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Bridging Virtual and Physical: Exploring Students' Computational Thinking and Creativity in Robot-Guided vs. Simulation-Based Learning

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Abstract

Computational thinking (CT) is a critical 21st-century skill that equips undergraduate students to solve problems systematically and think algorithmically. A key component of CT is computational creativity, which enables students to generate novel solutions within programming constraints. Humanoid robots are increasingly explored as promising tools to enhance CT skills, fostering teamwork and creativity in collaborative settings. However, gaps remain in understanding how different learning modalities impact the development of these skills. This study examines the comparative effects of robot-guided and simulation-based collaborative learning on undergraduate students' computational creativity and CT skills. The study involved 71 undergraduate students, divided into small groups and randomly assigned to begin with either a robot-guided or simulation-based modality, switching to the alternate modality in the following session. Data were collected through group log data and pre- and post-intervention questionnaires. The results indicated that the robot-guided modality significantly enhanced computational creativity in terms of originality and elaboration, while both modalities supported flexibility equally. Additionally, students reported higher CT skills following the robot-guided activity, with the most notable improvements in cooperation and creativity. Lastly, fewer group interaction difficulties were reported during the robot-guided activity, supporting its value for collaborative learning. These findings highlight humanoid robots as a valuable complement to virtual learning environments, offering unique opportunities to foster creativity, collaboration, and problem-solving in undergraduate education.

Notes for Practice

- The use of learning analytics to assess computational creativity in online collaborative learning remains underexplored.
- This study examined students' computational creativity and computational thinking (CT) skills using log data and self-report measures across robot-guided and simulation-based learning modalities.
- Students tended to create more complex, layered solutions and explore less conventional approaches during the robot-guided modality compared to the simulation-based modality.
- Students reported higher perceived creativity, cooperation, and enjoyment in the robot-guided modality compared to the simulation-based one.
- Programming log data can be used to assess students' computational creativity, offering a foundation for future formative assessment practices.

Keywords: Collaborative learning, computational creativity, computational thinking, higher education, robot-guided learning, student log data

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1. Introduction

In today's technology-driven world, computational thinking (CT) is widely recognized as a critical 21st-century skill, enabling students to approach problems systematically, think algorithmically, and develop creative solutions (Hershkovitz et al., 2019; Israel-Fishelson & Hershkovitz, 2022). As industries increasingly rely on automation, data-driven decision-making, and artificial intelligence (AI), the need for students to master higher-order thinking skills, including CT, has grown exponentially (Hooshyar et al., 2021; Liu et al., 2023; Usher & Amzalag, 2025; Usher, 2025). Far from being limited to computer science, CT is now seen as an interdisciplinary framework that enhances problem-solving abilities across diverse fields, including engineering, science, mathematics, and the humanities (Luhmann & Burghardt, 2022; Wing, 2006). By fostering CT, educators prepare students for future careers that demand both technical expertise and creative problem-solving (Rehmat et al., 2020).

To address this need, educators are increasingly adopting innovative tools and methodologies, with humanoid robots (HR) emerging as a promising avenue for fostering CT skills (Hsu et al., 2022). These robots, characterized by their human-like appearance and interactive capabilities, provide students with a dynamic platform for applying CT in real-world scenarios (Ardito et al., 2020; Kurtz & Kohen-Vacs, 2024). The hands-on interaction and real-time feedback afforded by HRs enable students to observe the immediate outcomes of their programming efforts, making the learning process engaging and tangible (Evripidou et al., 2021; Rehmat et al., 2020). Moreover, programming HRs in collaborative settings fosters teamwork, creativity, and communication skills, key indicators for success in complex problem-solving environments (Ardito et al., 2020; Thornhill-Miller et al., 2023). For instance, collaboration in educational tasks encourages students to exchange ideas, refine solutions, and confront diverse perspectives, all of which are essential for developing computational creativity and critical thinking (Usher & Barak, 2020).

A key component of CT is creativity, often referred to as computational creativity when applied within computational frameworks. Computational creativity involves generating novel solutions within the constraints of programming and algorithmic thinking (Hershkovitz et al., 2019). This form of creativity bridges technical and creative skills, promoting a holistic integration of CT into educational settings (Israel-Fishelson & Hershkovitz, 2022). Research indicates that computational creativity not only enhances CT skills but also fosters critical thinking and interdisciplinary problem-solving, linking abstract concepts to real-world applications (Israel-Fishelson & Hershkovitz, 2022; Kurtz & Kohen-Vacs, 2024). Thus, incorporating tools such as HRs plays a pivotal role in cultivating computational creativity by blending technical skill development with opportunities for innovation and collaboration.

In recent years, learning analytics (LA) has emerged as a powerful framework for measuring creativity by tracking and analyzing student activities within digital systems (Chou et al., 2024; Marrone & Cropley, 2022). Methods such as interaction pattern analysis, real-time behavioural tracking, and sequence analysis provide detailed insights into how students approach tasks, identify patterns in their problem-solving processes, and capture moments of originality (Hershkovitz et al., 2019; Kovalkov et al., 2021). These approaches enable educators to dynamically evaluate creativity and provide continuous feedback to support student development over time (Chou et al., 2024; Marrone & Cropley, 2022). By doing so, LA provides unprecedented insights into creative processes, enabling personalized interventions and fostering a deeper understanding of how students engage with computational challenges.

Despite the growing interest in computational creativity and CT, significant gaps remain in understanding how higher education students develop these skills, particularly within higher education contexts (Israel-Fishelson & Hershkovitz, 2022; Kurtz & Kohen-Vacs, 2024; Tang et al., 2020). Additionally, while LA has demonstrated potential for capturing the multifaceted dimensions of creativity, its application in educational contexts, particularly in collaborative settings, remains underexplored (Chou et al., 2024; Hsu et al., 2022; Marrone & Cropley, 2022). Furthermore, there is limited empirical research comparing the impact of physical and virtual learning environments in fostering these critical skills among students.

The current study addresses these gaps by examining differences in students' computational creativity and CT skills within humanoid robot-guided and simulation-based collaborative learning environments. By integrating both learning analytics and self-report measures, the study examines how different learning modalities influence the development of computational creativity and key CT dimensions, providing new insights into the role of innovative educational tools in higher education.

2. Literature Review

2.1. Computational Thinking in Education

Since the mid-2000s, computational thinking (CT) has gained increasing recognition among stakeholders across sectors as a critical skill for the 21st-century labour market (Hershkovitz et al., 2019; Thornhill-Miller et al., 2023). Popularized by Wing in 2006, CT refers to a set of cognitive processes that enable individuals to approach problems systematically, think algorithmically, and develop efficient, creative solutions (Peracaula-Bosch & González-Martínez, 2023; Wing, 2006). Although its conceptual roots lie in early computer science education, pioneers such as Seymour Papert expanded the use of computational tools to foster problem-solving and logical reasoning, laying the groundwork for modern CT applications

(Papert, 1971). Over time, CT has evolved into a universal problem-solving framework applicable across diverse disciplines, including engineering, mathematics, science, and the humanities (Luhmann & Burghardt, 2022; Weintrop et al., 2021).

