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Computational thinking skills of prospective mathematics teachers in an e-handout-supported online learning environment: An exploratory mixed-methods study

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Abstract

Deficiencies in computational thinking (CT) skills among prospective mathematics teachers have been documented across diverse educational contexts, particularly in higher-order calculus topics. This exploratory study describes the CT profiles, comprising decomposition, pattern recognition, abstraction, and algorithmic thinking, of three prospective mathematics teacher students at Universitas Timor enrolled in an e-handout-supported online calculus course. A mixed-methods design combining rubric-based assessment with in-depth interviews was used to examine performance on two problem-solving tasks concerning Riemann sums and the fundamental theorem of calculus. Because only three purposively selected participants were involved, with neither a pre-test nor a comparison group, the findings are descriptive and hypothesis-generating rather than evaluative of instructional effectiveness. Within this small sample, students performed the strongest in decomposition (3.67 out of 4) and algorithmic thinking (3.00), whereas pattern recognition (1.83) and abstraction (1.67) were markedly weaker, particularly on the more conceptual second task. Procedural CT dimensions were therefore more readily displayed than higher-order ones in this setting, although no claim is made about the relative effectiveness of e-handouts. The findings identify design features worth investigating in future studies with larger samples and experimental designs, including visual tools, project-based tasks, and conceptual scaffolding embedded within e-handout materials.

Keywords: algorithmic thinking; calculus; computational thinking; e-handout; online learning; prospective mathematics teachers

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Introduction

The rapid development of digital technology in the Fourth Industrial Revolution (4.0) and Society 5.0 has generated unprecedented demands for sophisticated cognitive abilities in mathematics education (Aboderin & Havenga, 2024; Van den Berg & Verster, 2023). Among these, computational thinking (CT) has emerged as a fundamental competency that transcends mere technical proficiency. Wing (2006) described CT as a cognitive approach enabling individuals to understand, analyze, and systematically resolve problems. The four pillars of CT, namely decomposition, pattern recognition, abstraction, and algorithmic thinking, equip learners to formulate problems in ways solvable by both humans and machines (Lye & Koh, 2014). These skills are increasingly regarded as essential for navigating contemporary society's complex, data-driven challenges (Dolgopolovas & Dagiene, 2021).

Prospective mathematics teachers occupy a dual position: they must master mathematical content while simultaneously developing the capacity to integrate technology into future teaching practice. Research has consistently documented deficiencies in CT skills among this population, attributable to insufficient technology integration in curricula, limited access to technology-based learning resources, and the prevalence of traditional instructional approaches (Hooshyar et al., 2021). This concern is particularly acute in under-resourced regional contexts such as the 3T (*terdepan*, *terluar*, *tertinggal*) regions of Indonesia, where infrastructure constraints further limit students' exposure to technology-enhanced learning.

Empirical evidence from the researchers' own instructional context reinforces this concern. Survey data from the Mathematics Education Study Program at Universitas Timor indicated that 27.59% of students repeated Calculus I and Calculus II during the 2018/2019 and 2019/2020 academic years. This high repetition rate reflects broader difficulties in engaging with abstract calculus concepts, which require sophisticated CT processes. Specifically, understanding Riemann sums demands decomposition and algorithmic reasoning, while the fundamental theorem of calculus requires pattern recognition and abstraction to link derivatives and integrals meaningfully. Examining CT within an e-handout-supported calculus course is significant on two grounds. Theoretically, it clarifies which CT dimensions can be elicited by structured but largely static digital materials and which appear to require richer forms of mediation, thereby refining broad assumptions about the relationship between digital learning media and distinct CT constructs. Practically, in 3T regions where bandwidth and device constraints make e-handouts the most feasible and often the only viable online medium, evidence about their affordances and limits bears directly on how courses and materials should be designed.

Online learning has emerged as a pertinent response to geographic and resource constraints in higher education. Defined as an educational approach employing information and communication technology to deliver instructional content via the internet (Hakim et al., 2023), online learning offers temporal and spatial flexibility, extensive accessibility, and potential for adaptive content (Weihua, 2024). Its advantages include equitable access to quality education across diverse regions (Lowenthal & Lomellini, 2023), flexible scheduling (Bergene et al., 2023), adaptive content tailored to individual needs (Ingkavara et al., 2022), and cost efficiency

(Hudawi, 2020). However, the effectiveness of online learning depends substantially on the quality of the learning media employed.

