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Students' Critical Thinking Disposition in Artificial Intelligence-Assisted Mathematics Learning

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ABSTRACT

Artificial Intelligence (AI) can be used by students to learn and solve math problems in seconds. However, the learning habits of Indonesian students tend to rarely involve the ability to think at a higher level. This study aims to analyze students' critical thinking dispositions in AI-assisted learning based on factor structure and experience category mapping. This study involved students (N=99) at a junior high school in the city of Jambi, Indonesia, so the findings are exploratory and limited to the context of the school. Data were collected using a perception-scale questionnaire on AI-assisted math learning behavior, analyzed with Exploratory Factor Analysis (EFA) and Rasch analysis. The findings identified five factors as the basis of student response patterns associated with critical thinking dispositions in AI-assisted math learning—reflective monitoring, internalization of understanding, passive dependence on AI, critical evaluation, and cognitive load. The mapping results showed that most students rarely experienced cognitive overload or internal understanding. At the same time, only a small percentage routinely performed reflective monitoring and critical evaluation, accompanied by early indications of a tendency toward passive dependence on AI. However, these findings need to be interpreted conservatively given the relatively low reliability of these factors. Based on the difficulty level of item approval in Rasch's analysis, student responses showed inconsistencies in several factors, which could indicate a risk of cognitive passivity; However, these findings reflect the overall difficulty level in item approval, not a direct classification of each student's level of disposition. This is especially true of the passive dependency factor on AI, which has the lowest reliability among the five factors. Therefore, strengthening working memory in AI-assisted mathematics learning requires an emphasis on reflection, evaluation, and justification activities to support knowledge development through internalization.

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1. INTRODUCTION

The development of AI technology and applications makes it easier for students to learn mathematics, including solving mathematical problems and problems quickly [1], [2], [3]. Various AI-based applications are able to help students solve mathematical problems in seconds, as an information provider, facilitate the exploration of knowledge, provide direct explanations of concepts, and provide personalized feedback [4], as well as assist educators and policymakers in the decision-making process [5]. These advances promise a major transformation in the way students learn mathematics, along with the increasing availability of AI-based generative tools in educational settings, while potentially hindering the development of mathematical abilities independently due to the lack of students' cognitive involvement in the thinking and problem-solving processes [6]. In mathematics learning, the use of generative AI is growing, especially in helping explain concepts gradually, presenting problem-solving steps in a structured manner, providing exercises that are in accordance with students' abilities, checking the correctness of solutions, and supporting the problem-solving process through dialogical interaction [7]. It is not surprising that the use of AI in mathematics learning continues to increase significantly, as empirical evidence shows that generative AI is able to have a positive impact on students' mathematics learning, especially in supporting deeper cognitive engagement and adaptive learning [8].

Although often used interchangeably in the literature, mathematical achievement, critical thinking ability, and critical thinking disposition are conceptually distinct constructs, so they need to be explicitly distinguished. Mathematical achievement, as measured by PISA, reflects a student's general academic achievement and does not necessarily directly reflect higher-order thinking or critical thinking skills, as the two are interrelated but distinct constructs. Critical thinking ability refers to what students can actually do when thinking critically (skill dimension), while critical thinking disposition refers to students' tendency to consistently engage in such thinking (dispositional dimension) [9]. These two dimensions are both closely related to metacognition and self-regulation, which is the capacity of students to monitor and manage their own thought processes. AI dependency, or cognitive offloading, which is an action used to reduce the demands of information processing in a task, can inhibit this self-regulation if it occurs excessively [10]. Meanwhile, cognitive load is a condition that can affect this process, although it does not automatically determine whether a critical thinking disposition will arise.

However, behind the rapid development of AI in education, there is a worrying reality regarding the thinking skills of students in some developing countries, such as Indonesia. The results of the 2022 Programme for International Student Assessment (PISA) put Indonesia in an alarming position: Indonesian students' math scores reached 366, down from 379 in 2018, well below the OECD average of 472 points, only 18% of Indonesian students were able to achieve Level 2 or above in mathematics, well below the OECD average of 69%, and almost no students were classified as the best students at Level 5 or 6 [9]. PISA scores only reflect general math achievement, not direct critical thinking disposition. These findings can only be an indirect indication that students are not used to dealing with problems that require high-level thinking skills and still tend to focus on solving

problems procedurally [10]. On the other hand, the results of a study by Susilo et al. [13] and Minarti et al. [14] revealed that students' critical thinking skills tend to improve along with their disposition. In other words, the disposition for critical thinking is also in accordance with the level of students' critical thinking ability [15], [16]. Instead, temuan studi oleh Li et al. [17] reports that an increase does not automatically follow the ability to use AI in critical thinking disposition.

