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Enhancing Computational Thinking through FluidSIM: Preparing Future Vocational Teachers for Quality Education

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Abstract

Computational thinking ability is an essential 21st-century competency that prospective vocational teachers need to develop to support technology-based learning. However, its development is still dominated by programming-based approaches, while the use of engineering simulation software remains limited. This study aims to analyze the effectiveness of FluidSIM in improving the computational thinking ability of prospective Electrical Engineering teachers. A quasi-experimental method with a one-group pretest-posttest design was employed, involving 21 students from the Electrical Engineering Education Study Program. The research instrument was a computational thinking test measuring four dimensions: decomposition, pattern recognition, abstraction, and algorithmic thinking. The results of the paired-sample t-test showed a significant improvement in students' computational thinking ability after FluidSIM-based learning was implemented. Furthermore, the N-Gain analysis produced an average score of 0.734, which falls into the high category. The highest improvement occurred in decomposition, with an N-Gain value of 0.750, followed by algorithmic thinking at 0.736, pattern recognition at 0.721, and abstraction at 0.714. These findings indicate that FluidSIM is effective not only in supporting students' understanding of engineering concepts but also in developing essential computational thinking skills. The simulation environment enables students to decompose engineering problems, recognize patterns, construct abstract representations, and formulate systematic solution procedures through interactive learning activities. Therefore, FluidSIM-based learning can serve as an alternative technology-supported approach for strengthening computational thinking in vocational teacher education. This study contributes empirical evidence for integrating engineering simulation into teacher preparation and supports Sustainable Development Goal 4 by promoting quality education through meaningful technology integration in learning.

Keywords: *Fluidsim, Computational Thinking, Vocational Preservice Teachers, Electrical Engineering Education, Quality Education.*

1. Introduction

Entering the digital and technology-based era of the 21st century, computational thinking abilities have become one of the most important skills for student teachers to have, especially vocational teachers who are prepared to face the challenges of quality future education [1]. Computational thinking is a basic skill that involves problem solving, system design, and understanding human behavior through processes such as decomposition, pattern recognition, abstraction, and algorithm design. These skills are not only important for student teachers as professional preparation, but are also a core competency for 21st century teachers who must integrate technology in learning to equip students to face the demands of an increasingly complex and digital world of work and society [2], [3]. Mastery of computational thinking is very relevant to the needs of vocational education which emphasizes the practical and efficient application of science and technology. Teachers who master computational thinking will be able to design effective project and technology-based learning methods, thereby improving the quality of vocational education and the competitiveness of graduates. This is in line with the development of 21st century pedagogy which demands critical, creative and collaborative thinking skills, which can be developed through the development of computational thinking [2].

This computational thinking ability helps both teachers and students develop systematic, analytical and creative problem solving abilities, which are key competencies in 21st century learning [4]. Systematic studies show that teachers who have good computational thinking skills will be more adaptive to curriculum changes that require the integration of technology and innovative learning methods [5]. This computational capability also supports prospective teachers in developing interactive and contextual learning strategies so that vocational

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students are able to master material with practical application in the world of work [6]. Apart from that, mastery of computational thinking by prospective teachers also contributes to the formation of 21st century character skills, such as creativity, collaboration and communication skills which are essential for student career success at the Vocational High School education level [7]. The importance of mastering computational thinking for prospective vocational teachers is based on their role as agents of change in educational transformation which is increasingly influenced by digital technology and automation [8]. As the front guard of technical and vocational education, teachers must be able to integrate computational thinking principles into teaching practice so that they can stimulate students to think critically, logically and innovatively and be able to solve complex problems effectively [9]. Improving computational thinking skills is a crucial aspect in electrical engineering education because computational thinking facilitates analytical skills, problem solving, and modeling complex technical systems [10]. In the context of teaching electrical engineering, simulation software is an effective tool for training computational thinking because it provides an interactive and experimental learning experience without the risk of damage to physical equipment [11].

