QUBAHAN ACADEMIC JOURNAL
VOL. 4, NO. 3, July 2024
https://doi.org/10.48161/qaj.v4n3a699

The Analyze Comparative of Physics Computational Thinking Skill (CTs) in Experiment Laboratory

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ABSTRACT: *Objective:* This study aimed to analyze students' response to the use of computational thinking from the perspective of computational tools and to analyze the influence of gender on students' computational thinking skills. *Method:* Research design using a comparative approach with data collection techniques involved a survey using a Likert scale questionnaire comprising 25 items, covering five dimensions of computational thinking skills: abstraction, decomposition, algorithm thinking, evaluation, and generalization. The study subjects involved five classes: physics, physics education, geography, mining engineering, and vocational-technical education, focusing on students' ability to analyze data using JASP and IBM SPSS. The data analyze methods included: (1). Comparative Analyze; (2). Correlation analyzes (Spearman); (3). Chi-square test. *Finding:* The results showed that the computational thinking skills of students from various classes varied, with significant correlations between the skill dimensions. Physics and Physics Education stood out with exemplary achievements, while Geography and Mining Engineering also showed good progress. The vocational-technical education program displayed nearly perfect correlations in all aspects of computational thinking skills. Meanwhile, from the gender aspect, gender significantly influenced computational thinking skills (Sig<0.00). The analyze highlighted the differences in computational thinking skills between classes and the significant influence of gender. *Implication:* This emphasized the importance of developing computational thinking skills in higher education and the need for inclusive approaches to enhance computational excellence among students. The implications of this study give valuable insights for improving the teaching of computational thinking in physics education. Steps that might be addressed include identifying and enhancing weak components, such as abstraction and generalization, and using particular tactics to increase students' knowledge.

Keywords: computational thinking, abstraction, decomposition, algorithm thinking, evaluation, & generalization, experiment.

I. INTRODUCTION

Computational thinking (CT) refers to essential for students in the 21st-century learning era. Computational thinking (CT) is a foundational skill that involves problem-solving using concepts and methods from computer science, can be applied across various disciplines, and is essential for modern education and a technology-driven society[1]. According to Yadav [2], CT is broadly defined as a mental activity involved in abstracting problems and formulating solutions that can be automated, highlighting the importance of integrating CT into K–12 education to develop students' ability to think computationally. Jeannette Wing, who popularized the term CT, described it as an essential analytical skill for all children, including the ability to think abstractly, solve problems systematically, and use computational tools effectively [3]. In physics education, computational thinking improves students' understanding by enabling them to model and solve complex physics problems through computer simulations. This approach allows for creating models that offer a deeper understanding of physical phenomena than conventional methods and simplify problem-solving beyond analytical handling [4]. Computational literacy theory, adapted to physics education, emphasizes material, cognitive, and social aspects, helping to diagnose students' difficulties and tailor educational approaches [5]. Integrating computational thinking into project-based learning helps students develop skills in decomposition, abstraction, and simulation, thus training them to solve problems analytically and precisely [6]. In addition, using computational essays in undergraduate physics education improves computational literacy by identifying students' practices, knowledge, and beliefs. A study also showed that computational thinking interventions significantly improved students' understanding of physics concepts and visual thinking compared to traditional methods [7].

Computational thinking provides several advantages in a variety of sectors. As a problem-solving strategy, it entails developing algorithms that can be implemented as computer code [8, 9]. This concept can be applied to a variety of subjects, including psychology, to improve problem-solving abilities and provide graduates with practical, marketable skills. In education, computational thinking improves critical and analytical thinking, strengthens STEM abilities, enhances pedagogy, and promotes learning through game-based methodologies[10], [11]. However, issues like as instructor comprehension, lack of confidence, and student acceptability must be addressed through teacher training and preparedness. Furthermore, appropriate evaluation and assessment techniques specific to each subject are required [12, 13]. Overall, computational thinking helps students become inventive problem solvers by challenging them to think outside the box and extract relevant elements to generate solutions.

This skill involves systematic, analytical, and creative thinking processes to solve problems like how a computer processes information [14, 15]. In the educational context, computational thinking helps students develop problem-solving abilities, modelling, abstraction, and data representation skills [16, 17]. Students learn to break down problems into smaller parts through computational thinking skills, identify patterns, and design effective solutions [18, 19]. This capability is not limited to computer science but can also be applied across various disciplines and everyday life, such as data processing [20, 21]. In the context of laboratory experiments or practical work, computational thinking serves as a crucial foundation for designing experimental procedures and processing data. Students with computational thinking skills can systematically plan experimental steps, identify relevant variables, and design accurate measurement methods [22, 23]. The application of computational thinking in experiments also involves analytical capabilities to analyze data obtained using algorithms and mathematical models [24, 25]. Understanding abstraction and data representation is critical to effectively interpreting experimental results. Students with computational thinking skills can identify patterns in data, recognize cause-and-effect relationships, and draw conclusions with strong logic [26]. Integrating computational thinking (CT) into physics education significantly enhances student engagement and understanding of complex concepts. CT skills such as problem-solving, abstraction, algorithmic thinking, and data analysis are crucial in modern STEM education. Evidence shows that incorporating CT in physics fosters a deeper grasp of material through hands-on activities and modeling, encouraging active participation [27]. Collaborative modeling-based learning in high school improves theoretical understanding, science process skills, and CT attitudes[28]. CT activities also help students develop methodical problem-solving skills, enhancing critical and creative thinking [29]. Implementing CT in physics leads to better cognitive comprehension and visual thinking [7], while hands-on, inquiry-based, and student- centric approaches further boost engagement and retention of scientific concepts [30]

In addition, in the context of the laboratory, computational thinking can assist students in designing models or simulations. Integrating physical laboratory experiments with computational modeling improves understanding and teaches computational thinking (CT) to engineering students through custom VPython simulations [31]. This approach combines modeling and simulation with disciplinary learning, helping students understand computing tools and their limitations, thus fostering an engineering workforce that supports CT [32] Virtual labs with topics such as electrostatics educate students in the field of CT by providing practical exercises in decomposition, pattern recognition, abstraction, and algorithms [33]. Model-building activities in engineering courses strengthen CT skills more effectively than traditional lectures by improving problem-solving, collaboration, and solution identification [34].

This activity, for example, can be found in the introductory physics practical process 1, where students can use computational methods to design physics experimental simulations that include basic concepts such as motion, force, and energy [35, 36]. Using simulation or computational modelling software, students can create virtual environments that allow them to explore various scenarios of experimental phenomena without relying on physical equipment directly[37, 38]. Examples of applying computational thinking in physics practicum can include creating a parabolic motion model by considering initial velocity, throw angle, and gravitational acceleration[39, 40]. Students can use algorithms to calculate and visualize interactively. By involving students in designing physics simulations, the learning process becomes more exciting and allows for deeper exploration of physics principles [41, 42]. Additionally, students can identify patterns and test their hypotheses efficiently in this simulated environment. Thus, integrating computational thinking in introductory physics practicum 1 increases understanding of concepts and equips students with computational skills practical in various physics/science learning contexts.