Several studies have discussed the use of AI for students in learning math. Students in school are familiar with AI, but the pattern of using AI in math learning tends to be less productive. Instead of using AI as a means to deepen understanding, students tend to use AI as a shortcut to obtain answers instantly without being accompanied by a meaningful reasoning process [6]. The results of the study by Lapawi et al. [18] reveal that the integration of AI in learning causes an over-reliance on AI that must be overcome. Wang et al. [19] report that the use of AI in problem solving weakens critical thinking dispositions through the perception of dependence. According to Zhai et al. [20], over-reliance on this kind of AI system has been proven to empirically weaken students' cognitive abilities, including critical thinking, decision-making, and analytical reasoning skills that are needed in mathematics learning. This cognitive dependence is cumulative, the more often a student submits the thought process to the AI system, the weaker his critical thinking capacity will be in the long run [21]. Not only critical thinking, but the tendency to apply critical thinking, known as critical thinking dispositions, is also affected [15], [16], [22]. Without proper management, AI integration risks encouraging superficial learning, eroding independent thinking skills, and ultimately inhibiting the development of students' high-level thinking abilities [23].

Learning AI-assisted mathematics has received a lot of attention from researchers. A recent study by Lapawi et al. [18] has discussed the influence of the use of AI in the framework of inquiry on students' computational thinking dispositions and abilities. Tashtoush et al. [24] report that the critical thinking skills of students who participate in learning using AI are significantly improved. In addition, a study by Wu et al. [25] found that students' critical thinking skills improved through the Intelligent Dialogue-Based Approach. Lijie et al. [26] suggest that AI literacy has a positive and significant influence on critical thinking disposition, and ease of use can lead to superficial engagement, inhibiting deep cognitive processing for critical thinking. Then, the identification of bibliometric patterns and various findings regarding the influence of GenAI on students' critical thinking skills by Nasr et al. [27] reveals that its impact is still relatively limited and has not consistently shown how AI supports or limits the development of critical thinking, where AI used in a structured manner and accompanied by guidance is beneficial for the development of critical thinking. However, its passive or non-directional use potentially hinders the development of critical thinking. The development of critical thinking and reducing student involvement in the analysis process. In general, although these studies have uncovered the use of AI on disposition and critical thinking, they leave a more fundamental theoretical question: whether the disposition of critical thinking, as conventionally understood in the context of non-AI learning, takes a different form or structure when students interact with generative AI in math learning. Research that specifically identifies the structure of students' critical thinking dispositions and maps the frequency categories of their experiences in AI-

assisted math learning is still not widely discussed, so this research is important to conduct. Because the structure of students' critical thinking dispositions in the context of AI is not widely known, exploratory approaches such as EFA are more appropriately used than testing predetermined factor models.

This research was conducted to identify the structure of factors that shape students' critical thinking dispositions in AI-assisted mathematics learning. In addition, this study also maps the experience category of students' tendency to think critically based on their experience in using AI in mathematics learning. Through the identification of the structure of factors and the mapping, this study is expected to provide an empirical picture of students' critical thinking dispositions in the context of AI-assisted mathematics learning. This study aims to analyze students' critical thinking dispositions in AI-assisted learning based on factor structure and experience category mapping. This research is expected to contribute to the development of studies on critical thinking dispositions in mathematics learning assisted by AI. In addition, it can also be an informative material in designing AI-assisted mathematics learning that provides a learning experience to students based on factors that shape their critical thinking disposition.

2. METHOD

This study applies a quantitative approach with survey methods and cross-sectional design. This design is used to collect information on how a group's attitude or behavior is regarding a certain variable [28], which in this case is a critical thinking disposition. In this study, the design was used to identify students' critical thinking dispositions in AI-assisted mathematics learning. AI-assisted learning is the context that becomes the specification for instrument items that measure the variable disposition of critical thinking.

Critical thinking disposition refers to a tendency that encourages individuals to consistently use critical thinking when faced with various situations and problems [15], [29]. The indicators of critical thinking disposition used in this study refer to the dimensions formulated by Facione et al. [9] namely: (1) inquisitiveness, intellectual curiosity that encourages individuals to continue learning; (2) systematicity, the ability to think in an organized and directed manner in solving problems; (3) analyticity, the ability to use logical reasoning and evidence accompanied by sensitivity to potential difficulties; (4) truth-seeking, the attitude of seeking accurate information honestly and objectively; (5) open-mindedness, openness to various viewpoints and awareness of self-bias; (6) self-confidence, confidence in one's own reasoning ability in decision-making. In the context of mathematics learning, a critical thinking disposition is reflected in the tendency of students to examine, evaluate, and reflect on the strategies used in solving problems, rather than simply following predetermined procedures [15], [16].