FluidSIM is a simulation software that can be used as a learning medium to improve computational thinking skills effectively. The advantage of FluidSIM lies in its ability to visualize fluid and mechanical system concepts with interactive and applicable simulations that support deeper understanding and the development of analytical skills and systematic problem solving. The use of FluidSIM in the context of vocational education opens up opportunities for prospective teachers to integrate digital technology in learning practices that encourage real computational thinking [3]. The use of simulation software in electrical engineering classes significantly increases understanding of technical concepts and simultaneously hones computational thinking skills through design practice, debugging, and simulation iteration [12]. This software provides dynamic visualizations that reinforce abstract concepts and supports dimensions of computational thinking such as problem decomposition, pattern recognition, and algorithmization.

In addition, simulation-based learning strategies provide opportunities for direct practice in solving engineering problems with a computational thinking approach, thereby improving academic results and technical skills [13]. Simulation learning in the field of electrical engineering is also in line with the demands of 21st century skills, which prioritize creativity, collaboration and effective use of digital technology[14]. Thus, simulation software not only supports cognitive and technical aspects in electrical engineering education, but is also a strategic medium for building and developing holistic computational thinking skills. This is very crucial in preparing technicians and vocational teachers who are competent and adaptive to technology and the needs of modern industry.

Although various studies have reported that digital simulation-based learning can improve conceptual understanding, problem solving skills, and computational thinking abilities in the fields of science and engineering education, most of these studies still focus on engineering students or students at the school level [15]. Apart from that, the development of computational thinking is generally carried out through programming or coding activities, while the use of engineering simulation software as a medium for developing these capabilities is still relatively limited [16]. Research that specifically examines the increase in computational thinking among prospective vocational teachers in the field of Electrical Engineering is also rarely conducted, even though this group is required not only to master technical competencies, but also to have systematic, analytical and technology-based thinking skills to support 21st century learning.

To address this gap, the present study introduces the use of FluidSIM as a simulation-based learning medium to enhance the computational thinking skills of pre-service vocational teachers enrolled in the Electric Motor Use and Control course. Unlike previous studies that primarily relied on programming-based approaches, this study demonstrates that engineering simulation software can also serve as an effective pedagogical tool for developing the four core dimensions of computational thinking, namely decomposition, pattern recognition, abstraction, and algorithmic thinking. Therefore, the novelty of this study lies in its focus on pre-service vocational teachers, its application of FluidSIM as a non-programming environment for computational thinking development, and its comprehensive analysis of computational thinking across its four fundamental dimensions. These contributions extend the current understanding of computational thinking development in vocational teacher education and provide empirical evidence to support the integration of simulation-based learning in preparing future vocational teachers for technology-enhanced education while contributing to the achievement of Sustainable Development Goal (SDG) 4 on Quality Education.

2. Method

2.1. Research Design

This study used a quasi-experimental method with a one-group pretest-posttest design. This design is a type of experimental research that uses only one group of subjects, measured before (pretest) and after (posttest) the treatment or intervention is administered [17]. This design was chosen because it allows researchers to measure the effect of the intervention on the dependent variable without using a control group, suitable in situations where randomization is difficult or impractical [18]. An explanation of each element of this design is as follows:

a. Pretest: All participants will be given a computational thinking test before the intervention. Scores for each indicator and the total are measured to determine the average pretest score.
b. Intervention: A special treatment is provided, namely the implementation of FluidSIM in the Use and Control of Electric Motors course.
c. Posttest: After the intervention is completed, all participants are given another test with similar or equivalent questions (equivalent in difficulty and indicators) to measure changes in computational thinking abilities.

A sample of 21 students was taken using a purposive sampling technique. Purposive sampling here means the researcher selected participants based on certain criteria, namely:

a. Prospective electrical engineering vocational teacher students currently taking the course "Use and Control of Electric Motors"
b. Students who were willing to actively participate in all research interventions or treatments
c. Students with relatively similar backgrounds and basic abilities in computational thinking prior to the treatment (to minimize excessive initial variation).

