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Examining STEM Students' Computational Thinking Skills through Interactive Practicum Utilizing Technology

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Abstract

This research study explores and compares the computational thinking skills demonstrated by STEM students during interactive practicums involving both virtual laboratories and physical laboratories. The objectives of the study are to assess the performance of computational thinking skills in each practicum setting and to determine any differences between the two environments. An experimental approach was adopted, and 106 first-year STEM students from a distinguished private university in Indonesia participated in the study. The students were divided into two groups, one using virtual labs and the other using physical labs. The study employed a portfolio instrument to assess various aspects of computational thinking, including problem reformulation, recursion, problem decomposition, abstraction, and systematic testing. The findings show that both groups of students achieved "good" scores for computational thinking skills. However, students in the virtual labs group demonstrated superior skills compared to the physical labs group. The aspects of problem reformulation and abstraction received the highest scores in both groups, while problem decomposition received the lowest scores. A MANOVA test confirmed statistically significant differences in computational thinking skills between the two practicum environments. The study suggests that the use of virtual labs can positively impact students' computational thinking abilities. The results have implications for educators and institutions seeking to enhance students' computational thinking skills and design effective STEM practicums.

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INTRODUCTION

Computational Thinking (CT) serves as a fundamental framework for devising efficient and effective solutions to problems, whether through algorithms, with or without the assistance of computers (Shute et al., 2017). The solutions derived from CT can be adapted and employed in diverse scenarios (Shute et al., 2017). As the STEM field continues to flourish, prominent organizations and companies like Microsoft, Google, and others emphasize the importance of acquiring foundational CT skills for individuals (Durak & Saritepeci, 2018).

Consequently, the demand for CT skills in the 21st century has significantly influenced national education policies (Saritepeci, 2020). In response, countries such as the United States (US), Germany, and the Netherlands have updated their education policies to align with the CT approach, aiming to enhance students' CT abilities (Lin et al., 2020).

According to Wing (2008), the concept of computational thinking (CT) should not be misconstrued as thinking like a computer; instead, it involves actively engaging in five distinct cognitive processes aimed at effective and innovative problem-solving. These processes encompass the following key elements: (a) problem reformulation, wherein the challenge is redefined and transformed into a familiar and solvable format; (b) recursion, involving the incremental construction of a system based on previously acquired information; (c) problem decomposition, wherein the complex problem is broken down into manageable and approachable units; (d) abstraction, entailing the creation of simplified models that capture the fundamental aspects of intricate problems or systems; and (e) systematic testing, which entails purposefully taking actions to derive solutions systematically. By embracing these five cognitive processes, individuals can enhance their problem-solving capabilities, harnessing the power of computational thinking to tackle challenges with greater efficiency and creativity.

In recent times, there has been a growing emphasis on using the STEM approach to foster students' CT skills, as suggested by siswa Çiftçi and Topçu (2022). The integration of STEM and CT offers a more meaningful learning experience, as it connects CT concepts to students' daily lives and showcases their broader applications in education (Li et al., 2020). By adopting this approach, students are provided with an enriching learning environment where they can actively explore, learn, and apply CT principles in problem-solving scenarios (Yang et al., 2020). An additional benefit of employing STEM as a context for CT is its potential to facilitate the effective teaching of challenging science subjects, leading to increased learner self-efficacy in CT instruction (Çiftçi & Topçu, 2022). Moreover, the amalgamation of CT and STEM disciplines plays a pivotal role in enhancing CT skill development (Peel & Friedrichsen, 2018; Yang et al., 2021).

After conducting observations on teaching practices at various universities that offer STEM education, several challenges were identified in relation to CT training for STEM students. Firstly, a common challenge is the lack of access to comprehensive and specialized training programs that specifically focus on CT concepts and effective pedagogical strategies (Çiftçi & Topçu, 2023). This limitation can lead to a reduced understanding of how to incorporate CT into their learning methods. Secondly, the rapidly evolving nature of technology poses difficulties for students to keep up with the latest CT-relevant tools and applications. The absence of hands-on experience and practical application during training further hinders the development of a profound grasp of CT principles. Additionally, some students may struggle to acquire the necessary technical skills, especially in algorithmic problem-solving, particularly if they have limited prior knowledge in this area. These factors collectively create significant obstacles for STEM students seeking to attain the knowledge and skills essential for effective CT acquisition. Moreover, teaching CT in a context-detached manner, unrelated to any specific discipline, can hinder students' motivation to learn, resulting in a negative impact on their overall learning experience (Goode et al., 2006).