However, looking at current conditions, implementing computational thinking skills in the context of physics learning or experiments has yet to be implemented optimally [43]. Considering the conditions, learning physics is closely linked to modeling and simulation. Abstract physics learning that requires visualization is highly essential [44, 45]. Currently, physics or experimental learning emphasizes how to obtain results without considering how the process occurs. It requires special attention, an integral component important for instilling process knowledge in students. This knowledge can be built through a computational thinking skill concept. However, returning to the problem often faced is the lack of willingness and ability of teaching staff to apply computational thinking skills in the learning process [24, 46, 47]. Meanwhile, if we look at the potential and current needs, computational thinking skills involve various aspects of elements that are in line with the demands of 21st-century learning, namely creativity, algorithmic thinking, cooperation, critical thinking, and problem-solving [48– 50]. All these elements are the most important in supporting 21st- century learning today. Apart from the constituent elements of computational thinking skills, which consist of abstraction, decomposition, thinking algorithms, evaluation, and generalization, they also play an important role in establishing the basic pattern of implementing computational thinking skills in learning. Students can generate more effective and innovative solutions for various problems by synergizing these elements. Computational thinking (CT) skills, such as abstraction, decomposition, algorithmic thinking, evaluation, and generalization, are essential to develop effective and innovative problem-solving abilities in an educational setting. Research by Avila et al. [51] proposed an evaluation rubric highlighting these skills, while Shute et al. [52] emphasizing the importance of this in various disciplines. López & García-Peñalvo [53] underlined the importance of these skills in programming education, and Tsai et al. [54] validate a model that emphasizes the development of CT skills sequentially in the curriculum. Integrating these skills in education is essential for developing students' problem-solving abilities.

Abstraction, as the first step in Computational Thinking, helps students to simplify problems and focus on the most relevant aspects [55, 56]. Decomposition allows them to break down significant problems into smaller, manageable tasks [57]. Algorithmic thinking helps students to design solution steps systematically [58, 59], while evaluation allows them to evaluate the effectiveness of the resulting solution. As the final element, generalization helps students relate experiences and understanding from one context to another, enabling a broader understanding transfer. In this way, implementing computational thinking skills in learning involves applying each element separately and requiring the ability to integrate and apply these elements holistically. To effectively teach Computational Thinking, it is important to recognize the interrelated nature of its constituent elements and how they can complement each other. By designing the teaching process with this in mind, students can develop this skill comprehensively. One practical approach is utilizing computational thinking to tackle real-world physics experiments, enabling students to address practical problems and navigate complex challenges.

Research on computational thinking skills in physics practicum still needs to be completed, but several related studies exist. Caballero et al. [60] found that students in an introductory mechanic's course increased their proficiency in computational modeling through specific homework and evaluation approaches. Akmam et al. [29] identified factors that influence critical and creative thinking skills in computational physics, which are closely related to computational thinking. Therefore [61] mention that evaluated students' computational thinking skills in experimental physics classes, finding that the Problem-Based Learning model with Problem Solving Laboratory-based worksheets improved these skills. Meanwhile, Gambrell & Brewe [62] emphasized the importance of including computational thinking in the curriculum. Additionally, Fauzi & Zahroh [63], Tanjung et al. [64], and Weller et al. [41] found that computational thinking is particularly prevalent in secondary education.

More literature needs to delve into the concept of computational thinking in higher education, particularly in the context of practical work on fundamental physics. While several studies have been conducted on this topic, the information provided needs to be more comprehensive to fully explain the application of computational thinking in practical practical work in introductory physics. Consideration of gender factors is essential for optimizing the development of computational thinking skills in education. Research on the influence of gender on computational thinking has revealed a clear gender differentiation, with men playing more roles in this field [65]. It was further supported by research that finds differences in computational thinking skills among novice programmers, with men scoring higher on specific projects [66]. However, the potential of computational thinking to bridge the gender gap in science and technology has been highlighted, particularly in early childhood education [65]. The impact of project type on the evaluation process and its potential to influence the gender gap in computational thinking scores has also been emphasized [66]. These studies collectively underscore the need for further research and development of strategies to promote gender equality in computational thinking.

Therefore, by looking at the potential of CTs in the learning process and how gender influences computational thinking, the author is interested in analyzing students' computational thinking, especially when doing introductory physics practicum. Educators can design more effective learning strategies to develop computational skills by understanding these capabilities more deeply. Using computational thinking skills in physics education will have a particularly positive impact in Indonesia, where this approach is not commonly used. Through this analyze, a foundation can be built for learning management and become a reference for implementing computational thinking in the physics teaching curriculum. The research question in this study are : (1). How the perspective computational thinking skill in experiment of introductory physics 1 practicum? (2). How does gender affect the computational thinking skills of students.

II. LITERATURE REVIEW

1. COMPUTATIONAL THINKING

Computational thinking (CT) is an integral part of computer science and can be applied in various fields, improving the human ability to solve complex problems using computational methods. It covers three main dimensions: understanding computing concepts, applying them through practice, and developing new perspectives. CT involves step sequencing, parallel processing, conditional logic, and data management [67]. Computational thinking (CT) is a problem-solving methodology that combines critical thinking, problem- solving skills, and creativity, resulting in huge profits in several domains. This improves problem-solving abilities by allowing individuals to break complex problems, extract critical components, and create algorithmic solutions, resulting in a more effective and methodical approach [68]. In addition, CT promotes digital literacy, which is important in an increasingly digital society [69]. It also promotes new teaching methods such as game-based learning, which actively engage students and improve their understanding of computational ideas [10]. Therefore, CT provides a variety of advantages, such as improved problem-solving skills, improved educational outcomes, broad practicality, increased digital literacy, and new teaching approaches.

Introducing CT into K-12 education equips students with essential skills for STEM learning, including problem-solving, systems design, and understanding human behavior through computational concepts [3]. Computational Thinking (CT) instructs students in the skills necessary for problem representation, abstraction, decomposition, simulation, verification, and prediction. These skills are essential in science and mathematics [70], [71]. Furthermore, Computational Thinking (CT) includes the ability to analyze problems, develop systems, and understand human behavior using agent-based simulation and modeling techniques [72]. Integrating CT into the K-12 curriculum improves students' analytical skills, problem-solving abilities, and data understanding and interpretation, particularly in STEM fields [73]. Research conducted by [2] found that CT education has the potential to have an impact on the understanding and attitude of pre-service teachers towards the concept of CT. In addition, it can also affect their tendency to incorporate computer principles into their teaching practices in the future. Therefore, the use of CT in K-12 education provides children with essential abilities that enhance STEM learning success. CT is considered as fundamental as reading, writing, and arithmetic, covering abstraction, decomposition, algorithm design, and debugging, which are essential for problem-solving and efficient system design [74]. In addition to computer science, CT supports problem-solving in disciplines such as mathematics and science, providing a conceptual foundation for effective and efficient problem-solving in a variety of contexts [25].

