Analysis of Students' Difficulties in Applying Computational Thinking in Numerical Physics Learning

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Abstract - *Computational thinking skills are essential for numerical physics learning; however, students' mastery of these skills remains considerably below expectations. This study aims to analyze the difficulties experienced by Physics Education students in applying computational thinking to numerical physics learning. A survey research design employing a quantitative descriptive approach was used. Data were collected through a 15-item questionnaire administered via Google Forms to 31 students from the 2022 and 2023 cohorts of the Physics Education program, selected using purposive sampling. The questionnaire demonstrated good reliability, with a Cronbach's alpha coefficient of 0.82, while its content validity was established through expert judgment. Descriptive statistical analysis revealed an overall mean difficulty score of 3.68 on a five-point scale, indicating a relatively high level of difficulty. The highest level of difficulty was found in the conceptual understanding aspect (M = 3.72), particularly in integrating physics theory with computational implementation, whereas the practical application aspect showed a slightly lower mean score (M = 3.63). These findings indicate that students face substantial challenges in both understanding and applying computational thinking in numerical physics contexts. The study provides an empirical basis for improving instruction, particularly through the development of curricula and teaching strategies that more effectively support students' computational thinking competencies in physics education.*

Keywords: *Computational Thinking Skills; Conceptual Understanding; Numerical Physics Learning; Students' Difficulties*

INTRODUCTION

The 21st century is characterized by rapid digital transformation, in which technology has become integral to nearly all aspects of human life, including communication, work, and education (Tucker, 2014). In this context, digital literacy has emerged as a fundamental competency that every individual must possess. However, digital literacy extends beyond the mere ability to operate technological devices. It also encompasses the capacity to think systematically and solve problems using computational approaches (Juškevičienė & DagienĖ, 2018). One of the key frameworks for developing this capacity is computational thinking, as described by DiSessa (2018), which is defined as a fundamental skill for everyone, not just computer scientists, akin to reading, writing, and arithmetic.

The National Science Foundation (NSF) also emphasizes that computational thinking is essential for all individuals in the modern era, as it enables effective and efficient information management through technology (Lee & Malyn-Smith, 2020). In the field of education, computational thinking has gained significant attention as a critical competency for preparing students to face global competition (Belmar, 2022). The National Science Teachers Association (NSTA) asserts that thinking and problem-solving skills must be actively developed in 21st-century learning environments (Szabo et al., 2020). Computational thinking, as a problem-solving approach, enables students to break down complex problems into manageable steps, formulate solutions in a logical and structured manner, and leverage technology to implement those solutions effectively (Yadav et al., 2016).

Seymour Papert first introduced the concept of computational thinking in the 1980s. However, it gained broader recognition through DiSessa's (2018) seminal work, which framed it as a universal skill encompassing problem formulation, abstraction, and algorithmic reasoning. Furthermore, computational thinking trains students to think logically, structurally, and creatively, thereby enhancing their capacity to understand and utilize technology in everyday life (Rao & Bhagat, 2024). Although computational thinking originated within computer science, its application has expanded across various disciplines, including mathematics, social sciences, and the natural sciences (Tekdal, 2021). This expansion aligns with the demands of the Society 5.0 era, where human resources are expected to integrate technological competence with interdisciplinary problem-solving abilities (Poláková et al., 2023). In this context, higher education institutions, particularly physics education programs, play a crucial role in producing teachers who are not only proficient in physics content but also capable of integrating computational approaches into their pedagogical practices (Kotsis, 2025).

The integration of computational thinking into physics education is particularly critical in numerical physics. Numerical physics is a subdiscipline that inherently requires computational methods to solve problems that cannot be addressed analytically. Many physical phenomena, such as chaotic systems, fluid dynamics, quantum-mechanical systems, and electromagnetic field simulations, involve complex differential equations, iterative processes, and large-scale data analysis that require computational approaches for solution (Wang et al., 2024). In learning numerical physics, students are expected not only to understand physical theories but also to translate them into computational algorithms, implement them with programming tools, and critically interpret the results (Odden et al., 2019).