Electronic handouts (e-handouts) represent a widely adopted media format in mathematics online learning. E-handouts are digital instructional materials designed to deliver structured, goal-aligned content and may incorporate text, images, videos, and interactive elements (Ramadan et al., 2020; Stacy & Cain, 2015). They afford students the flexibility to engage with material at any time and location, enhance engagement through dynamic content (Djono et al., 2024), and promote consistency in content delivery (Tania et al., 2020). In the online learning context, e-handouts serve as flexible, self-directed media that support individual learning processes. Previous studies have demonstrated positive effects of e-handouts on students' critical thinking skills and learning independence in science subjects (Ramadan et al., 2020; Tania et al., 2020), as well as improved student engagement and learning achievement in various educational settings (Djono et al., 2024). However, these studies predominantly examined general cognitive outcomes rather than specific CT dimensions, and were conducted in secondary school science contexts rather than higher education mathematics. Few studies, however, have investigated how e-handout-supported online learning relates to the four CT dimensions among prospective mathematics teachers, particularly in under-resourced regional university settings.

Taken together, the literature leaves three specific gaps. First, e-handout research has been conducted predominantly in secondary school science and has reported aggregate outcomes such as critical thinking, engagement, or achievement, rather than disaggregating performance by CT dimension. Second, studies of CT in mathematics education have concentrated on programming-based or unplugged environments, leaving open what happens when the digital medium is a structured but largely static document. Third, almost no empirical work situates these questions in under-resourced regional universities, where the very constraints that make e-handouts attractive also limit richer alternatives. The present exploratory study addresses these gaps by describing, at the level of individual learners, how the four CT dimensions were manifested by prospective mathematics teachers at Universitas Timor after learning integral calculus through an e-handout-supported online course. Two research questions guided the study: (1) How do prospective mathematics teachers perform across the four CT dimensions on a procedural (Riemann sum) task and a conceptual (fundamental theorem of calculus) task in an e-handout-supported online course? (2) What reasoning processes and difficulties, as reported by the students themselves, accompany the observed performance patterns? Consistent with its exploratory design, the study describes and interprets CT profiles rather than testing the effectiveness of the e-handout as an intervention.

Methods

This study employed a mixed-methods research design, integrating quantitative rubric-based assessment with qualitative in-depth interviews to examine students' CT skills in an e-handout-supported online calculus learning environment. The mixed-methods approach was selected because it enabled triangulation of numerical performance data with students' self-reported

reasoning processes, thereby providing a more comprehensive picture of CT development than either method alone (Creswell, 2014).

Participants were three students enrolled in the Calculus course at the Mathematics Education Study Program, Universitas Timor, Kefamenanu, East Nusa Tenggara, Indonesia. Participants were selected purposively as preliminary informants representing different ability levels within the class (low, medium, and high), based on their prior academic performance. This purposive sampling approach was appropriate for the exploratory nature of the study (Creswell, 2014), though the small sample precludes generalization to broader populations. Data were collected during the second semester of the 2023/2024 academic year.

The decision to work with three participants was deliberate and reflects the exploratory, profile-oriented purpose of the study rather than a constraint of convenience. The unit of analysis was the individual CT profile: each participant produced two complete task solutions scored across four dimensions, together with a transcribed interview, yielding a rich multi-source data set per case. In exploratory mixed-methods work of this kind the aim is analytic rather than statistical generalisation (Creswell, 2014), and a maximum-variation logic, selecting one low-, one medium-, and one high-achieving student, was used to span the ability range present in the class and to make cross-case comparison meaningful. Such a design is adequate for identifying candidate patterns and generating hypotheses about which CT dimensions are and are not elicited in this learning environment; it is not adequate for estimating population parameters or for attributing outcomes to the e-handout, and the findings are reported with that constraint in view.

The e-handout used in this study was developed by the first author in prior work (Ahzan & Simarmata, 2021) and had undergone quality testing for content validity and readability prior to use. The handout covered integral calculus topics including the Riemann sum method and the fundamental theorem of calculus. Students engaged with the e-handout independently as part of their regular online course activities across three learning sessions before data collection.

Two instruments were used for data collection. The first was an analytic scoring rubric assessing CT performance across four dimensions: decomposition (disaggregating a complex problem into manageable components), pattern recognition (identifying recurring regularities or structural relationships), abstraction (filtering irrelevant information to focus on essential elements), and algorithmic thinking (formulating systematic, sequential solution procedures). The rubric was developed in four stages. First, dimension definitions and indicators were derived from established CT frameworks (Lye & Koh, 2014; Wing, 2006) and adapted to the specific mathematical demands of Riemann sums and the fundamental theorem of calculus. Second, a five-level performance scale (0-4) was specified, in which 0 denotes no evidence of the dimension and 4 denotes complete and contextually appropriate application; each level was accompanied by a behavioural descriptor stated in terms of observable features of students' written work. Third, the draft rubric was reviewed by two experts in mathematics education, who evaluated the relevance, clarity, and representativeness of each indicator; their comments led to sharper wording of the descriptors distinguishing level 2 from level 3 and to the addition of task-specific exemplars. Fourth, the revised rubric was trialled on a set of student responses not included in the present analysis. To reduce single-rater bias, all responses were scored

independently by two raters; the few discrepancies that arose were resolved through discussion until full agreement was reached, and the consensus scores are those reported in the Results.

