International Journal of Innovative Teaching and Learning in Higher Education
Volume 5 • Issue 1 • January-December 2024

Fostering Computational Thinking Through Virtual Reality to Enhance Human-Robot Collaboration:
A Technological-Pedagogical Framework

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ABSTRACT

Virtual reality, a well-established educational technology, offers unique affordances such as immersion, interactivity, visualization, and co-presence, with significant potential to enhance learning experiences and outcomes. Computational thinking, a vital skill in science, technology, engineering, and mathematics, is essential for effective human-robot collaboration, enabling efficient problem-solving and decision-making in future work environments. Virtual reality provides a cost-effective, safe alternative to physical interaction with robots, reducing equipment risks and addressing the limitations of physical training. This study examines how virtual reality's affordances support computational thinking development, presenting a forward-looking training scenario and an assessment rubric for evaluation. The proposed framework and design strategies offer technological and pedagogical guidance for creating virtual reality environments that foster computational thinking in human-robot collaboration contexts.

KEYWORDS

Virtual Reality, Computational Thinking, Human-Robot Collaboration, Construction Workforce Development, Technological-Pedagogical Framework

INTRODUCTION

With advancements in automation in modern workplaces, the future of work will increasingly involve human-robot collaboration. McKinsey & Company predicts that by 2030, approximately 30% of activities in 60% of occupations could be automated but emphasizes that this will result in human-machine collaboration rather than widespread job displacement (McKinsey, 2022). In future workplaces, where human-robot collaboration will be the norm, it will be essential to leverage the

DOI: 10.4018/IJITLHE.367326

strengths of both to create more efficient and innovative environments. This collaboration is expected to enhance efficiency in decision-making, problem-solving, and innovation (Simões et al., 2022).

Computational thinking is an essential skill in the digital age, characterized as a problem-solving process involving several key steps: breaking problems into smaller components (decomposition), identifying recurring themes (pattern recognition), distilling underlying principles to understand relationships (abstraction), and designing systems to develop potential solutions (algorithmic design) (National Research Council, 2010, 2011; Wing, 2006, 2008). Wing (2006) emphasized that "[computational thinking] represents a universally applicable attitude and skill set that everyone—not just computer scientists—should be eager to learn and apply" (p. 33). As a foundational problem-solving framework that has been essential in STEM disciplines over the past few decades, computational thinking will continue to play a pivotal role in the Industry 4.0 era, particularly human-robot collaboration. In this context, computational thinking is not only essential for programming or controlling robots but also for understanding and navigating the complexities of human-robot collaboration. Skills such as abstraction and algorithmic thinking enable humans to optimize collaborative workflows with robots, fostering innovation in real-world applications (Nurassyl et al., 2023).

However, traditional classroom and pedagogical methods often face challenges in creating environments essential for effectively fostering computational thinking, particularly in the context of human-robot collaboration (Kerimbayev et al., 2023). For instance, the lack of access to robots due to their high cost can limit hands-on learning opportunities, while safety concerns and the potential for damaging expensive equipment may further hinder direct interaction. Additionally, physical limitations, such as the inability to simulate dynamic and diverse collaborative scenarios in a controlled environment, restrict the scope of practical learning. One promising approach is Virtual Reality (VR), which offers immersive, interactive, visualized, and co-present learning environments and experiences (Qian, 2009, 2014).

Using human-robot collaboration as a context for fostering computational thinking offers a unique opportunity to prepare the future workforce for Industry 4.0. VR enables the creation of immersive simulations where computational thinking can be applied to solve realistic problems within human-robot collaboration scenarios. These scenarios allow learners to develop, test, and refine computational thinking skills while engaging in tasks that mirror real-world interactions with robots. By combining the technological affordances of VR, such as dynamic visualizations and interactive environments, with the problem-solving processes of computational thinking, educators can design learning experiences that integrate the strengths of both approaches. VR provides a cost-effective, risk-free, and versatile platform for immersive learning. Leveraging VR's unique technological affordances, educators can develop simulations that not only illustrate complex concepts but also enable learners to actively practice and apply their computational thinking abilities in realistic human-robot collaboration scenarios.

This study explores the technological affordances of VR and the critical role of computational thinking in human-robot collaboration. It emphasizes the synergy between computational thinking, human-robot collaboration, and VR, arguing that the integration of these three elements can transform STEM education by creating realistic and impactful learning experiences. This study proposes a technological-pedagogical framework designed to foster computational thinking in VR environments for effective human-robot collaboration. The framework emphasizes key elements and strategies, illustrated by a case of human-robot collaboration in construction scenarios.