This integration of physics concepts with computational practices constitutes a distinctive challenge that differentiates numerical physics from other physics subdisciplines (Vieyra & Himmelsbach, 2022). Therefore, computational thinking skills, including decomposition, pattern recognition, abstraction, and algorithm design, are not merely supplementary but foundational to mastering numerical physics (Qian & Choi, 2023). Without adequate computational thinking competence, students struggle to bridge the gap between theoretical physics and its computational implementation, leading to difficulties in both understanding and application (Hamerski et al., 2022). This multidimensional demand often overwhelms students, as they must simultaneously master abstract physical concepts, mathematical formulations, computational algorithms, and programming skills within a single learning context (Magana et al., 2017). Consequently, students frequently experience frustration, disengagement, and superficial learning when confronted with numerical physics tasks that require computational thinking.

Despite the recognized importance of computational thinking in physics education, particularly in numerical physics, empirical studies investigating students' specific difficulties in applying it in this context remain limited. Previous research has examined computational thinking in K-12 science education (Wang et al., 2022), its integration into STEM curricula (Lee et al., 2020), and its potential for secondary-level physics learning (Tofel-Grehl et al., 2022).

However, few studies have systematically analyzed the specific challenges faced by university-level physics education students when applying computational thinking to numerical physics courses. Moreover, existing literature tends to focus on the benefits and potential of computational thinking rather than on identifying and measuring the specific obstacles students encounter, particularly in conceptual understanding and practical application (Shute et al., 2017).

This gap is significant because without a clear understanding of these difficulties, instructional interventions cannot be effectively designed to support students' learning needs. The distinct nature of numerical physics, which requires the simultaneous integration of physical theory, mathematical methods, and computational tools, creates unique challenges that warrant dedicated investigation (Kantaros et al., 2025). Students in physics education programs, who are being trained as future physics teachers, must not only overcome these difficulties themselves but also eventually guide their own students in navigating similar challenges. Therefore, understanding the specific difficulties faced by physics education students is essential for improving both their own learning outcomes and their future teaching effectiveness.

Given this background, the present study aims to analyze the difficulties experienced by Physics Education students in applying computational thinking to numerical physics learning. Specifically, this research examines two aspects of difficulty: (1) conceptual understanding, which includes challenges in integrating physics theory with computational concepts, and (2) practical application, which encompasses difficulties in implementing computational tools and algorithms in solving physics problems. By identifying the specific nature and extent of these difficulties, this study seeks to provide an empirical foundation for improving instructional strategies, curriculum design, and pedagogical support in numerical physics education. Ultimately, the findings are expected to contribute to the development of more effective learning environments that foster computational thinking competencies among future physics educators, thereby better preparing them to meet the demands of 21st-century education.

RESEARCH METHODS

General Background

This study employs a survey-based, descriptive quantitative research design to examine the difficulties students experience in applying computational thinking in numerical physics instruction. The present study adopts a descriptive quantitative approach, which is specifically intended to depict the characteristics or status of one or more independent variables without making comparisons or examining causal relationships with other variables. To ensure procedural clarity and reproducibility, the research process is depicted in a systematic flowchart (Figure 1).

