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Analyzing Senior High School Students' Mathematical Connection Ability in Solving HOTS Problems through AI-Assisted Learning

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ABSTRACT

In the era of digital transformation, integrating technology into mathematics instruction remains a critical focus to enhance higher-level cognitive skills. This study is a qualitative research aimed at describing and analyzing high school students' mathematical connection skills in solving Higher-Order Thinking Skills (HOTS) problems through Artificial Intelligence (AI)-assisted Problem-Based Learning (PBL) using ChatGPT, as viewed from high, medium, and low initial mathematical ability. The subjects were nine tenth-grade students at a public high school in Serang Regency, Indonesia, selected through purposive sampling and grouped into three initial ability categories. Data were collected using an initial ability test, classroom observations, a mathematical connection ability test featuring HOTS tasks, and semi-structured interviews. The results revealed that students with high initial ability fully mastered all three indicators of mathematical connections and effectively utilized AI as a reflective discussion partner. Students with medium initial ability demonstrated procedural mastery of connections and used AI to stimulate critical thinking. Conversely, students with low initial ability struggled to demonstrate written mathematical connections and could not leverage AI effectively without direct teacher guidance. The study concludes that AI-assisted PBL can facilitate mathematical connection skills depending on students' initial ability, highlighting that AI integration must be carefully balanced with the teacher's active role as a pedagogical facilitator.

Keywords: AI; HOTS; Mathematical Connection Ability; PBL

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INTRODUCTION

Mathematics is a discipline concerned with logical and systematic reasoning, which underpins the development of modern technology (Kemdikbudristek, 2022). It also provides essential 21st-century skills that integrate critical thinking, creativity, communication, collaboration, and digital literacy (Pramana, 2024). In line with these demands, the National Council of Teachers of Mathematics (NCTM, 2000) formulates five process standards for mathematics learning: problem solving, reasoning and proof, connections, communication, and representation. The connections standard warrants particular attention. It requires that students recognize and use connections among mathematical ideas, undestand how mathematical ideas interconnect and build on one another, and recognize and apply mathematics in contexts outside mathematics (NCTM, 2000). Students will struggle to understand mathematical concepts and meaning when concepts are learned in isolation, because deep mathematical understanding depends on connections among ideas (Stylianides & Stylianides, 2007). The zone of proximal development (ZPD) is the distance between what students can solve independently and what they can achieve with adult guidance or in collaboration with more capable peers (Vygotsky, 1978). Therefore, mathematical connection ability cannot be assessed solely from final answers. It must be examined through the thinking processes, strategy selection, representations, and arguments that emerge while students solve problems.

Mathematical connections are closely related to students' ability to solve Higher Order Thinking Skills (HOTS) problems, since HOTS items require students to think analytically, create, and evaluate solutions based on conceptual mastery (Kemendikdasmen, 2025; Rismawati et al., 2022). When students' mathematical connections are weak, they tend to make procedural errors and find challenging problems difficult to solve (Mone et al., 2022; Rumata et al., 2022). The low level of this ability is reflected in the Programme for International Student Assessment (PISA) 2022 results, which show that Indonesian students scored 366 in mathematics, far below the Organisation for Economic Co-operation and Development (OECD) average of 472, with only 18% of students reaching the minimum proficiency level (OECD, 2023). Field observations in senior high schools in Serang Regency reinforce this condition. Of 35 students in class X-2, 77% scored below the Kriteria Ketuntasan Minimal (KKM, minimum mastery criteria) on contextual problems. This suggests that most students have not yet been able to activate their mathematical connections, in contextual problems. Students' mathematical connections may therefore vary, because differences in prior mathematical ability contribute to conceptual understanding outcomes (Hendrayana, 2017). Ausubel (1968) argues that what the learner already knows is the most important single factor influencing learning, and that existing cognitive structure is the most significant variable for acquiring new knowledge. Students with limited prior knowledge tend to struggle to build knowledge relationships and need more time than student with adequate prior knowledge (Hasanuddin, 2020). Consequently, examining students' prior abilities is important so that learning strategies, including those for addressing HOTS problems, can be designed adaptively.

