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Artificial Intelligence, Critical Thinking, and Self-Regulated Learning in Education: A Secondary Data Analysis of University Students' Learning Questionnaire Data

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ABSTRACT

Background: Artificial intelligence (AI) is slowly shaping the field of education to support individual learning, feedback, and control by learners. However, educational value of AI is not only based on the technological performance but also on the capability of students to self-rule the learning process, critical thinking and judgment.

Aim: This study has explored the patterns of critical-thinking in self-regulated learning and comment on their potential in AI-supported education.

Methods: The publicly available Figshare dataset by Juřík et al. (2025) comprising questionnaire data of university students who participated in self-regulated learning activities was subjected to a secondary quantitative analysis. The discussion concentrated on the questionnaire items of critical-thinking. Response distribution and pattern stability were analyzed using descriptive statistics, item-level comparison, interpretation based on correlation, and exploratory analysis through recurrence quantification.

Results: It was found that the critical-thinking scores were moderate-to-high, which implied that students tended to report affirmative involvement with reflective and evaluative learning behaviours. Patterns at items were rather balanced in the critical-thinking measures, whereas recurrence-based indicators implied the consistency of the response organization. Nevertheless, due to the fact that the data were obtained using responses of a Likert-scale questionnaire, but not direct results of AI-intervention, the results must be viewed with caution.

Conclusion: This paper holds that critical thinking and self-regulated learning are crucial capabilities of humans in AI-mediated learning. The AI will be able to improve education processes, and its potential lies in the capacity of the learners to analyze information, track their learning, and utilize technological tools in a responsible manner. Longitudinal or experimental studies should be conducted in the future to explore the direct effect of AI tools on creativity, critical thinking, and self-regulated learning outcomes.

Keywords: Artificial intelligence in education, generative AI, critical thinking, creativity, self-regulated learning, recurrence quantification analysis.

INTRODUCTION

Artificial intelligence (AI) has emerged to be among the most significant drivers of modern education. Generative AI systems are able to summarize information, create explanations, create examples, give feedback and simulate a conversation with learners. These affordances have promoted a perception of AI as a personalization/productivity tool. However, the same affordances pose a significant pedagogical challenge: will AI reinforce learning, or will it only speed up task performance? This question can be raised more particularly in the sphere of higher learning when students have to not only retrieve information but also analyze evidence, support their claims, build arguments, and manage their learning.

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Educational value of AI must thus be evaluated based not only on what a system is able to generate but also what it allows the learners to accomplish intellectually. A text-generating tool can facilitate brainstorming and decrease cognitive load, but also can block the effort involved in concept generation and independent review. This tension is depicted in the literature on AI and creativity. Anantrasirichai and Bull (2022) believe that AI has the greatest value in creative fields when it enhances human agency instead of replacing it. Similarly, Habib et al. (2024) demonstrate that generative AI can assist in facilitating creative thinking but at the same time poses a threat to creative confidence and student autonomy. These researches indicate that AI is not educationally neutral. Its impacts are relative to the ways in which learners, teachers, institutions, and assessment systems designed use it.

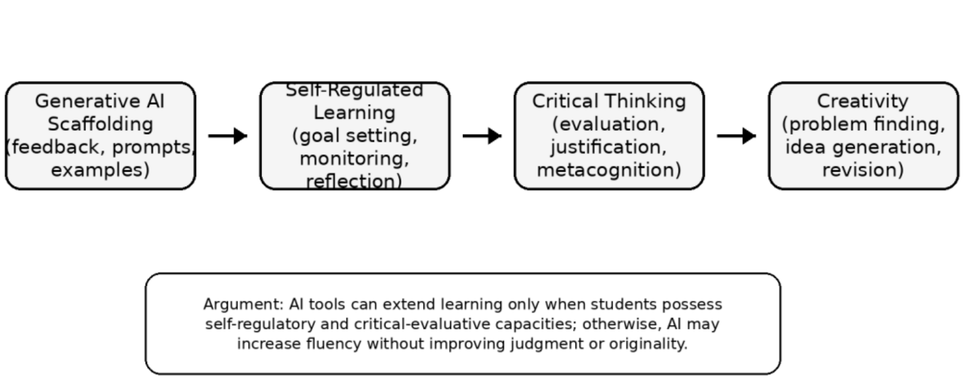
Self-regulated learning (SRL) is a useful conceptual framework to study this issue. SRL is the ability of learners to establish goals, track progress, choose strategies, regulate motivation and reflect on performance (Zimmerman, 2002). SRL becomes more significant in AI rich learning environment and not less so. Students will have to decide when to consult AI services, how to judge AI produced materials, whether to update or dismiss an output, and how to take responsibility of their knowledge. Markauskaite et al. (2022) contend that the epistemic agency, evaluative judgment, and adaptive expertise are new capabilities in human learning in a world that has AI. This stance is the opposite of the narrow technological optimism which presumes improved tools are automatically the source of improved learning.