2. COMPUTATIONAL THINKING IN PHYSICS LEARNING

Computational thinking in physics education uses computational tools and ideas to improve knowledge and problem-solving skills. By combining the principles of computer science with the teaching of physics, students can improve their problem-solving abilities and gain a better understanding of physical events. Recent research has identified many important elements and advantages of this integration. The paradigm for evaluating computational thinking skills in physics classes proposes seven indicators: deconstruction, problem reframing, modularity, data representation, abstraction, algorithmic design, and strategic decision- making. This framework allows students to focus on important factors and describe data in a variety of ways, which is essential for understanding and solving complex physics problems [75].

In addition, project-based learning (PBL) has shown efficacy in incorporating computational thinking into physics classrooms. PBL involves hands-on activities that challenge students to dissect problems, develop simulations, and solve problems using algorithmic thinking. These strategies not only improve their understanding of physics topics but also prepare them for real-world application by developing critical thinking and problem-solving skills [76]. Incorporating computational thinking (CT) into physics teaching dramatically improves students' cognitive capacity and problem-solving abilities. Studies have shown that incorporating CT into physics courses improves students' computational thinking and problem-solving skills, as well as providing broader cognitive benefits. For example, online learning resulted in a huge increase in CT abilities among undergraduate students [77]. Similarly, the problem-solving learning approach improves CT skills and self-efficacy of primary school students [78], while the cognitive skills and learning motivation of high school students improved when CT was combined with situational learning strategies in physics [79]. In addition, the use of CT in physics teaching improves strategic thinking and coding skills, as demonstrated by students who use Scratch for Arduino [80]. Overall, CT educational strategies are proven to increase students' confidence in computing and problem-solving activities [81].

It is important to incorporate computational thinking (CT) into physics education to improve students' problem-solving skills and comprehension of complex subjects. Research shows that the use of project-based learning in physics classes has a great positive impact on students' ability in deconstruction, abstraction, and simulation. This approach improves analytical and logical problem-solving skills [6]. The six-week intervention was conducted on grade 12 students, and the results showed that engaging in CT activities resulted in improved post-test performance. In particular, there was an important improvement in conceptual understanding and visual thinking skills [35]. In addition, the utilization of computational essays increases computational literacy and increases one's understanding of the theoretical and practical aspects of physics topics [5]. It is important to define and incorporate critical thinking (CT) into high school and college physics programs because it is essential for the development of analytical skills [40]. In addition, a model for incorporating computational thinking (CT) into science education for students in grades K-12 highlights its ability to supplement scientific knowledge, effectively assisting high school students in understanding the concepts of physics and biology [70]. Incorporating CT into physics teaching results in greater increases in understanding and academic achievement.

Figure 1 shows a study of students' reactions to computational thinking. The focus of this analysis is on students' computational thinking skills, which are impacted by their usage of computational tools, gender effects, and attitudes on computational tools. The incorporation of computational tools into education promotes the development of these abilities [3], but gender inequalities can influence student engagement and performance in computer science [82]. A good attitude toward computational tools also contributes to better learning results [83]. The development of computational thinking abilities is critical for problem solving and comprehending complex systems [68], as evidenced by student responses to instructional tactics and tools [84]. The use of computational tools in education enables students to acquire computational thinking abilities, which are critical in today's digital age [85]. Gender disparities impact student engagement and performance in this environment, with male and female students having significantly different levels of confidence and interest[86]. Students' favorable attitudes about computational tools influence their desire to utilize them and acquire strong computational thinking abilities. These computational thinking abilities are critical for problem solving and comprehending complex systems, demonstrating how successfully educational techniques have been adopted to optimize students' reactions to the development of these skills [87, 88]. As a result, students' reactions to computational thinking are impacted by a variety of factors, including computational tool use, gender effects, and viewpoints on computational tools. Students' computational thinking abilities have a significant impact on their replies, highlighting the necessity of providing instruction and the necessary tools to develop these skills. With a greater knowledge of these elements, we can build more effective educational programs to increase computational thinking abilities in children, preparing them for future problems in the digital era.

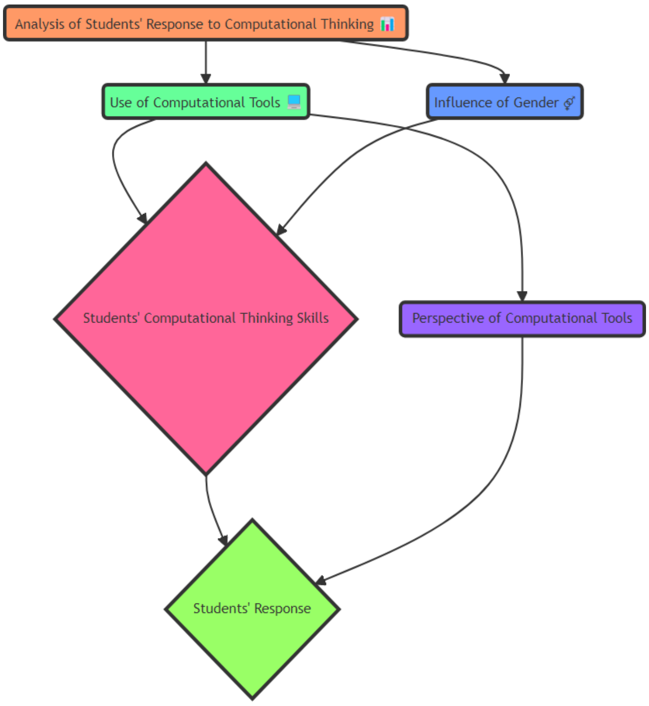

FIGURE 1. Flowchart framework computational thinking activity

III. MATERIAL AND METHOD

The study used a comparative approach to compare the computational thinking skills across different classes. This research adopted a survey method using a questionnaire as the primary tool for collecting data. Questionnaires were an effective research instrument because they could produce written or measurable responses from respondents related to predetermined research variables. Preparing the questionnaire was carried out carefully, involving designing clear, relevant, and quantifiable questions so that the data obtained could provide accurate and meaningful information. In the context of this research, the questionnaire used was adapted from Tsai et al. [89], which had been tested for validity and reliability. Each item has the reliability of Cronbach's alpha value for the overall scale and each dimension. The total variance described of the 19 items was 64.03%, which is an acceptable result, indicating excellent structural validity for the final version of the five factors. The reliability of the alpha is 0.91 for the overall scale and ranges from 0.74 to 0.83 for the subscale, indicating that the instrument is reliable for evaluating students' computational thinking [89]