One learning model that can support students in building mathematical connections while solving HOTS problems is Problem-Based Learning (PBL) assisted by Artificial Intelligence (AI) (Aisyah et al., 2022; Noviyana et al., 2025). In PBL, complex real-world problems motivate students to identify and investigate the concepts needed to solve them, and this approach has been shown to have a strong influence on improving HOTS skills (Jailani et al., 2017; Simanjuntak et al., 2021). Scaffolding that adapts to the diversity of students' prior abilities aligns with the ZPD concept (Vygotsky, 1978).

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Scaffolding that provides gradual guidance, feedback, and explanations tailored to learners' needs has been shown to be effective in online learning (Doo et al., 2020; Huang et al., 2024), and AI-based tools may serve this scaffolding function. ChatGPT, a large language model developed by OpenAI, has been shown to solve mathematical problems to a certain extent, although it still struggles to interpret graphical data (Dao & Le, 2023). Its use through well-directed prompts supports in-depth concept exploration and students' reflective thinking processes (Vasconcelos & Santos, 2023). However, research that examines in depth how students' mathematical connections develop, rather than merely their final scores, through the integration of HOTS problems, PBL, and AI as scaffolding remains very limited.

The novelty of this study lies in integrating HOTS problems, PBL, and AI as scaffolding to examine in depth how senior high school students build and activate their mathematical connections, based on high, medium, and low prior ability categories. This combination is rarely investigated in an integrated manner within a single research design (Campo-Meneses et al., 2021; Vasconcelos & Santos, 2023; Yuni et al., 2021). Based on this description, this study aims to:

1. Describe and analyze senior high school students' mathematical connections in solving HOTS problems through AI-assisted PBL, based on high, medium, and low prior ability categories.
2. Describe and analyze the role of AI as scaffolding in the mathematical connection process of students in each high, medium, and low prior ability category.

METHOD

Research Design and Setting

This research uses a qualitative descriptive approach with a case study design, as proposed by Creswell (2012) and Yin (2013). This design was chosen to investigate in depth the thinking processes and the formation of students' network of mathematical connections while they solve HOTS problems with AI assistance (ChatGPT). The study was conducted at one public senior high school in Serang Regency during the 2025/2026 academic year. Learning used the Problem-Based Learning (PBL) model combined with AI as scaffolding.

The use of AI in this study is limited to directed scaffolding that supports students' thinking processes. AI is not a replacement for the teacher, nor a source of final answers. Before interacting with ChatGPT, each student was required to submit an initial prompt that adopts a Socratic approach. The prompt asks ChatGPT to act as an object to be thought about together, stimulating students to reflect on their existing knowledge and refine their understanding, rather than providing direct answers (Vasconcelos & Santos, 2023). Permitted questions include concepts, understanding of the material, general solution steps, and examples of similar problems. Prohibited requests include asking for direct completion of the task and uploading complete photos or screenshots of the student worksheet. AI responses were not used as final answers. Instead, they were first discussed within groups and then rewritten in the students' own language, with teacher guidance to verify the accuracy of the concepts.

Participants, Instruments, and Procedures

Participants of the 35 students in class X-2, 29 took the initial ability test. Six students were absent: two were sick and four were absent without notice. The grouping of students' initial ability was based on the mean ($\bar{x}$) and standard deviation (S) of the total scores of the students who took the test. The complete criteria for grouping the research subjects are presented in the **Table 1.**

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Table 1. Criteria for Grouping Initial Ability

Score	Category
$score > \bar{x} + S$	High
$\bar{x} - S < score \leq \bar{x} + S$	Medium
$score < \bar{x} - S$	Low

Source: Riinawati (2021)
Note: Mean ($\bar{x}$) :44,48 Standard deviation (S) : 19,47

Participants were selected through purposive sampling in four stages: (1) completing the initial ability test; (2) participating actively and consistently in the AI-assisted PBL lessons; (3) submitting complete data on the mathematical connection test; and (4) agreeing to be interviewed. Of the 29 students, 21 submitted complete connection test data, and 8 were excluded due to incomplete data. Of these 21, 12 attended all three PBL meetings consistently and were invited for interviews on 6 March 2026. The remaining 9 were excluded for missing one or more meetings. Three of the 12 interviewees were then excluded because their transcripts were unclear and lacked depth, and they were unwilling to be re-interviewed. The final sample consisted of nine students, three per category.