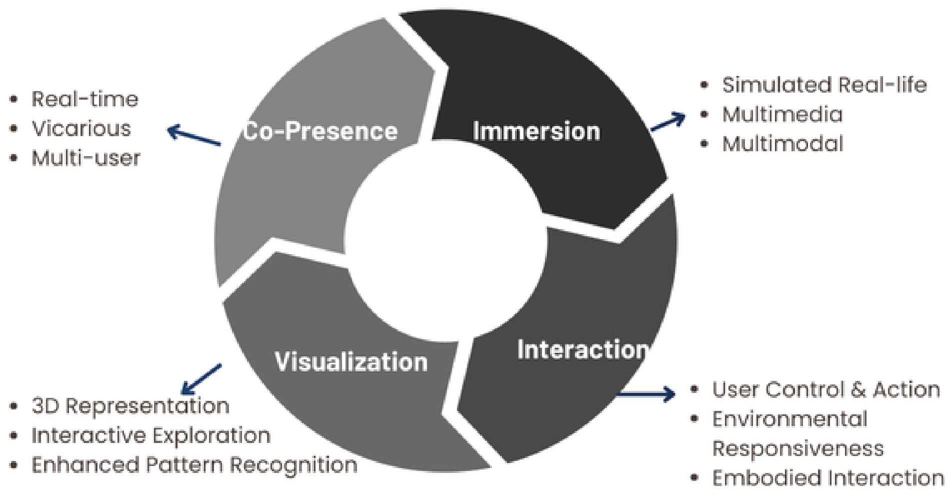
VIRTUAL REALITY AND ITS TECHNOLOGICAL AFFORDANCES

Virtual Reality (VR) is a specialized computing technology that enables the creation of immersive, three-dimensional simulations (TechTarget, n.d.). By engaging multiple senses, such as sight, sound, and sometimes touch and smell, VR creates a strong sense of presence and immersion within a digital space. This experience is supported by technologies such as head-mounted displays (HMDs), motion-tracking sensors, and haptic feedback systems. Since its inception in the 1960s with innovations like Ivan Sutherland's (1963) "Ultimate Display," which laid the foundation for modern VR technologies, VR has significantly evolved. Recent developments in VR technology include *Microsoft Flight Simulator 2024,* which integrates a VR mode for realistic pilot training and simulation, and *iRacing*, a VR-enabled platform widely used for professional racing simulations that replicate real-world physics and vehicle handling. These examples highlight the potential of VR for creating highly realistic training environments. Additionally, VR continues to advance in gaming with titles like *Thrill of the Fight 2*, which introduces a PVP mode for competitive interaction, and *Into the Radius 2*, a PCVR game popular among enthusiasts. Such developments demonstrate VR's versatility, spanning applications from professional training to immersive entertainment (Program-Ace, 2024).

William Gaver (1991) introduced the concept of "technological affordances," building on James Gibson's (1979) ecological psychology. Affordances are properties of the environment that facilitate specific interactions, linking perception with action (Gaver, 1991). James Gibson's (1979) notion of affordances emphasizes how individuals intuitively perceive and learn how to use objects based on their physical qualities without requiring explicit instructions. For example, a handle invites pulling, while a flat surface suggests resting or placing objects. Gaver extended this concept into the realm of technology, highlighting how the material properties and design of technological tools can influence how users interact with them, shaping both individual and collaborative actions (Gaver, 1996). In the context of VR, technological affordances encompass features that enable unique interactions with immersive environments by mimicking the physical world and allowing users to engage with virtual spaces in ways that feel intuitive and familiar. For example, users can move their bodies naturally, sense the spatial layout through vision and hearing, and interact with virtual objects as they would in the physical world.

VR's technological affordances can be grouped into four key categories, as illustrated in Figure 1. VR provides a strong sense of "being there" through **immersive presence** created by high-resolution displays and spatial audio that mimics real-world sensory inputs (Hameed & Perkis, 2024). Its interactive nature allows users to engage with and manipulate virtual objects and the environment, receiving immediate feedback in real-time. This **interactivity** makes VR especially valuable for training simulations and educational experiences (Dincelli & Yayla, 2022). Additionally, VR's ability to engage **multiple senses**—such as auditory, tactile, and even olfactory feedback—enriches the experience, enabling users to "feel" virtual textures through haptic devices (Ranasinghe et al., 2018). By supporting spatial understanding, VR is particularly useful in STEM fields like architecture, urban planning, and construction, where grasping spatial relationships is essential. Recent advancements in multi-user VR platforms have also revolutionized vicarious **co-presence**, allowing participants to interact with virtual objects as if physically co-located (He et al., 2020; Kavanagh et al., 2017; Qian, 2014). Co-presence is important in VR, either physically or through a sense of presence, encompassing both the physical contexts that facilitate interaction and the subjective experience of connection (Yousefdeh & Oyelere, 2024). Finally, VR excels at **immersive visualization**, offering three-dimensional representations of complex information, concepts, and processes, such as molecular structures, geological formations, or computational thinking models. These affordances collectively highlight VR's unique potential in fostering computational thinking for human-robot collaboration, transforming how humans interact with robotic systems in immersive, dynamic environments (Steffen et al., 2019).