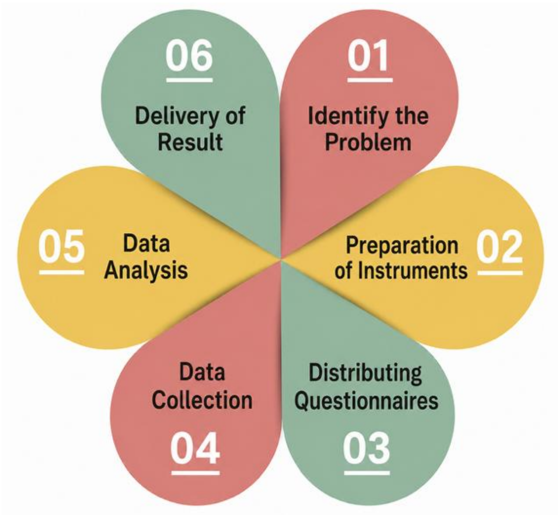

Figure 1. Flowchart of research stages

The flowchart delineates the sequential stages of the investigation, commencing from the initial planning phase and progressing through data collection, processing, and subsequent analysis. Its primary purpose is to provide a clear visual representation of the research workflow, thereby enhancing reader comprehension and facilitating methodological transparency.

Participant

This study involved 31 undergraduate students from the 2022 and 2023 cohorts of the Physics Education program at UIN Sunan Kalijaga Yogyakarta, all of whom had completed or were actively enrolled in the compulsory Numerical Physics course, which provided the substantive context for this investigation. Data collection was conducted over three days from October 27 to October 29, 2024. A purposive sampling technique was employed to select participants based on three inclusion criteria: active registration status in the department, formal exposure to numerical physics content through classroom instruction, and voluntary willingness to complete the entire research questionnaire. This sampling strategy was deliberately chosen to ensure that participants possessed the specific experiential knowledge relevant to the research focus, as purposive sampling is widely recognized as appropriate for studies prioritizing in-depth exploration of a particular phenomenon over broad statistical generalization (Ahmad & Wilkins, 2025).

The relatively modest sample size (n=31) is acknowledged as a limitation regarding statistical generalizability to the broader population of physics education students. However, this decision was consistent with the exploratory-descriptive nature of the research, which aimed not to produce population-level estimates but rather to capture nuanced patterns of difficulty within a specific, homogeneous cohort. The homogeneity of participants who share the same academic program and comparable course progression enhances internal validity by minimizing extraneous variation from curricular or institutional differences, thereby allowing the identified difficulties to be more confidently attributed to the instructional context of numerical physics learning.

Methodological literature supports that sample sizes in the range of 25–30 are often sufficient for descriptive survey research focused on internal consistency and preliminary trend identification (Lund, 2023), reinforcing the adequacy of this sample for the study's primary objective. Consequently, while the findings are not statistically generalizable, they provide a robust empirical foundation for diagnosing specific learning challenges and informing targeted instructional interventions, with the clear recognition that future replication studies employing larger and more diverse samples are essential to test the transferability of these results across broader educational settings.

Instruments and Data Collection Techniques

Data for this study were collected using a closed-ended questionnaire designed to measure students' difficulties in applying computational thinking to numerical physics. The instrument was constructed through a systematic item development procedure grounded in the theoretical framework of computational thinking proposed by Wing (2006) and its subsequent adaptations in physics education contexts (e.g., Hutchins et al., 2020). The initial pool of items was generated based on a comprehensive literature review encompassing four core dimensions of computational thinking relevant to numerical physics: decomposition, pattern recognition, abstraction, and algorithmic thinking, as well as the specific integration of these competencies with physics conceptual understanding and practical application. This initial pool comprised 20 items, which were subsequently refined through a two-stage validation process to ensure both content validity and construct relevance. In the first stage, the preliminary set of items was submitted to three expert judges: two senior physics education researchers with expertise in computational thinking and one practicing numerical physics lecturer, who evaluated each item for clarity, relevance, and representativeness of the intended construct.

Based on their feedback, five items were eliminated due to redundancy or ambiguity, and the wording of several others was revised to enhance precision and alignment with the operational definitions of the measured variables. Content validity was further quantified using the Content Validity Index (CVI), yielding an average CVI score of 0.89, which exceeds the recommended threshold of 0.80 for instrument acceptability (Govindasamy et al., 2024). The final version of the questionnaire consisted of 15 items, each presented as a declarative statement reflecting a specific difficulty experienced by students when engaging with computational thinking tasks in numerical physics. Responses were recorded on a five-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree), with a midpoint of 3 (Neutral), allowing respondents to indicate the degree of their perceived difficulty along a continuum of agreement. To establish the instrument's internal consistency, a pilot study was conducted with 25 students from the same population who did not participate in the main study, and the collected responses were analyzed using Cronbach's alpha.