This questionnaire comprised 19 items covering five dimensions of computational thinking skills: abstraction, decomposition, algorithm thinking, evaluation, and generalization. The questionnaire was adopted to adapt to the context of this research, but it still maintained accuracy and precision in measuring students' computational thinking abilities. The questionnaire was presented as a Likert scale consisting of points 1–5. The survey targets in this research were students taking the introductory physics practicum one course in the first semester of 2023 at the UPT Basic Physics Laboratory, Halu Oleo University, Kendari, Southeast Sulawesi. The students who were respondents came from various classes, reflecting the diversity of academic backgrounds of students who were registered in classes taking the introductory physics practical course 1 (Table 1). There are several strong reasons why the basic physics practicum 1 was chosen as a trial class to see the perspective of computational thinking. The basic principles taught in Basic Physics 1 include kinematics, dynamics, energy, and momentum which can all be solved using computational reasoning. This technique emphasizes systematic problem-solving, which can help students form a structured thinking style when faced with physics difficulties. In addition, the course's experiments often involve collecting and analyzing data, which can be better represented, simulated, and analyzed using computational thinking. Computer visualization and simulation can also help clarify physics problems that are difficult to understand through theory alone. This skill is especially useful when students move on to advanced physics courses, where modeling and simulation approaches become more complicated. Finally, combining physics and computational thinking provides students with invaluable cross-disciplinary skills in scientific research, engineering, and the technology industry.

Table 1. Respondents

Class	N (Student)
Class of Physics	19
Class of Physics Education	68
Class of Geography	45
Class of Mining Engineering	85
Program Study of Vocational Education in Electrical Engineering	31
Total	**248**

The data of this study was evaluated using a comparative analysis approach to find out the average and percentage of each dimension of computational thinking skills measured. According to the study, percentages can be used to analyze Likert scale data, not average values. The percentage of approval (Ya%) was shown to have a strong relationship with the average value of Likert scale items, making the data easier to understand. The Likert scale, which is neither an interval scale nor a ratio, makes the percentages more acceptable for this study and avoids the assumption of normal distribution. This strategy addresses the problem of equality on the Likert scale, where differences in response categories are not necessarily consistent [90]. The number of items collected from the questionnaire will be grouped based on the measured computational thinking skill dimensions, and then the average value and percentage will be calculated. This step aims to provide a general overview of the extent to which students have internalized each dimension of Computational Thinking and determine whether there are variations between these dimensions. After conducting a comparative analyze to gain an overview, a confirmatory factor analyze approach was utilized to assess the validity of the question items within each class. This approach focused on factor loading, assuming a standard value estimate of >0.5 indicates validity. The factor loading output was obtained using JASP tools.

The next stage is to see how significant the relationship is between the Computational Thinking Skill dimensions in various classes. Spearman correlation analyze (*Rs*) was used in this analyze with the help of IBM SPSS statistical software. The reason for using Spearman Correlation is that the data generated is not distributed regularly. Therefore, non-parametric analysis is highly recommended. When the data does not follow the normal distribution, the Spearman correlation is generally preferred over the Pearson correlation due to its greater robustness and dependence. According to research, Pearson correlations tend to increase Type 1 errors and reduce statistical strength when dealing with abnormal data, but Spearman correlations are better able to overcome such anomalies [91] . Altering the data to get close to the normal distribution before performing Pearson correlation can be useful in some situations, but it is not always optimal for small samples; In contrast, Spearman correlations often yield more consistent results with small and very abnormal data [92]

Spearman correlation can help minimize the bias and inaccuracies associated with Pearson's correlation on abnormal data, resulting in more conservative and accurate estimates [93]. Survey data from each respondent will be processed and analyzed to determine the extent of the relationship between these dimensions. Correlation indicators, such as the Spearman correlation coefficient (r_s), will be used to evaluate the strength and direction of the relationship between variables. The results of the correlation analyze will then be mapped into correlation indicators, providing a more precise visual picture of the extent of the relationship between Computational Thinking Skill dimensions in each class or department.

Next, an analyze investigated the correlation between gender and students' computational thinking skills. The analyze utilized data from the total number of students enrolled in introductory physics courses across five classes: Physics, Physics Education, Geography, Mining Engineering, and Vocational Education in Electrical Engineering. The total number of students involved was 248 people, consisting of 113 men and 135 women. Then, the data was analyzed based on gender to see computational thinking skills (abstraction, decomposition, algorithm thinking, evaluation & generalization). Data analyzed uses the Chi-Square Test ($\chi 2$) to test the relationship or influence of two nominal variables and measure the strength of the relationship between one variable and another (C = Coefficient of contingency). Chi-square analysis is a powerful non- parametric approach that is widely used for data that does not follow a normal distribution. This statistical method is particularly useful because of its sensitivity to abnormalities, making it suitable for categorical data where assumptions of normality may not apply [94]. Chi-squared tests are widely used to assess fit, test independence between variables, and compare nested models, particularly in contexts such as confirmatory factor analysis and structural equation modeling, where sustainable outcomes may be abnormally distributed [95, 96]. This research hypothesizes that *H0* = no relationship between gender and computational thinking skills, and *H1* = there is a relationship between gender and computational thinking skills

IV. RESULTS

1. ANALYSIS OF STUDENT COMPUTATIONAL THINKING SKILLS

In the context of introductory physics experiments, computational thinking skills are key to optimizing understanding and solving physics problems. Experiments in introductory physics often involve measurements, data processing, and analyze of results, and this is where computational thinking skills can significantly contribute. This research aimed to analyze the initial computational thinking skills of students programming the introductory physics practicum one course with class divisions consisting of a physics class, a physics education class, a geography class, a mining engineering class and an electrical engineering vocational education study program. The results of the analysis of 5 dimensions of computational thinking skills are presented in Table 2.