Figure 1. VR's technological affordances



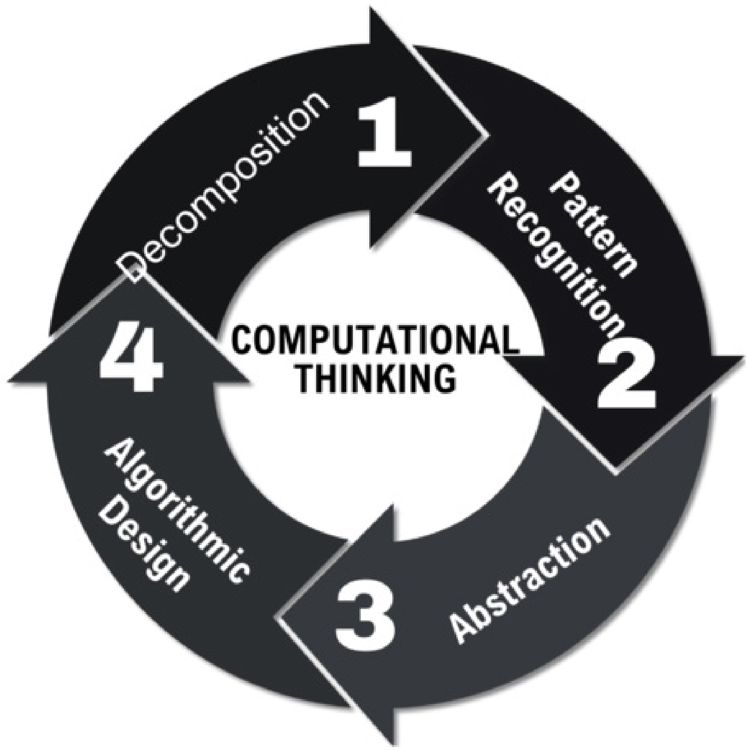
COMPUTATIONAL THINKING

The concept of computational thinking was first articulated by Jeannette Wing in her seminal 2006 article, where she defined it as a fundamental skill for everyone, not just computer scientists. Wing described computational thinking as a problem-solving process that involves formulating problems in a way that enables their solution through computational methods. Key elements of computational thinking include decomposition, pattern recognition, abstraction, and algorithm design (Wing, 2006), which are often referred to as the "four pillars" of computational thinking, as illustrated in Figure 2. Wing's work was pivotal in framing computational thinking as an essential literacy for the 21st century, akin to reading and mathematics (Wing, 2006). This reconceptualization has led to its integration into educational curricula worldwide, particularly within STEM (Science, Technology, Engineering, and Mathematics) disciplines (Mohaghegh & McCauley, 2016).

Computational thinking is significant in STEM education because it equips learners with the skills to analyze and solve problems systematically, fostering innovation and adaptability in an increasingly digital world. For instance, engineering students use computational thinking as a problem-solving technique for designing computing systems and algorithms, biologists apply it to model ecosystems, and mathematicians employ it to explore complex theories. As STEM fields become more interdisciplinary, computational thinking serves as a unifying framework for tackling cross-domain challenges (Buckler, Koperski, & Loveland, 2017).

The intersection of computational thinking and evolving technologies, like VR, presents promising opportunities for fostering deeper and richer learning experiences. By combining the affordances of VR with the analytical and problem-solving framework of computational thinking, educators can create dynamic environments where learners actively engage in computational problem-solving. This synergy holds the potential to redefine how learners interact with and understand complex systems in both academic and real-world contexts.

Figure 2. Four pillars of computational thinking



HUMAN-ROBOT COLLABORATION

Human-robot collaboration (HRC) has evolved from the isolated use of industrial robots in the 1960s, designed for repetitive and hazardous manufacturing tasks, to the development of collaborative robots, or cobots, which work safely alongside (Galin & Meshcheryakov, 2019; Hentout et al., 2019). The emergence of cobots, enabled by advances in sensor technology and control systems, marked a shift toward robots complementing human cognitive skills with their physical capabilities, fostering more adaptive work environments for humans (Hans-Jürgen, 2020; Villani et al., 2022). Recent advancements in HRC focus on seamless and intuitive interactions, including partner-aware control systems and joint action capabilities, further enhancing collaboration between humans and robots (Tirupachuri et al., 2020).