2.2. Instrument

The instrument used was a Computational Thinking (CT) ability test that measures four main aspects [19]. These four aspects are design decomposition, which involves breaking down problems into smaller parts; pattern recognition, which involves recognizing patterns and relationships; abstraction, which involves extracting important information from the core information; and algorithm design, which involves systematically designing steps to solve problems [19], [20]. These four indicators have been widely used in research related to

computational thinking and have proven valid for comprehensively measuring computational thinking abilities. The instrument grid for measuring computational thinking abilities is as follows:

Table 1. Computational Thinking Indicators

Aspect	Indicator
Decomposition	Identifying problem components
	Determining priority order
Pattern Recognition	Finding patterns
	Developing strategies
Abstraction	Formulating the core of the problem
	Creating simple models
Algorithmic	Developing solution steps
	Evaluating algorithms

The instrument for measuring computational thinking skills uses a Likert scale. A Likert scale is an attitude measurement scale that asks respondents to indicate their level of agreement or disagreement with a particular statement. This scale is commonly used in educational, social, and psychological research because it makes it easier for researchers to measure perceptions, attitudes, and levels of understanding quantitatively [21]. In research, a Likert scale of 1–4 was chosen to avoid neutral answers, requiring respondents to provide a positive or negative tendency towards the statement. The use of an even scale such as 4 points encourages clarity of respondents' attitudes and reduces bias in the middle answer [22], [23].

Table 2. Likert Scale

Score	Assessment Criteria
4	Strongly Agree
3	Agree
2	Disagree
1	Strongly Disagree

Before being used in the research, the computational thinking ability instrument underwent a validation process to ensure its validity and reliability. The research instrument was developed based on computational thinking ability indicators. Each indicator was broken down into several items tailored to the characteristics of the Electric Motor Use and Control course. The instrument was then reviewed by three experts to assess the appropriateness of the content, construct clarity, and representativeness of each indicator before being tested for reliability. The instrument's content validity was assessed by three experts with expertise in vocational education and computational thinking using the Aiken's V index [24]. The validation results showed that all dimensions had Aiken's V values above the recommended minimum limit of 0.80 [25], [26], thus all instrument items were deemed to have excellent content validity. Specifically, the Aiken's V value for the decomposition dimension was 0.92, pattern recognition 0.89, abstraction 0.91, and algorithmic thinking 0.94.
Furthermore, instrument reliability was analyzed using Cronbach's Alpha coefficient to determine internal consistency between instrument items [27]. The analysis results showed a Cronbach's Alpha value of 0.91, which is considered excellent reliability [28]. These results indicate that the instrument has a very good level of internal consistency, making it suitable for use as a measurement tool for computational thinking skills in prospective vocational teachers. Therefore, the instrument used in this study met validity and reliability requirements, producing accurate and reliable data.

2.3. Data analysis techniques

The research data was analyzed using descriptive and inferential analysis to obtain a comprehensive picture of the improvement in computational thinking skills after implementing FluidSIM-based learning. Prior to hypothesis testing, the pretest and posttest data were tested for normality using the Shapiro–Wilk test to ensure that the data met the assumption of a normal distribution. This test was chosen because the study's sample size was relatively small, making it more appropriate than other normality tests [29], [30]. If the data met the assumption of normality, the analysis continued using a paired sample t-test to examine the difference in mean computational thinking scores before and after the treatment [31]. The hypothesis of this research is:
H_0: There is no significant difference between students' computational thinking scores before and after the implementation of FluidSIM.
H_1: There is a significant difference between students' computational thinking scores before and after the implementation of FluidSIM.
Furthermore, pretest and posttest data were also analyzed using the N-gain (normalized gain) approach to determine the level of improvement in computational thinking skills after treatment [32]. N-gain is a measure of intervention effectiveness that calculates changes in learning outcomes relative to the potential maximum increase in value, thus providing a more accurate picture of changes in participant abilities [23]. The N-gain formula [33]:

$$g = (\text{posttest} - \text{pretest}) / (\text{maximum score} - \text{pretest}) \quad (1)$$

