Future-Ready Workforce Development: Integrating Computational Thinking into Construction Education Using Virtual Reality

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# ABSTRACT

The construction industry is rapidly evolving with the increasing adoption of robotics and automation. However, traditional construction education often falls short in equipping students with the computational thinking (CT) skills required to address the challenges of technology-driven workplaces. This study aims to bridge this gap by developing a virtual reality (VR) training environment that incorporates CT as a core competency. Through immersive human-robot interaction (HRI) scenarios in both terrestrial and extraterrestrial construction contexts, the VR environment offers hands-on learning experiences to enhance problem-solving and adaptability through iterative learning with progressively complex tasks. Participants engage in structured pick-and-place tasks designed to develop key CT components: decomposition, abstraction, pattern recognition, and algorithmic thinking. The study applies a knowledge-skill-attitude framework to assess the training program’s impact on CT competencies and future readiness. A pilot human-subject experiment with five construction management students demonstrated the VR environment’s effectiveness, with results indicating significant improvements in computational thinking and adaptability to novel scenarios.

# INTRODUCTION

The construction industry is undergoing a rapid technological transformation driven by advancements in robotics (Bock, 2015; Sawhney et al., 2020). Due to quasi-repetitive and highly variable tasks in construction, there is a need to advance human-robot interaction (HRI) and adapt construction training environments to equip students for these challenges (Yu et al., 2024; Lafhaj et al., 2023; Davila-Delgado et al., 2019). This evolution in training is further underscored by the ambitious goals of the National Aeronautics and Space Administration (NASA) and the European Space Agency (ESA) to establish permanent human habitats on the Moon and Mars by 2040, marking the 50th anniversary of the first manned lunar landing (Naser, 2019). Extraterrestrial construction—building structures on planetary bodies outside Earth's atmosphere—represents a significant frontier for the construction industry (King, 2019). Due to the extreme and hazardous conditions of outer space, extraterrestrial construction will be technology-intensive, fundamentally changing the role of construction workers (Zhou et al., 2019).

While traditional construction education emphasizes technical skills such as project planning, materials management, and construction methods, it often neglects the future-oriented skills essential for adapting to emerging technologies (Liang et al., 2021). Recent studies highlight a widening skill gap reflects a mismatch between higher education systems and the dynamic needs of the workforce with rapid advancements in robotics, posing challenges for industries like construction seeking to adopt advanced technologies effectively (Rikala et al., 2024). Addressing this gap requires innovative training environments that not only meet current technical demands but also foster transferable competencies—skills enabling adaptability and cross-disciplinary application (Carvalho, 2015; Justice et al., 2009). The demand for a future-ready workforce capable of adapting to constantly evolving workplaces has led to a focus on integrating transferable skills into training programs (Muhamad, 2012). Among the various transferable skills identified (e.g., Forbes Human Resource Council, 2020), computational thinking (CT) stands out as a core competency critical for future technology-intensive construction work. CT, a problem-solving process widely used in computer science, involves steps such as decomposition, pattern recognition, algorithms, and abstraction (ISTE Standards, 2024). CT can be fostered through iterative learning, where progressively complex tasks challenge learners to build upon prior knowledge, encouraging deeper problem-solving and adaptability.

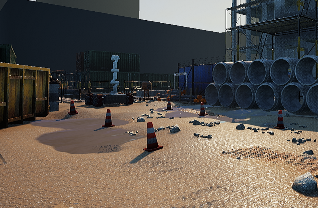
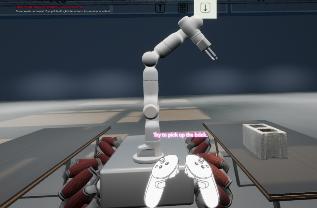
However, traditional classroom methods often struggle to create effective environments for fostering CT, particularly in the context of HRI (Kerimbayev et al., 2023). Hands-on learning opportunities with robots are limited or infeasible due to high costs, safety concerns, and the potential for damaging expensive equipment. Physical constraints (e.g., limited space) also limit the ability to simulate dynamic and diverse collaborative scenarios in controlled environments. Virtual Reality (VR) emerges as a promising solution, offering immersive, interactive, and visualized learning experiences that enable co-present, dynamic training scenarios (Qian, 2014).