The second instrument was a semi-structured interview protocol administered individually after task completion. The protocol comprised four blocks of questions, one per CT dimension, each opening with a task-referenced prompt (for example, asking students to explain how they had decided on the subintervals they used) and followed by probes concerning the reasoning behind the decision, the alternatives considered, and the points at which the student felt uncertain. A final block addressed students' experience of learning with the e-handout. The protocol was reviewed by the same two experts for clarity and for non-leading phrasing. Interviews lasted approximately 30 to 40 minutes, were conducted in Indonesian, audio-recorded, and transcribed verbatim; excerpts reported here were translated into English and back-checked against the original transcript.

Quantitative rubric data were analysed descriptively. For each participant, scores were reported per dimension and per task; cross-participant means were then computed for each dimension on each task and overall. Given the sample size, no inferential statistics were applied, and means are used only to summarise the pattern visible in the individual scores, which are reported in full in Table 1. Qualitative interview data were analysed through thematic coding. Transcripts were read repeatedly, segmented into meaning units, and coded first with descriptive codes close to the participants' own wording; codes were then grouped into categories aligned with the four CT dimensions and finally consolidated into cross-cutting themes concerning conceptual understanding, reasoning strategies, and sources of difficulty.

Several procedures were used to support the trustworthiness of the qualitative findings. Credibility was addressed through methodological triangulation, in which each quantitative pattern was cross-checked against the interview data, and through member checking, in which a summary of the interpretation of each interview was returned to the participant for confirmation or correction. Dependability was supported by an audit trail documenting coding decisions and their revisions, and by independent coding of the transcripts by a second researcher, with disagreements resolved through discussion. Confirmability was addressed by anchoring every interpretive claim in specific transcript segments and by the first author's reflexive memos, which recorded her dual role as course lecturer and researcher and the steps taken to avoid leading the participants during interviews. Transferability is supported by the description of the setting, the e-handout, and the tasks provided above; readers are nevertheless cautioned that the findings are context-bound.

Results

Summary of student performance

Table 1 presents students' rubric scores across the four CT dimensions for both problem-solving tasks. Student 1, 2, and 3 represent participants at low, medium, and high ability levels, respectively.

Table 1. Student performance scores across CT dimensions and tasks

Student	CT Dimension	Task 1	Task 2	Average
Student 1	Decomposition	4	4	4.0
	Pattern Recognition	3	0	1.5
	Abstraction	2	0	1.0
	Algorithmic Thinking	2	4	3.0
Student 2	Decomposition	4	3	3.5
	Pattern Recognition	4	0	2.0
	Abstraction	4	0	2.0
	Algorithmic Thinking	2	4	3.0
Student 3	Decomposition	4	3	3.5
	Pattern Recognition	4	0	2.0
	Abstraction	4	0	2.0
	Algorithmic Thinking	2	4	3.0

As shown in Table 1, performance varied considerably across CT dimensions and, more strikingly, between the two tasks. All three students scored at or near ceiling on decomposition in Task 1, whereas scores on pattern recognition and abstraction fell to zero in Task 2 for every participant. Algorithmic thinking showed the inverse trend, with modest scores on Task 1 and maximum scores on Task 2. Two features of the tasks help account for this divergence. Task 1, on Riemann sums, is procedurally open but structurally explicit: the partition, the sample points, and the summation are all visible on the surface of the problem, so the regularities students needed to notice were available for direct inspection, while the solution path itself had to be constructed rather than recalled. Task 2, on the fundamental theorem of calculus, is the mirror image: the computational routine is short and well rehearsed, but the relationship that makes the routine legitimate, namely that a definite integral can be evaluated through an antiderivative, is implicit and must be reconstructed by the learner. Students were therefore able to execute Task 2 successfully while showing no evidence of the pattern recognition or abstraction that the task presupposes, and were able to perceive structure in Task 1 while faltering in its procedural execution. Rather than indexing a general level of CT proficiency, the scores appear to reflect the fit between what each task made visible and what these students had had opportunity to practise. The individual profiles reported below, together with the interview data, qualify this reading.