Where g is gain, which is the increase in the mean score from pretest to posttest.
N-gain is calculated by averaging across all participants for each indicator and for the total score, using the following criteria:

Table 3. Interpretation of N-Gain

N-Gain value	Interpretation
$g \geq 0.70$	High
$0.30 \leq g < 0.70$	Medium
$g < 0.30$	Low

Normalized Gain (N-gain) is a measure of improvement in learning outcomes calculated based on the comparison between the difference between posttest and pretest scores with the maximum achievable score. This concept was introduced in a large-scale study on physics

learning, which aimed to assess the effectiveness of teaching methods by normalizing differences in scores so that they could be compared between classes or populations with different starting levels [33].

3. Result And Discussion

3.1. Data Analysis Result

Before testing the hypotheses, a normality test was performed on the pretest and posttest data using the Shapiro–Wilk test. This test aims to determine whether the research data are normally distributed, thus meeting the assumptions for using parametric statistical tests. The results of the normality test showed that the pretest data had a Shapiro–Wilk statistic of 0.959 with a significance value (Sig.) of 0.493. Meanwhile, the posttest data had a Shapiro–Wilk statistic of 0.928 with a significance value (Sig.) of 0.126. Because the significance values for both data groups were greater than 0.05, it was interpreted that the pretest and posttest data were normally distributed. Thus, the assumption of normality was met, allowing further analysis to be conducted using parametric tests, namely paired-sample t-tests, to determine differences in computational thinking scores before and after the implementation of FluidSIM-based learning.

Table 4. Normality Test Results

Test	Shapiro–Wilk Statistics	Sig.	Interpretation
Pretest	0.959	0.493	normally distributed data
Posttest	0.928	0.126	normally distributed data

To determine whether there was a significant difference in students' computational thinking skills before and after the implementation of FluidSIM-based learning, a paired-sample t-test was conducted. The null hypothesis (H_0) stated that there was no significant difference between students' computational thinking scores before and after the intervention, whereas the alternative hypothesis (H_1) stated that a significant difference existed. The results of the paired-sample t-test revealed a statistically significant improvement in students' computational thinking skills following the implementation of FluidSIM-based learning ($t(20) = 22.826$, $p < 0.001$). Therefore, the null hypothesis was rejected, indicating that the intervention significantly improved students' computational thinking skills. The mean score increased from 59.82 on the pretest to 89.29 on the posttest, demonstrating that FluidSIM-based learning was effective in enhancing the computational thinking skills of prospective vocational teachers.

Due to the significant difference, we continued with N-gain testing. The research phase consisted of a pretest, treatment, and posttest. The pretest was administered before students began learning. The treatment phase involved using FluidSIM in the Electric Motor Use and Control course. The final phase was the posttest, which was administered to measure improvements in computational thinking skills. The pretest, posttest, and gain scores are presented in the table 4.

Table 5. N-Gain Result

Pretest	Posttest	N-Gain
59.82	89.29	0.734

Based on the data above, the average pretest score was 59.82 and the average posttest score was 89.29, with an N-gain of 0.734. These average pretest and posttest scores were obtained from the assessment of 21 prospective vocational teacher students. The results indicate that this improvement falls into the high category. This indicates that the use of FluidSIM can improve the computational thinking skills of prospective vocational teacher students. Computational thinking is an important aspect in preparing prospective vocational teachers to work as educators [34], [35]. Computational thinking can support teachers as effective facilitators in developing critical thinking and problem-solving skills in students in the digital era [36], [37]. In the field of Electrical Engineering, computational thinking refers to logical, creative, and structured thinking [38], which can be applied to various electrical materials and their applications in everyday life.