This study involved students (N=99) at one of the State Junior High Schools in Jambi City, Indonesia. Students responded to an 18-item Likert scale about the suitability of their behavior to the indications of a critical thinking disposition. The items were developed based on AI-assisted math learning conditions that are operationally common to students and within the scope of critical thinking disposition indicators. Examples of AI-assisted math learning conditions used in statement items are AI-assisted geometry shape visualization, AI

explanation of mathematical concepts, AI-assisted problem-solving steps, AI-assisted self-paced exercises, AI-assisted solution verification, and comparison of AI-based solution strategies. This is in line with the use of AI in math learning that can provide explanations of concepts, step-by-step completion instructions, feedback, problem-solving support, and personalized learning for students [4]. An example item from the Analyticity dimension is: "I am able to explain the reasoning behind each step of the solution provided by the AI." The items were distributed using questionnaires in the form of paper sheets. The data collection process like this is carried out directly by the researcher by visiting the classroom where the students who are the subject of this study learn mathematics. Questionnaires are distributed to each student in the class during math lesson hours. The researcher assists directly during the questionnaire filling process to ensure that all students understand the filling instructions and each existing statement item, as well as to minimize the possibility of misinterpretation of the statement items in the instrument. After all students finish filling out the questionnaire, the answer sheets are collected again by the researcher before leaving the class.

The data were analyzed by applying Exploratory Factor Analysis (EFA) and Rasch analysis. EFA is used to identify the factors that shape a student's critical thinking disposition. EFA was chosen because this study groups the instrument items into empirically interrelated factors, without first determining the structure of the factors. Analysis of factors suitable for ordered categorical variables was carried out with IBM SPSS Statistics 24 to extract factors so that latent constructs were formed. The feasibility of factor analysis was examined based on the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and Bartlett's Test of Sphericity. The Promax rotation method was chosen in factor analysis, as it allows for correlations between factors, so that oblique rotation is more appropriate than orthogonal rotation. The standard value of the loading factor is more than 0.4 [30], [31]. The result of reducing items into a number of factors is evaluated using Cronbach's alpha reliability coefficient to estimate the internal consistency of each subscale.

Meanwhile, Rasch's analysis was used to map items from each factor into the category of critical thinking disposition experiences based on the logit value of variables, ranging from the most frequent to the least experienced, using Winsteps v3.73. Rasch's analysis allows researchers to understand the difficulty level or generality of each item in an interval measurement scale [32]. Several outputs, such as logit values and reliability of items and persons, including separation index, mean (M), and standard deviation (SD), are used as the basis for forming categories with each Logit Value Item (LVI) interval purposively using $M \pm k \times SD$. The types of categories formed are adjusted to the response in the measurement scale, namely: very rare, rare, occasional, frequent, and very frequent.

3. RESULTS AND DISCUSSION

In the data from the study, the KMO and Bartlett's tests were applied to identify whether the correlation patterns between items were strong enough to form factors before being extracted into latent constructs. The results are presented in Table 1.

Table 1. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.675
Bartlett's Test of Sphericity	Approx. Chi-Square	455.732
	df	153
	Sig.	0.000

The test results presented in Table 1, based on the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy, show that there are sufficient samples to perform factor analysis. The score of 0.675 is in the medium category, but still meets the minimum requirement of more than 0.50. This indicates that the pattern of relationships between variables is sufficient for factor extraction. Furthermore, the results of Bartlett's Test of Sphericity, with a value of $\chi^2(153) = 455.732$ (p-value<0.001), confirm that the correlation between items is statistically significant, meaning that the correlation matrix is not an identity matrix. The results of this analysis imply that the variables in the instrument are interrelated and can be extracted into several latent factors. The correlation values on the anti-image matrix range from 0.539 to 0.807, and all of them are more than 0.5. With the fulfillment of these two conditions, the next step is to perform factor extraction to identify the structure of the underlying factors of the research instrument.

3.1. Structure of Factors in Critical Thinking Disposition

The results of factor extraction are shown in Table 2, based on the eigenvalues and percentage of variance described.

Table 2. Eigenvalues and total variance

Factor	Initial Eigenvalues			Factor	Initial Eigenvalues		
	Total	% of variance	Cumulative %		Total	% of variance	Cumulative %
1	3.728	20.711	20.711	10	0.667	3.707	81.517
2	2.190	12.168	32.879	11	0.575	3.192	84.709
3	1.864	10.355	43.234	12	0.530	2.946	87.655
4	1.587	8.815	52.049	13	0.473	2.627	90.282
5	1.222	6.791	58.840	14	0.441	2.450	92.732
6	0.981	5.452	64.291	15	0.432	2.402	95.134
7	0.938	5.213	69.504	16	0.346	1.920	97.054
8	0.773	4.292	73.796	17	0.275	1.529	98.584
9	0.723	4.015	77.810	18	0.255	1.416	100.000

Based on Table 2, the extraction results show that there are 5 main components (hereinafter called F1, F2, F3, F4, and F5) that have eigenvalues of more than 1, and together explain 58.840% of the total variance. This five-factor structure effectively represents respondents' perception of the instrument being measured. The residual correlation matrix shows that 75 (49%) of its absolute values are more than 0.05. Field [31] has stated that if the percentage of residual nonredundant with an absolute value of more than 0.05 is below 50%, then the obtained factor model has a good fit with the data. Furthermore, Promax rotation is carried out to clarify and simplify the factor structure. Table 3 shows the results of the analysis of the rotation of these factors.