Decomposition

The decomposition dimension yielded the highest overall scores, with a cross-student average of 4.00 on Task 1 (computed as (4+4+4)/3) and 3.33 on Task 2 (computed as (4+3+3)/3), resulting in an overall average of 3.67. These scores indicate that students generally possessed strong capacity to disaggregate complex mathematical problems into smaller, manageable components.

The slight decline on Task 2 arose from students' tendency to partition the integral into unnecessary subintervals without logical justification. As illustrated in Figure 1, one student's response showed that the integral of a single continuous function was divided into multiple

components in a manner that added computational complexity without conceptual value. This error reflects an incomplete understanding of when decomposition is contextually appropriate.

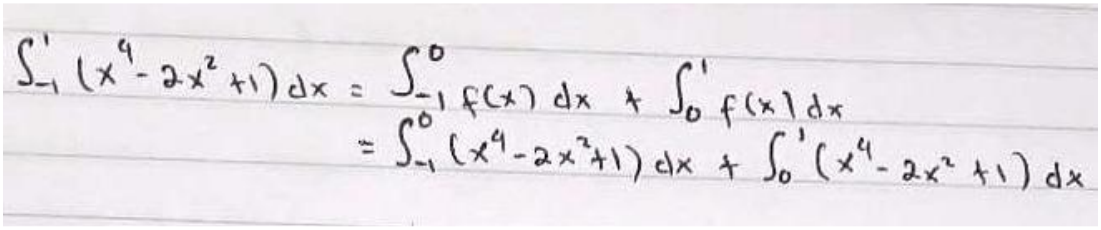


Figure 1. Example of an incorrect response in the decomposition dimension

Pattern recognition

Pattern recognition showed stark divergence between the two tasks. The cross-student average for Task 1 was 3.67, indicating adequate performance in identifying patterns within the Riemann sum context. However, the average for Task 2 was 0.00, as all three students scored zero on the second task. The overall average was 1.83, representing the second weakest CT dimension.

This performance gap reveals that students could recognize explicit, procedural patterns in Riemann sum calculations but were unable to identify the implicit relationship between integrals and antiderivatives required by the fundamental theorem of calculus.

Abstraction

Abstraction was the weakest overall CT dimension, with a cross-student average of 3.33 on Task 1 and 0.00 on Task 2, yielding an overall average of 1.67. Students demonstrated reasonable capacity for abstraction in the more procedural Riemann sum context but entirely failed to condense integral concepts into simplified, calculable forms when dealing with the fundamental theorem of calculus.

Figure 2 illustrates a representative error in the abstraction dimension. A student successfully identified the pattern within the problem structure but was unable to articulate the correct function formula, suggesting the student could perceive the structure but could not translate it into a valid mathematical abstraction.

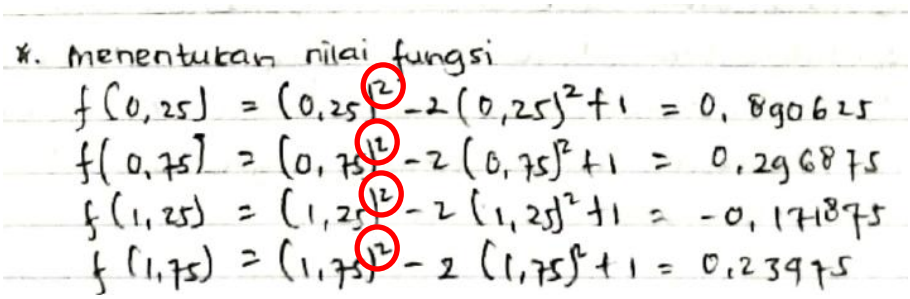


Figure 2. Example of an incorrect response in the abstraction dimension

Note. The handwritten Indonesian phrase "*menentukan nilai fungsi*" in the figure means "determining the value of the function."

Algorithmic thinking

Algorithmic thinking demonstrated an inverse pattern compared to the other three dimensions. The cross-student average was 2.00 on Task 1 but 4.00 on Task 2, producing an overall average of 3.00. This improvement indicates that students were more proficient in formulating systematic, sequential solution procedures when confronted with a structured problem requiring application of the fundamental theorem, compared to the more open-ended Riemann sum task.

The lower score on Task 1 arose from systematic procedural errors, particularly students' failure to define subintervals clearly before proceeding to subsequent steps, as illustrated in Figure 3. This suggests that while students understood the overall algorithmic framework, they struggled with procedural precision in novel applications. The improvement on Task 2 may reflect students' stronger familiarity with the step-by-step procedures associated with antiderivative calculations, even when underlying conceptual understanding was limited.