To address this critical need, this study proposes a transformative VR training environment designed to foster CT as a core transferable competency. CT is increasingly vital for construction professionals working with intelligent, automated, and semi-automated machines. The VR environment employs iterative learning with increasing complexity, immersing participants in structured tasks that progressively build on foundational skills. The iterative nature of the learning process ensures participants not only grasp foundational skills but also develop the confidence and adaptability needed to tackle increasingly complex tasks. By fostering CT through this approach, the proposed VR environment equips construction professionals to thrive amidst technological change, becoming truly “future-ready.”

# RESEARCH METHODOLOGY

**Scenario Design and Iterative Learning.** We developed a series of HRI scenarios to incrementally build CT competency through iterative learning with increasing task complexity. These scenarios focus on pick-and-place tasks using a robotic arm mounted on a Mecanum wheel platform—a critical task that is becoming essential for the future construction workforce. This foundational task involves basic object manipulation in a controlled environment, progressing to more complex tasks requiring spatial reasoning, precision, and problem-solving. The six levels of difficulty include four training tasks and two testing tasks: *Training Task 1* introduces simple pick-and-place operations with static obstacles to familiarize participants with basic controls. *Training Task 2* incorporates dynamic, moving obstacles to develop real-time navigation and adaptability. *Training Task 3* adds static obstacles with inclined and sloped surfaces, challenging participants to account for uneven terrain. *Training Task 4* combines dynamic obstacles with inclined surfaces, requiring advanced planning and precise maneuvering. *Testing Task 1* involves a realistic construction site environment with authentic obstacles and varied surface conditions to assess terrestrial performance. *Testing Task 2* introduces a futuristic extraterrestrial construction site, featuring low-gravity conditions and unique spatial constraints.

**VR Training Environment Development.** The designed scenarios were integrated into a VR training environment using Unreal Engine, replicating real-world construction conditions with high fidelity. The VR framework includes spatial constraints, realistic equipment, and dynamic challenges across three distinct environments (Figure 1): a training warehouse for skill acquisition and practice (Training Tasks 1–4), a realistic construction site with authentic terrestrial conditions (Testing Tasks 1), and a futuristic extraterrestrial construction site simulating the challenges of space construction (Testing Tasks 2).



***Figure 1: The developed VR environment for HRI scenarios***

**Assessment Framework.** The study adapts the knowledge-skill-attitude (KSA) framework (Bloom et al., 1964; Kirschner and Stoyanov, 2020; Etik and Setiyono, 2021) to measure CT competency. This approach combines established metrics with rubric-based questions tailored to each competency for structured, detailed assessment. Skills are quantified through metrics such as accuracy, speed, and safety, recorded during pick-and-place tasks involving the robotic arm and Mecanum wheel system. These metrics capture trainees' ability to perform precise and efficient material-handling tasks in complex environments. Knowledge is assessed through qualitative surveys evaluating understanding and application of core CT concepts like decomposition, pattern recognition, abstraction, and algorithm design. Attitude is measured through interviews exploring willingness to learn, adaptability to new technologies, and persistence in overcoming challenges, providing insights into trainees' openness to integrating CT into their workflows.

**Pilot Human-Subject Experiment Procedure**. As a pilot study, we conducted an experiment with five LSU students. The study achieved approval from LSU’s Institutional Review Board (IRB) to ensure compliance with ethical standards, informed consent, and the protection of participant confidentiality throughout the process. Each participant received a thorough explanation of the experiment's purpose, procedures, and risks. Consent forms were used to obtain consent and inform participants of their right to withdraw without any repercussions. To ensure participant suitability and gather baseline demographic data, students completed a screening questionnaire covering eligibility factors (age, visual and hearing impairments, history of motion sickness, and neurological conditions), demographic information, and familiarity with VR.

Participants first completed a survey to assess their baseline knowledge and attitudes toward computational thinking. Then, they watched a 15-minute video lecture introducing CT concepts and their applications in construction. Next, they interacted with a tutorial scenario within a VR-simulated warehouse to learn the controls for operating the robotic arm and the Mecanum wheel system using a controller. After a short break, they progressed through Training Tasks 1 to 4, performing pick-and-place tasks of increasing difficulty. Following another break, participants performed Testing Tasks 1 and 2 involving pick-and-place scenarios in realistic construction and extraterrestrial environments. Skill metrics were recorded, and surveys evaluated knowledge and attitudes at the end of each scenario. Figure 2 illustrates the experiment's structure.