The primary instrument in this study was the researcher. The supporting instruments were: (1) an initial mathematics ability test; (2) an observation guide for AI-assisted PBL activities; (3) a HOTS-based mathematical connection test; and (4) a semi-structured interview guide. The mathematical connection test consisted of three HOTS essay items on the topics of measures of data dispersion and scatter diagrams. Each item measured one indicator of mathematical connection according to NCTM (2000) at cognitive levels C4 to C6. The first item asked students to analyze the audition scores of a music team using measures of data dispersion and data equity, connected to algebraic inequalities. The second item presented monthly sales data from micro, small, and medium enterprises (UMKM), linking scatter diagrams to the field of economics. The third item used students' attendance and semester grade data, linking scatter diagrams to everyday life.

Each student response was scored on a scale of 0 to 4 using a rubric developed for each item. A score of 0 was given if the student did not answer, did not perform any calculation or analysis, used irrelevant concepts, or provided an answer outside the context of the problem. A score of 1 was given if the answer consisted only of copying data, writing formulas, or a small part of a procedure without a conclusion. A score of 2 was given if the student carried out part of the procedure correctly, for example by calculating the mean or standard deviation, but had not yet determined the number of members meeting the criteria or had not clearly evaluated the conclusion. A score of 3 was given if the student carried out nearly all of the procedure correctly and the conclusion was consistent with the context, although minor errors remained in the steps, rounding, or explanation. A score of 4 was given if all calculations were correct, the conclusion was consistent with the context and based on data, and the explanation was presented in a systematic and clear manner. The test was declared valid in content and empirically, with an r-count greater than the r-table value of 0.374, and it had high reliability with a Cronbach's Alpha of 0.800.

Data collection was carried out in three main stages: preparation, implementation, and analysis. The initial ability test was administered face to face on 24 February 2026. Three PBL meetings with AI assistance were held on 26 February, 2 March, and 4 March 2026. The mathematical connection test was administered on 5 March 2026, and interviews were conducted on 6 March 2026. Observations were carried out during the three classroom meetings.

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Data Analysis

Data validity was tested through method triangulation, comparing written test results, observations, and interviews, and through source triangulation. Data were analyzed using the interactive model of Miles & Huberman (1994), which consists of data reduction, data display, and conclusion drawing. NVivo was used to support coding. Results for each category were compiled from the three students selected per category.

RESULTS

The initial ability test was taken by 29 students of class X-2. Scores ranged from 25 to 90. Applying the criteria in **Table 1**, 4 students were categorized as high, 20 as medium, and 5 as low.

Table 2. Distribution of Students' Initial Ability Categories

Initial Ability Category	Frequency
High	4
Medium	20
Low	5
Total	29

Nine students were designated as the main informants after participating in three AI-assisted PBL meetings and the mathematical connection test. They represent each category equally, as presented in **Table 3.**

Table 3. Research Informants

Code	Category	Initial Ability Score	Mathematical Connection Test Score
ST-1	High	90	83
ST-2	High	90	92
ST-3	High	75	75
SD-1	Medium	60	67
SD-2	Medium	55	67
SD-3	Medium	50	75
SR-1	Low	25	50
SR-2	Low	25	50
SR-3	Low	25	25

Observations were conducted during the three PBL meetings. The first meeting, held on 26 February 2026, addressed measures of data dispersion linked to algebraic inequalities, so the focus was on connections between mathematical topics. Most students identified the relevant concepts only after teacher guidance. ST-2 correctly used an algebraic inequality to determine the range boundaries of the selected members, whereas SR-1 and SR-2 could not explain the relation between dispersion measures and algebra. Relevance to daily life was recognized by only two students, SD-2 and SD-3, who linked the task to selecting a school volleyball team. ChatGPT served mainly as an evaluation tool. ST-3 re-audited his work and found a calculation error in the formula for squared deviations. SD-3 and SR-3

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could not follow the AI's explanation and asked the teacher for confirmation, while SD-2 used the AI's guidance to work more independently. SR-3 did not formulate a conclusion about the relation between concepts.