In the context of HRC, computational thinking serves as a foundational skill, enabling humans to effectively interact with and guide robotic systems (Funk et al., 2022). For instance, in collaborative tasks, humans must interpret robotic actions, anticipate outcomes, and adjust inputs to ensure seamless coordination. This dynamic requires not only technical proficiency but also the ability to conceptualize and communicate tasks in ways that robots can execute (Tsao et al., 2023). VR environments amplify this collaboration by providing immersive, interactive spaces where humans can simulate, visualize, and refine their interactions with robots. These virtual settings allow for experimentation with computational models and task scenarios, helping users develop the computational thinking skills necessary for designing, troubleshooting, and enhancing human-robot collaboration in real-world applications.

FRAMEWORK FOR COMPUTATIONAL THINKING IN HUMAN-ROBOT COLLABORATION VIA VIRTUAL REALITY

As discussed earlier, computational thinking is, in essence, a structured problem-solving approach. By integrating computational thinking into human-robot collaboration, it becomes possible to enhance the synergy between human cognitive abilities and robotic precision, leading to improved task performance and decision-making. The proposed framework integrates CT as a core skill for HRC within VR environments. By leveraging VR's affordances, this framework fosters real-time co-presence and effective problem-solving in dynamic, immersive scenarios. The following sections explore various aspects of this integration in the context of HRC.

First, **decomposition** is a key CT skill learners can practice in VR-based HRC simulations. By breaking down complex tasks into smaller, manageable components, learners can allocate actions effectively between human and robotic collaborators. For example, a VR scenario might involve a delivery task where learners decompose the process into segments. They could plan specific maneuvers for a robot to navigate obstacles while humans monitor and adjust the path dynamically. This decomposition highlights how humans and robots complement each other in task execution, enabling learners to analyze workflows and improve efficiency.

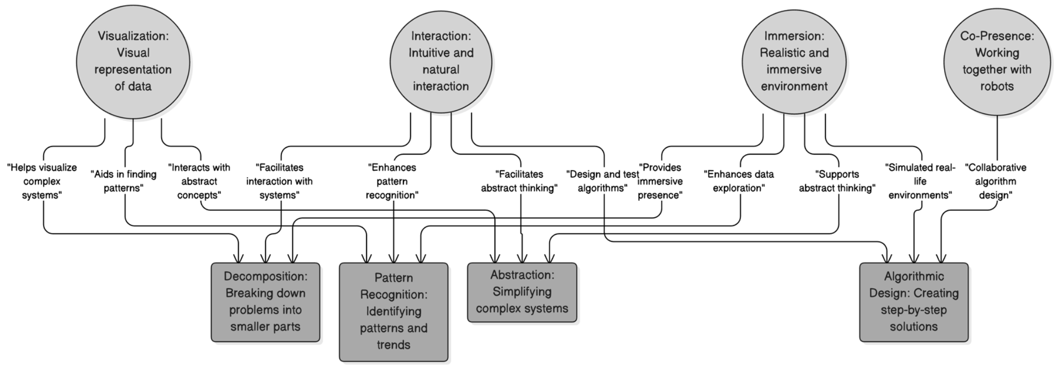
Second, **pattern recognition** is cultivated as learners identify recurring trends and behaviors within VR-based HRC scenarios. For example, learners might observe patterns in a robot's movement or response to specific tasks, such as repeated calibration needs when switching between operational contexts. Recognizing these patterns enables learners to adapt and refine instructions or algorithms, optimizing the collaboration process.

Next, **abstraction** is a critical component of computational thinking that focuses on simplifying complex scenarios by focusing on relevant details while ignoring extraneous information. In the context of HRC, abstraction involves identifying and defining key parameters that govern human-robot interactions, such as task sequences, spatial constraints, or performance metrics. For instance, learners might create an abstract representation of a collaborative task by parametrizing robot movements and expected human actions to streamline communication and coordination. This focus on abstraction emphasizes the importance of generalizable models that can be applied across various HRC scenarios while still accommodating specific operational details as needed.

Finally, **algorithmic design** is reinforced as learners engage with VR systems that require step-by-step problem-solving processes for effective HRC. For instance, learners might develop an algorithm to guide a robotic arm through a sequence of precise movements for assembly tasks, incorporating constraints like time efficiency and safety. By testing and iterating their algorithms within the VR environment, learners refine their ability to design structured workflows that optimize human-robot collaboration.

Figure 3 depicts the intricate interplay between computational thinking skills and the affordances offered by VR in the context of human-robot collaboration. Computational thinking, encompassing decomposition, pattern recognition, abstraction, and algorithmic design, is essential for effective problem-solving in this domain. VR, with its immersive nature, facilitates visualization and interaction, enhancing pattern recognition and abstract thinking. The interactive capabilities of VR enable intuitive and natural interaction with robots, supporting algorithmic design and collaborative problem-solving. This framework provides a flexible structure that can be applied across various domains involving human-robot collaboration, leveraging VR to enhance learning and performance in dynamic environments.