The results of the study showed a significant increase with average N-Gain value is 0.734 in computational thinking through FluidSIM. This indicates that prospective vocational teachers experienced a significant increase in computational thinking in learning FluidSIM. FluidSIM supports prospective teachers' thinking skills through the creation, simulation, and learning of electrical circuits [39]. By using FluidSIM, learning is carried out cooperatively and supports the thinking power of prospective Electrical Engineering teachers through effective learning, skill improvement, broad application of electronics and preventing errors before they occur in the real environment [40]. N-Gain analysis is also carried out on every aspect of computational thinking to determine the level of improvement in students' abilities after participating in FluidSIM-based learning. The results of the analysis show that all aspects have experienced an increase which is included in the high category (N-Gain ≥ 0.70). The decomposition aspect obtained the highest N-Gain value, namely 0.750, which shows that students have increased their ability to identify problem components and decompose complex systems into simpler parts. Furthermore, the algorithmic aspect obtained an N-Gain value of 0.736, which indicates an increase in students' ability to develop problem-solving steps systematically and logically. The pattern recognition aspect obtained an N-Gain value of 0.721, which shows that students are increasingly able to recognize patterns, relationships and characteristics between components in an electrical system. Meanwhile, the abstraction aspect obtained an N-Gain value of 0.714, which shows an increase in students' ability to simplify complex problems by focusing attention on the most relevant information.

Table 6. N-Gain Results for Each Aspect

Computational Thinking Dimension	N-Gain	Category
Decomposition	0.750	High
Pattern Recognition	0.721	High
Abstraction	0.714	High
Algorithmic Thinking	0.736	High

Overall, these results show that the implementation of FluidSIM-based learning is able to improve all dimensions of computational thinking for prospective vocational teachers in the high category. The greatest increase in the decomposition aspect indicates that the use of interactive simulations provides students with the opportunity to analyze and break down engineering problems more systematically before designing solutions. On the other hand, the high increase in the algorithmic aspect shows that the process of designing, testing and

evaluating circuits using FluidSIM is able to train students to think logically, procedurally and structured in solving engineering problems. These results show that simulation-based learning not only improves conceptual understanding, but also contributes to the development of computational thinking skills which are important competencies for prospective vocational teachers in the digital era.

3.1.1. Decomposition

Based on the presented data, the decomposition indicator shows significant improvement, indicating that students' ability to identify problem components and prioritize solutions has been implemented systematically. The use of FluidSIM encourages students to break down complex electrical systems into simpler subcomponents such as sensors, actuators, and controllers, which can be simulated separately. Decomposition is a fundamental aspect of computational thinking because it helps someone manage complex problems by dividing them into smaller parts that can be solved step by step [41]. In the context of engineering and vocational education, this ability is crucial for mastering systematic analysis and problem-solving skills [42]. Simulation-based virtual laboratories can improve students' ability to analyze and decompose electro-pneumatic systems into functional units [43]. The FluidSIM-assisted Problem-Based Learning model improved logical and systematic thinking skills in solving technical problems [44]. Thus, the improvement in the decomposition indicator indicates that students have developed analytical and structured thinking patterns that are essential for the design and improvement of electrical systems.

3.1.2. Pattern Recognition

Pattern recognition also experienced significant improvement, indicating that students' ability to recognize recurring relationships between electrical system components has strengthened. Through repeated simulations using FluidSIM, students can observe the relationships between voltage, current, and circuit response, enabling them to predict system behavior based on the patterns formed. The ability to recognize patterns is a crucial component of computational thinking because it helps students identify structural similarities and generalize solutions across contexts [45]. Curriculum-integrated computational thinking training can improve pattern recognition skills in both teachers and students [46]. Vocational teachers with high digital competencies demonstrated superior computational thinking and pattern recognition skills compared to traditional teachers [11]. Therefore, improvements in these indicators demonstrate that FluidSIM effectively functions as an interactive visual learning medium, helping students build robust mental representations of technical system dynamics and strengthening their knowledge generalization abilities.