Practicum is commonly used in STEM education to refer to a period of practical training, often as part of a formal academic program. It allows students to apply theoretical knowledge and skills in real-world settings relevant to the STEM field. Practical experiences help students develop technical skills, communication skills, teamwork, and other important qualities necessary for success in STEM fields. Traditionally, practicum experiences have taken place in a physical environment, such as a real-world workplace, laboratory, or classroom setting, where learners can directly interact with materials, equipment, and people relevant to their area of study (Serrano-Perez et al., 2023). However, with the rapid advancement of technology, particularly in the realm of virtual reality and online learning tools, practicum experiences are now increasingly being conducted in a virtual laboratory environment. This means that learners can engage in practical training and exercises through digital platforms, simulated environments, or computer-based applications that replicate real-world scenarios (Reginald, 2023). The growing demand for learning structures within the rapidly advancing STEM field has sparked a heightened interest in creating and implementing virtual laboratories (Kleine & Pessot, 2023).

The development of thinking skills in the field of STEM education has been explored through two practicum models: physical and virtual laboratories. The traditional physical practicum, conducted within the scientific inquiry framework, has proven effective in enhancing students' critical thinking and science process skills, as supported by research conducted by siswa Ernita et al. (2021). Similarly, virtual laboratories have also demonstrated positive results in improving students' thinking abilities, as indicated in studies by Bilad et al. (2022). Moreover, the combination of both approaches has been shown to enhance students' scientific reasoning (Bicak et al., 2021). However, the investigation of STEM students' computational thinking skills in interactive practicum using technology is an area that has not yet been thoroughly explored. Therefore, the present study aims to address this gap by examining STEM students' computational thinking skills through the utilization of interactive practicum involving technology (virtual laboratories) and without the involvement of technology (physical laboratories).

In relation to the research objectives, the research problems are outlined below:

1. What is the performance of computational thinking skills demonstrated by STEM students during practicums that utilize virtual laboratories?
2. What is the performance of computational thinking skills demonstrated by STEM students during practicums that utilize physical laboratories?
3. How do STEM students' computational thinking skills compare between the two practicum environments (virtual labs vs. physical labs)?

METHOD

General design of study

This study constitutes an exploratory research conducted through an experimental approach, targeting a specific study group. The research incorporates an intervention in the form of interactive practicum, utilizing both technology (virtual labs) and a traditional approach (physical labs). Within this experimental approach, the researcher manipulates the intervention variables (virtual labs vs. physical labs) to observe their influence on the computational thinking skills of STEM students. By employing this methodology, the study aims to discern the potential impact of these different laboratory settings on the students' skills in computational thinking.

Participants

The study encompassed a cohort of 106 first-year STEM students who were pursuing their education at a distinguished private university in Indonesia. They were divided into practicum groups using virtual labs (N = 54) and physical labs (52). With an average age of 17.5 years, these young learners were engaged in the fields of STEM, displaying their passion and commitment to the pursuit of knowledge in these domains. The participants' demographics featured a relatively balanced distribution across genders, reflecting inclusivity in the research sample. Over the course of an intensive and transformative two-month period, these students actively partook in the learning process, embracing challenges, expanding their horizons, and developing a profound understanding of the subjects they explored.

To ensure ethical conduct and adherence to research guidelines, the implementation of this significant investigation was formally sanctioned and received written permission from the reputable university research institute. This approval underscored the rigorous approach and respect for academic standards in the study's design and execution, ensuring the protection of participants' rights and welfare.