Figure 3. Computational thinking for human-robot collaboration in VR



THE CASE OF FUTURE-READY CONSTRUCTION WORKFORCE DEVELOPMENT

The proposed conceptual framework addresses the urgent need for a future-ready workforce in construction. As the construction industry rapidly evolves with advancements in automation and robotics, human-robot collaboration emerges as a critical competency. VR offers an ideal platform to integrate computational thinking into construction education, equipping learners to meet the demands of Industry 4.0 and beyond.

In this context, VR environments simulate dynamic construction sites, where learners engage in tasks such as programming robotic arms to navigate obstacles or optimizing workflows for various construction scenarios. These immersive tasks align with core computational thinking principles: **decomposition** (breaking down tasks), **pattern recognition** (identifying trends in robotic movements), **abstraction** (simplifying complex problems by focusing on essential elements), and **algorithmic thinking** (developing efficient task sequences).

For instance, learners operate a 6-axis robotic arm mounted on a Mecanum wheel platform using a VR-based robotic training environment developed in Unreal Engine. Scenarios range from basic material handling in a warehouse to advanced simulations in terrestrial and extraterrestrial environments. learners progress through stages of increasing complexity, starting with understanding the mechanics of the robotic system and advancing to designing algorithms for novel tasks in extreme conditions. These scenarios not only build technical proficiency but also foster adaptability and problem-solving skills critical for real-world applications. Learners can program a robotic arm to execute a series of tasks, such as sorting materials or navigating an obstacle course. The interactive feedback mechanisms inherent in VR systems allow learners to iteratively refine their solutions, mirroring real-world problem-solving (Bock, 2015; Liang et al., 2021). Figure 4 illustrates an example of a futuristic robot navigating through a VR-based construction environment.

Figure 4. Simulation of a 6-axis robotic arm navigating through a VR-based construction environment

In this VR environment, learners can assume distinct roles—such as algorithm design, testing, or troubleshooting—while working toward a shared goal. This mirrors professional settings where teamwork and cross-disciplinary collaboration are essential. For example, one learner might focus on designing an algorithm for a robotic arm while another tests its implementation, fostering both technical and interpersonal skills (Burden et al., 2022; Muhamad, 2012). Figure 5 illustrates an example of a collaborative VR scenario with users operating a robotic system in a warehouse.

Figure 5. Collaborative VR scenario with users operating a robotic system in a simulated warehouse

PEDAGOGICAL STRATEGIES FOR COMPUTATIONAL THINKING FOR HUMAN-ROBOT COLLABORATION IN VR

Effective use of VR in education requires the integration of pedagogical strategies that are both relevant and meaningful, designed to support the specific learning tasks. For teaching computational thinking in human-robot collaboration, three such approaches—scenario-based learning, iterative learning, and collaborative role-playing—stand out. These instructional approaches leverage VR's immersive, interactive, visualization, and co-presence capabilities to create engaging, authentic, and scalable learning experiences.

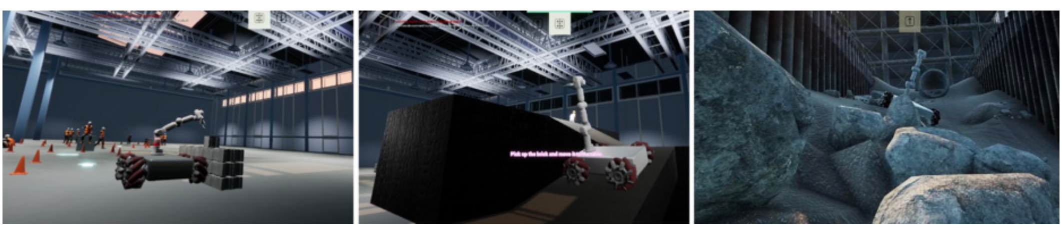
Scenario-Based Learning. Scenario-based learning immerses learners in context-rich, realistic environments where they engage with practical, real-world challenges. For instance, a VR simulation might task learners with optimizing the movement of a robotic arm in a simulated manufacturing process. This scenario allows learners to explore CT principles in action, such as decomposing tasks into manageable components, designing efficient algorithms, and debugging systems to improve performance (Sacks & Pikas, 2013). Through these scenarios, learners develop problem-solving skills that are transferable to real-world robotics and automation contexts. Table 1 provides an example of scenario-based robotic tasks in VR designed to foster CT skills, illustrating how learners can move from understanding simple mechanical motions to addressing more complex optimization challenges. This strategy encourages active engagement, contextual relevance, and the application of theoretical knowledge to practical settings.