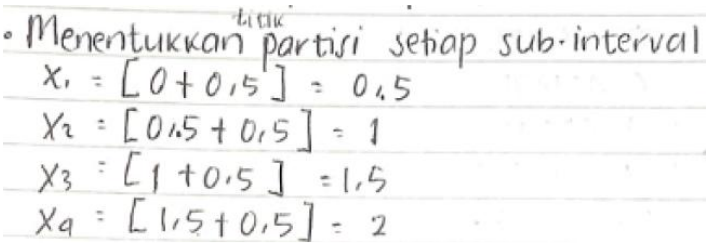


Figure 3. Example of an incorrect response in the algorithmic thinking dimension

Note. The handwritten Indonesian phrase "*Menentukan partisi titik setiap sub-interval*" in the figure means "Determining the partition point for each sub-interval."

Summary of CT dimension averages

Table 2 summarizes the average scores for each CT dimension across both tasks and overall, providing a comparative overview of students' strengths and weaknesses in computational thinking.

Table 2. Summary of average CT dimension scores

CT Dimension	Task 1 Average	Task 2 Average	Overall Average
Decomposition	4.00	3.33	3.67
Pattern Recognition	3.67	0.00	1.83
Abstraction	3.33	0.00	1.67
Algorithmic Thinking	2.00	4.00	3.00

Following the table, the overall pattern indicates that decomposition ranked highest (3.67), followed by algorithmic thinking (3.00), pattern recognition (1.83), and abstraction (1.67). This ranking suggests that students were more proficient in procedural CT dimensions than in conceptual ones, particularly when confronted with abstract calculus problems related to the fundamental theorem of calculus.

Individual computational thinking profiles

Because the sample comprises three cases, the averages above are best read alongside the individual profiles from which they are derived.

Student 1 (lower prior achievement). Student 1's profile was the flattest of the three. Decomposition was fully realized on both tasks (4 and 4), the only participant to sustain it, but this appeared to reflect a habit of systematic listing rather than conceptual selectivity: components were separated correctly, yet without evaluation of whether separation was warranted. Pattern recognition (3, 0) and abstraction (2, 0) were the weakest of the three participants on Task 1 and absent on Task 2. In the interview, this student described the Riemann sum method as comparatively accessible while misreading sample points from the interval notation, indicating that the procedural surface had been learned in the absence of its geometric referent. The profile is that of a learner who can organize a problem but has little conceptual structure around which to organize it.

Student 2 (intermediate prior achievement). Student 2 recorded the highest Task 1 scores on the two conceptual dimensions (pattern recognition 4, abstraction 4) and, like the others, zero on both in Task 2. Decomposition declined from 4 to 3 because the integral in Task 2 was partitioned into subintervals that the problem did not require. The interview showed that this student understood what a Riemann sum represents but struggled to identify appropriate sample points, and could state the steps of antiderivative calculation without connecting them to the idea of accumulation. This profile is the clearest instance of the study's central pattern: conceptual dimensions that are demonstrably available where structure is visible disappear entirely when the same structure has to be inferred.

Student 3 (higher prior achievement). Student 3's scores were numerically identical to those of Student 2 across all four dimensions on both tasks, yet the interview data distinguish the two. Student 3 initially misunderstood the Riemann sum procedure and reached a clearer account only after targeted clarification, suggesting that the score was attained through repair rather than through initial fluency. That the highest-achieving participant required this repair, and that prior achievement conferred no advantage whatsoever on Task 2, suggests that the difficulty encountered with pattern recognition and abstraction was bound up with the task and its instructional preparation rather than with individual student ability. The uniformity of the zero scores across all three participants on Task 2 is itself the most informative feature of the data set.

Qualitative findings from interviews

Thematic analysis of interview data revealed four cross-cutting themes that elaborated and triangulated the quantitative findings.

Conceptual understanding of Riemann sums varied among participants. Student 2 grasped the significance of Riemann sums, correctly articulating the full procedural sequence (determining Delta X, partition points, midpoints, function values, and the Riemann sum itself) earlier in the interview, but struggled to identify appropriate sample points. When subsequently asked how the sample point for a given subinterval had been chosen, this student admitted, "*Ya,*