The integration of CT into education has grown rapidly, reflecting its potential to transform how students learn and solve problems across disciplines (Tang et al., 2020). Once regarded as a skillset specific to programmers, CT is now incorporated into curricula at all levels, as educators increasingly recognize its value in fostering critical thinking, collaboration, and creativity (Hershkovitz et al., 2019; Rehmat et al., 2020). A recent scoping review identified several instruments for assessing CT in education, with Korkmaz et al.'s (2017) definition emerging as one of the most cited. This definition highlights five core components of CT: algorithmic thinking, cooperativity, creativity, critical thinking, and problem-solving. This multidimensional view underscores CT's versatility in equipping students with essential skills for addressing interdisciplinary challenges and advancing innovation across various fields (Israel-Fishelson & Hershkovitz, 2022).

However, the incorporation of CT into educational curricula faces significant challenges, including limited teacher training, curriculum overload, and unequal access to technological resources (Kong et al., 2020; Lee et al., 2019; Yeni et al., 2024). Moreover, CT assessments are more commonly available and used in elementary education than in high school, college, or professional development, highlighting disparities across educational levels and the need for greater focus on later stages (Tang et al., 2020).

Addressing these challenges requires innovative strategies to make CT more accessible, engaging, and scalable across all educational levels (Kong et al., 2020). To overcome these barriers, educators have turned to technology-enhanced learning environments such as block-based programming languages, robotic systems, and adaptive educational games (Hershkovitz et al., 2019). These tools make abstract CT concepts more tangible by allowing students to experiment with visual representations of algorithms and receive immediate feedback on their problem-solving approaches (Ardito et al., 2020; Evripidou et al., 2021). For instance, a study by Hooshyar et al. (2021) demonstrated the potential of adaptive educational games with the introduction of AutoThinking, which significantly improved both conceptual understanding and CT skills in elementary students. Such environments not only enhance engagement but also foster creativity and innovation, which are integral to the CT framework.

In addition to technological solutions, collaborative and project-based learning approaches have proven effective in fostering CT development (Rehmat et al., 2020). By encouraging teamwork and the exchange of diverse perspectives, these methods enhance critical thinking, problem-solving, and creativity (Barak & Usher, 2020; Luhmann & Burghardt, 2022; Usher & Barak, 2020). Creativity, in particular, plays a vital role within the CT framework, as it enables students to generate novel and innovative solutions to complex problems (Hershkovitz et al., 2019).

2.2. The Role of Computational Creativity in CT Development

In recent years, there has been growing recognition that creativity is an essential skill for the 21st century, deserving a prominent place in educational curricula from an early age (Hershkovitz et al., 2019; Israel-Fishelson et al., 2020). Creativity is commonly regarded as a multidimensional construct comprising four key dimensions: fluency, flexibility, originality, and elaboration, with originality being the most widely studied (Marrone & Cropley, 2022). Fluency refers to the ability to generate many ideas for solving a problem, while flexibility involves producing ideas that differ substantially from one another or considering multiple uses for a concept. Originality reflects the ability to think of ideas that are unconventional or deviate from the norm, while elaboration measures how well an idea is expanded, refined, or integrated with new insights (Hershkovitz et al., 2019; Israel-Fishelson & Hershkovitz, 2022).

These dimensions, originally developed by Torrance in his seminal work on creative thinking (Torrance, 1974), have since been adapted to computational contexts to capture the creative processes involved in programming and algorithmic design (Kovalkov et al., 2021; Manske & Hoppe, 2014). Often referred to as computational creativity, this form of creativity involves generating innovative solutions within the constraints of programming and algorithmic logic (Hershkovitz et al., 2019). For example, fluency might reflect the number of alternative solutions generated for a programming challenge, while originality involves the use of unconventional programming constructs or unique approaches to problem-solving (Israel-Fishelson & Hershkovitz, 2022; Marrone & Cropley, 2022).

Creativity in CT can be explored through two distinct approaches: creativity within the scope of CT and creativity outside the scope of CT. The first approach focuses on the creativity inherent in computational artifacts, such as programs designed by learners. Studies in this category examine how digital tools enable learners to create unique products and explore the relationship between creativity and other educational variables, such as engagement and problem-solving abilities (Yadav & Cooper, 2017). The second approach investigates the interplay between creativity as a broader cognitive skill and the acquisition of CT. This includes inquiries into whether creative thinking supports CT development and whether CT instruction enhances creativity across disciplines (Israel-Fishelson & Hershkovitz, 2022).

Computational creativity extends beyond technical proficiency, fostering interdisciplinary thinking that connects computational skills with broader applications in science, engineering, and the arts (Israel-Fishelson & Hershkovitz, 2022). Encouraging creativity within CT not only deepens student understanding of core concepts but also promotes experimentation, adaptability, and risk-taking. Tasks that challenge students to generate unique solutions, optimize algorithms, or design efficient systems are particularly effective in promoting originality, as they mimic real-world scenarios where creative thinking is essential for addressing complex, dynamic problems (Manske & Hoppe, 2014; Liu et al., 2023).

Collaborative learning environments also play a pivotal role in fostering creativity within CT. By encouraging students to work together, exchange ideas, share diverse perspectives, and co-construct solutions, collaboration enhances critical thinking and creative problem-solving (Ardito et al., 2020; Barak & Usher, 2020; Usher & Barak, 2020). Furthermore, teamwork fosters essential CT skills, such as designing algorithms collaboratively, debugging solutions, and iterating designs, while preparing students for teamwork-driven innovation in real-world contexts (Hsu et al., 2022; Kurtz & Kohen-Vacs, 2024).

The relationship between creativity and CT is multifaceted, with research highlighting the bidirectional influence between these constructs. Foundational CT principles, such as sequencing, loops, and conditions, serve as essential tools for supporting creative thinking (Resnick, 2017; Yadav & Cooper, 2017). Conversely, creativity enhances CT acquisition by enabling students to explore unconventional problem-solving strategies and innovate beyond standard approaches (Israel-Fishelson & Hershkovitz, 2022). For example, Hershkovitz et al. (2019) reported significant correlations between general creative thinking and computational creativity, suggesting that creativity in programming aligns with broader creative constructs.