3.1.3. Abstraction

Among all indicators, abstraction demonstrated the highest improvement. This indicates that students successfully developed the ability to formulate core problems and construct simple models that represent complex systems. Through FluidSIM, students can visualize and manipulate virtual representations of electrical circuits, focusing attention on essential relationships between components while ignoring less relevant details. Abstraction skills enable students to focus on important variables and construct mental models that simplify complexity, which is the essence of advanced conceptual thinking [3]. In the context of electrical engineering, this skill includes representing physical systems in the form of logic diagrams or conceptual models. Educational simulations enhance the ability to transfer concepts from abstract representations to real-world applications [45]. Simulation-based learning developed the conceptual representation skills of electrical engineering students [47]. Therefore, the high abstraction indicator in this study demonstrates that FluidSIM facilitates the development of conceptual thinking, generalization, and synthesis skills, which are key characteristics of advanced conceptual thinking.

3.1.4. Algorithmic

Based on the presented data, it was found that the algorithmic thinking indicator also increased significantly. This indicates that students' ability to systematically organize problem-solving steps and evaluate the efficiency of the procedures used has improved. At this stage, students undertake a learning process that begins with the design, testing, and improvement of circuits in the FluidSIM simulation. Students are trained to think logically, analytically, and reflectively to develop algorithmic skills. Algorithmic thinking is the pinnacle of computational thinking because it integrates decomposition, pattern recognition, and abstraction into structured problem-solving steps [48]. The results of this study support the findings of the previous study, where students developed procedural analysis skills and systematic thinking skills in accordance with the practical topics in the Electric Motor Use and Control course. Simulation- and coding-based computational thinking learning can improve students' creative and procedural thinking skills [49]. Algorithm-based simulation activities can improve students' self-confidence and self-efficacy. Based on this study, it can be concluded that improvements in algorithmic indicators demonstrate that students not only understand technical concepts but also possess the reflective, logical, and systematic thinking skills required in vocational education [50].

Furthermore, an analysis was conducted for each aspect. There are four aspects used to measure computational thinking in prospective vocational teachers. As shown in the graph above, the aspect with the highest score is the decomposition aspect. This aligns with the purpose of using FluidSIM as software for designing and testing virtual electrical models, allowing prospective teachers to visualize, analyze, and understand circuit behavior before physically implementing it [51], [52]. With Fluidsim, simple models can be simulated within a system and applied to the real world. These simulations require strong computational thinking, as prospective teachers need to visualize, analyze, and understand the behavior of interacting circuits within a system before physically implementing them [53]. In general, computational thinking is needed to be able to design innovative and effective learning [54], [55]. This is particularly useful for prospective teachers, as it incorporates innovative learning methods such as simulation software like FluidSIM. Simulations indirectly build prospective teachers' confidence in their teaching abilities, supported by FluidSIM [56], besides improving the quality and self-efficacy of prospective teachers [57]. The integration of computational thinking in Electrical Engineering material will be able to prepare students to face the challenges of a future full of technology [58], such as the use of FluidSIM simulation software, so that 21st century competencies can be improved through the application of computational thinking [59].

3.2. Implications for SDG 4: Quality Education

Research results show that improving computational thinking through the use of FluidSIM is directly correlated with strengthening 21st-century skills, such as critical thinking, creativity, collaboration, and communication. Computational thinking is the cognitive foundation of 21st-century skills because it encourages students to think systematically and innovatively in solving complex problems [1]. In the

context of vocational education, computational thinking plays a crucial role in developing adaptive, creative, and resilient abilities to technological change in the Industry 4.0 and Society 5.0 eras. Mastering computational thinking can improve digital literacy and innovation skills, which are highly relevant for prospective vocational teachers preparing students for a technology-based workplace [2]. Therefore, it can be concluded that improving computational thinking through simulation not only impacts cognitive aspects but also strengthens metacognitive skills, which are the foundation of lifelong learning skills.