The second meeting, held on 2 March 2026, addressed scatter diagrams in an economic context, namely managing students' pocket money. Connections with daily life increased substantially, and most students proposed realistic recommendations. ST-2 interpreted the direction of the point distribution to read a negative correlation, and ST-1 and ST-3 linked the solution to the movement of the x and y variables. ST-2 and SR-2 defended their group's answer when it differed from the AI's suggestion. SR-3 found the AI's explanation too complex and asked the teacher directly. No student explained the relations between concepts orally at this stage.

The third meeting, held on 4 March 2026, retained the scatter diagram content but placed it in an environmental context concerning climate and rainfall. Connections with daily life dominated the discussion. ST-1, ST-2, and SR-1 identified that the AI's conclusion had been drawn without rainfall data, and they criticized this conclusion in their worksheets. ST-3 and SD-3 used the AI's output to find that their group's own description of steps lacked detail. SD-1 and SD-2 copied steps from ChatGPT without critical examination. ST-2 stated that the media's conclusion was correct even though she noticed that the data were insufficient. SR-3 did not link the task to daily life and did not formulate a conclusion.

Data analysis began with selecting the necessary data, namely the students' answer sheets for the mathematical connection test and the interview transcripts. The following presents students' mathematical connection abilities in solving HOTS problems based on their initial ability.

High Category (ST-1, ST-2, ST-3)

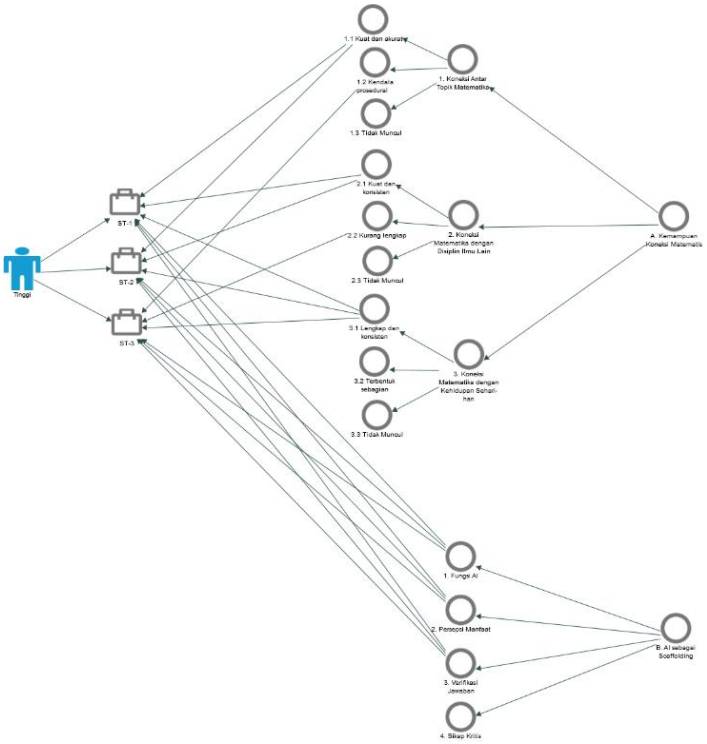

Figure 1. NVivo Coding Results for the High Category

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ST-1 and ST-2 mastered all three indicators. Both integrated statistical formulas into algebraic inequalities to determine the number of members who met the equity requirement, and both explained the reason for this connection in interviews. For the economic task, both calculated the percentage growth in sales and plotted the data on a Cartesian graph. For the attendance policy task, both proposed minimum attendance requirements with reasoned tolerance limits.



Figure 2. Representative written answer of ST-1 on item 1

ST-3 showed a connection between topics but encountered a procedural error in the equity requirement calculation, and did not state a specific number of members in the final answer. ST-3 identified economics only partially, describing the economic task as part of a combined subject rather than a distinct discipline. The policy recommendation was reasoned, but the tolerance limit proposed was not realistic.

All three high-category students used ChatGPT as a scaffold for their reasoning rather than as a source of final answers. ST-1 used the AI to clarify the relation between variables and correlation, and described its contribution as small: the AI indicated which answer to consider, while the solution was reasoned independently. ST-2 requested step-by-step explanations without final answers and used them to check whether the solution was correct, but still consulted the teacher to verify AI responses. ST-3 first completed the calculations independently and then used ChatGPT to evaluate them, comparing the results with the textbook, and reported that the AI helped deepen understanding of the concepts rather than only the sequence of steps. None of the high-category students expressed a critical attitude toward the AI's responses, and none showed confusion about its answers.