Despite the growing recognition of creativity as a vital dimension of CT, significant gaps remain. Creativity is notoriously difficult to measure due to its context-dependent nature and the challenge of defining it as a multifaceted competency rather than a single skill (Kovalkov et al., 2021; Marrone & Cropley, 2022). Additionally, research exploring how different learning modalities influence computational creativity is limited. Virtual simulations and video games encourage abstract, logic-driven exploration, emphasizing creative algorithmic thinking without the constraints of physical execution (Astutik & Prahani, 2018; Hooshyar et al., 2021). On the other hand, physical tools, such as HRs, provide opportunities for students to experiment with real-world scenarios, fostering creativity through hands-on interactions and dynamic feedback (Evripidou et al., 2021; Israel-Fishelson & Hershkovitz, 2022).

2.3. The Role of Humanoid Robots in Education

Humanoid robots (HR) have gained increasing attention as versatile educational tools, offering innovative ways to engage students in active and collaborative learning. With their human-like design and interactive capabilities, these robots have the potential to enhance problem-solving, teamwork, and algorithmic thinking by bridging the gap between abstract concepts and real-world applications (Ardito et al., 2020; Hsu et al., 2022). By simulating real-life scenarios, HRs allow students to experiment with programming tasks, blending technical skill development with innovation and collaboration (Evripidou et al., 2021; Hsu et al., 2022).

Studies exploring the use of HRs in education suggest that they are particularly effective in promoting CT skills. HRs provide a dynamic platform for students to apply CT skills by offering immediate feedback on programming efforts (Ardito et al., 2020; Chen & Chung, 2023; Stewart et al., 2021). This immediate feedback loop encourages experimentation and iterative problem-solving, enhancing both engagement and learning outcomes (Evripidou et al., 2021). Furthermore, HRs stimulate creativity by providing a flexible platform for designing novel solutions, such as implementing unique robot movements, speech patterns, or interactive behaviours (Hsu et al., 2022; Kurtz & Kohen-Vacs, 2024). Additionally, the tangible nature of robots makes abstract CT concepts more accessible, particularly for younger learners or those new to computational frameworks (Ardito et al., 2020).

HRs also promote collaboration, serving as focal points for group activities to guide students through CT activities (Ardito et al., 2020; Norman et al., 2022). Collaborative activities involving HRs foster social-emotional learning, helping students to develop communication, teamwork, and shared decision-making skills in addition to technical competencies (Evripidou et al., 2021; Hsu et al., 2022; Stewart et al., 2021). These features collectively make HRs a powerful tool for integrating creativity and CT into educational settings, as they engage students in interactive, hands-on learning while making CT concepts more accessible and enjoyable (Rehmat et al., 2020).

Research supports the use of HRs to scaffold CT learning in various educational contexts. Israel-Fishelson and Hershkovitz (2022) found that nearly 30% of studies in this field utilized robotics or tangible programming tools in physical environments for CT learning. Case studies, such as those involving NAO humanoid robots in classrooms, show that HRs can significantly enhance student engagement, comprehension of programming concepts, and collaboration skills (Buchem & Baecker, 2022; Kurtz & Kohen-Vacs, 2024).

Despite their potential, the implementation of HRs in education faces several challenges. Cost remains a significant barrier; these robots are often expensive to acquire and maintain, limiting their accessibility for under-resourced schools (Evripidou et al., 2021). Additionally, many educators lack the technical expertise or pedagogical training needed to design effective robot-assisted learning activities (Kong et al., 2020). Scalability is another concern, as the logistical demands of robot-guided learning — including setup, maintenance, and equitable student access — complicate broader adoption (Hsu et al., 2022).

Another critical challenge lies in assessing the impact of HRs on students' computational creativity and CT skills. Existing methodologies, often reliant on self-report measures, struggle to capture the nuanced interactions and learning processes facilitated by these tools (Israel-Fishelson & Hershkovitz, 2022; Marrone & Cropley, 2022; Evripidou et al., 2021). This is where learning analytics can play a transformative role, offering data-driven insights into how students engage with HRs and how these interactions shape creativity and CT development.

2.4. Learning Analytics and Measuring CT and Creativity

Learning analytics (LA) has emerged as a powerful approach for tracking and analyzing student activity in educational contexts. By collecting and analyzing data from digital platforms, LA provides educators and researchers with detailed insights into how students engage with tasks, develop skills, and achieve learning outcomes (Marrone & Cropley, 2022; Usher & Hershkovitz, 2022). In computational thinking (CT) education, LA enables the identification of patterns in student problem-solving processes, assessment of their understanding of key concepts, and monitoring of their progress over time (Chou et al., 2024). These insights allow for targeted interventions and personalized feedback, supporting skill development in a systematic and data-driven manner (Hershkovitz et al., 2019; Kovalkov et al., 2021).

While the potential of LA in assessing creativity is significant, its application in educational contexts remains underexplored (Chou et al., 2024; Marrone & Cropley, 2022). A lack of empirical research connecting creativity with LA persists, leaving a gap in understanding how data-driven approaches can fully capture the creative dimensions of learning (Marrone & Cropley, 2022). Despite extensive research on CT skills and creativity in computer science, most studies rely on self-report measures such as surveys and questionnaires (Israel-Fishelson & Hershkovitz, 2022). These methods, while useful, are often based on limited data and fail to capture the dynamic and multifaceted nature of creativity (Hershkovitz et al., 2019; Marrone & Cropley, 2022).

Recent advances illustrate the potential of LA to assess creativity holistically. For instance, Román-González et al. (2019) classified CT assessment tools, including CT data mining, which leverages log data from learning platforms. These tools assess problem-solving behaviours, task completion patterns, and the novelty of solutions, offering a data-driven approach to understanding creativity. Kovalkov et al. (2021) further demonstrated this potential by designing a machine-learning model to predict creativity in Scratch projects. Trained on expert evaluations, the model assessed code complexity, efficiency, and novelty, producing creativity scores that aligned closely with human expert judgments. Such studies highlight the scalability and objectivity of automated tools in measuring creativity within educational contexts.

Despite this promise, only a small number of studies have used such automated tools to quantitatively analyze creativity along learning paths. Initial attempts analyzed log files from online learning platforms to evaluate CT acquisition through metrics such as maximum level achieved, solution attempts, and completion time. These metrics were further correlated with personal characteristics, creative thinking dimensions, and computational creativity (Hershkovitz et al., 2019; Israel-Fishelson et al., 2020). Furthermore, the assessment of creativity in collaborative settings remains underexplored, even though group dynamics are known to play a pivotal role in fostering innovation (Barak & Usher, 2020; Hsu et al., 2022; Kurtz & Kohen-Vacs, 2024).