Improving computational thinking has important implications for the development of pedagogical competencies in prospective vocational teachers. Modern vocational teachers are not only required to be technical instructors but also to be digital learning designers capable of effectively integrating technology. Mastery of computational thinking enables teachers to develop computational learning models that simplify abstract concepts into visual representations that are easily understood by their students [3]. Simulation-based learning designs such as FluidSIM also align with the principles of experiential learning theory, in which students go through four stages of learning: concrete experience, reflective observation, abstract conceptualization, and active experimentation. Simulation can improve the self-efficacy of prospective teachers through safe and reflective learning experiences [47]. Simulation contributes to improving reflection skills and professional decision-making [60]. Thus, the results of this study confirm that FluidSIM simulation-based learning can strengthen pedagogical innovation, self-confidence, and professional readiness of prospective vocational teachers in the digital era.

3.3. Research Limitations and Future Directions

Although the research results indicate that the implementation of FluidSIM-based learning significantly improved the computational thinking skills of prospective vocational teacher students, several limitations should be considered when interpreting these findings. The study used a quasi-experimental one-group pretest-posttest design, thus not including a control group for comparison. This condition means that the improvements in computational thinking skills obtained cannot be fully attributed exclusively to the use of FluidSIM, as there are still potential influences from other factors, such as prior learning experience (history), student development during the learning process (maturation), and learning environment factors that could not be fully controlled.

Furthermore, this study only involved 21 students from a single vocational education study program at a single university. The relatively limited sample size and homogeneous characteristics of the respondents mean that the results cannot be broadly generalized to various vocational education contexts or other disciplines. Therefore, careful interpretation of the research results requires considering the characteristics of the sample and the context in which the research is implemented.

Nevertheless, this study provides initial empirical evidence regarding the effectiveness of integrating engineering simulation software, FluidSIM, in developing the computational thinking skills of prospective vocational teachers. Unlike most previous research that develops computational thinking through programming-based learning, this study demonstrates that engineering simulation software also has the potential to serve as a learning medium for training decomposition, pattern recognition, abstraction, and algorithmic thinking skills in the context of vocational education. These findings expand the use of simulation media as an alternative learning strategy that supports the development of 21st-century competencies while also supporting the achievement of Sustainable Development Goal (SDG) 4, namely the provision of inclusive and sustainable quality education.

To enhance the internal and external validity of this study, future research is recommended to employ a more robust experimental design, such as a pretest-posttest control group design or a randomized controlled trial (RCT), involving a larger number of respondents and a wider range of vocational education institutions. Future research could also investigate the effectiveness of FluidSIM in various engineering courses, compare it with other simulation software, and assess its impact on other 21st-century competencies, such as problem-solving, critical thinking, creativity, and engineering design skills. This way, empirical evidence on the effectiveness of simulation-based learning in vocational education could become more comprehensive and have greater generalizability.

4. Conclusion

This study shows that FluidSIM-based learning significantly improves the computational thinking skills of prospective vocational teachers in Electrical Engineering. A paired-sample t-test showed that the difference between pretest and posttest scores was statistically significant with a significance value <0.05, confirming that FluidSIM implementation contributed to improving students' computational thinking skills. This improvement was further supported by a high N-Gain score of 0.734, reflecting substantial learning improvement after the treatment. These findings indicate that FluidSIM provides an effective simulation-based learning environment for developing decomposition, pattern recognition, abstraction, and algorithmic thinking in vocational teacher education. Unlike most previous studies that develop computational thinking through programming-based learning, this study demonstrates the potential of engineering simulation software to strengthen computational thinking in the electrical engineering context. Therefore, this research contributes to the integration of computational thinking into vocational teacher education while supporting the achievement of Sustainable Development Goals 4 through technology-enhanced quality education.

However, this study used a single-group pretest-posttest quasi-experimental design involving participants from a single institution. Future studies are recommended to use experimental designs incorporating a control group, a larger sample size, and multiple institutions to further validate the effectiveness and generalizability of FluidSIM-based learning.

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