Table 2. Results of comparative analyze on 5 Dimensions of Computational Thinking Skill and Total Score survey of Computational Thinking Skill perspective in Each Class

Class	CT	Item mean	SD	% of each Item Mean	% Overall total Item Mean
Physics	Abstraction	3.26	0.89	65.26%	65.65%
	Decomposition	3.23	0.76	64.56%	
	Algorithm Thinking	3.26	0.73	65.26%	
	Evaluation	3.36	0.67	67.11%	
	Generalization	3.30	0.76	66.05	
Physics Education	Abstraction	0.61	0.77	61.25%	62.54%
	Decomposition	0.62	0.69	61.96%	
	Algorithm Thinking	0.64	0.68	63.68%	
	Evaluation	0.64	0.68	64.26%	
	Generalization	0.61	0.63	61.47%	
Geography	Abstraction	0.59	0.85	59.00%	60.99%
	Decomposition	0.60	0.83	60.15%	
	Algorithm Thinking	0.63	0.79	63.11%	
	Evaluation	0.62	0.78	61.89%	
	Generalization	0.61	0.74	60.78%	
	Abstraction	0.62	0.79	62.24%	

Mining Engineering	Decomposition	0.61	0.82	61.49%	63.45%
	Algorithm Thinking	0.65	0.75	65.00%	
	Evaluation	0.65	0.70	65.29%	
	Generalization	0.63	0.73	63.24%	
Vocational Education in Electrical Engineering	Abstraction	0.66	0.71	66.45%	67.66%
	Decomposition	0.69	0.69	68.60%	
	Algorithm Thinking	0.68	0.74	68.23%	
	Evaluation	0.68	0.75	68.06%	
	Generalization	0.67	0.72	66.94%	

Based on the findings of the Computational Thinking (CT) study in various courses in Table 2, it is clear that the skills of each class are different. In the Physics class, the Evaluation component has the highest average score (3.36), while the Decomposition component has the lowest score (3.23). The standard deviation varies between 0.67 and 0.89, indicating considerable diversity between students. The mean proportion of each item ranges from 64.56% to 67.11%, with an overall mean of 65.65%. The Physics Education class has a lower average score of question items overall. The highest score was found in the Algorithmic Thinking and Evaluation component with an average score of 0.64, while the lowest score was found in the Abstraction and Generalization component with an average score of 0.61. The standard deviation varies from 0.63 to 0.77, indicating very small fluctuations. The mean proportion of each item ranged from 61.25% to 64.26%, with a total mean of 62.54%.

Meanwhile, in the geography class, the highest average item score was found in the Algorithmic Thinking component (0.63), while the lowest was in the Abstraction component (0.59). The standard deviation varies between 0.74 and 0.85, indicating considerable fluctuations. The mean proportion of each item ranged from 59.00% to 63.11%, with an overall average of 60.99%. The Mining Engineering class had the largest average score in the Thinking Algorithm and Evaluation component (0.65) and the lowest in the Decomposition component (0.61). The standard deviation varies between 0.70 and 0.82, indicating a large variation. The mean proportion of each item ranges from 61.49% to 65.00%, with a total mean of 63.45%. In the Electrical Engineering Vocational Education class, the Decomposition component has the highest mean item value of 0.69, while the Abstraction component has the lowest value of 0.66. The standard deviation varies from 0.71 to 0.75, indicating a very small variance. The mean proportion of each item ranged from 66.45% to 68.60%, with an overall average of 67.66%.

Overall, this study revealed that each class has different strengths and limitations in many CT elements. The Physics class has the highest overall average score, particularly in the Evaluation component, which shows a strong ability to assess and analyze situations. In contrast, the Physics Education class received the lowest overall average score, particularly on the Abstraction and Generalization components, indicating the need for further assistance in understanding and generalizing the topic. Geography classes performed consistently, with the largest scores on the algorithmic thinking component. However, the Mining Engineering class obtained a high average score on the Algorithmic Thinking and Evaluation component, which demonstrates logical and analytical thinking skills. Electrical Engineering Vocational Education classes have the best grades on the Decomposition component, demonstrating a strong capacity to break down problems into smaller, more manageable components. The results show that the CTS dimension is an important signal to measure students' ability to solve computational problems. Vocational education programs, especially in electrical engineering and mining, excel in applying computational theory to practical and real-world situations. Although some groups show significant improvements, there is still room for growth in many elements of the CTS. Furthermore, a Conffirmatory Factor Analysis (CFA) will be carried out to assess the validity of the variables measured by questionnaires. CFA allows researchers to relate observable variables and measurements, such as question items. The findings of the CFA, including factor loading, are shown in Table 3.

Table 3. Results of comparative analyze on 5 Dimensions of Computational Thinking Skill and Total Score of Computational Thinking Skill in Each Class

Factor	Indicator	Estimate	Std. Error	*z*-value	*p*	Std. Est. (all)
Physics	Abstraction	0.449	0.148	3.032	0.002	0.697
	Decomposition	0.432	0.118	3.668	<.001	0.821
	Algorithm Thinking	0.588	0.12	4.908	<.001	0.977
	Generalization	0.555	0.139	3.99	<.001	0.858
	Evaluation	0.559	0.124	4.49	<.001	0.936
Physics Education	Abstraction	0.517	0.065	7.917	<.001	0.805
	Decomposition	0.428	0.059	7.226	<.001	0.756
	Algorithm Thinking	0.523	0.051	10.25	<.001	0.942
	Generalization	0.448	0.054	8.369	<.001	0.836
	Evaluation	0.505	0.053	9.569	<.001	0.905
Geography	Abstraction	0.56	0.081	6.874	<.001	0.848
	Decomposition	0.625	0.08	7.778	<.001	0.905
	Algorithm Thinking	0.566	0.082	6.922	<.001	0.844
	Generalization	0.549	0.073	7.48	<.001	0.884
	Evaluation	0.599	0.077	7.75	<.001	0.904
Mining Engineering	Abstraction	0.496	0.051	9.805	<.001	0.869
	Decomposition	0.504	0.062	8.145	<.001	0.767
	Algorithm Thinking	0.517	0.055	9.429	<.001	0.846
	Generalization	0.482	0.059	8.136	<.001	0.769
	Evaluation	0.494	0.051	9.672	<.001	0.862
Vocational Education in Electrical	Abstraction	0.488	0.076	6.389	<.001	0.901
	Decomposition	0.52	0.075	6.895	<.001	0.941
	Algorithm Thinking	0.564	0.079	7.166	<.001	0.96
	Generalization	0.504	0.08	6.335	<.001	0.896
	Evaluation	0.604	0.091	6.629	<.001	0.92

The standard estimated factor loading values in Table 3 exceed 0.5, indicating that they meet the requirements. Factor loading measures the strength of the relationship between measurement variables (indicators) and the proposed model factors. When the factor loading exceeds 0.5, it suggests a robust relationship between the indicator and the factor it represents. A higher loading value signifies a more substantial contribution of the indicator to that specific factor. A qualifying loading value is essential because it shows that the selected indicators can be considered suitable measures of the construct proposed in the model. In other words, these indicators effectively represent or measure the construct in question. These results show that the standard estimate is 0.7–0.9, indicating all question items.