Table 3. Results of Factor Rotation Using the Promax Method

Code	Loading factor					Factor	Code	Loading factor					Factor
	1	2	3	4	5			1	2	3	4	5	
P1	0.574	-	-	-	-	1	P10	-	0.639	-	-	-	2
P2	-	-	-	0.543	-	4	P11	0.725	-	-	-	-	1
P3	-	-	-	0.661	-	4	P12	0.609	-	-	-	-	1
P4	-	-	0.703	-	-	3	P13	0.710	-	-	-	-	1
P5	-	-	0.746	-	-	3	P14	-	-	-	-	0.517	5
P6	0.612	-	-	-	-	1	P15	-	-	-	-	0.763	5
P7	-	-	-	0.834	-	4	P16	-	-	-	-	0.775	5
P8	-	0.635	-	-	-	2	P17	-	-	0.480	-	-	3
P9	-	0.582	-	-	-	2	P18	-	0.725	-	-	-	2

The results of the factor rotation in Table 3 show five different groups of factors. These results show that the P1 to P18 codes can be grouped into five groups of factors: F1 as the first factor, F2 as the second factor, F3 as the third factor, F4 as the fourth factor, and F5 as the fifth factor. These five factors, namely metacognitive monitoring, internalization, passive dependence, critical evaluation, and cognitive load, need to be explained as to why they are treated as dimensions of critical thinking dispositions, rather than as separate constructs. The disposition of critical thinking is not limited to the instantaneous act of evaluating information. This concept also includes the capacity to reflexively monitor one's own cognitive engagement [33]. In addition, this disposition involves the ability to regulate the cognitive demands of a learning task [34]. In addition, there is also an element of self-restraint from receiving external information prematurely through an active internalization process [35]. In this view, F1, F2, and F4 represent the constructive and engagement-oriented expression of the disposition, while F3 and F5 represent the conditions that limit or allow the emergence of such dispositions, rather than being a core part of them. Therefore, framing the five factors under the umbrella of critical thinking dispositions remains consistent with the self-regulatory conception of this construct, as long as F3 and F5 are understood as boundary conditions, rather than as direct markers of critical thinking itself.

Nonetheless, it is worth acknowledging that this five-factor solution can also be interpreted through a broader framework, namely AI-related cognitive engagement—which includes metacognitive regulation, internalization of knowledge, dependence, critical evaluation, and cognitive burden—rather than merely as a critical thinking disposition. This research maintains a critical thinking framework because it is in line with the theoretical model that underlies the development of the instrument; However, further research needs to empirically test whether these five dimensions are more appropriately explained through the broader cognitive engagement construct. In summary, the five extracted factors showed the following Alpha-Cronbach reliability values: F1 (reflective monitoring, α=0.733), F2 (internalization of understanding, α=0.640), F3 (passive dependence on AI, α=0.195), F4 (critical evaluation, α=0.684), and F5 (cognitive load, α=0.618). These values indicate that F1 and F4 have adequate internal consistency, F2 and F5 are at a moderate level, while F3 shows low reliability and therefore requires more careful interpretation. A detailed description of each factor, including empirical interpretation and its relation to the literature, is presented in the following sections.

F1 is formed from items P1, P6, P11, P12, and P13, with an Alpha-Cronbach reliability value, α=0.733, which identifies student activities when interacting with AI, namely: activation of cognitive schemas, representational elaboration, epistemic evaluation, transfer of analogies and generalizations, and self-learning. Student responses to these five items indicate a tendency toward reflective monitoring patterns for example, students report that they double-check the AI's answers or the results of their own work to assess whether the information or steps provided are logical. This pattern of responses consistently appears in students who report not directly receiving AI solutions, but rather test their mathematical feasibility internally, and ask follow-up questions when their own understanding is not considered to meet satisfactory standards. Because these data were sourced from self-report questionnaires, these findings reflect students' self-perceptions, and the consistency of their actual behavior cannot be ascertained without additional observational data.

This behavior was introduced by Kember et al. [33] as a model of reflective thinking that contains habitual actions, understanding, reflection, and critical reflection. Here, critical reflection is the process of consciously and deeply assessing the assumptions, values, and beliefs that shape the way a person thinks, feels, and acts to produce a more rational and transformative perspective [33]. This factor has also been discussed in the study of Nizaruddin and Kusmaryono [37], which found that critical thinking skills and self-regulation are closely related and interrelated. In the study of Mohammadi et al. [35], it is reported that all components of SRL are strongly associated with the achievement of critical thinking skills. In addition, Zeng et al. [39] have integrated critical thinking into SRL models developed for the purpose of improving metacognitive skills. These findings indicate that some students perceive themselves to have the capacity to self-evaluate AI outputs.