Bu, saya lupa bagaimana caranya, bagaimana cara cari titik sampelnya?" ("Yes, Ma'am, I forgot how, how do I find the sample point?"), indicating that the procedural sequence had been memorized without a stable conceptual anchor for the sample-point step specifically. Student 1 found the method relatively accessible and correctly recalled and evaluated the formula Delta X = (b − a)/n, but committed errors in reading sample points from the interval notation, writing subinterval bounds as isolated points rather than as proper intervals. The interviewer's observation captures this precisely: "*Berarti memang sudah keliru dalam mengerjakan sub-sub intervalnya ya, tapi rumusnya yang untuk titik sampel itu sudah betul*" ("So there was indeed an error in working out the sub-intervals, but the formula for the sample point itself was correct"). Student 3 initially misunderstood the procedure, repeatedly writing each subinterval as a single numeric value rather than as a bounded interval, until the interviewer clarified: "*Sub-interval itu sendiri juga sebuah interval, bukan satu titik/angka*" ("A subinterval is itself an interval, not a single point or number"). Notably, when later asked to reflect on whether her steps had been systematic, Student 3 spontaneously identified this same earlier error without prompting: "*yang tadi di bagian penentuan sub-interval — seharusnya ditulis sebagai interval [0; 0,5] dan [0,5; 1], bukan angka tunggal*" ("earlier, in determining the sub-interval, it should have been written as the interval [0; 0.5] and [0.5; 1], not a single number"), suggesting that the clarification had been internalized rather than merely echoed in the moment, and developed clearer understanding following targeted clarification. These variations suggest that the e-handout adequately introduced the Riemann sum framework but may not have sufficiently scaffolded the conceptual interpretation of sample points.

Regarding the fundamental theorem of calculus, all students were able to articulate the general procedural steps for antiderivative calculation but encountered difficulty identifying critical structural components, such as determining integration boundaries and connecting the theorem to broader antiderivative relationships. Student 3 illustrated this gap between procedural execution and structural insight: after correctly substituting the upper bound into the antiderivative, she did not proceed to the lower-bound substitution until prompted by the interviewer, who asked, "*Bagaimana dengan batas bawah, 0?*" ("What about the lower bound, 0?"). When later asked which step of the procedure would most need additional explanation for peers, she identified the boundary-substitution step itself — "*hasil integral, dengan x diganti batas atas, dikurangi dengan hasil integral, dengan x diganti batas bawah*" ("the integral result with x replaced by the upper bound, minus the integral result with x replaced by the lower bound") — yet when asked to elaborate on what additional explanation she would give, she could only restate the same procedure: "*Begitu saja, Bu. Tidak ada tambahan lain*" ("That's all, Ma'am. There is nothing else to add"). This pattern — correctly executing the boundary-substitution step while being unable to articulate why it works or how to make it more accessible to others — suggests the procedure was reproduced rather than structurally understood.

Concerning decomposition and subinterval identification, most students understood the formula for computing subinterval length but struggled with the deeper interpretation of interval notation. This fragility extended even to recalling values the student had herself just computed: when asked to restate the sample-point value $\bar{x}1$ for Task 1, Student 1 answered "0.9", which the interviewer immediately corrected to the value actually recorded on the worksheet, 0.25.

Errors in sample point identification were frequent and appeared to stem from incomplete conceptual mapping between the symbolic notation and its geometric interpretation.

Pattern recognition and abstraction were universally described by participants as the most cognitively demanding aspects of the tasks. Students consistently prioritized mechanical, step-by-step procedures over pattern exploration. When asked directly whether noticing a pattern among the computed function values had made the calculation any easier, Student 2 stated: "*Hemat waktu, tidak. Waktu menyelesaikan soal itu, tidak pakai pola-pola. Itu sebenarnya cuma hitung-hitung lurus saja, nanti terakhir baru dilihat*" ("It didn't save time. When solving the problem I didn't use any patterns — I just calculated straight through, and only looked [for a pattern] at the end"). This mechanistic orientation aligns with the quantitative finding that pattern recognition and abstraction collapsed to near-zero performance on the conceptual task. Thematic analysis of interview data revealed four cross-cutting themes that elaborated and triangulated the quantitative findings.

Conceptual understanding of Riemann sums varied among participants. Student 2 grasped the significance of Riemann sums but struggled to identify appropriate sample points. Student 1 found the method relatively accessible but committed errors in reading sample points from the interval notation. Student 3 initially misunderstood the procedure but developed clearer understanding following targeted clarification. These variations suggest that the e-handout adequately introduced the Riemann sum framework but may not have sufficiently scaffolded the conceptual interpretation of sample points.

Regarding the fundamental theorem of calculus, all students were able to articulate the general procedural steps for antiderivative calculation. However, they encountered difficulty identifying critical structural components, such as determining integration boundaries and connecting the theorem to broader antiderivative relationships.

Concerning decomposition and subinterval identification, most students understood the formula for computing subinterval length but struggled with the deeper interpretation of interval notation. Errors in sample point identification were frequent and appeared to stem from incomplete conceptual mapping between the symbolic notation and its geometric interpretation.