The focal point of this debate is critical thinking. Critical thinking in the context of AI-assisted education encompasses the possibility to analyze the credibility of sources, evaluate unsupported arguments, compare explanations, notice bias, and justify. Creativity is also applicable but creativity that lacks critical analysis can turn to the depth of superficial novelty. On the other hand, thinking critically without creative exploration may be conservative and risk averse. Creativity and critique is thus not an option but a combination of the two as the strongest educational model. Such integration can be promoted by AI when it is employed as a dialogic and reflecting partner. It can undermine it when the learners substitute inquiry with AI.

This paper constructs an empirical and critical argumentation on that issue. It explores the distributions and the stability of responses in questionnaire data of critical-thinking among students using a publicly-controlled learning data set. The research does not imply the study directly measures the effect of AI-tools as the original data were not gathered via an AI-intervention study. Rather, the analysis considers critical thinking in SRL as a facilitating characteristic of responsible AI-facilitated education. The research questions are:

- RQ1. What is the distribution of critical-thinking scores in the selected SRL dataset?
- RQ2. How balanced are students' responses across the critical-thinking questionnaire items?
- RQ3. What exploratory insight can recurrence quantification analysis provide about response-pattern stability?
- RQ4. What implications do these findings have for the design of AI-supported learning environments?

Figure 1. Conceptual model linking generative AI, self-regulated learning, critical thinking, and creativity.



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LITERATURE REVIEW

AI in education: productivity, personalization, and dependence

Generally; The use of AI in education is often suggested to address the enduring issues of lack of feedback, differentiated needs of learners, and the inability to scale individualized teaching. Generative AI tools are capable of generating explanations, quiz questions, summaries, and examples nearly instantly. According to Kohnke et al. (2023), these tools can facilitate language learning and instructor readiness, whereas Chiu (2024) claims that generative AI will ensnare high education to reconsider the teaching, assessment, and research agenda. Kong and Yang (2024) carry this argument further by suggesting a human-centered model whereby generative AI can be employed to facilitate domain learning and SRL creation.

Nevertheless, the risk of cognitive outsourcing needs to be weighed against the promise of personalization. Students might avoid uncertainty, struggle, and revision that are often required to deep learn by relying on AI giving answers too fast. According to Luckin et al. (2022), teachers are not just to be AI-equipped; rather, they need to be AI-ready. This difference is significant. AI-readiness encompasses the capability to create learning activities where the use of AI is clear, intentional, and pedagogic. AI-equipment, in contrast, can imply adopting tools without paying enough attention to cognition, ethics, or assessment.

Recently; Deepshikha D and Hermita, M. et al. (2026), investigated that Self-regulated learning acts as a cognitive filter and guide for AI feedback by setting goals, observing, and reflecting, helping learners filter relevant advice, monitor its application, and reflect on its long-term value.

Creativity and critical thinking in AI-supported learning

The correlation between AI and creativity is not that simple. Other researchers present AI as a multiplier of divergent thought since it is capable of producing numerous options in a short time. As an example, habib et al. (2024) state that the fluency and diversity of creative products can be impacted by generative AI. Nonetheless, the same literature also cautions that AI can decrease the confidence of students in their creative abilities. This is a paradox because AI can lead to more ideas generated, but fewer senses of ownership or evaluative responsibility develop in the learner.

Similar conclusion is made by creative industries research. Anantrasirichai and Bull (2022) demonstrate that AI played a strong role in music, image creation, and media creation, but the review also emphasizes that the most fruitful using is human-centered. Wingström et al. (2024) also believe that co-creativity is a more accurate characterization of the relationship between humans and AI than replacement narratives are. When applied to education, this implies that AI ought to be viewed as an aid to deepening research, not as a kind of tool that finishes the process of learning on behalf of a student.

This type of co-creativity education is defended by critical thinking, which contributes to its educational significance. When AI-generated content is not critiqued, it risks acceptance due to its fluency rather than accuracy or sound reasoning. Critique will enable students to compare AI output with evidence, update prompts, determine limitations, and defend their final decision. The issue of AI in education is thus not whether or not students should use AI but how they can use it and at the same time maintain judgment.