Procedures

In this research, first-year STEM students were engaged in a comprehensive and interactive practicum focused on fundamental physics courses. The facilitation of this practicum was expertly guided by a dedicated lecturer over a span of two months, allowing for an immersive and transformative learning experience. Central to this innovative learning approach was the utilization of cutting-edge technology, which incorporated three distinct practicum simulation tools: Physics Education Technology (https://phet.colorado.edu/in/), Go-Lab (https://www.golabz.eu/), and O-Labs (https://www.olabs.edu.in/). These simulation tools were thoughtfully employed at different stages during the learning process, thoughtfully tailored to complement and reinforce specific course materials and learning objectives. Meanwhile, a different group carried out practicum using physical labs with the same practicum material as those who practicum used virtual labs.

A key aspect of this research involved measuring and evaluating the STEM students' computational thinking skills throughout the practicum. To achieve this, performance assessment techniques were implemented, ensuring consistency and precision in evaluating the participants' proficiency in computational thinking. The assessment parameters were thoughtfully designed to comprehensively capture the students' computational thinking abilities, providing valuable insights into their problem-solving, analytical, and logical reasoning capabilities. Upon the completion of the practicum, the research underwent a rigorous analysis of the results pertaining to the students' computational thinking skills. This analysis was conducted using a combination of appropriate analytical methods, both descriptive and statistical in nature. By employing these robust analytical techniques, researchers could derive meaningful conclusions from the data, illuminating the impact of the interactive practicum and technology integration on the students' computational thinking abilities.

Instruments and Analysis

The assessment of computational thinking skills involves evaluating various aspects, such as problem reformulation, recursion, problem decomposition, abstraction, and systematic testing (Wing, 2008). To measure these skills, performance assessment techniques with portfolio instruments were utilized. Portfolios are particularly suitable for this purpose as they offer a comprehensive and holistic evaluation of an individual's abilities in computational thinking contexts. Unlike single assessments or standardized tests, portfolios provide a more nuanced understanding of an individual's computational thinking capabilities, capturing a broader range of skills. The portfolio instrument grid consists of a series of assignments, integrated with computational thinking skills, that students must complete during practicums. Prior to its implementation, this instrument underwent validation by two experts, ensuring its content and construct validity for use in the study. As a result, the instrument has been declared valid, so it can be used in this study.

The scoring technique for evaluating thinking skills largely follows the rules used in previous studies (Prayogi et al., 2022). However, for computational thinking, the criteria for success have been slightly modified, resulting in the categorization of student performance as excellent (CT > 2.20), good (1.40 < CT ≤ 2.20), sufficient (0.60 < CT ≤ 1.40), under satisfactory (–0.20 < CT ≤ 0.60), and unsatisfactory (CT ≤ –0.20). To analyze the data on students' computational thinking skills, both descriptive and statistical methods were employed, using a significance level of 0.05. A different test was carried out on students' computational thinking performance scores between five aspects of computational thinking (problem reformulation, recursion, problem decomposition, abstraction, and systematic testing). This approach helps to provide a comprehensive understanding of the students' abilities in computational thinking and facilitates meaningful insights into the study's findings.

RESULTS AND DISCUSSION

In pursuit of examining the computational thinking skills of STEM students, a research study was undertaken, employing interactive practicums that harnessed the power of technology (virtual labs) and without the involvement of technology (physical labs). The primary objective was to gain insights into how students in STEM fields tackle intricate problems by leveraging computational thinking as a fundamental framework. To achieve this, the researchers meticulously crafted interactive practicums, harnessing the potential of cutting-edge technologies like Physics Education Technology, Go-Lab, and O-Labs. The findings of this investigation, encompassing the descriptive analysis of STEM students' computational thinking skills, have been meticulously compiled and are presented in Table 1.