In AI-assisted math learning, students actively connect information with pre-owned knowledge structures. This is the process of activating cognitive schemas that is the foundation for the formation of meaningful knowledge schema connections [40], [41]. More than just accessing visualizations presented by AI, reflective students use these representations as a means of elaboration. They utilize them to explore dimensions of understanding that have not been reached by verbal explanations alone [42], [43]. When AI presents a solution, it turns out that students do not always accept it right away; rather, they test the mathematical feasibility of the results internally—a form of epistemic vigilance that distinguishes active learners from passive recipients of algorithmic information [21], [44]. At a more abstract level, students evaluate whether AI-provided solving patterns have any application to similar problems—a process of structural abstraction that reflects the capacity for analogous transfer across mathematical contexts [45]. Furthermore, when the understanding achieved has not met the internal standards set by themselves, students do not stop, but rather ask follow-up questions—help-seeking actions driven by conscious detection of gaps between actual and targeted understanding [34], [46].

F2 is formed from items P8, P9, P10, and P18, with an alpha-Cronbach reliability value, α=0.640, which discusses student activities after interaction with AI, namely: independent pattern reformulation, deep cognitive elaboration, independent practice as a test of understanding, and procedural-conceptual justification. The students' responses to these four items indicated a tendency for the pattern of internalization of understanding; students

reported not stopping at the acceptance of the AI solution, but rather reformulating the solution pattern independently and using the AI response as a stimulus for deeper cognitive elaboration. Because the reliability of this factor is moderate (α=0.640) and the data are self-reported, generalizations on actual behavior still need to be further validated.

This pattern reflects self-explanation, a strategy that has been shown to increase the simultaneous transfer of conceptual and procedural knowledge [45]. The use of AI responses as stimulus material for deeper elaboration—not just a source of final answer—distinguishes the productive use of AI from passive dependency that risks undermining long-term understanding[6]. This awareness of the limitations of understanding prompts students not to stop after receiving an AI answer, but to experiment with similar questions independently—an action that metacognitively serves to detect the fluency of illusions, i.e. feelings of pseudo-understanding that are not accompanied by the ability to solve problems without help [34]. The culmination of this entire process is the student's ability to articulate the reasons behind each step of the solution that AI provides—a form of justification that integrates procedural and conceptual knowledge into a single coherent and responsible understanding [45]. This entire set of behaviors—from pattern reformulation, deep elaboration, self-practice, to step-by-step justification—collectively represents the internalization of understanding, which is the process by which externally sourced knowledge (AI) is actively integrated into the student's personal cognitive structure through the construction of self-contained meaning, as conceptualized within the self-regulated framework of learning and self-explanation in education Mathematics [43], [45]. According to Álvarez-Espinoza [46], this internalization refers to the stage of information processing in which knowledge from the outside is processed and personalized into individual understanding. This process is demonstrated through the ability to reformulate concepts, apply knowledge independently, and explain the reasons behind a solution.

F3 is formed from items P4, P5, and P17. However, these factors have low reliability, with a Cronbach's alpha value, α=0.195, which addresses the pattern of students' interaction with passive and non-critical AI, namely: neglect of the completion process in favor of final answers, acceptance of solutions without critical evaluation, and vulnerability to irrelevant information interference. The students' responses to these three items indicated a tendency toward a pattern of passive dependence on AI, which is a condition in which students perceive themselves to position themselves solely as recipients of algorithmic outputs without active cognitive involvement. Because the reliability is relatively low (α=0.195) and this data is sourced from self-reports, this pattern is indicative, not conclusive, and its limitations are discussed again in the implications section.

This pattern reflects what in the literature is called cognitive surrender: accepting AI output with minimal supervision and relinquishing cognitive control instead of delegating only a portion of tasks, which interferes with the continuous formation of knowledge[6]. Accepting an AI solution without questioning its validity also reflects a cognitive liberation mechanism of full surrender of thought processes to external systems that has been shown to be negatively correlated with critical thinking and mathematical problem-solving skills[19], [47]. Filtering out irrelevant information that has not been trained in AI responses further leaves students vulnerable to extrinsic cognitive loads, draining working memory and

inhibiting learning efficiency [48]. Collectively, these behaviors are in line with the concept of passive dependence on AI the tendency to accept AI-generated information without performing, examining, or verifying interactions that risk resulting in a fragile illusion of mastery, rather than true understanding, especially given the low reliability of this factor as mentioned earlier [20].

F4 is formed from items P2, P3, and P7, with an Alpha-Cronbach reliability value, α=0.684, which discusses the student's cognitive orientation in critically assessing AI output, namely: an explanatory understanding of the mathematical procedures displayed by AI, epistemic vigilance of the suitability of the concepts presented by the AI with the student's internal understanding, and a comparative evaluation between the completion strategies to determine the most appropriate approach. The students' responses to these three items indicate a tendency in the pattern of evaluation of critical understanding; students report not just following the steps of mechanical AI completion, but actively looking for logical justifications behind each stage of the procedure. These findings indicate that some students perceive themselves to have a fairly good evaluative attitude towards AI output. Because the reliability of this factor is moderate (α=0.684) and the data is self-reported, the actual ability may not be evenly distributed across the student population studied.