Self-regulated learning as a foundation for AI-era education

SRL is a well-developed theoretical paradigm of explaining the way learners control their cognition, motivation, behavior, and learning setting. According to Zimmerman (2002), self-regulated learners are proactive learners, who plan, monitor, and reflect on their learning. As Pintrich and De Groot (1990) showed, motivational and cognitive elements of learning are closely related to academic performance. These background studies are still pertinent since AI-rich environments require even more, rather than less, learner agency.

It is educative to contrast SRL with AI automation. The information, feedback and suggestions provided by AI systems are also capable of doing, however, they cannot be able to know whether a learner has made a personal meaning out of a concept or not. Neither can they take the role of the learner to judge of sources or to contemplate misconceptions. According to Markauskaite et al. (2022), students in AI-mediated classes should be provided with the skills that will enable them to engage with smart systems without relinquishing epistemic authority. In

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this sense, SRL is not a non-essential addition to AI-aided learning, but that is where AI becomes educationally fruitful.

Another point of contrast can be made between AI as a technical infrastructure and AI as a learning relation. Technical descriptions usually focus on capacity of model, precision, automation and size. Educational accounts, however, need to raise the question of whether the learner is in a position to be more competent following the use of the system. This distinction is important since an artificially intelligent system with great abilities can still yield poor performance in education due to the absence of the ability to plan, trial, fail, and correct. On the contrary, a less advanced system could be pedagogically useful in case it encourages students to reason, compare alternatives and think about mistakes. Learner, task, teacher, tool, and assessment culture are therefore the sources of quality AI-supported learning: the product of interaction between the learner and the task. This relational perspective aligns with the human-centered scholarship of AI and prevents deterministic assertions that technology completely reshapes education.

AI Robustness and Adaptability

In artificial intelligence, the decision between a stable and flexible pattern is conditional on factors including context, adaptability, and safety. Table 1 displays Stability and Flexibility key points that include predictability, resilience, and resource use. Predictability, robustness, and context must be considered when comparing stable versus flexible AI processes. Flexible patterns respond dynamically, while stable patterns are reliable (Surana, I., et al.,2026 and Zjavka, Ladislav. 2023).

Table 1. The key points for AI Stability and Flexibility.

Persistence (Extremely Recurring Patterns)	**Level of adaptability (Pattern Variation)**
High predictability: Outputs and behaviors are very predictable and exhibit very little variation over time. *Lower risk:* Safety-critical operations, such as medical dosage or flying controls, benefit greatly from the reduced risk. *Inflexible conduct*: does not adapt well to novel or unexpected circumstances.	*Extremely flexible*: Responds rapidly to changes in rules, data, or users. *Improved learning*: Assists AI in resolving unstructured or creative issues. *Unpredictability*: Mistakes, drift, or harmful outcomes may occur if the tolerance is too low.

Methodology

Research design

The secondary quantitative research design was used in this study. This was not intended as a test of a new AI intervention but as an exploration of critical-thinking data of an already existing SRL dataset and how it is applicable to AI-supported education. A secondary design would be suitable in cases where the research question can be answered through publicly available information and the role of the researcher is reanalysis, reinterpretation or extension of a methodology.

Dataset and sample

The information was extracted in the form of the publicly available Figshare data that was linked to Juřík et al. (2025), describing an experiment of the eye-tracking activity in self-regulated learning. The original study employed a 2 x 2 factorial study which was controlled, and the focus was on learning processes of university students according to multimedia content and metacognitive prompts. The current paper is limited to the issue of the questionnaire component that deals with critical thinking. The valid analytical sample comprised 109 working responses, which is in line with the values in the analyzed table of the manuscript. Since the data were open and anonymized, no new human-participant data were gathered.

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Variables and measures

Moderate-to-high critical thinking scores help students avoid AI faults by allowing for active evaluation, error identification, and resistance to automation bias. Students develop the ability to critically evaluate information and move beyond just receiving misleading information (Baki, Y. ,2025).

Critical thinking in SRL was the focal construct. The questionnaire questions were responses that were of a Likert-type-ordinal response to a seven-point scale. The analysis was conducted on the aggregated critical-thinking distribution and relative contribution of five critical-thinking items. Since Likert-type data are ordinal, a statistical analysis will focus on patterns and tendencies instead of effective causal or parametric inference.