Table 1. The results of computational thinking skills among STEM students engaged in practicums utilizing both physical and virtual labs

Computational thinking	Group	Valid	Mean	Std. Error of Mean	Std. Deviation	Coefficient of variation
Problem reformulation	Physical Labs	52	1.962	0.082	0.593	0.302
	Virtual Labs	54	2.278	0.067	0.492	0.216
Recursion	Physical Labs	52	1.846	0.069	0.500	0.271
	Virtual Labs	54	2.093	0.061	0.446	0.213
Problem decomposition	Physical Labs	52	1.788	0.057	0.412	0.231
	Virtual Labs	54	2.204	0.061	0.451	0.204
Abstraction	Physical Labs	52	1.769	0.065	0.469	0.265
	Virtual Labs	54	2.056	0.056	0.408	0.199
Systematic testing	Physical Labs	52	1.827	0.060	0.430	0.236
	Virtual Labs	54	2.093	0.061	0.446	0.213
Average Score	Physical Labs	52	1.838	0.029	0.210	0.114
	Virtual Labs	54	2.144	0.026	0.188	0.088

The data in Table 1 illustrates the computational thinking skills of STEM students who participated in practicums using both virtual labs and physical labs. In the virtual labs group, students achieved an average score of 2.144 (SD = 0.188), which was higher compared to the physical labs group with an average score of 1.838 (SD = 0.114). Notably, both groups met the 'good' criteria (2.40 < X < 3.21) for computational thinking skills. Quantitatively, STEM students who engaged in learning with virtual labs demonstrated superior computational thinking skills compared to their counterparts using physical labs. The graph in Figure 1 visually represents the average score of STEM students' computational thinking skills.

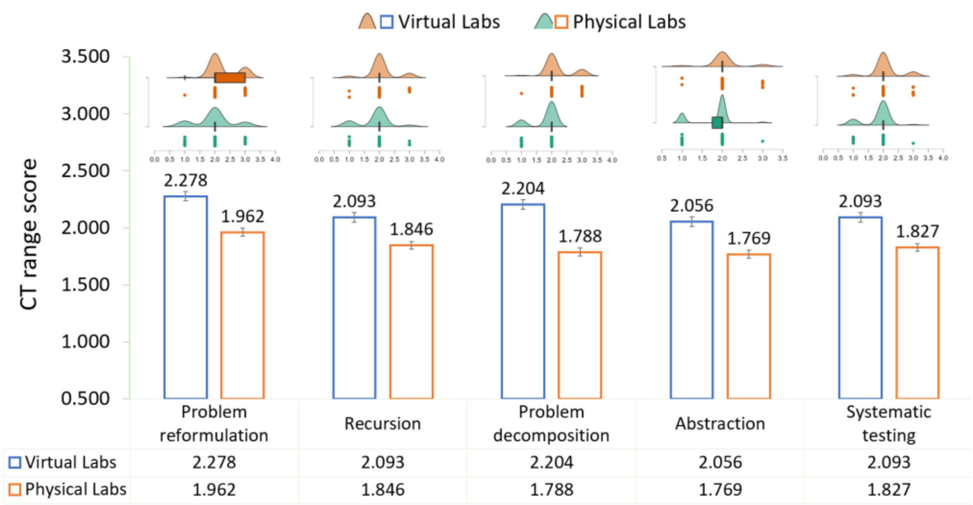

Figure 1. Graph of differences in computational thinking skills of STEM students

Figure 1 illustrates a graphic plot comparing the average scores of computational thinking skills among STEM students who participate in virtual labs and physical labs. It is evident that students in virtual labs exhibit higher average scores across all aspects compared to their counterparts in physical labs. Within the virtual labs group, the aspect of 'problem reformulation' received the highest score (M = 2.278, SD = 0.492), while 'abstraction' received the lowest score (M = 2.056, SD = 0.408). Similarly, in the physical labs group, 'problem reformulation' also received the highest score (M = 1.962, SD = 0.593), while 'abstraction' obtained the lowest score (M = 1.769, SD = 0.469).

To examine the differences in computational thinking skills in each aspect between the two groups, a MANOVA test was conducted. The results, presented in Table 2, provide further insights into the variations in STEM students' computational thinking abilities between virtual and physical lab environments.