**Introduction Session**

**Training Session**

**Testing Session**

Lecture on CT + Introduction to robot and its control

**Testing 1**

Construction Site

**Testing 2**

Extraterrestrial Environment



**Training Task 1**

**Training Task 2**

**Training Task 3**

**Training Task 4**

***Figure 2: The structure of the pilot human-subject experiment***

# RESULTS AND DISCUSSIONS

This study details the outcomes of a pilot experiment involving five participants from LSU’s Construction Management program: three undergraduate students (ages 19–23) and two graduate students (ages 23–26). The group comprised four males and one female with varying prior experience with VR: two had never used VR, one rarely used it, one occasionally used it, and one was a frequent user. The results of this experiment are presented in the following section.

**Skill Metrics.** This study evaluates participants' ability to maneuver the robotic system with precision and efficiency using the Accuracy, Speed, Energy, and Safety (ASES) framework. Accuracy is assessed as a binary variable (0 or 1), indicating successful object placement. Speed measures the total time (in seconds) to complete tasks, while Energy records the cumulative control usage time. Safety tracks the number of collisions during task execution. Metrics are normalized based on average performance; for example, if the average task completion time is 5 minutes, a participant finishing in 6 minutes would have a speed index of 1.2.

Figure 3 illustrates the pilot experiment results for skill metrics. All five participants completed the pick-and-place tasks with 100% accuracy, which was excluded from further analysis. Results for Speed, Energy, and Safety provide key insights. Speed improved steadily during training, with a slight dip in Testing Task 1 (construction site) reflecting challenges in adapting to real-world conditions. Performance improved in Testing Task 2, demonstrating adaptability under extraterrestrial conditions. Energy usage fluctuated during training, with early inefficiencies increasing consumption and later dips reflecting improved control as participants adapted to the VR interface. Individual learning variations also contributed to these inconsistencies Similarly, Safety Index spikes, particularly in Training Task 2, suggest participants experimented with movement strategies, causing temporary increases in collisions before refining their precision. By Testing Task 2, significantly reduced collision rates indicated improved maneuverability. These results show that participants required time to adapt but achieved significant improvements, demonstrating efficient, precise, and safe task execution across diverse environments during testing phases.

***Figure 3: Skill metrics results***

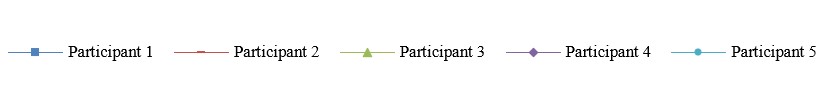
**Knowledge Metrics**. This study evaluates participants' understanding of CT concepts through a survey targeting four components: Decomposition, Pattern Recognition, Abstraction, and Algorithmic Thinking, measured on a Likert scale. Decomposition assesses confidence in breaking tasks into manageable steps during robotic arm operation. Pattern Recognition evaluates the ability to identify patterns in movements for successful task execution. Abstraction measures understanding of creating simplified representations for robotic arm tasks. Algorithmic Thinking assesses confidence in designing step-by-step procedures to solve problems.

Figure 4 shows positive trends in CT skill development. Confidence in decomposition steadily improved during training and remained stable during testing, reflecting effective skill transfer to both real-world and extraterrestrial tasks. Pattern recognition showed consistent growth during training, with a minor dip in Testing Task 1 that rebounded in Testing Task 2, demonstrating adaptability. Abstraction improved gradually throughout training and remained consistent in testing, indicating participants’ ability to apply abstract thinking across contexts. Algorithmic thinking showed significant progress during training, with slight challenges in Testing Task 1 followed by a recovery in Testing Task 2, reflecting resilience and adaptability. The pilot results demonstrate that the training program effectively enhanced CT skills, enabling participants to apply these competencies across diverse and complex scenarios.