Pattern recognition and abstraction were universally described by participants as the most cognitively demanding aspects of the tasks. Students consistently prioritized mechanical, step-by-step procedures over pattern exploration. As one student explained, they preferred "following the steps" rather than looking for structural regularities that could simplify calculations. This mechanistic orientation aligns with the quantitative finding that pattern recognition and abstraction collapsed to near-zero performance on the conceptual task.

Discussion

This study investigated CT skill development among prospective mathematics teachers in an e-handout-supported online calculus course, yielding findings that both corroborate and extend prior research. Taken together, the results reveal a consistent structural pattern: students performed substantially better on CT dimensions that could be accomplished through

procedural execution (decomposition and algorithmic thinking) than on those requiring conceptual abstraction (pattern recognition and abstraction).

The strength observed in decomposition (overall average 3.67 out of 4) is consistent with Rich et al. (2019), who found that procedural decomposition is typically the first CT dimension to emerge among learners encountering formal problem-solving instruction. Students' capacity to break down Riemann sum problems into sequential components appears to be supported adequately by the e-handout's structured content presentation. However, the partial decline in Task 2 decomposition scores, arising from contextually inappropriate decomposition of a single continuous integral, suggests that students' decomposition skills were procedural rather than conceptually grounded. As Popova et al. (2022) observed, over-reliance on mechanical decomposition without evaluating contextual applicability is a hallmark of insufficient mathematical intuition, an area that structured e-handout content alone may not adequately address. This is consistent with more recent evidence that decomposition tends to be the most readily elicited computational thinking dimension among undergraduate learners, regardless of the specific task domain (Zhu et al., 2025).

The near-total failure in pattern recognition (overall average 1.83 out of 4) and abstraction (overall average 1.67 out of 4) on the fundamental theorem task represents the most significant finding of this study. This finding corroborates Rosali et al. (2024), who reported that learning obstacles in CT pattern recognition are particularly severe for abstract mathematical concepts, and Kumala et al. (2023), who found that prospective teachers frequently fail to leverage the antiderivative-integral relationship as a pattern-simplification strategy. Students' inability to identify the implicit relationship between integrals and antiderivatives, as documented in the Results section, further supports this pattern. The lack of visual scaffolding in the e-handout may have exacerbated these difficulties, as Barrón-Estrada et al. (2022) demonstrated that visual tools significantly improve pattern identification in abstract mathematical contexts. Regarding abstraction, the finding that students could perceive problem structure but failed to translate it into valid mathematical abstraction aligns with Ezeamuzie et al. (2022), who noted that abstraction difficulties frequently arise from students' inability to distinguish essential from extraneous elements in novel mathematical contexts. A recent systematic review of abstraction teaching and assessment in K-12 computational thinking education similarly concludes that abstraction is rarely taught as an explicit, assessable skill in its own right, which may help explain why it remains the most fragile CT dimension even among prospective teachers (Oser & Standl, 2025). Tang et al. (2018) similarly linked abstraction deficits to failures in recognizing relational patterns that enable simplification. Bilbao et al. (2021) further identified abstraction as the CT dimension most dependent on instructional support, as it requires learners to move beyond surface-level features and attend to relational structure.

The inverse performance pattern in algorithmic thinking, with lower scores on the Riemann sum task (2.00) but near-perfect scores on the fundamental theorem task (4.00), warrants specific attention. This finding suggests that students developed stronger procedural fluency for antiderivative calculations, possibly because these algorithms are more linear and formulaic than the iterative, context-sensitive procedures required by Riemann sums. This interpretation is consistent with Niemelä et al. (2018), who distinguished between algorithmic

performance on well-defined versus ill-structured problems. The improvement on Task 2 does not indicate broader algorithmic proficiency but rather reflects students' familiarity with a specific algorithmic routine. This distribution of CT skills across problem-solving stages is consistent with recent task-based interview evidence showing that algorithmic thinking and pattern recognition tend to surface during the exploration and implementation stages of mathematical problem solving, whereas abstraction and decomposition are more closely tied to the initial analysis stage (Lehmann, 2025).