Data analysis

In Recurrence Quantification Analysis (RQA), high recurrence assesses physical or systemic stability and repetition, whereas critical thinking prioritizes cognitive flexibility in adapting to and solving novel issues. The two ideas represent distinct fields: mathematical systems and human reasoning (Cloude, E. B., et al., 2026 and Jenkins, B. N.,et al., 2019). The statistical aggregated critical-thinking variable was calculated using descriptive statistics, such as count, mean, standard deviation, minimum, quartiles, median, maximum. They compared item-level with the aim of examining whether or not the five critical-thinking items contributed to the construct equally. Recurrence quantification analysis was added as an exploratory procedure of studying response-pattern regularity. Complex, sequential or dynamic data, as well, is typically applied to RQA since it is able to determine recurrent structures and stability of patterns (Marwan et al., 2007). It has been used as well to classify categorical and behavioral sequences in social and cognitive studies (Coco and Dale, 2014).

The application of RQA in the present study is carefully prudent. Questionnaire items are not a natural time series except insofar as their sequence is based on a theoretically interesting order. Thus the RQA findings do not imply to provide direct evidence about cognitive processes. Instead, they are considered as exploratory measures of response-pattern regularities that can inform future work with more detailed sequential data like eye-tracking, log data or interaction traces of AI learning systems.

Table 2. Descriptive statistics for the aggregated critical-thinking score.

Statistic	Value
Valid cases	109
Mean	4.16
Standard deviation	1.53
Minimum	1
25th percentile	3
Median	4
75th percentile	5
Maximum	7

RESULTS

Descriptive statistics

The descriptive statistics indicated that the mean of the aggregated critical-thinking score was 4.16 and a standard deviation of 1.53 on a seven-point scale. The lowest score was 1 and the highest score was 7. The median was 4 with an interquartile range of 3 to 5. These values indicate that critical-thinking responses of students were focused on moderate standards, and the significant variability in any respondent. The ceiling effect is not reflected in the distribution, as the top score was achieved but the central tendency was close to the scale middle.

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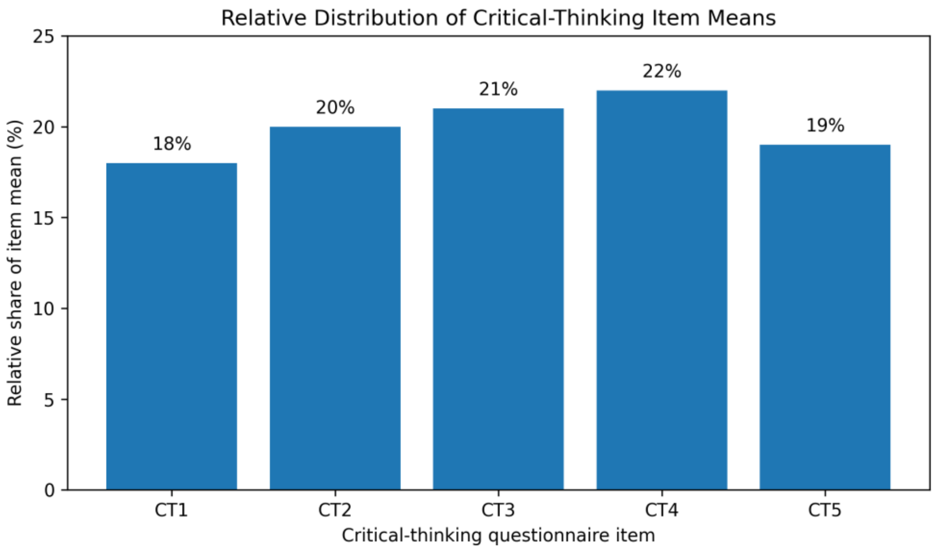
A summary of the descriptive profile is presented in Table 2. The findings can be construed as a baseline description of critical-thinking reactions in an SRL environment. They do not show that AI lead to an increase or decrease in critical thinking. Instead, they demonstrate the degree of critical thinking attitude or strategies that are involved in the chosen data, which can be talked about as a topical learner feature in the AI-based learning.

Item-level comparison

The five critical-thinking items had fairly balanced contributions of item-means. The relative shares were 18%, 20%, 21%, 22%, and 19%. The pattern indicates that there was no item that prevailed in the aggregate score. A balanced profile of the item is good as it shows that one statement was not the most influential on the critical-thinking construct. Nevertheless, reliability analysis, item-total correlations and confirmatory validation would be essential to producing a complete psychometric interpretation which were not available in the reported statistics.