The analysis yielded an alpha value of 0.82, indicating a high level of internal reliability, as this value surpasses the commonly accepted threshold of 0.70 for exploratory research in educational settings (Pakala & Guniganti, 2026). The questionnaire was administered electronically via Google Forms, which enabled efficient distribution and real-time data collection while minimizing data entry errors. The Google Forms link was distributed through the official WhatsApp group of the Physics Education program to the 2022 and 2023 cohorts, and respondents were given approximately 10 minutes to complete the instrument. This time allocation was deliberately chosen to provide sufficient opportunity for thoughtful reflection on each statement without inducing respondent fatigue, thereby enhancing the quality of self-reported data. Upon completion, the response data were automatically compiled and exported for descriptive statistical analysis, including calculating mean scores and frequency distributions for each item and the instrument overall.

Table 1. Alternative answer score

Alternative Answer	Score
Strongly Disagree (SDA)	1
Disagree (DA)	2
Doubtful (D)	3
Agree (A)	4
Strongly Agree (SA)	5

The procedural transparency established through this detailed account of item development, expert validation, reliability testing, and administration protocol ensures that the instrument is both methodologically sound and replicable, thereby strengthening the credibility of the findings derived from this study. Table 1 presents the complete list of questionnaire items, along with their corresponding computational thinking dimensions and descriptive statistics.

Based on Table 1, the scores for the questionnaire responses completed by the respondents, namely the 2022 and 2023 Physics Education students, were obtained. The questionnaire statements based on practical application are presented in Table 2.

Table 2. List of statements based on aspects of conceptual understanding

Aspect	Statement
Conceptual Understanding	1. It is challenging to integrate the concept of numerical physics with computation.
	2. I need more help understanding how to apply computational thinking to numerical physics learning.
	3. I find it difficult to understand the integration between the theory of numerical physics and computational practice.
	4. I often have difficulty solving numerical physics problems using a computational thinking approach.
	5. I find it hard to understand the relationship between the concept of numerical physics and the concept of computer programs.
	6. It is challenging to apply computational thinking to solve numerical physics problems.
	7. I have difficulty understanding the relationship between physics theory and computational implementation in numerical problems.
	8. I often feel frustrated because I cannot apply computational thinking in formulating and solving numerical physics problems.

Based on Table 2, 8 statements about conceptual understanding describe the difficulties students face in integrating concepts in numerical physics through computational thinking. The questionnaire statements based on practical application aspects are shown in Table 3.

Based on Table 3, 7 statements regarding the difficulties students face in the practical application of computational thinking in numerical physics learning are in the practical application aspect.

Table 3. List of statements based on practical application aspects

Aspect	Statement
Practical Application	1. I need more profound help from the lecturer to understand the concept and implementation of computational thinking in learning numerical physics.
	2. I often face difficulties in designing numerical solutions to physics problems using computational tools.
	3. I find it difficult when asked for simulations or numerical analysis to apply computational thinking in the context of physics learning.
	4. I am not confident in my computational thinking abilities to solve numerical physics lessons.
	5. I find it difficult when asked to carry out simulations or numerical analysis using computing software in learning numerical physics.
	6. I often have difficulty finding learning resources that are clear and easy to understand about learning computational thinking in numerical physics.
	7. I often find it difficult to ask questions to lecturers regarding learning computational thinking in numerical physics learning.Saya memerlukan bantuan lebih dalam dari dosen untuk memahami konsep dan implementasi berpikir komputasi dalam pembelajaran fisika numerik.