To address these gaps, this study adopts a dual approach, combining learning analytics with self-report measures to investigate how different collaborative learning modalities — robot-guided and simulation-based — shape students' computational creativity and CT skills. By exploring these modalities, the study aims to provide new insights into the role of technology-enhanced learning environments in fostering creativity and CT development in higher education.

3. Methods

3.1. Research Goal and Questions

The goal of the current study is to examine and compare students' computational creativity and computational thinking (CT) skills in humanoid robot-guided and simulation-based collaborative learning environments. The study is guided by the following research questions:

1. How do robot-guided and simulation-based modalities impact students' computational creativity, as measured through their collaborative learning activities?
2. How do these modalities influence students' computational thinking (CT) skills?

3.2. Research Participants and Procedure

The study involved 71 undergraduate students (59 females and 12 males), with an average age of 23 (*SD* = 1.53). All students were enrolled in a mandatory first-year computational thinking (CT) course at a higher education institution, marking their initial formal exposure to CT and programming concepts. The students were divided into 23 small groups of 3–4 members. Groups were randomly assigned to begin either in the robot-guided condition or the simulation-based condition, following a within-subjects crossover design. A pre-questionnaire provided additional data about students' prior experience and perceived knowledge relevant to the study. On a scale of 1 (“not at all”) to 5 (“to a large extent”), students reported moderate perceived knowledge in computational thinking (*M* = 3.73, *SD* = 0.84) and relatively high prior experience in group work (*M* = 4.00, *SD* = 1.02). In contrast, their prior experience working with robots in educational settings was low (*M* = 1.70, *SD* = 0.74). Participation in the study was voluntary, and all students provided informed consent prior to the start of the study. The Institutional Review Board approved the study.

The study was conducted over two separate lecture sessions. In the first session, half of the students participated in the robot-guided condition, using a humanoid robot (SoftBank NAO version 6.00), while the remaining students engaged in the simulation-based condition using a custom-designed simulator. The tasks and objectives were identical in both conditions. In the second session, the groups switched conditions, allowing all participants to experience both learning modalities. During the robot-guided sessions, while students were responsible for programming the humanoid robot through the visual interface, a facilitator — a trained master’s student — was present in the room to provide technical support as needed. The facilitator assisted students with troubleshooting minor issues and navigating the robot’s physical interface to ensure that technical difficulties did not interfere with the learning experience.

In both conditions, students used a custom-designed online technological environment developed specifically for this study. This environment presented tailored CT challenges designed to engage students in solving problems through a block-based programming interface with drag-and-drop functionality. The environment enabled students to construct visual sequences of commands and introduced students to core CT concepts such as problem-solving, abstraction, and pattern recognition. It also supported the implementation of key programming constructs, including variables, conditional statements, and loops.

In each session, students completed one structured CT challenge per group, which was followed by an extension designed to deepen the task’s complexity and encourage more advanced use of computational constructs. The same challenges were used across all groups and both platforms to ensure comparability. In the first session, students were tasked with programming a number-guessing game. The robot (or simulated agent) randomly generated a number between 1 and 5 and prompted the user to guess it. Students programmed the system to provide positive or negative feedback based on the accuracy of the guess. In the extension, students were asked to dynamically customize the number range based on user input: pressing the robot’s left foot generated a random number in the range of 1–5, while pressing the right foot generated a random number in the range of 1–10. The environment offered flexibility in feedback delivery — through speech, movement, or a combination of predefined actions.

In the second session, the robot (or simulated agent) generated a random number from a fixed range (e.g., 1–10). The user was required to press the left foot if the number was even and the right foot if it was odd, triggering corresponding feedback. In the extension, students defined custom number ranges based on group preferences. This required incorporating user input and modifying the logic structure to support broader input scenarios.

Both challenges supported the use of key computational constructs. The first session’s task (number guessing) required the use of variables and conditional statements, while its extension (range selection) introduced additional input handling and encouraged the use of nested conditionals. The second session’s task (even/odd detection) similarly required variables, conditionals, and user input handling. In the extension, where students defined custom number ranges, additional nested conditionals were often used to handle input flexibility and feedback logic. Although loops were not explicitly required for the completion of these tasks, many student groups chose to incorporate loop structures such as “repeat” or “forever” blocks to ensure automatic task reset and continuous execution. This strategic use of loops — beyond the assignment’s minimal requirements — demonstrates students’ deeper understanding of control flow and initiative in refining user interaction.

Figure 1a. Students working on the task in the simulator-based modality.

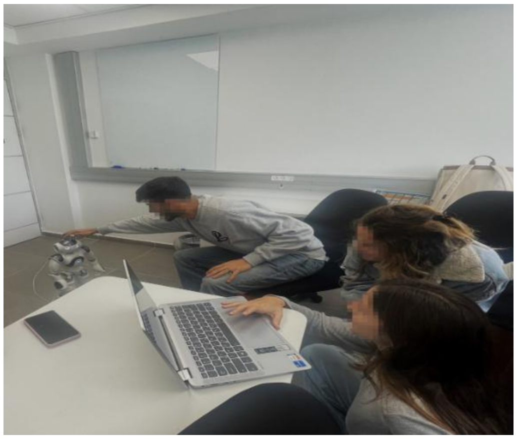


Figure 1b. Students working on the task in the robot-guided modality.

The solutions students developed were executed in two ways: either through an animated simulator that mimicked the robot's behaviour virtually (see Figure 1a) or through the physical humanoid robot, which offered real-world interaction and immediate physical feedback (see Figure 1b). The robot-guided modality provided a more immersive and engaging experience due to its tangible feedback. In contrast, the simulator replicated the robot's actions on-screen without physical interaction, offering a more abstract, screen-based experience.

3.3. Research Method and Tools

This study employed a repeated measures experimental design to examine the impact of robot-guided and simulation-based collaborative learning on undergraduate students' computational creativity and computational thinking (CT) skills. The repeated measures approach was chosen to minimize individual differences among participants, thereby enhancing the study's internal validity. Students were randomly assigned to begin with either the robot-guided or simulation-based modality, switching to the alternate modality in the following session, allowing for a direct within-subject comparison (Creswell, 2015). The assignment of groups to modalities was performed by the course instructor without applying any specific selection criteria, serving as an arbitrary allocation.

Data were collected using two research tools: group log data and individual pre- and post-intervention questionnaires.

Group log data were extracted from the custom-designed online system specifically developed for this study. The system captured student programming activities in real-time as they solved CT problems in both learning modalities. Key metrics recorded included timestamps, the number and type of blocks used, and the sequences of operations. Unlike other learning environments, such as Kodetu, where participants are prompted to advance to the next level upon producing a correct solution, this system allowed students to continue refining and experimenting with their solutions even after achieving success. This design supported iterative problem solving and enabled the analysis of students' solution-building processes in greater depth.