The distribution of items is shown in Figure 2. The minor variations between the items suggest that the answers of the students were quite similar between the indicators of critical thinking. Consistency is important in AI-assisted education since critical thinking is not a one-time event but a habit of appraisal, justification, and contemplation. However, strong evidence of the validity should not be conflated with item balance. Further studies must document reliability coefficients and questions can be asked whether the items are working in a similar manner across groups of learners.

Figure 2. Relative distribution of five critical-thinking items means.



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.

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- 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).

Evaluation

Figure 3. Raw survey data transformed into a pseudo-time series (TS) using a simple moving average.

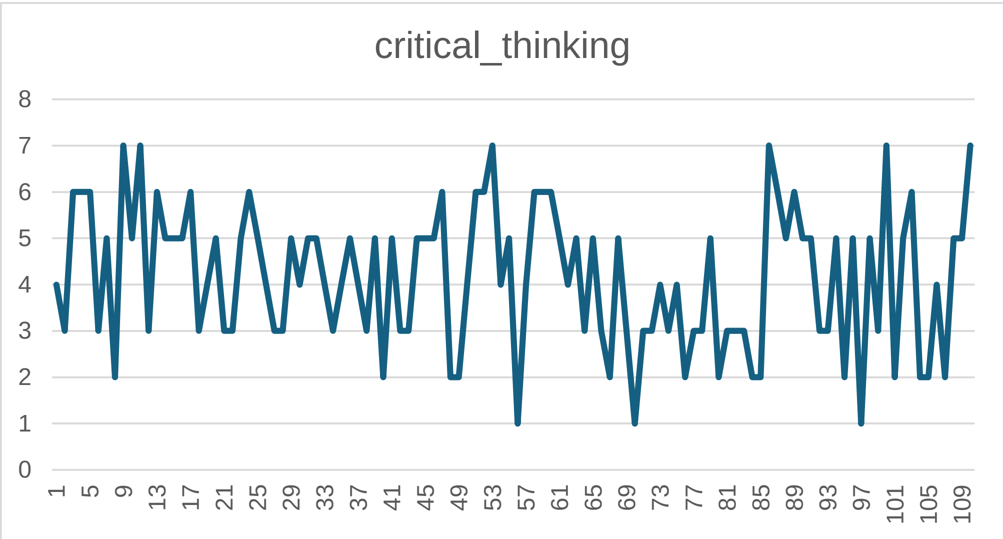
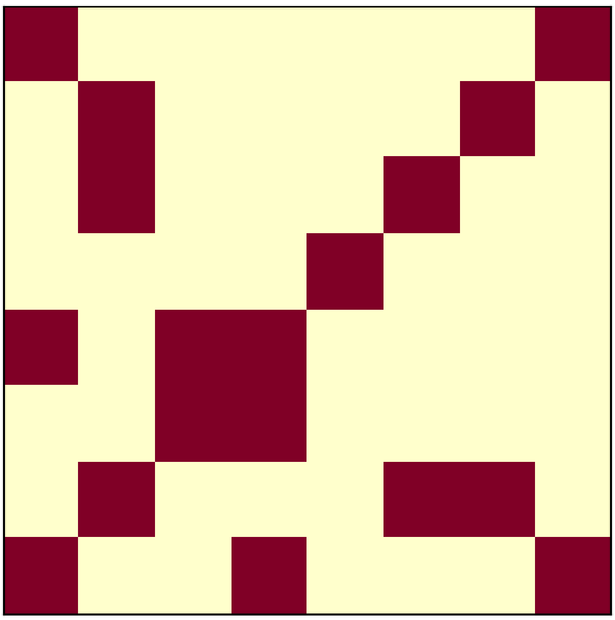


Figure 4. The pseudo-TS of the raw data utilized is shown in a recurrent plot. When adjacent horizontal or vertical recurrence spots are found, it means that the sequence has stabilized or is only slightly altering.



We carried out our experiment utilizing the Python programming language, version 3.13. In our investigations, we utilized a variety of Python libraries, including those listed below.

- Pandas Library – For reading data.

- Matplot Library – For visualizing the applied algorithms.
- Scipy Library -For data sequences and image.

Python is the programming language that we make use of when we are practicing improving 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. 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 Figure 3.