Why an e-handout should be associated with procedural rather than higher-order CT dimensions can be reasoned about in terms of what the medium does and does not do. An e-handout is an exposition: it presents worked structure in a fixed, linear, and complete form. Such presentation is well matched to decomposition and algorithmic thinking, because both dimensions consist largely of following and reproducing an ordering that a text can display directly, and because worked examples are effective precisely for acquiring procedural schemas. Pattern recognition and abstraction are not displayable in this way. A pattern becomes a pattern for a learner through comparison across multiple varied instances, and an abstraction is formed by discarding features, which presupposes that the learner has manipulated those features and observed which of them do not matter. A static document can assert that the fundamental theorem links differentiation and integration, but it cannot make the learner vary a bound and watch the accumulated area respond, nor can it withhold a step so that the learner must supply the connecting idea. Two further properties of the medium plausibly reinforce this asymmetry: the absence of feedback means that a procedurally correct but conceptually empty solution is never challenged, which is a limitation also identified by secondary mathematics teachers using digital textbooks, who report that the absence of feedback mechanisms for tests and self-study exercises limits students' ability to learn from their own mistakes (Wijaya et al., 2025), and the completeness of the exposition removes the productive difficulty through which relational understanding is typically constructed. Under these conditions students may reasonably be expected to optimise for what the medium supports and assesses, which is precisely the mechanistic orientation the participants themselves described. This account is an interpretation consistent with the present data rather than a tested explanation; distinguishing it from alternatives, such as insufficient prior knowledge of the fundamental theorem irrespective of medium, would require a design that varies the medium while holding prior instruction constant.

Within the limits of this exploratory design, the findings are consistent with the possibility that the e-handout as used here was associated with the display of procedural CT dimensions while offering little apparent support for higher-order CT skills such as pattern recognition and abstraction. Because no comparison condition was included, this remains a conjecture to be tested rather than a demonstrated limitation of the medium. This is not entirely surprising: e-handouts as traditionally designed are primarily content-delivery media rather than environments that provoke conceptual inquiry. This constitutes the primary novelty of the present study, as prior research on e-handouts in mathematics education has predominantly examined general learning outcomes rather than disaggregated CT dimensions in under-resourced higher education contexts. As directions for future design research rather than as

established remedies, several enrichments of e-handout design merit investigation. One is the incorporation of visualization tools such as interactive graphs and dynamic representations linking integrals to their geometric and antiderivative interpretations (Šiaulys, 2021; Sneider et al., 2014). Project-based learning tasks that require students to develop and justify their own algorithms can reinforce both algorithmic and abstraction skills (Maharani et al., 2019; Ugur & Çakiroglu, 2024), a direction recently reinforced by evidence that design-based learning tasks strengthen computational thinking specifically among preservice elementary mathematics teachers (Tadeu et al., 2025). Collaborative activities in which students explain patterns to peers have also been shown to deepen pattern recognition (Barnes et al., 2018; de Jesus & Silveira, 2022). Finally, process-oriented assessment strategies such as reflective journals and portfolio tasks can make students' reasoning processes visible and promote metacognitive engagement with CT dimensions (Rojas López & García-Peñalvo, 2016).

Conclusion

This exploratory study examined computational thinking skill profiles among three prospective mathematics teachers at Universitas Timor who engaged in e-handout-supported online integral calculus learning. Decomposition and algorithmic thinking emerged as the strongest dimensions, reflecting students' relative proficiency in procedural problem-solving. In contrast, pattern recognition and abstraction were considerably weaker, particularly in conceptual problem contexts involving the fundamental theorem of calculus. Within the limits of a three-participant exploratory design that included neither a pre-test nor a comparison condition, these results suggest that e-handout-supported online learning may scaffold procedural CT competencies more readily than higher-order CT dimensions demanding conceptual engagement with mathematical structure. They do not establish that e-handouts are deficient; rather, they identify specific design features whose contribution warrants examination in future studies.

A tentative practical implication for mathematics educators and e-handout developers is that digital instructional materials may benefit from being enriched with embedded visual tools, guided inquiry tasks, and collaborative problem-solving activities that actively require students to identify, explain, and apply patterns and abstractions. These enhancements are especially critical in under-resourced contexts such as the 3T regions of Indonesia, where e-handouts may constitute the primary or sole instructional medium available to students. These suggestions are best treated as design hypotheses rather than validated prescriptions, and their effects on CT development remain to be tested.

This study has several limitations that should be acknowledged. The purposive sample of three students limits the generalizability of findings, and results should be interpreted as exploratory and hypothesis-generating rather than confirmatory. The absence of a pre-test or comparison condition also means that observed CT profiles cannot be attributed specifically to the e-handout intervention rather than to prior learning experiences. Future research should employ larger and more diverse samples, longitudinal designs, or experimental comparisons to establish more robust evidence regarding the effects of specific e-handout design features on

CT skill development across different calculus topics and student populations. In particular, a design in which comparable groups learn the same calculus content with and without embedded visual and inquiry-oriented features would allow the interpretations offered here to be tested rather than inferred.

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