To analyze computational creativity, we drew from the Torrance framework of creativity, which typically includes four dimensions: fluency, flexibility, originality, and elaboration (Torrance, 1974). However, as noted in prior studies (e.g., Israel-Fishelson et al., 2020), not all dimensions are equally applicable in programming environments. In our context, students were tasked with solving a single CT challenge per session (followed by an advanced extension of the same task). While the challenge itself was well-defined, the task design allowed for considerable variation in how solutions could be constructed — including the choice and combination of programming constructs, depth of logic, and use of robot-specific features. We therefore characterize our programming tasks as constrained yet open-ended, enabling students to pursue diverse implementation strategies within a shared problem space. Still, without an explicit prompt to generate multiple solutions, a meaningful operationalization of fluency was less feasible. Moreover, measuring fluency based on total block count does not reliably indicate creativity, as longer solutions may simply involve repeated or redundant actions (e.g., using the same block type many times). For these reasons, we omitted fluency from our framework and focused on the three dimensions that could be validly and reliably inferred from the log data: flexibility, originality, and elaboration.

The dimensions were operationalized as follows:

1. Flexibility: Refers to the variety of block types incorporated into the solution. Across all groups, a total of 31 unique blocks were presented, each corresponding to a distinct programming construct. For interpretive clarity, these constructs were grouped into four broader categories: 1) robot actions (e.g., asking questions, detecting foot touches, triggering predefined behaviours), 2) conditionals and loops (e.g., if, repeat, wait until), 3) operators and arithmetic functions (e.g., and, or, random, mod), and 4) variable creation and use. A higher flexibility score indicates the use of a wider range of block types, reflecting adaptability and the exploration of diverse programming structures.
2. Originality: Measures the uniqueness of a solution by identifying block types that were rare across all participant solutions. Blocks that appeared in fewer than 5% of all solutions were classified as unconventional and contributed to a higher originality score, following the inverse-frequency approach (Hershkovitz et al., 2019).
3. Elaboration: Reflects the structural complexity of a solution, based on the number of hierarchical layers or nested constructs (e.g., loops within loops or conditional statements within other structures). This dimension captures the depth of logical organization and the extent to which students developed and refined a single idea through layered control structures. While elaboration and flexibility may sometimes co-occur, they reflect distinct aspects of creative computational thinking: flexibility pertains to the diversity of distinct block types used, reflecting the range of programming strategies employed, whereas elaboration pertains to the depth and sophistication of how those constructs are organized within the solution.

In addition to the three creativity dimensions, we also examined solution length — defined as the total number of blocks used in a group's final program. While this metric does not directly reflect creativity, it offers insight into how extensively students engaged with the task.

Individual CT questionnaires were employed to assess student skills before and after participating in each learning activity (simulation-based or robot-guided collaborative learning). Adapted from Korkmaz et al. (2017), one of the most widely used scales for measuring CT skills among learners (Israel-Fishelson & Hershkovitz, 2022), the questionnaire consisted of 15 items across five dimensions: creativity, algorithmic thinking, cooperation, critical thinking, and problem-solving. Participants rated each item on a five-point Likert scale, ranging from 1 ("not at all") to 5 ("to a large extent"). The questionnaire was administered at three time points: The *pre-questionnaire* was administered before any participation in the experimental sessions to assess baseline CT skills. Post-questionnaires assessed the same CT skills dimensions as the pre-questionnaire and were administered after the first experimental session (either robot-guided or simulation-based), and after the second experimental session following the crossover. The Cronbach's alpha values for internal consistency at each time point were $\alpha = .71$ for the pre-questionnaire, $\alpha = .94$ for the questionnaire after the first experimental session, and .90 for the questionnaire after the second experimental session.

Some sample items related to these dimensions are as follows:

Creativity: "I have a belief that I can solve the problems possible to occur when I encounter a new situation."

Algorithmic Thinking: "I can digitize a mathematical problem expressed verbally."

Cooperativity: "More new ideas occur to me when I learn with other people."

Critical Thinking: "I use a systematic method while comparing the options at hand and while reaching a decision."

Problem Solving: "I come up with many options while thinking of possible solutions to a problem."

In addition to assessing CT skills, the post-questionnaires included four closed-ended questions on a five-point scale, aimed to assess student emotional engagement and perceived difficulties during each learning modality. The first question focused on measuring student perceptions of how enjoyable the activity was. The remaining three questions addressed specific challenges encountered during the learning process:

- To what extent was the learning task difficult?
- To what extent did you experience difficulties engaging with the system?
- To what extent did you encounter challenges in group collaboration?

3.4. Data Analysis

To explore differences in students' computational creativity between the two learning modalities, we conducted a quantitative analysis of groups' log data extracted from the custom-designed system. After data cleaning, the dataset comprised about 11,000 rows, which were anonymized and securely stored for analysis. Each of the three creativity dimensions — flexibility, originality, and elaboration — was calculated based on the definitions outlined above. Each dimension initially had different numerical scales, as they represented distinct types of activities. To allow meaningful comparisons, all scores were normalized to a 0–1 range using min-max normalization. However, since each dimension represents a distinct aspect of creativity, the results are interpreted within each dimension only (i.e., robot vs. simulation) rather than compared across dimensions. Paired-sample t-tests were performed to compare student activities between the two learning modalities across each of the dimensions of computational creativity. Effect sizes (Cohen's d) were calculated to assess the magnitude of differences between the two modalities. In addition to the creativity dimensions, a paired-sample t-test was conducted to compare solution length across the two learning modalities.

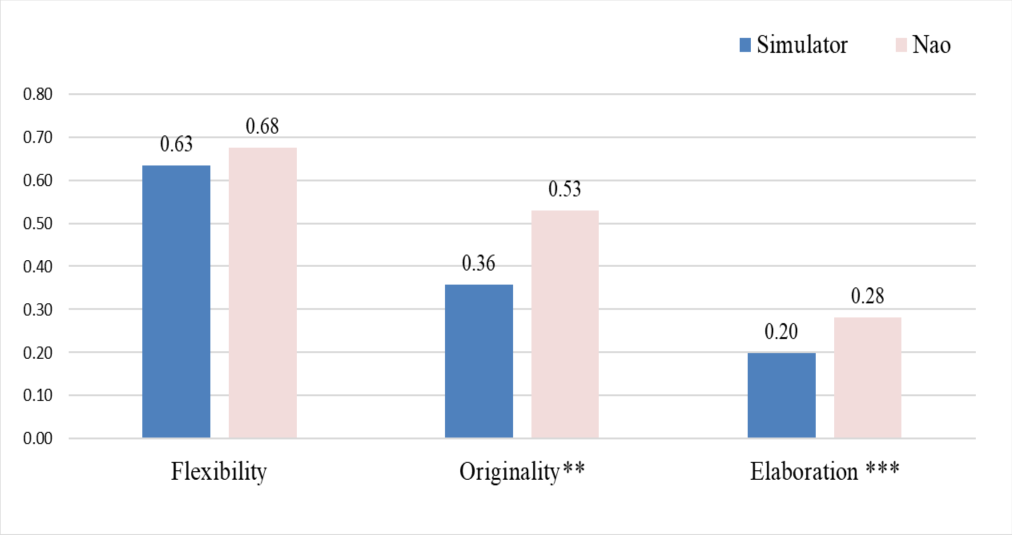
To examine differences in student CT skills following each learning modality, paired-sample t-tests were first conducted to compare post-questionnaire responses between the robot-guided and simulation-based conditions. These comparisons were performed separately for each of the five CT dimensions: creativity, algorithmic thinking, cooperation, critical thinking, and problem-solving, as well as four additional items related to students' emotional engagement and perceived difficulty.