These results show that the standard estimate obtained is 0.7–0.9, which generally indicates that all question items strongly relate to the factors proposed in the model. This range of loading values shows that each indicator significantly contributes to measuring the factor it represents. A high loading value indicates that the question items effectively represent the construct. When the loading value is 0.7–0.9, the question items have a powerful relationship with the proposed factors. It indicates that each question item consistently and accurately measures the aspect of the construct it represents. High factor loadings are a good predictor of construct validity, the degree to which a test measures what it claims to measure. In this scenario, the high loading values demonstrate that the indicators measure the constructs of interest, such as computational thinking skills or conceptual knowledge in physics. Furthermore, high factor loadings indicate good discriminative power, an indicator's capacity to distinguish between individuals with varying degrees of the construct. For example, in the study of computational thinking capabilities, indicators with strong discriminative power can effectively distinguish

QUBAHAN ACADEMIC JOURNAL
VOL. 4, NO. 3, July 2024
https://doi.org/10.48161/qaj.v4n3a699

between students with varying levels of these abilities. This ability is critical for educational examinations, which frequently seek to identify pupils' strengths and areas for improvement. The high standard estimate values found in the study have important implications for educational research and practice. First, they demonstrate that the selected indicators are appropriate measures of the investigated variables. This appropriateness is critical to assuring the validity and trustworthiness of the research results. Second, the high factor loadings show that the indicators may accurately judge students' talents. In the context of computational thinking skills, for example, the indications can help identify pupils who thrive in these areas and others who may want further assistance. This information can be utilized to personalize educational interventions and enhance learning outcomes.

Thus, these results provide additional evidence of the construct validity of the proposed factor model. Apart from that, a high loading value in this range also indicates that the question items have good discriminative power, namely the ability to differentiate between individuals with different construct levels. It means that these question items can be used to differentiate individuals who differ in the level of the variable being measured. The following analyze examines the relationship or correlation between dimensions within each class. These correlations are instrumental in gaining insights into the degree of association between different dimensions and whether a consistent pattern of relationships exists across classes. The outcomes of the analyze are detailed in Table 4.

Table 4. Correlation (r_s) analyzes of each CT dimension in each class

	CT Dimension	Abstraction	Decomposition	Algorithm Thinking	Evaluation	Generalization	r_s
Class of Physics	Abstraction	1					
	Decomposition	.504**	1				
	Algorithm Thinking	.684**	.701**	1			.001
	Generalization	.417*	.751**	.839**	1		
	Evaluation	.478*	.777**	.807**	.738**	1	
	CT Dimension	Abstraction	Decomposition	Algorithm Thinking	Evaluation	Generalization	r_s
Class of Physics Education	Abstraction	1					
	Decomposition	.621**	1				
	Algorithm Thinking	.722**	.675**	1			.001
	Generalization	.666**	.592**	.818**	1		
	Evaluation	.709**	.545**	.727**	.748**	1	
	CT Dimension	Abstraction	Decomposition	Algorithm Thinking	Evaluation	Generalization	r_s
Class of Geography	Abstraction	1					
	Decomposition	.625**	1				.001
	Algorithm Thinking	.693**	.663**	1			

	Generalization	.713**	.717**	.745**	1		
	Evaluation	.715**	.786**	.625**	.742**	1	
Class of Mining Engineering	CT Dimension	Abstraction	Decomposition	Algorithm Thinking	Evaluation	Generalization	r_s
	Abstraction	1					
	Decomposition	.711**	1				.001
	Algorithm Thinking	.692**	.571**	1			
	Generalization	.652**	.572**	.729**	1		
	Evaluation	.606**	.566**	.586**	.678**	1	
Class of Vocational Education in Electrical Engineering	CT Dimension	Abstraction	Decomposition	Algorithm Thinking	Evaluation	Generalization	r_s
	Abstraction	1					
	Decomposition	.882**	1				.001
	Algorithm Thinking	.868**	.909**	1			
	Generalization	.782**	.829**	.859**	1		
	Evaluation	.817**	.837**	.849**	.833**	1	

In Table 4, the correlation analyzes results show a strong link between computational thinking skills in all five classes. These skills include abstraction, decomposition, algorithmic thinking, evaluation, and generalization. If we look at the correlation coefficient in each class, it shows a positive relationship with computational thinking skills, with different levels of correlation between classes. For example, in Physics Class, there is a strong correlation (r_s = 0.837) between evaluation and algorithmic thinking, while abstraction and evaluation have a moderate correlation (r_s = 0.417). Similar findings were also found in the Physics.

Education Class, where algorithmic thinking ability strongly correlated (r_s = 0.818) with evaluation and a moderate correlation (r_s = 0.454) between decomposition and generalization. A similar thing is also seen in the Mining Engineering Class, where all aspects of computational thinking skills correlate highly, with a value range between (r_s) = 0.61 - 0.80. Meanwhile, in the Electrical Engineering Vocational Education Study Program, the correlation in each aspect of computational thinking skills has a high correlation and is close to perfect correlation, with correlation values in the range (r_s) = 0.782–0.882. Correlation is considered high if the correlation value (r_s) = 0.61–0.80 and perfect if (r_s) = 0.81–1 [97].

2. *ANALYZE OF THE EFFECT OF GENDER ON COMPUTATIONAL THINKING SKILLS*

Computational thinking skills are the cognitive ability to solve problems systematically using computational concepts, including abstraction, decomposition, algorithmic thinking, evaluation, and generalization. It is not limited to programming but includes the ability to think logically and analytically when dealing with complex challenges in various fields. If related to gender, Computational Thinking Skills can experience differences in development, where gender stereotypes and social factors can influence interest, self-confidence, and participation, raising challenges in achieving equality in the development of computational skills. In this section, the results of the Chi-Square ($\chi 2$) analyze regarding the influence of gender on computational thinking skills will be displayed. The analyze results are presented in Table 5.

Table 5. Results of analyze of the influence of gender on computational thinking skills

CT Skill	Gender							
	Male (N=113)				Female (N=135)			
	M	SD	$\chi 2$	Sig.	M	SD	$\chi 2$	Sign
Abstraction	3.12	0.66	88.90	.00	3.10	0.60	140.69	.00
Decomposition	3.13	0.66	76.49	.00	3.12	0.60	83.20	.00
Algorithm thinking	3.26	0.60	100.54	.00	3.22	0.57	147.17	.00
Evaluation	3.26	0.60	159.60	.00	3.23	0.58	145.66	.00
Generalization	3.19	0.60	118.38	.00	3.11	0.56	115.14	.00

$\chi^{2table} < \chi^{2count}$ (Sig < 0.00: H0: rejected)

Table 5 reports statistical data related to computational thinking skills based on gender. This analyze focuses on comparing computational thinking skills between male and female participants. Several skills or abilities are evaluated: Abstraction, Decomposition, Algorithmic Thinking, Evaluation, and Generalization. Data on these skills was displayed for male (N=113) and female (N=135) participants. In this analyze, the statistical data presented for each group includes the mean (M), standard deviation (SD), chi-square statistic (χ^2), and significance (Sign.). Gender plays a significant role in influencing computational thinking skills. Computational thinking involves abstraction, decomposition, algorithmic thinking, evaluation, and generalization. The study depicted in the image highlights the impact of gender on these skills. The data presented in the image shows the performance of individuals based on gender in different aspects of computational thinking skills. Table 5 displays mean (M) values and standard deviations (SD) for males and females in the study group.