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. Figure 4 depicts the recurrent plot for the data that was used. The score of RQA indicators of the recurrence rate is presented in table 3. This figure is shown with the proper threshold.

Table 3. Exploratory RQA for pseudo-time series (TS) in Figure 3.

RQA indicator	**Value**	**Interpretive note**
Recurrence rate (RR)	0.927	High recurrence of similar response states
Determinism (DET)	0.960	Strong patterned structure in the ordered responses
Average diagonal length (L)	17.575	Extended repeated structures
Longest diagonal length (Lmax)	64	Long uninterrupted pattern
Divergence (DIV)	0.016	Low divergence indicator
Laminarity (LAM)	0.980	Strong vertical/horizontal stability
Trapping time (TT)	33.667	Stable states in the response structure
Longest vertical line (Vmax)	40	Longest stable vertical structure

Nevertheless, the significance of the findings is contingent upon the characteristics of the data. Recurrence patterns are often used to depict temporal or behavioral phenomena in the field of dynamic systems. In accordance with Mhamd, Halah. (2024), there is a mutual and shared utility between data representation variations. As a digital image is just a matrix of static numbers, it can be converted into a pseudo-TS or represented as a sequence of numerical elements.

The data in this paper are questionnaire answers and thus, the order could be the consequence of item or respondent order. This is why the RQA results can be considered more of an exploratory and methodological than a confirmatory type of research. They show that the recurrence-based techniques might be applicable to future studies of AI-in-education, provided they are used with actual sequential data, e.g. with the interactions of students to AI tutors, revisions of the responses, history of prompts, or track of eye-tracking.

DISCUSSION

The results endorse a tentative yet significant claim: critical thinking in SRL is one of the prerequisites of responsible AI-assisted learning. As indicated by the descriptive results, there are moderate scores in critical-thinking, whereas the comparison of the items indicates consistency among critical-thinking signalers. These results are similar to SRL theory which considers good learners to be active observers and controllers of their own cognition (Zimmerman, 2002). They are also in line with Pintrich and De Groot (1990) perception that the use of cognitive strategies and motivation are interdependent during academic learning.

The research is also beneficial in elucidating a gap in certain AI-in-education arguments. Much of the popular debate focuses on what AI can achieve: creating explanations, responding to questions, creating personalised content, and facilitating creativity. This is useful, but not complete. The more critical educational question is

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what the learners can do with AI. In the case that students do not have the ability to judge output, AI can become a shortcut leading to less intellectual activity. AI can be used as an inquiry, comparison and revision resource in case students are equipped with good SRL and critical-thinking abilities. This tool can thus result in varying educational outcomes based on the regulatory and evaluative abilities of the learner.

Such interpretation is opposed to excessively optimistic ones regarding generative AI as an automatic creativity boosting tool. Habib et al. (2024) demonstrate that AI can facilitate creative production but the same literature demonstrates that creative confidence and reliance are also a cause of concern. On the same note, Anantrasirichai and Bull (2022) highlight the use of augmentation as opposed to substitution in creative sectors. That argument is applied to the present study: AI can be best defenseable on the grounds of assisting human agency, rather than replacing it. Practically it would imply that educators are to create the activities which would entail the students to critique AI-generated output, contrast it with peer-reviewed materials, revise it, and justify their choices.

Learners engaging in self-regulated learning are able to scan AI information for relevant guidance, apply it, and reflect on its long-term worth through goal setting, monitoring, and reflection (Sooyohn Nam, et al., Deepshikha D and Hermita, M. et al., 2026). Goal setting; Aiming clearly allows you to evaluate whether the AI's response aligns with your immediate learning objectives. Off-topic or too complicated AI recommendations that don't align with your strategy can be disregarded. Defined objectives provide a benchmark to evaluate the efficacy of the information provided by the AI. Monitoring; You can see how effectively you apply the AI's suggestions as you complete your task. Proactive monitoring enables immediate identification of errors or misleading suggestions from the AI. You adjust your actions instantaneously according to how the AI's responses align with your existing comprehension. Reflection; You reflect on whether adhering to the AI's suggestions has enhanced your output. Contemplation transforms a basic AI adjustment into a more profound insight for subsequent endeavors. Reflecting on the procedure diminishes your reliance on AI as time progresses (Sooyohn Nam, et al., 2026). Practically, Fu, Y. et al. (2026) introduced Self-Regulated Reading with AI Support. They investigated the manner in which college students employ AI chatbots to facilitate self-regulated reading over an eight-week period.