To further assess the effect of learning modality while accounting for individual differences in baseline CT levels and exposure sequence, a repeated measures ANCOVA was conducted. In this analysis, modality (robot vs. simulation) was included as a within-subjects factor, pre-questionnaire scores were entered as a covariate, and starting modality (i.e., whether students began with the robot or the simulation condition) was included as a between-subjects factor. Bonferroni-adjusted pairwise comparisons were performed following significant main effects to determine the direction and magnitude of differences between conditions.

4. Findings

4.1. Computational Creativity: Robot-Guided vs. Simulation-Based Learning

The log data analysis revealed an overall significant difference in students' computational creativity between the two learning modalities. Specifically, the robot-guided modality resulted in a significantly higher mean score ($M = 0.50$, $SD = 0.23$) compared to the simulation-based modality ($M = 0.40$, $SD = 0.25$), with statistical significance ($t(22) = -3.17$, $p = .004$, Cohen's $d = 0.66$). Further analysis, illustrated in Figure 2, shows the average scores for each of the three dimensions of computational creativity across the two modalities.



*Note: **p < .01; *** p < .001.*

Figure 2. Average scores for student computational creativity between the learning modalities.

Regarding the dimension of flexibility, students in both learning modalities utilized a similar variety of block types in their final solutions. As shown in Figure 2, students in the robot-guided modality demonstrated a slightly greater variety of blocks (*M* = .68, *SD* = .26) compared to those in the simulation-based modality (*M* = .63, *SD* = .27); however, this difference was not statistically significant. In contrast, the other two dimensions of computational thinking showed statistically significant differences favouring the robot-guided modality, as follows.

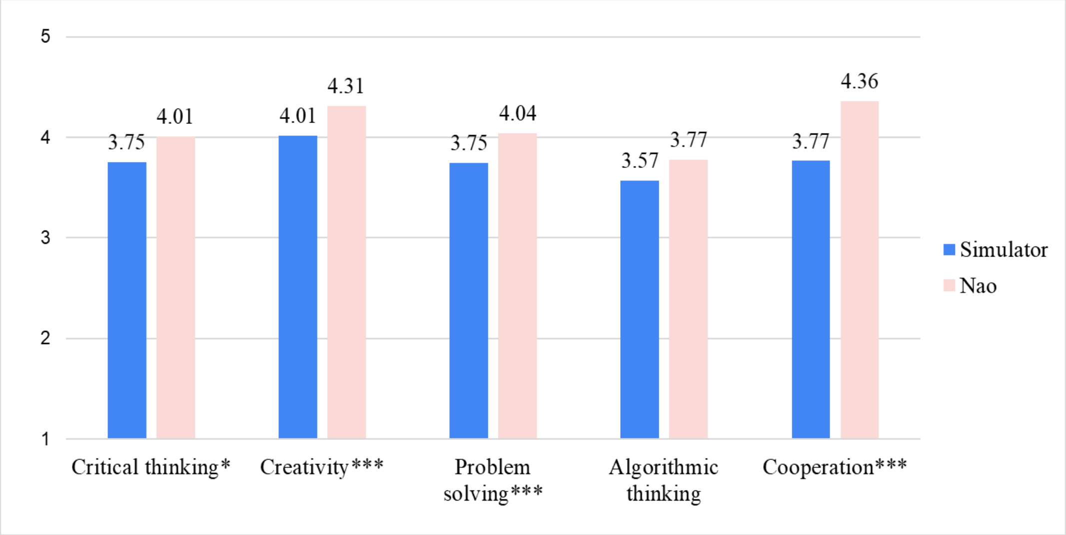
First, students scored significantly higher in the elaboration dimension during the robot-guided activity (*M* = .28, *SD* = .15) compared to the simulation-based modality (*M* = .20, *SD* = .14), with a statistical significance and a large effect size (*t*(22) = –4.04, *p* < .001, Cohen's *d* = 0.84). Second, the originality dimension was also significantly higher in the robot-guided activity (*M* = .53, *SD* = .13) compared to the simulation-based modality (*M* = .36, *SD* = .12), with statistical significance and a large effect size (*t*(22) = –3.47, *p* = .01, Cohen's *d* = 0.72). Moreover, solution length scores in the robot-guided modality (*M* = 0.22, *SD* = 0.14) were slightly higher than those in the simulation-based modality (*M* = 0.14, *SD* = 0.09), though this difference was marginally significant (*t*(22) = –2.06, *p* = .05, Cohen's *d* = 0.43).

4.2. Computational Thinking Skills: Robot-Guided vs. Simulation-Based Learning

The analysis revealed that students demonstrated significantly higher overall CT scores following the robot-guided activity (*M* = 4.10, *SD* = 0.46) compared to the simulation-based activity (*M* = 3.77, *SD* = 0.64), with statistical significance (*t*(70) = 4.37, *p* < .001, Cohen's *d* = 0.64). Figure 3 illustrates the average scores for each of the five CT skill dimensions — critical thinking, creativity, problem-solving, algorithmic thinking, and cooperation — following student participation in either the robot-guided or simulation-based learning modalities. It shows that students exhibited slightly higher average scores across all five dimensions after engaging in the robot-guided modality.

The analysis revealed significant differences in student CT skills after engaging in the robot-guided modality compared with the simulation-based one. The most pronounced improvements across the learning modalities were observed in the CT dimensions of *cooperation and creativity*. The *cooperation* dimension showed the most substantial difference, with students reporting significantly higher cooperation scores after the robot-guided activity (*M* = 4.36, *SD* = 0.45) compared to the simulation-based activity (*M* = 3.77, *SD* = 0.76), with statistical significance and a large effect size (*t*(70) = 6.18, *p* < .001, Cohen's *d* = 0.81). Similarly, *creativity* scores were significantly higher following the robot-guided activity (*M* = 4.31, *SD* = 0.42) compared to the simulation-based activity (*M* = 4.01, *SD* = 0.73), with statistical significance (*t*(70) = 3.57, *p* < .001, Cohen's *d* = .70).