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Medium Category (SD-1, SD-2, SD-3)

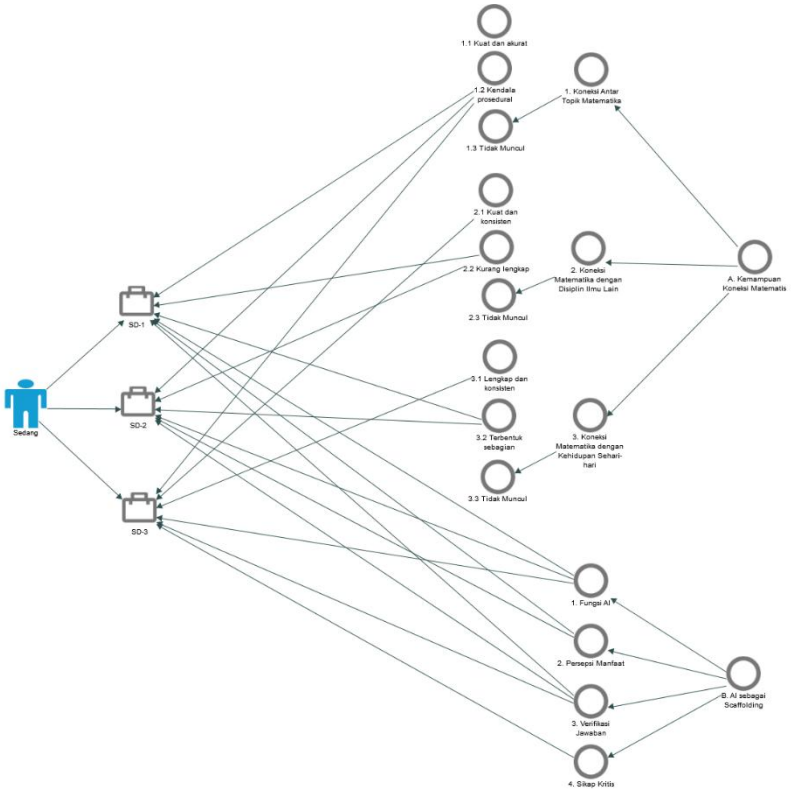

Figure 3. NVivo Coding Results for the Medium Category

SD-1 and SD-2 connected topics at a basic procedural level. Both correctly identified the algebraic inequality to be used, but calculation errors in the term $(x_i - \bar{x})$ led to inaccurate variance and standard deviation values. Both recognized economics as a relevant field in the economic task, but neither evaluated the conclusion of the UMKM owner. In the attendance task, SD-1 and SD-2 produced policy recommendations whose tolerance limits were judged illogical.

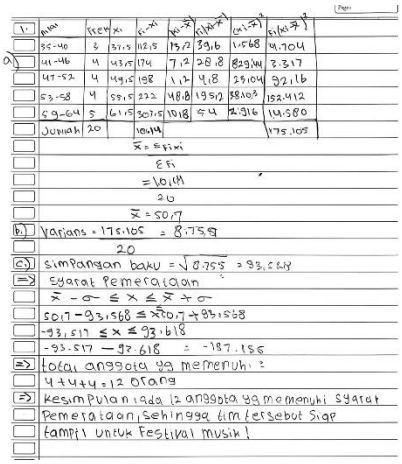

Figure 4. Representative written answer of SD-2 on item 1

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SD-3 identified the algebraic inequality, but misinterpreted the sigma notation and therefore did not complete the conclusion based on the data. SD-3 showed strong and consistent connections with economics in the economic task. In the attendance task, SD-3 gave a realistic policy recommendation with detailed reasons. When asked about the relations between concepts in the first task, SD-3 initially answered that there were none, but later identified the connections between cells in the calculation table.