For the aspect of abstraction, males scored higher, with a mean value of 3.12, compared to females, with a mean value of 3.10. Similarly, in decomposition, males scored 3.13 while females scored 3.12. In algorithmic thinking, males scored 3.26, and females scored 3.22. For evaluation, males scored 3.26, and females scored

3.23. Lastly, in generalization, males scored 3.19, and females scored 3.11. The standard deviations for both genders were relatively similar across the different aspects, indicating consistency in performance within each group. The statistical significance (Sig.) values were all below 0.00, suggesting a significant difference in performance between males and females in computational thinking skills. The significance value (Sign.) indicates whether the difference is statistically significant. All significance (Sig.) values in chi-square analyze are ".00". This value indicates that the difference in computational thinking skills between genders is considered statistically significant, assuming that ".00" refers to a p-value lower than the conventional threshold ($p < 0.05$). It shows fundamental differences between men and women regarding the computational thinking skills evaluated. The data implies gender-based differences in computational thinking skills, with males performing better in abstraction, decomposition, algorithmic thinking, evaluation, and generalization than females. Further analyze and research may be required to understand the underlying factors contributing to these gender differences and how they can be addressed to promote gender equality in computational thinking skills.

V. DISCUSSION

1. *ANALYSIS OF STUDENT COMPUTATIONAL THINKING SKILLS*

The analyzed aimed to assess students' computational thinking skills across various classes, including Physics, Physics Education, Geography, Mining Engineering, and Electrical Engineering Vocational Education. The results showed that Electrical Engineering Vocational Education had the largest overall average (67.66%), followed by Physics (65.65%), Mining Engineering (63.45%), Physics Education (62.54%), and Geography (60.99%). Each subject has different computational thinking skills, where Evaluation often has the largest average and percentage, such as Physics (67.11%) and Electrical Engineering Vocational Education (68.06%). The standard deviation also varied, with Abstraction of Physics reaching 0.89 and Evaluation of Mining Engineering of 0.79. In total, computational thinking abilities make a significant contribution to the total average, with Electrical Engineering Vocational Education outperforming all other areas of computational thinking. Several studies have emphasized the importance of CT, which includes abilities such as algorithmic thinking, abstraction, and automation [83]. CT capabilities are particularly useful in electrical engineering, with a focus on programming and computational problem solving [74] . According to research, engineering students develop CT abilities that stand out more than students in other fields because of their practical application in engineering projects [98]. As a result, electrical engineering students have significantly improved in CT ability, which is critical to their academic and professional performance, more than in any other scientific field [99]. Meanwhile, several references reported that electrical classes mainly involved computational thinking and provided evidence of the relationship between computational thinking skills and various aspects such as problem-solving abilities, creative problem-solving skills, and self-efficacy—the use of technology in education. Computational thinking skills could be applied in the field of electronics in a variety of ways. Electronics involves designing, manufacturing, and testing electronic circuits and devices. Computational thinking skills such as algorithmic thinking, problem-solving, and critical thinking were used to create and simulate electronic circuits. Electronics, especially in the field of semiconductor device simulation, relied heavily on computational thinking [100]. This approach, which emphasized problem-solving and knowledge acquisition, was closely related to the power of modern electronic computers [101]. Computational thinking skills were crucial, including using electronic computers and programming concepts [102]. Efficient use of computers, a crucial aspect of computational thinking, was essential in electronics[103] . It resulted in vocational education classes being quite familiar with computing.

The CFA analysis revealed a strong relationship between variables and computational thinking skills in different classes (p-value <0.001). In the field of Physics, the 'Algorithmic Thinking' indicator has the highest estimation score (0.588) and the estimation standard (0.977), which shows a significant correlation. In Physics Education, the same indicator has a high score (0.523) and an estimation standard of 0.942. In the field of Geography, the 'Decomposition' indicator has the best prediction score (0.625) and standard (0.905). In Mining Engineering, the 'Algorithmic Thinking' indicator has the highest estimated score (0.517) and standard (0.846). In Electrical Engineering Vocational Education, the 'Evaluation' indicator has the best prediction score (0.604) and standard (0.920). Overall, 'Algorithmic Thinking' and 'Evaluation' are commonly referred to as important indicators in various domains, indicating a significant impact on the development of computational thinking skills across several disciplines. This study revealed a substantial relationship between CT dimensions in all classes (p-value <0.001). Algorithmic thinking and evaluation are key components for improving computational thinking (CT) skills in a variety of educational settings. Juškevičienė [104] emphasizes the importance of algorithmic thinking in building programming skills and computational problem-solving abilities. This requires building step-by-step solutions to challenges. This type of teaching greatly improves students' performance in programming activities and increases their self-efficacy in solving algorithmic problems, improving their CT abilities [105].

Meanwhile, in terms of correlation relationships, it is found that in the Physics Class, there is a strong relationship between algorithm thinking and evaluation ($r_s = 0.839$) and evaluation and generalization ($r_s = 0.738$). In the Physics Education Class, evaluation and generalization showed the strongest correlation ($r_s = 0.818$), showing a significant relationship between assessment and generalization. In the Geography Class, the strongest relationship was found between evaluation and generalization ($r_s = 0.742$), emphasizing the relevance of assessment and generalization. The Mining Engineering class has the strongest relationship between abstraction and decomposition ($r_s = 0.711$), which highlights the importance of abstraction and deconstruction. In the Electrical Engineering Education Class, all dimensions of CTs show a very significant correlation, especially between algorithm thinking and evaluation ($r_s = 0.859$) and evaluation and generalization ($r_s = 0.833$), emphasizing the importance of algorithmic thinking and assessment in electrical engineering education. One of the main components of CT is algorithmic thinking, which is creating a systematic process to solve a problem [23]. Furthermore, CT requires assessment, specifically reviewing the resulting solution to ensure its efficacy and efficiency, which in the context of physics education means evaluating a program or algorithm to verify that the solution is operating correctly and meeting the required objectives [106]. Meanwhile, Generalization is an essential skill in physics education and other STEM disciplines, as it allows the application of lessons from one context to another [53].