In AI-assisted learning, highly engaged students are not just following the completion steps mechanically presented by AI; rather, they are actively seeking to understand the logical justification underlying each stage of the procedure—an orientation that distinguishes learners who build conceptual understanding from those who rely solely on procedural skills, and which is a key marker of high-level cognitive engagement in context Technology-Assisted Learning [50], [51], [52]. In addition, students do not stop at accepting mathematical concepts that AI conveys just like that, but rather actively question whether they are truly aligned with existing structures of understanding—an attitude of epistemic vigilance that is crucial given that over-reliance on AI occurs precisely when users accept AI-generated recommendations without questioning them, which can ultimately result in the erosion of critical thinking and reasoning abilities [20]; even the tendency to outsource thought processes to AI has been shown to empirically mediate a significant weakening of students' critical thinking abilities [50]. At a more complex level, students compare the AI-suggested solution strategy with other approaches that have been mastered before—an act of comparative evaluation that goes beyond the acceptance of a single solution and reflects a critical thinking capacity that allows learners to evaluate AI suggestions more rigorously and adjust their confidence levels proportionally to the AI output in the context of mathematical problem-solving [41], [52]. This entire set of behaviors—from trying to understand the rationale behind the procedures that the AI displays, questioning the fit of its concepts with its own understanding, to strategically comparing them to known alternative solutions—collectively represent the activity of evaluating critical understanding, namely: the learner's ability to consciously assess, verify, and compare AI-generated mathematical content based on standards of reasoning and comprehension conceptualize itself, as conceptualized in a critical thinking framework in the use of AI that emphasizes the importance of learners not only accepting AI output, but actively evaluating and calibrating beliefs about the content they generate [20], [54].

According to Leighton et al. [55], critical comprehension evaluation is a thinking skill that includes the activity of analyzing information, assessing the accuracy of concepts, and comparing different strategies before making a decision or drawing conclusions.

F5 is formed from items P14, P15, and P16, with an Alpha-Cronbach reliability value, α=0.618, which addresses the cognitive problems students experience when interacting with AI, namely: overload due to the integration of several concepts, mental overload due to the length of explanations, and focus disorders caused by visual displays. F5 represents a boundary condition, not a direct marker of a critical thinking disposition. A low cognitive load score on the questionnaire does not directly indicate a strong or weak critical thinking tendency, as this condition may reflect the effectiveness of scaffolding, rather than just surface involvement. This difference can only be approached through its relationship to the internalization factor (F2), and like other factors, these findings remain limited to what students self-report through questionnaires.

In AI-assisted math learning, students often encounter situations where a number of concepts are presented simultaneously in a single explanation, so the mind must process many interdependent elements simultaneously—demands that can directly exceed the natural capacity of working memory as a limited workspace [56]. This condition is exacerbated by the lengthy explanations generated by AI systems: without a systematic instructional structure, students are forced to use cognitive resources not to build understanding, but simply to survive in the midst of an uncontrolled flow of information—an additional form of burden that comes from the way of delivery, not from the complexity of the material itself [57]. In addition, the unstructured visual appearance of the AI interface causes the effect of divided attention, i.e. a condition when students' attention is divided between various non-integrated visual elements, so that the focus on the core of the problem is eroded and the working memory capacity that should be allocated for understanding is actually taken away by the effort to integrate information from dispersed sources [58]. These three conditions—conceptual complexity that exceeds the capacity of the process, unstructured length of explanations, and visual chaos that divides attention—collectively put a student's cognitive system at a critical point that could exceed its tolerance threshold. This factor is in line with the concept described by Sweller [58], namely, cognitive load refers to the overall information processing demands imposed on working memory during learning activities, where a load that exceeds the available capacity will directly hinder the process of building understanding and forming a meaningful knowledge schema. According to Sweller [59], cognitive load is a condition in which a person's working memory capacity is limited in processing information, so that that comprehension can be impaired due to material complexity, excess information, or disruption in the presentation of information.

This separation verifies the hypothetical framework for estimating the loading factor derived from the theoretical model. These five factors—F1 (reflective monitoring), F2 (internalization of understanding), F3 (passive dependence on AI), F4 (evaluation of critical understanding), F5 (cognitive load)—indicate that students perceive the experience of using AI in mathematics learning through these five main domains.

3.2. Students' Critical Thinking Disposition

The following are the results of data analysis that inform how students' experiences shape their disposition to think critically based on the structure of the factors found.