The medium-category students used ChatGPT in different ways. SD-1 asked the AI for suggestions on solution steps, and when the explanation was unclear, went directly to the teacher. SD-1 preferred face-to-face guidance and explained that typed explanations were harder to understand: “I understand more when someone explains it face to face” (interview). SD-2 used the AI for a single point of difficulty, finding the correlation in the scatter diagram, and valued guidance that gave hints without giving answers: “It doesn’t just give the answer, because we also have to think” (interview). SD-3 used the AI to find the formulas needed for unsolved parts, checked the calculation independently, and asked the AI for corrections before confirming with the teacher. SD-3 found the AI’s responses partly incorrect and concluded that it helped only a little: “It helps a little, but there are still mistakes in it” (interview). SD-3 was the only medium-category student who showed a critical attitude toward the AI.

Low Category (SR-1, SR-2, SR-3)

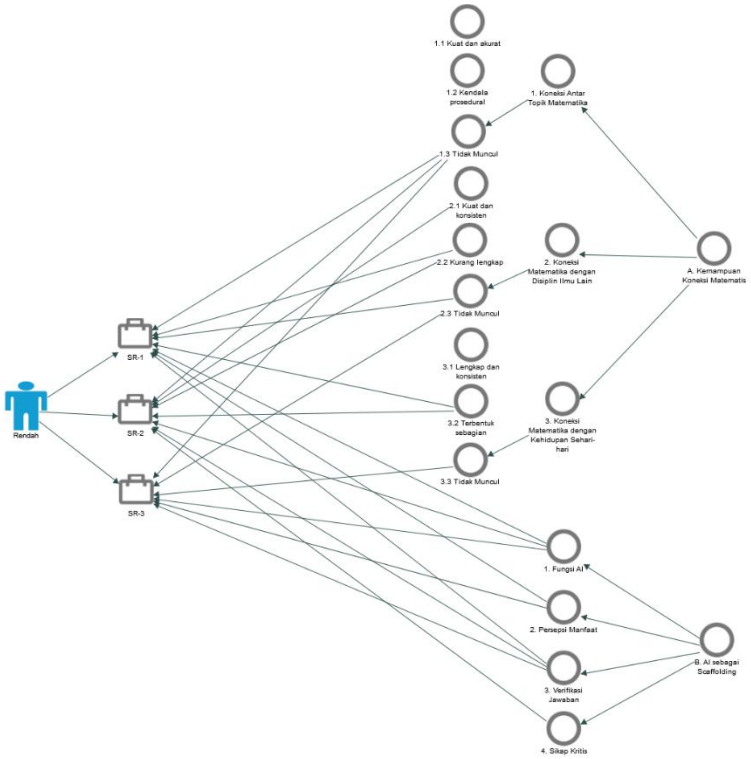

Figure 5. NVivo Coding Results for the Low Category

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SR-1 and SR-2 did not show the connection between topics in their written answers. SR-1 calculated the mean, variance, and standard deviation correctly but did not determine the number of selected members or conclude the team's readiness.