Table 2. MANOVA test results for each aspect of computational thinking in practicum (virtual and physical labs)

Computational thinking	Cases	Sum of Squares	df	Mean Square	F	p	Vs-Mpr*	η²
Problem reformulation	Group	2.649	1	2.649	8.958	0.003	18.804	0.079
	Residuals	30.756	104	0.296				
Recursion	Group	1.609	1	1.609	7.179	0.009	9.014	0.065
	Residuals	23.306	104	0.224				
Problem decomposition	Group	4.568	1	4.568	24.446	< .001	9810.906	0.190
	Residuals	19.432	104	0.187				
Abstraction	Group	2.172	1	2.172	11.257	0.001	48.786	0.098
	Residuals	20.064	104	0.193				
Systematic testing	Group	1.870	1	1.870	9.733	0.002	25.927	0.086
	Residuals	19.979	104	0.192				

*Vovk-Sellke Maximum *p* -Ratio

The MANOVA test outcomes (Table 2) reveal a comparison of computational thinking aspects between STEM students who took part in the practicum, utilizing either virtual labs or physical labs. The subsequent section provides interpretations of the findings for each aspect.

- *Problem reformulation.* The sum of squares for problem reformulation between the two groups was 2.649. The F-statistic value was 8.958 with a p-value of 0.003, indicating a statistically significant difference between the two groups' performance in problem reformulation. The effect size (η^2) for problem reformulation was 0.079, suggesting that approximately 7.9% of the variation in the participants' problem reformulation skills could be attributed to the lab type they were engaged in. The Vovk-Sellke maximum p-ratio (Vs-Mpr) was 18.804, which indicates strong evidence against the null hypothesis.

- *Recursion.* The sum of squares for recursion was 1.609, reflecting the differences in performance between the virtual lab and physical lab groups. The F-statistic value was 7.179 with a p-value of 0.009, signifying a statistically significant difference in recursion skills between the two groups. η^2 results for recursion was 0.065, suggesting that approximately 6.5% of the variance in recursion abilities could be attributed to the type of lab used. The Vs-Mpr was 9.014, indicating strong evidence against the null hypothesis.
- *Problem decomposition*. The sum of squares for problem decomposition was 4.568, indicating notable differences between the two groups in this aspect. The F-statistic value was 24.446 with a p-value of less than 0.001, demonstrating a highly significant difference in problem decomposition skills between the virtual lab and physical lab groups. η^2 results for problem decomposition was 0.190, suggesting that around 19.0% of the variation in problem decomposition skills could be attributed to the lab type. The Vs-Mpr was 9810.906, providing strong evidence against the null hypothesis.
- *Abstraction*. The sum of squares for abstraction was 2.172, showing differences in performance between the two groups. The F-statistic value was 11.257 with a p-value of 0.001, indicating a significant difference in abstraction skills between the virtual lab and physical lab groups. η^2 for abstraction was 0.098, meaning that approximately 9.8% of the variance in abstraction abilities could be attributed to the lab type. The Vs-Mpr was 48.786, providing strong evidence against the null hypothesis.
- *Systematic testing*. The sum of squares for systematic testing was 1.870, indicating differences in performance between the two groups. The F-statistic value was 9.733 with a p-value of 0.002, signifying a significant difference in systematic testing skills between the virtual lab and physical lab groups. The results of η^2 for systematic testing was 0.086, suggesting that approximately 8.6% of the variation in systematic testing skills could be attributed to the lab type, and the Vs-Mpr was 25.927, providing strong evidence against the null hypothesis.

The MANOVA test results demonstrate that STEM students who participated in the practicum using virtual labs and physical labs exhibited statistically significant differences in various aspects of computational thinking. The effect sizes suggest that the lab type had a notable impact on the STEM students' performance in problem reformulation, recursion, problem decomposition, abstraction, and systematic testing. These findings indicate that the choice of lab environment may influence the development and proficiency of specific computational thinking skills among students.

This finding is consistent with the conclusions made by Chen et al. (2020) that virtual technology can effectively promote students' computational thinking. Our present study's results align with prior research demonstrating that students' computational thinking abilities generally improve when they engage in practical learning with virtual labs, particularly in abstraction, algorithms, and decomposition aspects (Kusmiati, 2022). Another recent investigation by Rakhmawati et al. (2022) similarly indicated that employing virtual labs-based worksheets focusing on electrostatic forces, fields, and equipotential lines can effectively enhance students' computational thinking. The benefits are evident as the artificial environment of virtual labs provides an enriched learning experience that effectively cultivates students' computational thinking skills (Agbo et al., 2023).