Another prominent CT skill was *problem-solving*, with a mean score of 4.04 (*SD* = 0.62) following the robot-guided session compared to 3.75 (*SD* = 0.70) following the simulation-based one, with statistical significance (*t*(70) = 3.44, *p* < .001, Cohen's *d* = 0.72). A similar pattern was observed in *critical thinking*, with significantly higher scores following the robot-guided activity (*M* = 4.01, *SD* = 0.64), compared with the simulation-based activity (*M* = 3.75, *SD* = 0.78), with statistical significance (*t*(70) = 2.50, *p* = .01, Cohen's *d* = 0.87). Yet, the dimension of *algorithmic thinking* showed a different pattern. While students reported slightly higher scores in algorithmic thinking following the robot-guided activity (*M* = 3.77, *SD* = 0.75) compared to the simulation-based (*M* = 3.57, *SD* = 0.82), this difference was not statistically significant.

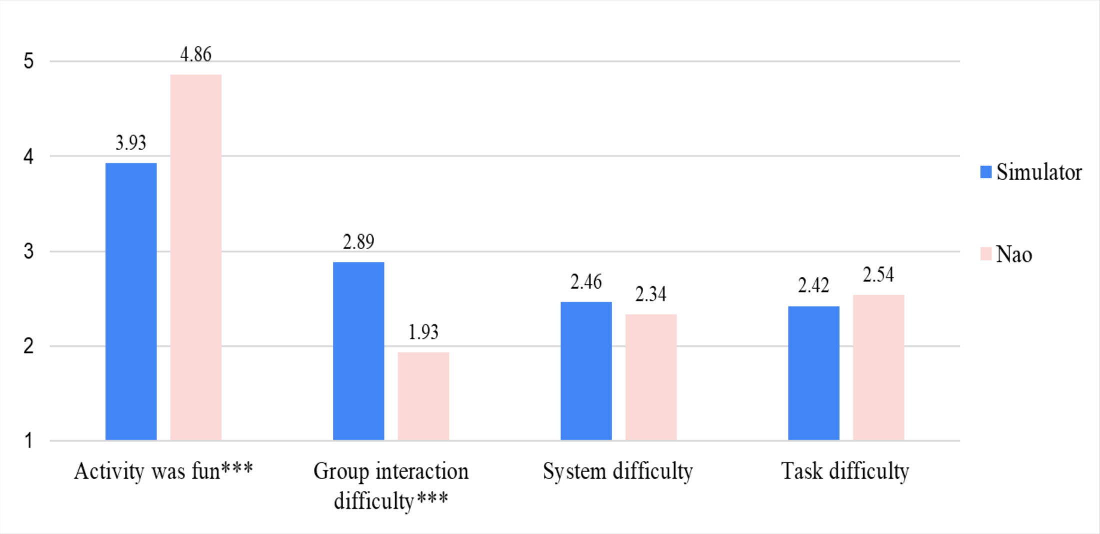


*Note: * p < .05; *** p < .001.*

Figure 3. Average CT scores after engaging with the robot-guided and simulation-based learning modalities.

A repeated measures ANCOVA was conducted to further assess the effect of learning modality while accounting for pre-questionnaire CT scores and exposure sequence (whether students began with the robot or the simulation condition). The analysis revealed a significant main effect of learning modality ($F(1, 68) = 8.14$, $p = .006$, $\eta p^2 = .11$), confirming that the robot-guided modality led to significantly higher CT outcomes. Moreover, the interaction between learning modality and starting condition was not significant ($F(1, 68) = 1.59$, $p = .21$, $\eta p^2 = .02$), indicating that the order in which students experienced the two conditions did not affect the observed results. Bonferroni-adjusted pairwise comparisons confirmed a significant advantage for the robot-guided condition ($p < .001$).

In addition to assessing CT skills, the post-questionnaires evaluated student engagement and perceived difficulties associated with the robot-guided and simulation-based learning activities. A series of paired-sample t-tests were conducted to compare student perceptions following each modality. The results, summarized in Figure 4, indicate significant differences in several areas, with notable effect sizes highlighting meaningful variations in student experiences across the two modalities.



*Note: *** p < .001.*

Figure 4. Comparison of students’ emotional engagement and perceived difficulties in robot-guided and simulation-based modalities.

The analysis revealed that students rated the robot-guided activity as significantly more enjoyable ($M = 4.86$, $SD = 0.39$) compared to the simulation-based activity ($M = 3.93$, $SD = 0.76$), a difference that was statistically significant ($t(70) = 9.60$,

$p < .001$, Cohen's $d = 0.82$). In terms of perceived difficulties, the most pronounced difference emerged in student perceptions of group interaction challenges. Students reported considerably fewer difficulties with group interactions during the robot-guided activity ($M = 1.93$, $SD = 1.10$) than during the simulation-based activity ($M = 2.89$, $SD = 0.97$), with a statistically significant difference ($t(70) = 9.62$, $p < .001$) and a large effect size (Cohen's $d = 1.18$). In contrast, no significant differences were observed between the two modalities in perceived task difficulty or system difficulty, suggesting that the nature of the tasks and the challenges associated with system use were consistent across both learning environments, regardless of the modality.

5. Discussion

This study examined the comparative impact of humanoid robot-guided and simulation-based collaborative learning environments on undergraduate students' computational creativity and computational thinking (CT) skills. By employing both learning analytics and self-report measures, the research provides valuable insights into how these two distinct modalities influence the development of critical skills in higher education. The findings reveal notable differences between the modalities, underscoring the unique affordances of physical, hands-on learning environments in fostering creativity and collaboration, while also recognizing the complementary strengths of virtual environments. While the findings suggest meaningful differences between the robot-guided and simulation-based modalities, they should be interpreted with caution due to the relatively small sample size. The limited number of participants may affect the statistical power and the extent to which the results can be generalized to broader populations.

5.1. Computational Creativity Across Modalities

The findings reveal that the robot-guided modality offered significant advantages in specific dimensions of computational creativity, particularly elaboration and originality. Students working with the humanoid robot (HR) generated more complex and layered solutions, incorporating intricate logical structures and nested components. These results suggest that the robot's ability to provide real-time, interactive feedback facilitated iterative refinement, enabling students to dynamically experiment and improve their strategies. This aligns with previous research highlighting the importance of tangible, hands-on interaction in fostering sophisticated problem-solving and detailed exploration (Ardito et al., 2020; Rehmat et al., 2020).

