy, it is possible to study system dynamics, complexity, and stability, even with brief or non-stationary data. This is accomplished by breaking down complex visual patterns in an RP into statistical measures.

Because visual inspection alone is not sufficient for comparing different systems, the RQA that was established was developed with the purpose of quantifying features that are present in a recurrence plot. We apply the following Primary Measures:

- The percentage of recurrence points in the plot is referred to as the Recurrence Rate (RR), which allows for the measurement of the density of points.
- Determinism, sometimes known as DET, refers to the proportion of recurrence points that are arranged in diagonal lines, which indicates the predictability of the system.
- Laminarity, also known as LAM, is the proportion of recurrence points that form vertical lines. This percentage helps to determine the occurrence of laminar states, which occur when a system remains in a particular state for an extended period of time.

- The chaotic nature of the system is indicated by the longest diagonal line, also known as Lmax, which exhibits a relationship with the biggest Lyapunov exponent values.
- Entropy, often known as ENTR, is a measure that displays the degree of complexity of the deterministic structures present in the plot. We have more than one Entropy: Entropy white vertical lines (W_entr), Entropy vertical lines (V_entr), and Entropy diagonal lines (L_entr).

Based on Table 4 we found, $0 < LAM < 1$, 0 is less than DET, which is less than 1, and lower entropy which indicates all of the answers are stable.

That is the data demonstrates significant consistency and reliability. This specifically suggests that the participants' responses under the subscales SRL and Critical Thinking were consistent, and if the poll were to be administered again under same settings, the participants would likely produce the same or very similar answers.

CONCLUSIONS

The integration of AI with education signifies a groundbreaking leap in millennial education, rather than just an incremental change. By utilizing personalized learning and adaptive systems, artificial intelligence improves education and fosters human creativity by identifying gaps with tailored practice and promoting a re-assessment of the curriculum to focus on higher order cognitive skills: conceptual understanding, critical thinking, problem solving, logical reasoning, and question formulation.

Humans and AI exist in a vibrant partnership where their unique strengths—human creativity, intuition, and abstract thinking; AI's computational power, pattern recognition, and data processing abilities—are seamlessly integrated. Students who independently organize their learning and regularly engage in critical thinking achieve exceptional academic outcomes. AI should not replace human activities like creativity, research, investigation, and artistic endeavors; rather, it should function as a tool to enhance these efforts through human intellect. This is the purpose for which it is intended to be used.

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Competing Interests

The author has stated that there are no competing interests to disclose.

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