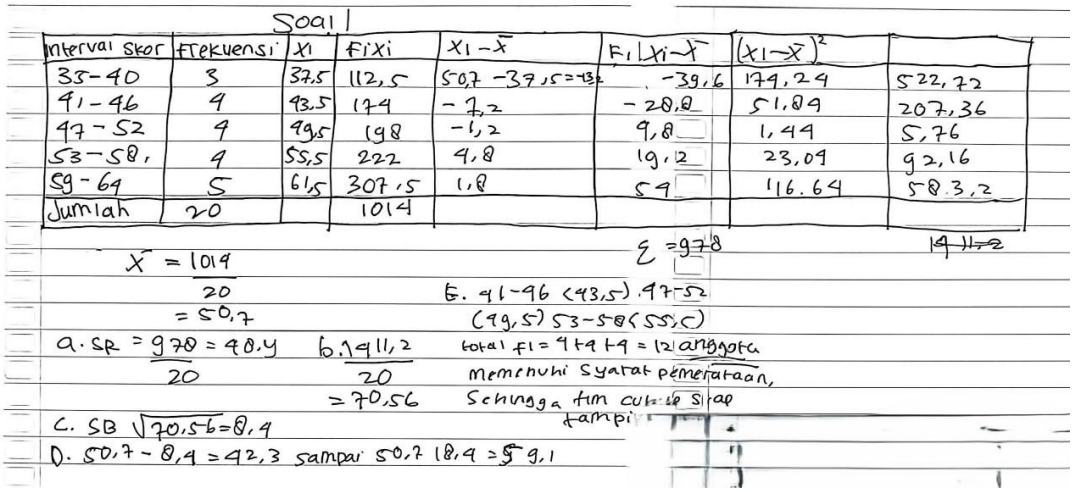

Figure 6. Representative written answer of SR-2 on item 1

In interviews, SR-2 identified algebra as a related topic and explained that the mean must be computed before the equity requirement, but this relation did not appear in the written answer. SR-3 did not show a connection in writing and identified several components of the problem only verbally. In the economic task, SR-2 used the concept of scatter diagrams and linked the task to economics, calculating the sales growth as 36%. SR-1 drew a line graph instead of a scatter diagram and did not determine the variables. SR-3 did not solve the economic task in writing because of time constraints, but verbally identified the connection to economics. In the attendance task, SR-1 identified the correlation without explaining it, and SR-2 and SR-3 did not produce a solution in writing. SR-1 described the attendance problem verbally in terms of attendance percentages and illness or permission, and SR-3 analogized the sales task to managing monthly money.

The low-category students used ChatGPT mainly to obtain guidance on concepts and formulas, and their trust in its answers changed after they found discrepancies. SR-1 first found the AI helpful because it indicated which material and formulas to use. After noticing a difference between the AI's answer and the teacher's, however, SR-1 felt less confident in the AI and found its summaries unclear. SR-2 cross-checked the formulas from the AI against the textbook. When the AI gave different formulas, SR-2 was confused and asked a friend, then moved the verification process into group discussion until the group agreed. SR-2 judged the AI as unreliable: "ChatGPT is not completely correct, and sometimes its answers are far from the question" (interview). SR-3 used the AI minimally, asking only for the root and steps of the calculation, and verified the answers with the teacher. SR-3 did not experience confusion

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because the AI was used so rarely, and considered it helpful mainly because it clarified the order of solution steps: “I know where to start, so I’m not confused” (interview).

The summary below presents each informant’s mastery of the NCTM indicators, based on written answers, interview transcripts, and NVivo coding.

Table 4. Mastery of Mathematical Connection Indicators by Informant

Code	Category	Indicator 1	Indicator 2	Indicator 3
ST-1	High	Mastered	Mastered	Mastered
ST-2	High	Mastered	Mastered	Mastered
ST-3	High	Mastered	Mastered	Mastered
SD-1	Medium	Partial	Partial	Mastered
SD-2	Medium	Partial	Partial	Partial
SD-3	Medium	Partial	Mastered	Mastered
SR-1	Low	Not Shown	Not Shown	Partial
SR-2	Low	Not Shown	Mastered	Not Shown
SR-3	Low	Not Shown	Not Shown	Not Shown

DISCUSSION

High Category

The high-category students mastered the connection indicators most completely. ST-1 and ST-2 mastered all three indicators, while ST-3 mastered the daily-life indicator with weaker argumentation. This pattern is consistent with Ausubel (1968) meaningful learning theory, in which new information is understood when it is linked to existing cognitive structures. Campo-Meneses et al. (2021) similarly found that success in complex problem solving depends on well-formed networks of procedural, representational, and meaning-based connections. For ST-1 and ST-2, these networks appear to support reasoning at the analysis, evaluation, and creation levels.

These students used ChatGPT to validate solution steps, clarify logic, and broaden their argumentation, rather than to obtain final answers. This use fits the concept of scaffolding within the zone of proximal development (Vygotsky, 1978). AI responses serve as material to test against the student’s own reasoning. Vasconcelos and Santos (2023) reported that structured prompts can stimulate reflective thinking, which is consistent with these interactions. All three students verified AI responses independently or with the teacher. Because the supporting evidence comes from higher education (Doo et al., 2020), the principle of adaptive scaffolding is used here as a general guide rather than direct evidence for senior high school students.

Medium Category

The medium-category students connected mathematical topics at a basic procedural level, and their connections with daily life were simple and contextual. Calculation errors affected their variance and standard deviation values, and none evaluated the economic conclusion of the UMKM case. SD-3 was

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the exception, showing consistent connections with economics and realistic policy recommendations, which indicates that this category was not uniform.