Data Analysis Techniques

The data analysis technique in this research is descriptive. Descriptive analysis is a statistical method used to analyze data by describing or depicting the collected data as it is, without intending to draw general conclusions or generalizations. The data obtained in this study are managed as follows: After data collection through questionnaires is complete, the next step is to calculate scores to analyze the results. The data collected from the questionnaire will be automatically integrated and analyzed using the data analysis features available in Google Forms. This feature allows researchers to quickly and efficiently obtain statistical summaries, including the percentage of respondents for each statement. To calculate the average score for each aspect of difficulty, calculate the frequency distribution for each difficulty level. Present the data in tables, bar charts, or pie charts to facilitate interpretation. The data will be processed using SPSS or Microsoft Excel. However, manual calculations can also be performed if necessary to ensure the accuracy and validity of the data.

RESULTS AND DISCUSSION

A survey has been conducted to collect data on the difficulties faced by the 2022 and 2023 cohorts of Physics Education students in applying computational thinking to numerical learning. This survey aims to explore students' opinions and experiences regarding the challenges they face when applying computational thinking in numerical learning. Tables 4 and 5 present survey results on the obstacles students face in applying computational thinking to numerical learning, with a focus on conceptual understanding and practical application.

Survey Results in the Aspect of Concept Understanding

This statement is prepared to identify the difficulties students face in computational thinking related to concept understanding among respondents who are physics education students from the 2022 and 2023 batches.

Table 4. Survey results in the aspect of concept understanding

No	Statements	Presentation				
		SDA	DA	D	A	SA
1	It is challenging to integrate the concept of numerical physics with computation.	0%	9.4%	37.5%	43.8%	6.3%
2	I need more help understanding how to apply computational thinking to numerical physics learning.	0%	6.3%	15.6%	62.5%	12.5%
3	Understanding the integration between the theory of numerical physics and computational practice is challenging.	0%	6.3%	43.8%	40.6%	6.3%
4	I often have difficulty solving numerical physics problems using a computational thinking approach.	0%	6.3%	37.5%	43.8%	9.4%
5	I find it hard to understand the relationship between the concept of numerical physics and the concept of computer programs.	0%	9.4%	37.5%	40.6%	12.5%
6	It is challenging to apply computational thinking to solve numerical physics problems.	0%	0%	43.8%	40.6%	12.5%
7	I have difficulty understanding the relationship between physics theory and computational implementation in numerical problems.	0%	6.3%	40.6%	46.9%	6.3%
8	I often feel frustrated because I cannot apply computational thinking in formulating and solving numerical physics problems.	0%	15.6%	40.6%	25%	12.5%

Based on the results in Table 4, some respondents chose answers on a scale of 3 (neutral) and 4 (agree). The results of this study on conceptual understanding indicate that some respondents still struggle to integrate numerical physics concepts with computational thinking. Some respondents still struggle to solve numerical physics problems using a computational thinking approach. Some respondents frequently encounter difficulties formulating and solving numerical physics problems using computational thinking.

Survey Results in Practical Application Aspects

This statement is prepared to identify the difficulties faced by students in computational thinking in the practical application aspect from respondents who are physics education students of the 2022 and 2023 batches.

Table 5. Survey results in practical application aspects

No	Statements	Presentation				
		SDA	DA	D	A	SA
1	I need more profound help from the lecturer to understand the concept and implementation of computational thinking in learning numerical physics.	0%	6.3%	9.4%	53.1%	31.3%
2	I often face difficulties in designing numerical solutions to physics problems using computational tools.	0%	0%	21.9%	59.4%	12.5%
3	I find it difficult when asked for simulations or numerical analysis to apply computational thinking in the context of physics learning.	0%	0%	21.9%	59.4%	12.5%
4	I am not confident in my computational thinking abilities to solve numerical physics lessons.	0%	6.3%	43.8%	34.4%	15.6%
5	I find it difficult when asked to carry out simulations or numerical analysis using computing software in learning numerical physics.	0%	9.4%	43.8%	31.3%	15.6%
6	I often have difficulty finding learning resources that are clear and easy to understand about learning computational thinking in numerical physics.	0%	18.8%	31.3%	37.5%	9.4%
7	I often find it difficult to ask questions to lecturers regarding learning computational thinking in numerical physics learning.	0%	25%	21.9%	40.6%	9.4%