With the advancement of current technology, there is a growing suggestion to replace traditional practicum involving physical labs with digital labs that utilize virtual technology. While physical laboratories offer the advantage of providing hands-on experience, allowing students to directly engage with real equipment and materials, leading to a deeper understanding of scientific principles through practical application, virtual labs have their merits, particularly in training computational thinking skills. In virtual labs, technology is more advanced, offering adequate visualization that aids in the development of computational thinking. This visual environment proves to be more suitable for training students to enhance their computational thinking skills (Lye & Koh, 2014). Furthermore, the integration of technology in the design, structure, and content of learning can significantly enrich the educational process, especially in developing students' computational thinking skills in the field of science education (Rubinstein & Chor, 2014). Research has shown that the use of technology in science experiments among STEM students can enhance their computational thinking skills and computational perceptions in science (Fuhrmann et al., 2021).

In our research results, the utilization of virtual labs technology has demonstrated a significant influence on STEM students' computational thinking skills in various key areas. These areas include problem reformulation, recursion, problem decomposition, abstraction, and systematic testing. It is widely acknowledged that technology-based learning is a prominent approach for fostering computational thinking, particularly in assisting with abstraction and iteration processes for effective problem-solving (Resnick et al., 2009). Numerous prior studies have also pointed out the effectiveness of digital learning designs in promoting the acquisition of computational thinking knowledge (Ung et al., 2022). Furthermore, the integration of 3D visual learning using virtual technology has been shown to enhance students' computational thinking processes, specifically in aspects such as problem decomposition, algorithm design, and algorithm efficiency skills (Ou Yang et al., 2023). The use of visual technology learning environments has proven to be more appealing to students, leading to increased motivation and enhanced learning effectiveness (Barak & Assal, 2018). Additionally, technology-based systems play a crucial role in fostering the development of students' computational thinking abilities (Chevalier et al., 2022).

CONCLUSION

The study investigated the computational thinking skills of STEM students in interactive practicums utilizing virtual laboratories and physical laboratories. This study found that STEM students who engaged in learning with virtual labs demonstrated superior computational thinking skills compared to those using physical labs. The average scores of computational thinking skills were consistently higher in the virtual labs group across all aspects, including problem reformulation, recursion, problem decomposition, abstraction, and systematic testing. The statistical analyses, including the MANOVA test, indicated significant differences in computational thinking skills between the two practicum environments. These findings highlight the potential benefits of incorporating technology-based interactive practicums, such as virtual labs, to enhance and develop students' computational thinking abilities in STEM education.

RECOMMENDATION

One potential limitation of this research is the specific study group targeted for the experimental approach. The study focuses solely on STEM students, which may limit the generalizability of the findings to students in other disciplines. The unique characteristics and background knowledge of STEM students may influence their performance in computational thinking skills, and the results might not be applicable to students in non-STEM fields. Therefore, caution should be exercised when extrapolating the findings to a broader student population. Future research could consider including students from diverse academic backgrounds to provide a more comprehensive understanding of the impact of different laboratory environments on computational thinking skills across various disciplines. Additionally, the study's duration and sample size could be considered potential limitations, as a longer-term study with a larger sample size could offer more robust and representative results.

Author Contributions

The authors have sufficiently contributed to the study, and have read and agreed to the published version of the manuscript. Conceptualization, N.N.S.P. Verawati and K. Rijal; Methodology, N.N.S.P. Verawati, K. Rijal and N.W.B. Grendis; Validation, K. Rijal; Formal analysis, K. Rijal; Investigation, N.N.S.P. Verawati and K. Rijal; Writing—original draft preparation, N.N.S.P. Verawati and K. Rijal; Review and editing, N.W.B. Grendis.

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Declaration of Interest

The authors declare no conflict of interest.

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