Based on study findings regarding computational thinking (CT) skills in various classrooms, there are several specific recommendations for educators and policy makers. For educators, it is recommended to increase the teaching of algorithms and evaluation in the curriculum, especially in Physics and Vocational Electrical Engineering classes, which have been shown to have a significant impact on CT. More practical exercises involving step-by-step problem solving and solution evaluation, such as programming and simulation projects, also need to be reinforced. The development of special modules that focus on CT aspects such as abstraction, decomposition, and generalization can help students understand and apply these concepts in various contexts. The integration of modern technology such as simulation software and programming tools must also be improved to support CT learning through visualization and hands-on practice. For policymakers, it is important to design curriculum policies that support the integration of CT at all levels of education, especially in STEM fields, by ensuring educational standards include clear CT competencies. Investment in technology infrastructure at schools and universities is also needed to ensure all students have equal access to technology- based learning. In addition, it is also important to provide funding for further research and development regarding CT teaching as well as promote collaboration between educational institutions and industry. This includes the development of CT-focused vocational and retraining programs, to upgrade workers' skills according to the demands of modern technology and a rapidly evolving job market.

2. *THE EFFECT OF GENDER ON COMPUTATIONAL THINKING SKILLS*

This analyzed aimed to determine the influence of gender on students' computational thinking skills in introductory physics practical experiments from the results of introductory physics practical experiments 1. The results of the analyze show that gender influences computational thinking skills. The results of the analyze found that males and females had a significant effect (sig < 0.00) on each aspect of computational thinking skills (abstraction, decomposition, algorithm thinking, evaluation, generalization). According to several studies, gender significantly influences various aspects of computational thinking skills. A study conducted on secondary school students in Singapore found that male students had a higher level of computational thinking ability than female students [107]. In a study involving junior high school students solving number pattern problems, male and female students showed evidence of computational thinking processes. It was demonstrated through their ability to decompose problems, recognize patterns, think algorithmically, abstract complex concepts, and generalize patterns [108]. A study that analyzed differences in abstract thinking dispositions and gender perspectives among students found that female students had a more concrete thinking disposition than male students [109].

From the results of the analyze in Table 4, in terms of the mean value of computational thinking skills, each aspect was dominated by male compared to female, although the difference was not much different compared to CT for male (M= 3.19; SD=0.62) and female (M= 3.16, SD= 0.58). Paucar-Curasma et al. [110] reported in their paper that there were no significant differences between male and female students in the computational thinking skills contest. In this context, using STEM as a strategy that focused on solving real problems raised the same enthusiasm in female and male students compared to other activities that only generated motivation in male students. Thus, these findings suggested that gender significantly impacted computational thinking skills, with observable differences in aspects such as abstraction, decomposition, algorithmic thinking, evaluation, and generalization. This research highlighted the importance of considering gender factors in the development of education and training in the context of computational thinking skills, as well as identifying strategies that could be used to minimize the gender gap in these abilities. Additionally, these results could serve as a basis for developing more inclusive and results-oriented educational programs, enabling better participation and achievement for all individuals, regardless of gender.

In the end, the findings revealed that gender considerably impacted computational thinking skills, with variations seen in areas such as abstraction, decomposition, algorithmic thinking, assessment, and generalization. The gap is insignificant, although male college students have higher average computational skills. These findings underscore the need to consider gender while developing computational thinking skills through education and training and creating measures to close the gender gap in these capacities. Therefore, it is vital to perform more investigations. Further study should investigate the elements that influence the variations in computational thinking skills between male and female students. Studies can broaden their reach by considering educational background, technology experience, and learning preferences.

Furthermore, research can incorporate more inclusive and problem-based learning approaches in STEM topics to assess their influence on student involvement and accomplishment among different genders. A future study might focus on developing instructional practices that stress the development of computing abilities to establish a dynamic learning environment for all individuals, independent of gender. Further research can look into the impact of gender on computational thinking skills (CTS), focusing on various educational contextual factors, the development of inclusive educational interventions, and a better understanding of other influencing factors such as STEM interest and social support. Longitudinal research and comprehensive assessment tools are also required to understand better CTS abilities' development and how technology affects gender disparities in computational learning. This study will likely enhance efforts to promote inclusive and adaptable education to improve computational thinking abilities among pupils.

VI. CONCLUSION

Based on the findings, it is possible to conclude that students' responses to the application of computational thinking, as well as the effect of gender on their computational thinking skills, are relevant across several disciplines. The analysis results suggest that vocational education in electrical engineering has the greatest average in computational thinking skills (67.66%), followed by physics (65.65%), mining engineering (63.45%), physics education (62.54%), and geography (60.99%). Variation in computational thinking abilities is observed in each subject. Evaluation frequently stands out as the element with the highest average, as evidenced by the proportion of evaluation in physics (67.11%) and vocational education in electrical engineering (68.06%). Standard deviations vary among fields, demonstrating the variety in student responses to computational skill aspects. The confirmatory factor analysis (CFA) revealed a robust correlation between computational thinking skills and particular components and indicators in each class (p-value < 0.001). Across disciplines, markers such as 'Algorithm Thinking and 'Evaluation' have emerged as critical components in developing computational thinking abilities, exhibiting a significant effect in the context of their respective education. The study also found substantial variations in computational thinking skills between male and female college students. Although the gap is not great, data suggests that male students have slightly better computational thinking skills than female students. Previous research has also found that gender influences computational thinking capabilities, with male college students consistently outperforming female college students in comprehending and implementing computational thinking principles. This study has significant implications for developing education and training in computational thinking skills. The relevance of gender considerations in curriculum design and learning methodologies was demonstrated to close the gender gap in these capacities. Education programs may promote participation and accomplishment for all individuals, regardless of gender, using more inclusive and results-oriented tactics. These findings emphasize the need to incorporate computational thinking into various educational curricula and a sensitive approach to individual variances in reaction to this learning. As a result, this study gives in-depth insights into computational thinking skills across multiple fields and provides a solid platform for establishing a more inclusive and outcome-oriented education policy.

Funding statement

This research was supported funding by Lembaga LPDP (Pengelola Dana Pendidikan Indonesia), BPPT (Balai Pembiayaan Pendidikan Tinggi) Kemendikbudristek (Ministry of Education, Culture and Research Higher Education of Indonesia), and Indonesian Education Scholarship (BPI).

Author contribution

Suritno Fayanto (Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Visualization), Sul Daeng Naba (Resources, Investigation, Project administration) , Aris Kurniawan (Writing - Review & Editing, Project administration, Funding acquisition), Utami Putri (Writing - Review & Editing, Project administration, Funding acquisition) and Veronika Dua Padang (Writing - Review & Editing, Project administration, Funding acquisition) contributed to the initial drafting of the paper.

Conflict of Interest

The authors declare no conflict of interest.

Acknowledgement

The author would like to Mr. La Ode Wero and the Basic Physics Assistant Team, for their assistance in data collection.

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