Methodological implications of the results are also made. The results of the exploratory RQA suggest that learning can be studied as a process, which is patterned and not just as a final score. Particularly in the case of AI-assisted learning, the interaction between students and an AI generates dense sequential traces: prompts, revisions, feedback loop, response times and decision paths. However, this study also has one limitation. Critically, it is only in cases where the sequence has meaning in terms of theory that the application of RQA to questionnaire data can be informative. Recurrence algorithms should be applied in future studies to real data of the actual learning process that incorporates eye tracking, log of clickstreams, or records of AI interactions.

To obtain high-quality AI-in-education research, a more robust empirical design would compare learners who utilize AI in various pedagogical settings. An example is a group of people who use AI without restrictions, a second group prompts AI with critical-evaluation, and a control group will do it without AI. The results may be in the form of creativity, critical thinking, SRL performance quality and confidence. This design would enable researchers to test if AI enhances learning, whether it just enhances fluency or alters the sense of agency among students. Those causal claims are not made in the present article, yet it will give conceptual and empirical foundation to ask them in a more rigorous way.

The comparison between creativity studies and SRL research is particularly important. Research on creativity tends to be interested in the generation of new products whereas research on SRL is interested with how learners plan, monitor, and appraise their work. These two traditions intersect in AI. The generative model allows a student to generate a large number of ideas, the educational value of such ideas rests in the ability of the student to pick, adapt and justify. In that way, the corresponding outcome is originality, as well as, justified originality. Critical thinking, in this capacity, serves as the critical process through which AI-aided idea generation is converted into learning.

Transforming recurrent plots

The recurrence plot displays a variety of graphical characteristics:

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- Initially, observe the continuous line of recurrence that extends along the main diagonal, from the lower-left corner to the upper-right corner of the plot. This is known as the line of identity (LOI). The LOI consistently manifests in the recurrence plot, irrespective of whether the sequence comprises randomly generated values. The line of identity demonstrates all the recurrences at lag 0, which entails comparing each value in the sequence with itself. By definition, every value is the same as itself, thereby affirming its repetitive nature. The implication of this is that, in the context of a recurrence plot, the line of identity does not offer valuable insights into the structure of a sequence, and thus, it should be set aside.

- The recurrence plot displays a symmetrical pattern in relation to the Line of Identity (LOI). The pattern of recurrences in the lower-right triangle of the RP mirrors that in the upper-left triangle, with both reflecting lagged recurrences in the sequence. The patterns are lagged, as analyzing the diagonals to the right and left of the LOI involves examining how the shifting of the sequence by a specific number of certain lags alters the pattern of recurrences.

- Other types of recurrence plots, like a cross-recurrence plot (CRP), lack a line of identity and display distinct patterns of recurrences in the lower-left and upper-right sections of the plot.

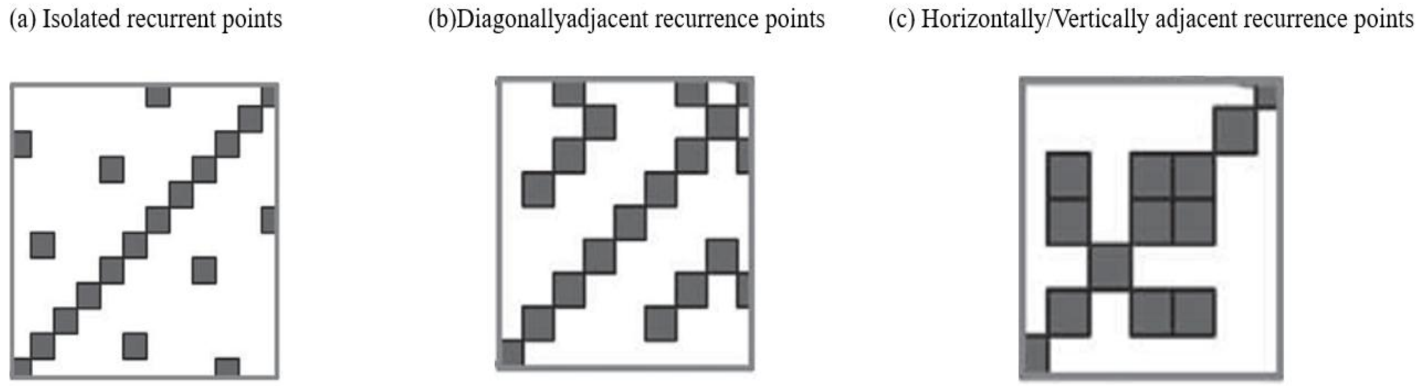

Figure 5. Recurrence plot examples include: (a) Isolated or Random recurring points indicate a distinct relationship between values in a sequence that is not part of a larger systematic pattern within the sequence. (b) Diagonally adjacent recurrence points or chaotic behavior suggest the existence of a subsequence of values within the sequence that reappears at later intervals. (c) Recurrence points that are adjacent either horizontally or vertically indicate that the time series or sequence has attained a stable or gradually changing state.