Table 1. Examples of scenario-based tasks in VR for CT education

Task	Computational Thinking	Pedagogical Strategy
Robotic arm programming	Algorithmic design	Stepwise instruction for novices
Obstacle navigation	Decomposition, abstraction	Real-time feedback and adaptation
Workflow optimization	Pattern recognition, algorithmic design	Iterative refinement and testing

Iterative Learning for Progressive Task Complexity. Building CT skills requires learners to iteratively engage with tasks of increasing complexity. This approach ensures a gradual and supportive learning curve, starting with foundational skills and progressing to advanced problem-solving. For example, beginners might begin by mastering the basic mechanics of robotic arm control, such as precise movement and simple programming tasks. As learners gain proficiency, they tackle open-ended challenges, such as adapting algorithms to handle new constraints or variables, like changes in weight distribution or unexpected system malfunctions. This progression reflects the iterative nature of CT, emphasizing continuous refinement and adaptation of strategies based on feedback (Tan et al., 2021). Figure 6 illustrates a VR-based task progression, where learners evolve from basic manipulation tasks to designing and testing complex algorithms within a simulated robotic system. Iterative learning in VR not only builds confidence but also cultivates resilience and creativity by encouraging learners to approach problems systematically.

Figure 6. VR task progression from basic manipulation to advanced algorithm design



Co-presence and Role-Based Learning. VR's multi-user capabilities enable collaborative, role-based learning, fostering teamwork and communication skills essential in modern STEM fields. In this approach, participants assume distinct roles within a shared problem-solving environment. For instance, in a human-robot collaboration scenario, one learner might design a robotic workflow, another might focus on debugging the system, and a third might evaluate and optimize its overall performance. This division of labor mirrors real-world STEM practices, where interdisciplinary collaboration is key. Moreover, role-based learning provides learners with opportunities to specialize while understanding how their contributions fit into the broader system. As they collaborate in a VR setting, learners also enhance their CT skills by negotiating strategies, sharing insights, and integrating diverse perspectives. This pedagogical approach not only builds technical competencies but also prepares learners for the collaborative demands of future workplaces (Chalupa & Chadt, 2021).

ASSESSMENT FRAMEWORK FOR VR-ENABLED COMPUTATIONAL THINKING EDUCATION

Assessing the effectiveness of VR in teaching computational thinking requires robust evaluation methods that capture cognitive, technical, and affective learning outcomes. The Knowledge-Skill-Attitude (KSA) model provides an ideal foundation for this framework, encompassing the three critical dimensions of CT education: understanding key concepts (knowledge), applying practical abilities (skills), and fostering positive dispositions toward the learning process (attitudes). The KSA model can holistically measure how VR environments enhance learning experiences and outcomes in computational thinking and human-robot collaboration.

Knowledge Assessment. Knowledge assessment evaluates learners' understanding of CT concepts. For instance, learners might be asked to explain the logic behind an algorithm they designed or identify patterns in system behavior. Knowledge acquisition can be measured through quizzes, written reflections, or in-task observations (Xu & Zheng, 2021). In the training program, knowledge metrics are designed to assess participants' understanding and application of core computational thinking concepts, focusing on four main areas:

- Decomposition: This metric evaluates the participants' ability to break down complex tasks or problems into smaller, more manageable parts. This skill is crucial for understanding and tackling intricate tasks in a step-by-step manner. Participants are assessed on their confidence and frequency of using decomposition in their daily tasks, with pre- and post-experiment surveys rating their self-assessment on a scale of 1 to 5.
- Pattern Recognition: Pattern recognition involves identifying trends and regularities in data or events. This skill is vital for predicting outcomes and making informed decisions. Participants are asked to rate their ability to recognize patterns and provide examples of how they have used this skill to solve work-related problems.
- Abstraction: Abstraction measures the participants' capability to create simplified models or representations of complex systems, focusing on the most critical elements. This helps in understanding the underlying principles without getting bogged down by extraneous details. Participants' understanding of abstraction is rated, and they are encouraged to discuss instances where they abstracted information to facilitate problem-solving.
- Algorithm Design: This metric assesses the participants' proficiency in designing step-by-step instructions or algorithms to solve problems. It is a fundamental skill in computational thinking, enabling the creation of efficient and repeatable processes. Participants are evaluated on their confidence in algorithm design and asked to describe how they have used this skill to address complex challenges.

This comprehensive assessment ensures that the participants' understanding of computational thinking concepts is thoroughly measured, providing insights into their readiness to apply these skills in real-world scenarios. Table 2 shows an example of survey questions designed to measure the knowledge of the users in our VR environment.