Based on the results in Table 5, some respondents selected answers on a scale of 3 (neutral) and 4 (agree). The results of this study on practical application indicate that some respondents still require assistance from lecturers to understand the concept and implementation of computational thinking in numerical physics learning. Some respondents still face difficulties when conducting simulations or analyses of numerical physics learning when applying computational thinking. Additionally, some respondents have already found clear and easily understandable learning resources about computational thinking in numerical physics learning.

Discussion

This study aimed to analyze the difficulties experienced by physics education students in applying computational thinking to numerical physics learning. The findings reveal that students encounter substantial challenges across two primary dimensions, conceptual understanding and practical application, with an overall mean difficulty score of 3.68 on a five-point scale. However, reporting these descriptive statistics alone does not illuminate the underlying cognitive and pedagogical mechanisms that produce such difficulties. To move beyond mere repetition of results, this discussion interprets the findings through the lens of computational thinking theory, specifically examining how the four core pillars of CT decomposition, pattern recognition, abstraction, and algorithmic thinking manifest (or fail to manifest) in students' engagement with numerical physics tasks. This theoretical anchoring is essential because computational thinking in physics education is not a monolithic skill but rather a suite of distinct yet interrelated cognitive processes, each of which may present unique obstacles for learners (Sengupta et al., 2013).

The most salient difficulty identified in this study concerns conceptual understanding, particularly the integration of physics theory with computational implementation (M = 3.72). From a CT perspective, this integration requires students to engage in abstraction, the process of distilling essential physical principles from a complex real-world system and representing them in a form amenable to computation (Zhu et al., 2026). Abstraction in numerical physics involves not only identifying the governing equations but also determining which variables are relevant, which boundary conditions apply, and which simplifications can be legitimately made without sacrificing physical fidelity. The finding that 46.9% of students struggled to connect physics theory with computational implementation suggests that their abstraction skills are underdeveloped.

This is consistent with prior research indicating that novices often perceive physics equations as static formulas to be memorized rather than as dynamic representations of relationships that can be manipulated algorithmically (Bai et al., 2026). The difficulty is compounded when students are required to translate a physical phenomenon, such as projectile motion or heat diffusion, into a computational model, as this translation demands not only domain-specific physics knowledge but also the metacognitive ability to evaluate which features of the phenomenon are essential and which are extraneous. In the absence of explicit instruction on abstraction strategies, students may resort to superficial pattern matching, attempting to fit problems into pre-existing templates without genuinely understanding the underlying structure (Ayasrah et al., 2026). This interpretation aligns with the observed high level of difficulty in conceptual integration and points to the need for pedagogical interventions that deliberately scaffold abstraction, such as requiring students to articulate their modeling assumptions before writing any code.

Closely related to abstraction is the pillar of pattern recognition, which emerged as another significant source of difficulty, evidenced by 43.8% of students struggling to solve numerical physics problems using a computational approach. Pattern recognition in CT refers to the ability to identify similarities, regularities, and recurring structures across different problems or datasets (Lindberg, 2020). In numerical physics, this skill is critical because many physical systems share mathematical formalisms. For instance, the same differential equation structure governs oscillations, electrical circuits, and thermal decay. Students who recognize these underlying patterns can transfer computational solutions across domains, thereby reducing cognitive load and accelerating problem-solving. However, the results suggest that students in this study tend to treat each numerical problem as an isolated case rather than as an instance of a broader class of problems.