Table 4. Summary of statistics

	Item	Person
N	18	99
Measure (logit)		
Mean	0.00	0.44
Standard deviation, SD	0.46	0.50
Standard Error, SE	0.11	0.05
Separation	3.84	1.45
Reliability	0.94	0.68
Raw variance	20.9%	6.1%
Chi-Square ($\chi 2$)	4599.80	
df	1663	
p-value	0.000	

Based on Table 4, the set of items (N=18) showed excellent psychometric quality, with a reliability coefficient of 0.94 and a separation index of 3.84, indicating that the instrument was able to distinguish respondents at different levels of latent properties into about four statistically different strata. The chi-square test ($\chi^2(1663) = 4599.80$, *p*value<0.001) confirms that the parameters of the items differ significantly from each other, meaning that they are not redundant and collectively cover constructs well.

Furthermore, based on descriptive statistics (M=0.00, SD=0.46, Separation=3.84), five categories of experiences were formed purposively using M±k×SD, including very rare, rare, sometimes, frequent, and very frequent. A summary of the results of the categories is presented in Table 5.

Table 5. Categories of Students' Critical Thinking Disposition Experience

Category	Interval	Code Item (Logit)	N	Factor
Very rare	HVAC > 0.69	P15 (0.75), P16 (0.88)	23	F5
Rare	0.23 ≤ LVI < 0.69	P14 (0.29), P18 (0.32), P17 (0.60)	46	F5, F2
Sometimes	-0.23 ≤ LVI < 0.23	P10 (0.22), P6 (0.08), P8 (0.04), P4 (0.02), P5 (0.00), P12 (−0.03), P9 (−0.08), P1 (−0.15)	23	F1, F2, F3
Frequent	-0.69 ≤ LVI < -0.23	P3 (−0.47), P7 (−0.50), P13 (−0.50), P2 (−0.66)	5	F4, F1, F3
Very frequent	LVI < -0.69	P11 (-0.80)	2	F1

Based on Table 5, the following are known. First, students very rarely experience cognitive overload when learning AI-assisted math. This condition indicates that the explanations provided by AI and the visual display presented are not considered to burden the critical thinking process of students in understanding or solving mathematical problems. Second, students rarely internalize their understanding deeply after receiving an explanation from AI. This is demonstrated by items P14 (logit = 0.29), P17 (logit = 0.60) and P18 (logit = 0.32), which indicate that students have not consistently understood AI explanations that involve many concepts simultaneously, managing additional information that is less relevant to the problem, as well as providing justification for each solution step presented by AI.

Third, students fall into the moderate category in their experience making efforts to build and describe mathematical understanding through the help of AI. This is shown by items P10 (logit = 0.22), P6 (logit = 0.08), P8 (logit = 0.04), P4 (logit = 0.02), P5 (logit = 0.00), P12 (logit = −0.03), P9 (logit = −0.08), and P1 (logit = −0.15) which are in the sufficient category. These results indicate that students have utilized AI to support the learning process, such as connecting material with previous knowledge, independently testing comprehension, and evaluating the patterns of completion obtained. However, this behavior has not been carried out consistently among students. The use of AI functions in learning has also been discussed by X. Liu et al. [61], who found that AI is used in self-regulated learning strategies oriented towards evaluating AI outputs even though they are still unbalanced, because there are other strategies that are still rarely used.

Fourth, students feel that they often make critical evaluations of the information provided by AI. This is indicated by items P2 (logit= −0.66), P3 (logit= −0.47), P7 (logit= −0.50), and P13 (logit= −0.50). These results show that students tend not to receive information from AI directly, but rather try to understand the reasons behind the given solution, compare it with other strategies, and ask follow-up questions when the explanations obtained have not been considered adequate. This skeptical attitude encourages students to actively question the credibility of AI outputs as well as their own cognitive frameworks, attempting to trace the reasoning flow behind the answers given, while comparing those outputs to peer feedback or their own reasoning through a process of repeated reflection [62].

Fifth, students feel that they often verify the results provided by AI before receiving them. This is indicated by item P11 (logit= −0.80). These results show that re-examining the reasonableness and correctness of mathematical solutions is the most common behavior students do when using AI in mathematics learning. Sixth, between very rare and rare, relates to the aspect of deep understanding of AI explanations and the cognitive load that AI use entails. These findings suggest that students are less likely to feel overwhelmed by the information that AI presents. This is in line with Martin et al. [63], who explain that generative AI can reduce cognitive load through the provision of scaffolding so that the learning process becomes more manageable.

Nevertheless, the findings also reveal that students have not shown a strong tendency to deeply understand the explanations provided by AI, especially when the explanations involve multiple concepts simultaneously or require more complex reasoning processes. This ease does not automatically result in deep understanding, as learning involving complex concepts still requires active cognitive engagement and reasoning [64]. This condition is also consistent with the findings of X. Liu et al. [61], which show that although students often use AI to evaluate AI-generated outputs, they still use AI relatively rarely to conduct self-evaluation and reflection on their own understanding.