In the dimension of originality, students in the robot-guided modality demonstrated a greater inclination to take creative risks and explore unconventional approaches. The physical interaction with the robot appeared to stimulate divergent thinking, encouraging learners to step away from standard solutions and embrace innovative strategies. These findings highlight the potential of physical tools to create immersive learning experiences that extend beyond the capabilities of simulation-based environments. The tangible and interactive nature of HRs likely provided a heightened sense of engagement, prompting students to approach tasks with a renewed mindset and enthusiasm. These results align with studies showing that tangible technologies enhance creativity by making abstract concepts more concrete and accessible, while fostering experimentation and exploration (Ardito et al., 2020; Evripidou et al., 2021; Hsu et al., 2022).

In contrast, the flexibility dimension, which measures the diversity of block types employed, was equally well-supported in both modalities. This suggests that simulation-based environments are also effective in fostering diverse problem-solving strategies. These findings align with the broader literature on technology-enhanced learning, highlighting the capacity of virtual tools (Astutik & Prahani, 2018; Yadav & Cooper, 2017).

5.2. Computational Thinking Across Modalities

The study also revealed notable differences in students' self-reported CT skills across the two modalities, with the robot-guided environment showing significant advantages mostly in the dimensions of cooperation and creativity. The robot-guided modality significantly enhanced student perceptions of their cooperation skills compared to the simulation-based modality. Although students in both modalities engaged in face-to-face group interactions, those in the robot-guided group experienced a unique dynamic where the robot served as a physically present teaching model. The robot's tangible presence appeared to foster more effective collaboration, likely due to its role as a shared tool that encouraged group interaction and co-construction of solutions. These elements are more challenging to replicate in the simulated environment, where the robot's presence was limited to an online simulation. This aligns with prior research demonstrating the benefits of physical, interactive tools in promoting teamwork and social-emotional learning (Hsu et al., 2022; Rehmat et al., 2020).

The creativity dimension similarly benefited from the robot-guided modality. Students perceived that working with the HR enhanced their ability to generate innovative ideas and approach problems creatively. This could be attributed to the dynamic and engaging nature of the robot-guided modality, which provided immediate feedback and opportunities for hands-on experimentation. This finding aligns with prior research suggesting that tangible and interactive tools, such as robots, can enhance creativity by making the learning process more immersive and stimulating (Ardito et al., 2020; Evripidou et al., 2021).

Furthermore, the physical interaction with the robot likely fostered a sense of novelty and excitement, contributing to student perceptions of enhanced creativity after engaging with this modality.

Lastly, students reported the robot-guided modality as significantly more enjoyable and noted fewer group interaction difficulties during this activity compared to the simulation-based modality. These findings underscore the role of HRs in creating engaging and collaborative learning environments. The positive emotional responses associated with the robot-guided modality, such as enjoyment and satisfaction, align with prior studies emphasizing the motivational benefits of interactive technologies in education (Buchem & Baecker, 2022; Evripidou et al., 2021; Hsu et al., 2022). Emotional engagement likely contributed to the enhanced cooperation and creativity observed in the robot-guided setting. In contrast, no significant differences were observed between the two modalities in perceived task difficulty or system difficulty. This suggests that the nature of the tasks and the associated challenges were comparable across modalities, indicating that both environments provided similar levels of cognitive demand despite their differing interaction styles.

6. Study Limitations and Future Research

While this study provides valuable insights into the comparative effects of robot-guided and simulation-based collaborative learning on computational creativity and CT skills, several limitations must be acknowledged. First, the sample consisted of 71 undergraduate students from a single institution, which may limit the generalizability of the findings. Expanding future studies to larger and more diverse student populations across various educational levels, disciplines, and institutions could provide a broader understanding of how learners with diverse backgrounds respond to these learning modalities.

Second, although the repeated measures design allowed for within-subject comparisons, it may have introduced carryover effects between the modalities. For example, problem-solving strategies developed during the first session — whether in the robot-guided or simulation-based condition — may have been carried over to the second session, potentially minimizing differences between the two environments. As a result, some of the observed effects may reflect cumulative learning rather than the unique contribution of each modality.

Third, the study relied on group log data and self-reported questionnaires to evaluate computational creativity and CT skills. While these tools offer valuable insights, they may not fully capture the complexity of creativity or higher-order cognitive processes. In particular, self-perception questionnaires may not directly reflect actual CT abilities. Future research could incorporate more objective assessments — such as performance-based algorithmic thinking tests — as well as qualitative methods like interviews, observations, or think-aloud protocols to provide richer insights into student problem-solving and collaboration dynamics.

Lastly, the study did not examine the long-term retention or transferability of creativity and CT skills. Longitudinal research is needed to assess whether the gains observed in robot-guided and simulation-based learning environments persist over time and whether these skills can be applied in new contexts beyond the learning environment.

7. Conclusions and Implications

This study provides valuable insights into the integration of advanced technologies in education, emphasizing the complementary roles of HRs and simulation-based environments in fostering computational creativity and computational thinking (CT). The findings emphasize the unique advantages of HRs in fostering creativity by enabling students to produce more complex and original solutions through hands-on interaction and real-time feedback. These immersive experiences help bridge abstract computational concepts with practical implementation, fostering engagement and innovation in ways that simulation-based environments cannot fully replicate.

At the same time, simulation-based environments remain valuable for promoting diverse problem-solving strategies. The comparable support for flexibility across both modalities underscores their potential to nurture abstract, adaptive thinking, demonstrating their essential role in technology-enhanced learning. Together, these findings highlight the importance of strategically combining physical and virtual tools to maximize learning outcomes in CT education. For example, simulation-based tools can facilitate abstract planning and structural reasoning, while robot-guided sessions emphasize real-world execution and collaboration. Moreover, learning analytics emerged as a key enabler in this study, offering educators tools to monitor student progress, identify areas for improvement, and tailor interventions. By analyzing real-time data, learning analytics can provide actionable insights into students' creative processes and problem-solving behaviours, enabling adaptive instructional designs that respond to diverse learning needs.

These findings also underscore the social and emotional benefits of HRs in collaborative learning. The robot's physical presence fostered cooperation, teamwork, and communication more effectively than simulation-based environments, providing students with a shared, interactive focal point. Additionally, the novelty and engagement associated with HRs may enhance student perceptions of creativity and collaboration, highlighting their value in cultivating both cognitive and emotional learning outcomes.

To implement these insights effectively, educators should consider the distinct benefits and limitations of each modality. HRs excel in promoting collaboration, engagement, and immediate feedback, while virtual environments are cost-effective tools for fostering adaptability and flexibility. Combining these modalities offers a balanced approach to advancing creativity and CT, equipping students with the skills needed to navigate an increasingly digital world.

Declaration of Conflicting Interest

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