Table 2. Example survey questions to measure knowledge in VR tasks

Category	Understanding Core CT Concepts	Application of CT Concepts
Decomposition	On a scale of 1 to 5, how confident are you in breaking down the task of operating the 6-axis robotic arm into smaller steps?	How frequently do you use decomposition when planning the robotic arm's movements?
Pattern Recognition	On a scale of 1 to 5, how well can you identify patterns in the movements required to successfully pick up and place objects using the robotic arm?	Can you provide an example of how you used pattern recognition to improve the efficiency of the pick-and-place task?
Abstraction	On a scale of 1 to 5, rate your understanding of creating abstract representations of the robotic arm's tasks to simplify the operation	How do you approach problems that involve multiple variables and require systematic planning during the pick-and-place tasks?
Algorithmic Design	On a scale of 1 to 5, how confident are you in designing step-by-step procedures for moving and maneuvering the robotic arm?	Describe a situation in the training environment where you used algorithm design to solve a complex robotic task. What steps did you take?

The framework illustrated in Table 3 links theoretical understanding with practical application, helping to translate knowledge into actionable skills, representing how these computational thinking concepts transition from theoretical knowledge to practical skills, emphasizing the importance of each step in achieving effective Human-Robot collaboration.

Table 3. Linking theoretical understanding with practical application in CT

Task	Moving the robot arm to pickup/ drop off the object	Maneuvering the robot to move around to the goal spot
Decomposition: Decompose a task or problem into several steps or parts.	Breaking down the steps of operating the robot arm: optimizing the use of different joints for gripping and releasing the object	Breaking down the steps of maneuvering the robot: identifying obstacle(s) and planning the most efficient path(s).
Pattern Recognition: Predict the pattern of the problem and determine the pattern for testing.	Recognizing the common features or patterns of gripping successes/failures	Recognizing patterns in different paths by comparing their characteristics/obstacle(s)
Abstraction: Determine the principles or factors that led to this pattern.	Prioritizing key elements for what is most important in successful gripping/releasing object(s)	Prioritizing key elements for what is most important in successful maneuvering
Algorithm Design: Design an instruction flow that can solve similar problems and be repeatedly executed.	Creating a sequence of successful pick-up/drop-off moves with the robot arm	Creating a sequence of successful selections of the path(s) and maneuvering to the target spot

Skill Assessment. Skill development is assessed through performance metrics such as task completion accuracy, efficiency, and error rates. VR systems facilitate real-time data collection, enabling detailed analysis of learners' interactions. For example, a task might require learners to program a robotic arm to complete a sequence of actions, with success measured by the time taken and the accuracy of execution (Elfasakhany et al., 2011; Yousuf et al., 2016). In the training program, the skill metrics are crucial for evaluating the participants' proficiency in operating the robotic systems. The ASES framework focuses on four key aspects: Accuracy, Speed, Energy, and Safety.

- Accuracy: This metric assesses how accurately participants can perform tasks such as picking up and placing objects using the robotic arm. It includes a qualitative measure (Yes/No) for whether the task was completed correctly.
- Speed: Speed measures the time taken to complete specific tasks, such as the duration to pick up and drop off objects. It is quantified in seconds and is crucial for assessing efficiency in task performance.
- Energy: This metric evaluates the efficiency of the robotic arm's movements, specifically the number of joints used to accomplish tasks. It helps in understanding the optimization of the robot's actions during operations.
- Safety: Safety metrics involve counting the number of times the operator hits an object before successfully completing a task. It also includes the number of times the operator encounters obstacles while maneuvering the robot to the target area. This aspect is essential for assessing the participant's ability to operate the robot safely and avoid potential hazards.

These metrics collectively provide a comprehensive evaluation of the participants' skills in using the robotic systems, ensuring that they perform tasks not only accurately and efficiently but also safely. Table 4 shows an example of metrics designed to measure the skill of the users in our VR-based environment.

Table 4. Example metrics for assessing skills in VR tasks

Tasks	Accuracy	Speed	Energy	Safety
Moving the robot arm to pick up/drop off the object	The operator pick up/drop off the object correctly.	The time the operator spends pick-up/drop-off the object using the arm.	The number of joints that the robotic arm uses to pick up/ dropoff the object.	The number of times the operator hits the object before pick-up/ drop-off.
Maneuvering the robot to move around and transfer the object to the goal spot	The operator travels correctly to the unloading area.	The time the operator spends reaching the unloading area.	The distance that the robot travels to reach the unloading area.	The number of times the operator hits any obstacles traveling to the unloading zone.