Ausubel's theory helps explain the gap between procedural mastery and cross-disciplinary connections. These students had enough schemata to assimilate calculation steps, but those schemata were not yet integrated enough to support cross-disciplinary understanding. Pambudi (2020) found that weaknesses in problem solving often arise from inaccurate linking of mathematical ideas, which matches the errors and weak evaluation observed here. The effect of ChatGPT also varied. SD-3 judged some AI responses partly incorrect, rechecked the calculations, and concluded that the AI helped only a little, which is the clearest case of AI acting as a trigger for critical attitudes. SD-1 and SD-2 relied more on the teacher or copied AI steps without critical examination. The claim that AI consistently encouraged critical attitudes in this category is therefore not supported. Sutrisno et al. (2025) found that the ability to justify AI answers depends on procedural skill and conceptual understanding, which is consistent with the uneven pattern observed here and Halaweh (2023) stresses the continuing role of teachers in responsible AI use.

Low Category

The low-category students showed the weakest written connections. SR-2 computed the mean, variance, and standard deviation correctly but did not write the equity requirement these values were meant to inform (see **Figure 6**). In interview, SR-2 identified algebra as related and explained the order of calculation, so verbal awareness exceeded written representation. This gap is the central finding for this category and is consistent with Ausubel (1968) account, in which new knowledge is understood only when it can be anchored to existing structures. These students appeared to have some concepts available without a stable schema to link them into a coherent model.

Kurnila et al. (2023) and Mataheru (2024) linked weak connection ability to limited representational skill and strategic planning, and the present data fit this account. SR-1 drew a line graph instead of a scatter diagram and did not identify the variables, suggesting difficulty with representation rather than calculation. Sweller (1988) cognitive load theory offers one interpretation: when an authentic PBL task requires several concepts at once, working memory may be overloaded. This explanation is the researchers' interpretation and was not directly observed.

Low-category students' trust in ChatGPT declined after they noticed discrepancies with the teacher's answers or the textbook. SR-2 judged the AI unreliable and moved verification into group discussion, a critical response, but without the mathematical grounding to resolve the discrepancies independently. This matches Sutrisno et al. (2025) finding that students with weak procedural skills struggle to verify AI outputs. Some AI explanations appeared to exceed these students' zone of proximal development (Vygotsky, 1978) and therefore did not function as scaffolding. Without direct teacher guidance, AI assistance was insufficient for this group.

CONCLUSION

Based on the results and discussion, it can be concluded that students' mathematical connections in solving HOTS problems through AI-assisted PBL differ clearly across prior ability categories, both in final outcomes and in the thinking, processes formed during learning. Accordingly, the success of AI-assisted PBL in developing students' mathematical connections depends heavily on students' prior ability, so the use of AI needs to be adjusted to the thinking capacity of each student group. The presence of AI technology does not replace the teacher's role. Instead, it reinforces the teacher's position as an

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active facilitator who monitors, verifies, and guides students so that learning remains oriented toward building independent understanding rather than merely seeking instant answers

DECLARATIONS

Author Contributions: The first author contributed to conceptualization, research design, data collection, analysis, interpretation of results, and manuscript preparation. The second author contributed to conceptualization, research design, analysis, interpretation of results, and manuscript preparation. All authors reviewed and approved the final manuscript.

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Ethics Approval and Consent: This study involved tenth-grade (class X) students of one public senior high school in Serang Regency, conducted with the school's permission (Letter No. 423.6/143/SMA-BRS/2026). Data collection and analysis followed ethical guidelines, and students' data were kept confidential.

Data Availability: The data on students' mathematical connection ability are not publicly available to protect student privacy. They can be requested from the corresponding author with appropriate permission.

Conflict of Interest: The authors declare no conflicts of interest related to this research.

Use of Generative AI: ChatGPT was used as a learning tool within the AI-assisted problem-based learning intervention described in this study. Generative AI tools were also used to assist with drafting, language editing, and structuring the manuscript. The authors reviewed, verified, and revised all content, including references and interpretations, and take full responsibility for this manuscript.

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