This fragmentation may stem from the way numerical physics is typically taught, with an emphasis on completing specific programming assignments rather than on developing a conceptual map of recurring computational patterns (Qian & Lehman, 2017). The finding that 40.6% of students had difficulty understanding the relationship between numerical physics concepts and computer programming concepts further corroborates this interpretation, as such relationships are precisely what pattern recognition enables students to perceive. Without explicit training in recognizing cross-problem similarities, students may expend excessive cognitive effort on surface-level features such as variable names or syntax while neglecting the deeper structural analogies that would facilitate transfer (Dasu et al., 2026). Therefore, instruction should incorporate comparative tasks that prompt students to identify common patterns across diverse physics problems and to reflect on how the same computational approach can be adapted to different physical contexts.

Algorithmic thinking, the third pillar of CT, is implicated in the difficulties students encountered with practical application (M = 3.63), particularly in conducting simulations and numerical analyses. Algorithmic thinking involves the ability to specify a sequence of well-defined, executable steps that transform an input into a desired output (Munasinghe et al., 2023). In numerical physics, this translates to designing, implementing, and debugging code that solves differential equations, performs iterative calculations, or visualizes simulation results. The finding that students often lacked the technical skills to use simulation or numerical analysis software and experienced stress and confusion as a result indicates a breakdown in algorithmic thinking at multiple levels. First, students may struggle with decomposition, breaking a complex physical process into discrete, computationally tractable steps, which is a prerequisite for algorithmic design.

For instance, solving a projectile motion problem computationally requires decomposing the motion into time steps, iteratively updating velocity and position, and handling boundary conditions. This sequence may not be intuitively obvious to students accustomed to closed-form analytical solutions. Second, even when students can articulate the steps conceptually, they may encounter difficulties in algorithmic expression, that is, translating those steps into syntactically correct and logically coherent code (Qian & Lehman, 2017). This dual challenge, cognitive decomposition and syntactic implementation, explains why students frequently require extensive assistance from lecturers, as the findings note. The reliance on lecturer support may also reflect the inadequacy of the current curriculum’s time allocation, which appears insufficient to enable students to develop fluency in algorithmic thinking through repeated practice and debugging (Vassallo, 2025).

Research in computing education consistently demonstrates that algorithmic thinking is best developed through deliberate practice with increasingly complex problems, coupled with timely feedback that addresses both conceptual misunderstandings and coding errors (Mills et al., 2025). Consequently, curriculum reforms should allocate dedicated time for guided coding workshops, peer code reviews, and incremental, project-based assignments that progressively build algorithmic competence. The fourth pillar, decomposition, warrants explicit consideration, even though it was not measured directly as a separate item in this study, as it underpins all other CT dimensions. Decomposition, the ability to break a complex problem into manageable subproblems, is implicitly reflected in students' overall difficulty in integrating physics concepts with their computational implementation.

When faced with a numerical physics task, students must decompose the physical system into its constituent components, decompose the computational solution into functional modules, and decompose the overall workflow into stages of model formulation, algorithm design, coding, and validation. The high overall difficulty score (3.68) suggests that this hierarchical decomposition is not occurring automatically. Instead, students may be overwhelmed by the task's holistic complexity, leading to cognitive overload and avoidance behaviors (Koudsia & Kirchner, 2024). This is particularly concerning because effective decomposition is a prerequisite for both abstraction (identifying what to isolate) and algorithmic thinking (sequencing what to execute). Students who cannot decompose a problem meaningfully will inevitably struggle with all subsequent CT processes.

The educational implication is that instruction should begin with explicit training in problem decomposition, perhaps through unplugged activities that focus on breaking down physics scenarios into step-by-step procedures before any programming occurs (de Oliveira et al., 2025). Such scaffolding would reduce cognitive load and equip students with a strategic framework for approaching computational problems, thereby alleviating the anxiety and confusion reported in this study. Beyond the four CT pillars, the findings also reveal important affective and social dimensions that compound cognitive difficulties. A substantial proportion of students reported feeling embarrassed or afraid to ask questions, which hindered communication with lecturers, and limited interaction in large classrooms exacerbated this problem. These affective barriers are not merely peripheral concerns.