Attitude Assessment. Attitude assessment examines learners' confidence, persistence, and adaptability. Surveys, interviews, and observational data provide qualitative insights into learners' emotional and cognitive engagement. For example, learners might rate their confidence in applying CT principles before and after completing a simulation (Carvalho, 2015). In the training program, attitude metrics are designed to assess participants' mental approach and emotional readiness to engage with computational thinking and robotic technologies. These metrics are crucial for understanding the participants' openness to learning, adaptability, and resilience in the face of challenging and novel tasks, with a focus on several key areas:

- Confidence in Dealing with Complexity: This metric measures the participants' self-assurance when faced with complex problems, both in general and specifically in robotic tasks. Questions assess whether participants feel confident handling complex problems at work and if they can remain calm and composed in ambiguous situations.

- Persistence and Tolerance for Ambiguity: This area evaluates the participants' perseverance when working on difficult problems and their comfort with open-ended problems that lack clear solutions. It measures how persistent participants are in seeking solutions and their ability to handle uncertainty.
- Willingness to Learn and Adapt: This metric gauges the participants' eagerness to learn new methods and adapt to new technologies. It includes assessing their interest in computational thinking concepts, their openness to adapting new techniques in their work, and their proactive approach to seeking more information and knowledge about these concepts.

This comprehensive evaluation helps understand the participants' readiness to engage with complex computational tasks and their overall disposition towards learning and adaptation. Table 5 shows an example of metrics designed to measure the attitude of the users in our VR-based environment.

Table 5. Example metrics for assessing attitude in VR tasks

Category	Sample Questions
Confidence in Dealing with Complexity	● I feel confident in handling the complexity of operating the 6-axis robotic arm. ● I can remain calm and composed when faced with ambiguous scenarios during robotic arm operations.
Persistence and Tolerance for Ambiguity	● I persistently work on difficult robotic arm tasks until I find a solution. ● I am comfortable dealing with open-ended problems in the training environment without clear solutions.
Willingness to Learn and Adapt	● I am always eager to learn new methods for operating the robotic arm and Mecanum wheel platform. ● I am open to adapting new techniques and methods in handling robotic tasks.

FUTURE DIRECTIONS

The integration of VR into higher education offers transformative potential for fostering computational thinking, particularly in the context of human-robot collaboration. Despite these advantages, several critical questions remain. Future research should investigate the **longitudinal impacts** of VR-enabled computational thinking education to understand how immersive learning experiences influence knowledge retention, skill development, and career readiness over time.

Another important avenue for exploration is the **transferability of skills** acquired in VR to real-world contexts. While VR provides a safe and controlled environment for learning, its ultimate value lies in equipping learners with competencies they can apply beyond the virtual space. Studies should examine how effectively learners transition from virtual simulations to practical applications in professional and academic settings, particularly in human-robot collaboration scenarios.

Finally, the application of VR in training for **human-robot collaboration** represents an exciting yet imperative frontier. As robots and automated systems become increasingly integrated into industries ranging from manufacturing to healthcare, there is a growing demand for professionals adept at collaborating with these technologies. VR can serve as a powerful tool for simulating realistic human-robot interaction scenarios, enabling learners to develop the technical, cognitive, and interpersonal skills needed for effective co-presence.

Recognizing the importance of these directions, the research team is currently conducting empirical studies to address scalability, skill transferability, and the application of VR in human-robot training. These investigations aim to provide actionable insights and practical solutions, paving the way for broader adoption and deeper integration of VR into computational thinking education and beyond.

CONCLUSION

The integration of computational thinking, virtual reality, and human-robot collaboration represents a critical intersection in the advancement of STEM education and future workforce development. As the line between humans and intelligent systems continues to blur, there is an increasing need to prepare learners with the skills necessary to navigate and contribute to this emerging landscape.

This study introduces a conceptual framework for embedding computational thinking education into virtual reality environments to support human-robot collaboration. However, this is just the beginning. Educators and researchers are encouraged to build on this foundation through empirical studies that test, refine, and expand the framework across diverse educational contexts. As VR learning environments and robotic technologies evolve, they will undoubtedly introduce new technological affordances and pedagogical possibilities, leading to even more transformative approaches to teaching and learning in STEM fields and future workforce development.

CONFLICTS OF INTEREST

The Editor-in-Chief of this journal acted as one of four authors for this manuscript.

FUNDING STATEMENT

This manuscript was given a full waiver by IGI Global Scientific Publishing.

PROCESS DATES

December 30, 2024
Received: December 28, 2024, Revision: December 30, 2024, Accepted: December 30, 2024

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ACKNOWLEDGMENT

This material is based upon work supported by the National Science Foundation under Grant No. 2222890. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. Dr. ShinHee Jeong, Dr. Suniti K Walimuni Devage, and Dr. Ali Kazemian are gratefully acknowledged for their valuable participation and contributions to the research process and activities.

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