Among the various metrics that can be established for a recurrence plot, three specific types of patterns are particularly noteworthy. Figure 5 illustrates the recurrence plots corresponding to the three distinct types of RP patterns. Typical patterns in RPs and their meanings and further RQA measures exist, and others are being developed – for the description of additional measure, one can find in (Marwan et al., 2007 and O. Mendes et al., 2017).

IMPLICATIONS

The initial implication is pedagogic. AI must be applied to learning activities which involve both evaluation and production. It is possible to ask students to recognize hallucinations, contrast AI output and academic sources, rewrite weak arguments, and defend final decisions. Such activities turn AI into a generator of answers and an incentive of critical inquiry.

The second implication is methodological. The use of AI should not be seen as a mere independent variable by researchers. The quality of AI-assisted learning will rely on the design of tasks, the level of expertise of the learner, feedback, evaluation criteria, and the institutional policy. Combination of process data and outcome measure should hence be employed in future research. Eye tracking, log tracking, think-aloud protocols and prompt-history analysis could be used to show how students actually control learning as they interact with AI.

The third implication is moral. Education based on AI has to maintain transparency, authorship and the responsibility of the learners. In case students use AI tools, they must reveal the manner in which they used the tools and show their personal comprehension. It is not a compliance issue; it is a component of learning itself.

Accountable use of AI entails that students be answerable to the arguments, evidence, and justifications they present.

LIMITATIONS

These limitations are to be noted. Firstly, the research relied on secondary data, limiting the analysis to its variables and design of the original data. Second, the analysis was based on reported values of questionnaires as opposed to complete psychometric re-validation of the instrument. Third, the application of RQA was exploratory and cannot be taken to be a statement of real- time cognitive dynamics. Fourth, the learners in the university were analyzed and thus the results might not be applicable to school learners, professional learners and other cultures.

CONCLUSION

This paper has explored critical thinking in self-regulated learning as a platform of AI-assisted learning. In exploratory RQA, the analysis of secondary data by Juřík et al. (2025) revealed moderate critical-thinking scores, equal item-level responses, and consistent response patterns. The key premise is that speed, personalization, and content creation should not be considered the sole determining factors in AI-assisted education. It must be examined by its ability to increase the ability of learners to monitor, challenge, critique, and defend their own thought.

The paper is a contribution to the AI-in-education literature because it correlates generative AI, SRL, critical thinking and creativity to a wary empirical context. It also points to a methodological direction of future research: the learning environment based on AI should be investigated within the framework of process sensitive designs that will be able to trace the interaction of students with intelligent systems in the course of time. Technology will not decide the future of AI in education. It will rely on how educators create learning environments where students become active, critical, creative, and accountable learners to themselves.

Recommendations for AI education initiatives in colleges and universities

Shifting Emphasis from Tool Use to Metacognitive Monitoring:

- Instruct students in the art of assessing the biases and limitations of AI output.
- Students should be asked to keep a reflection journal in which they record the times when they identified and fixed an AI mistake that occurred while working on an assignment.

Incorporate AI Ethics into Context:

- Data privacy, intellectual property, and academic integrity regulations should take precedence over broad, overarching values.
- Create coursework that focuses on analyzing failing examples of artificial intelligence (AI) in fields like engineering and medicine.

Combine Step-by-Step Instruction:

- Instead of holding separate, isolated workshops, incorporate progressing AI projects into current core courses for students of all grade levels.
- Construct a four-year competency map in which introductory students learn the fundamentals of verification and advanced students become experts in evaluating autonomous tools.

Data Availability Statement

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The data used in the present study is in the publicly accessible Figshare, as mentioned by Juřík et al. (2025). The current article utilized the chosen information in questionnaires concerning the self-regulated learning and critical thinking.

Ethics Statement

In this research, the publicly available anonymized secondary data were used. Human participants were not used to gather any new data.

Conflict of Interest Statement

The author declares no conflict of interest.

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