Seventh, between the rare and very rare categories and the frequent and very frequent categories, there is an imbalance between information processing problems and the development of metacognitive regulation in students' mathematical critical thinking dispositions when using AI. More students rarely internalize their understanding and are cognitively overloaded than students who frequently regulate their metacognitive abilities. Students generally do not experience a high cognitive load when learning AI-assisted math,

so the tendency to process information in depth from the explanations provided by AI is still relatively low. It's worth noting that low cognitive load is not inherently problematic; it may reflect the effectiveness of the scaffolding that AI provides, rather than a surface indication of cognitive engagement. However, in this study, low cognitive load was found to be associated with limited internalization of understanding, so that both conditions simultaneously exhibit efficient but superficial processing patterns, rather than simply indicating cognitive deficits. AI is more often used by students in terms of critical thinking behavior for the purpose of evaluating understanding rather than building or developing their knowledge through internalizing processes. Previous research has also shown that the use of AI in learning is more dominant as a means of metacognitive regulation than as a facilitator of meaningful knowledge formation [61], [65], especially when structured metacognitive support has not been optimized [66], [67].

It is worth noting that the behaviors reported above—such as verifying AI answers, comparing completion strategies, and questioning AI outcomes are entirely based on students' self-reports, rather than direct observations of their actual behavior. This kind of self-reporting data has the potential to be influenced by social attraction bias, i.e. the tendency of respondents to answer based on what is considered socially appropriate, rather than reflecting real behavior [68]. The direct presence of the researcher during the questionnaire filling process is suspected to have strengthened this tendency, considering that respondents realized that they were in a condition of direct observation when giving a response. This condition has the potential to encourage the emergence of a response that is more socially desirable than if the instrument is filled anonymously or without direct supervision. Therefore, these high frequencies of cognitive-positive behaviors need to be interpreted carefully, and ideally further validated through observational data or behavior-based tasks in future studies.

The results of the data analysis revealed that students' critical thinking dispositions in AI-assisted learning are shaped by the metacognitive ability to reflect and evaluate their own thoughts, the ability to internalize knowledge into personal understanding, cognitive load management that enables deep information processing, and the ability to maintain a balance between the use of AI and intellectual independence so that the thought process is not reduced to simply a cognitive dependence on technology. Students' critical thinking dispositions in AI-assisted learning are formed through a balance between cognitive efficiency characterized by low cognitive load, depth of knowledge construction through internalization of understanding [67], self-regulation through reflective monitoring and critical evaluation [50], and the ability to maintain intellectual autonomy amid a tendency to rely on AI [54]. Here, the most decisive factor is not the intensity of use of AI itself, but rather the extent to which students remain in control of their thought processes when interacting with AI. Reflective monitoring is a major reinforcing factor in critical thinking dispositions, while passive reliance on AI is a major inhibiting factor; while low cognitive load will only make a positive contribution if it is followed by adequate internalization of understanding and critical evaluation [53].

4. CONCLUSION

The study concluded that five factors were identified as the basis for the critical thinking disposition of junior high school students in AI-assisted math learning, namely: (1) reflective monitoring, (2) internalization of understanding, (3) passive dependence on AI, (4) critical evaluation, and (5) cognitive burden. These five factors reflect different dimensions of how students interact cognitively with AI in math learning. Students' perceptions of the AI-assisted math learning experience show a tendency that most students rarely experience excessive cognitive load and internalize understanding. At the same time, a small percentage frequently engage in reflective monitoring and critical evaluation, accompanied by early indications of a tendency toward passive dependence on AI. However, these findings need to be interpreted conservatively because the reliability of these factors is relatively low compared to other factors. These findings tentatively indicate that students' critical thinking dispositions have not been fully formed consistently; Despite positive indications, some patterns point to a potential risk of early cognitive passivity—although this interpretation needs to be interpreted with caution, as most rely on the least reliable passive dependency factor (F3) (α=0.195) among the five factors. This condition suggests that the use of AI in mathematics learning tends to encourage surface evaluation activities rather than the construction of deep and meaningful understanding.

This study has some limitations. The sample was limited to one school with a relatively small number of respondents (N=99), so the findings were exploratory with limited generalizability. The design of the study was cross-sectional, so it did not allow causal conclusions or observations of changes in disposition over time. Data were collected through self-reports that could potentially be influenced by social desirability bias, while the heterogeneity of students' experiences with AI had previously been unrecorded and could not be controlled. Some instrument factors, especially passive reliance on AI, show weak reliability and need to be interpreted carefully, and the Rasch analysis used has the potential to store multidimensionality that has not yet been fully explored. Further research is suggested using larger, multisite samples, performing confirmatory factor analysis on independent samples, revising and expanding factor items with weak reliability, and supplementing self-report data with behavior-based math tasks and recording of student interactions with AI. Longitudinal or experimental designs are also suggested to strengthen conclusions regarding the development of students' critical thinking dispositions over time. Therefore, a systematic effort is needed in designing AI-assisted math learning that explicitly encourages students' active cognitive engagement, critical thinking habits, and intellectual independence so that the use of AI can truly contribute to the development of high-level thinking skills.

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