They have a direct impact on computational thinking development, as CT is inherently a social and iterative process that thrives on dialogue, questioning, and collaborative debugging (Vassallo, 2025). When students refrain from seeking clarification, they miss critical opportunities to refine their mental models and correct misconceptions. The shame associated with asking seemingly "trivial" questions is particularly counterproductive in computational physics, where foundational misunderstandings such as incorrect loop boundaries or faulty conditional logic can cascade into catastrophic errors in simulation outcomes. This finding resonates with the broader literature on classroom discourse and self-efficacy, which demonstrates that perceived psychological safety is a prerequisite for productive intellectual risk-taking (Mills & Watson, 2021).

To address this, pedagogical interventions should foster a supportive classroom culture that normalizes mistakes as learning opportunities and incentivizes peer-to-peer questioning, perhaps through structured think-pair-share activities or anonymous digital feedback channels (Vedder-Weiss et al., 2018). Furthermore, small-group learning environments could mitigate the anonymity of large lectures, enabling instructors to monitor individual progress and intervene proactively before difficulties become entrenched. The synthesis of these findings through the lens of computational thinking theory yields several important implications for curriculum design and instructional practice. First, the integration of physics theory with computational implementation should not be treated as an add-on or an afterthought but rather as a core competency that requires systematic development across the curriculum.

This entails designing learning progressions that introduce decomposition and pattern recognition early, scaffolding abstraction through guided modeling exercises, and providing extensive opportunities for algorithmic practice with authentic physics problems. Second, assessment practices must evolve to capture not only the final output of computational tasks but also the reasoning processes students employ, perhaps through reflective journals or think-aloud protocols that make their CT strategies visible (Martin & Graulich, 2023). Third, the affective dimensions of learning must be addressed proactively, as students' emotional responses to computational challenges significantly influence their persistence and ultimate success. This may involve integrating collaborative project formats, reducing grading pressures on early coding attempts, and training lecturers to adopt a more facilitative rather than authoritative stance during computational sessions (Hundhausen et al., 2013).

Fourth, given that the difficulties identified in this study are likely not unique to this particular cohort, future research should investigate the transferability of these findings to other institutional contexts and educational levels, employing larger and more diverse samples and potentially incorporating qualitative methods such as interviews or observation to capture the lived experiences of students grappling with computational thinking in physics (Kieser et al., 2023). Additionally, intervention studies that explicitly teach CT strategies and measure their impact on both conceptual understanding and practical application would provide causal evidence to complement the correlational patterns observed here.

CONCLUSION

This study successfully identified the difficulties perceived by physics education students in applying computational thinking to numerical physics learning, revealing that students report relatively high levels of perceived difficulty in both conceptual understanding and practical application, with conceptual integration, particularly connecting physics theory with computational implementation, emerging as the most challenging aspect. However, a critical qualification must be emphasized: what has been measured is students' self-reported perceptions, not their objectively assessed computational thinking competence. High perceived difficulty does not necessarily equate to low actual ability, and any definitive claim about students' objective level of computational thinking would be unwarranted without performance-based assessment data. Beyond cognitive challenges, the study also uncovered significant affective and social barriers, including students' reluctance to ask questions due to fear of embarrassment and the constraints of large-class instruction, underscoring that computational thinking development is shaped not only by cognitive factors but also by classroom culture, self-efficacy beliefs, and emotional responses to challenge. The findings provide an empirically grounded diagnosis of where students struggle most, offering a roadmap for targeted instructional interventions that explicitly scaffold abstraction, pattern recognition, and algorithmic thinking within physics contexts.

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