***Figure 4: Knowledge metrics results***

**Attitude Metrics**. This study evaluates participants' progression in key behavioral aspects essential for dynamic problem-solving through the following metrics: (1) Confidence in Dealing with Complexity, (2) Persistence and Tolerance for Ambiguity, and (3) Willingness to Learn and Adapt. Confidence in Dealing with Complexity measures participants’ ability to manage complex operations and remain composed in ambiguous scenarios. Persistence and Tolerance for Ambiguity evaluate participants' determination to tackle challenging tasks and comfort with open-ended problems. Willingness to Learn and Adapt assesses eagerness to explore new methods and openness to adopting innovative techniques.

Figure 5 illustrates the results for attitude. Confidence in dealing with complexity improved steadily through all phases, with pre-training responses indicating lower levels and Testing Task 2 (extraterrestrial) responses reflecting consistent confidence in managing complex tasks. Calmness also improved incrementally during training and stabilized during testing, highlighting adaptability under uncertain conditions. Persistence and tolerance for ambiguity demonstrated steady growth, with testing phases showing enhanced resilience and greater confidence in addressing tasks with undefined solutions. The willingness to learn and adapt remained consistently high throughout all phases, underscoring participants’ openness to innovation and receptiveness to new methodologies. These results emphasize the program’s effectiveness in fostering adaptability and a willingness to engage with dynamic, technology-driven environments.



***Figure 5: Attitude metrics results***

**Interrelationship Between Skill, Knowledge and Attitude Metrics.** Our results provide preliminary understanding of how CT knowledge and attitudes influence participants’ skills in robotic tasks. Based on the limited number of experiments, there was a correlation between CT knowledge and attitudes, as illustrated in Figure 6, which highlights the foundational role of computational thinking in developing critical behavioral competencies. Pattern recognition emerged as a pivotal skill, showing high correlations with confidence in handling complexity and willingness to learn and adapt, underscoring its importance for technical innovation and self-assurance. Algorithmic thinking demonstrated strong relationships with persistence and tolerance for ambiguity, emphasizing its role in fostering determination and adaptability in problem-solving. These findings suggest that targeted CT skill development can significantly enhance participants’ attitudes, enabling them to address dynamic challenges effectively.

***Figure 6: Knowledge and Attitude metrics correlation***

The correlations between CT knowledge, attitudes, and skill metrics (Figure 7) reveal a nuanced relationship. Negative correlations with speed suggest that participants with higher CT competencies prioritize precision and safety over speed, reflecting a deeper understanding of task requirements and a focus on minimizing errors. Positive correlations with energy indicate that stronger CT skills and confidence enable participants to optimize robotic control usage, enhancing task efficiency. For safety, strong negative correlations—particularly with abstraction and confidence in handling complexity—highlight that participants with advanced cognitive and attitudinal competencies execute tasks more safely, avoiding collisions and errors.

The CT competencies and skill metric correlations yield some valuable insights, but these do not infer direct causality. The correlations become meaningful—higher CT competencies imply greater safety and energy efficiency but with a sacrifice in speed—while external factors may intervene. Factors such as participants' previous experience with robotics or VR controls, personal learning styles, and adaptability differences could have influenced performance.

***Figure 7: Knowledge and Attitude Correlation with Skill***

These findings suggest that while cognitive and attitudinal growth may not directly improve speed, they significantly enhance energy efficiency and safety, which are critical in high-stakes scenarios. A balanced training program that integrates CT skill development with practical execution is essential for equipping trainees to navigate complex scenarios effectively and safely.

# CONCLUSION

This study investigated the interplay between computational thinking knowledge, attitudes, and skill performance in a VR-based training environment for performing HRI pick-and-place tasks. The findings highlight the environment’s effectiveness at enhancing participants’ cognitive and behavioral competencies, particularly in abstraction and algorithmic thinking, which are critical for systematic problem-solving. Participants demonstrated notable improvements in attitudes such as persistence, comfort with ambiguity, and eagerness to adopt new methods, underscoring the program’s role in fostering resilience and adaptability in dynamic environments. Strong correlations between CT knowledge/attitudes and skill performance metrics, particularly safety and energy efficiency, emphasize that enhanced CT competencies contribute to precise and efficient task execution. While these improvements occasionally led to slower task completion, the prioritization of safety and precision aligns with the program's objectives. Importantly, all participants consistently achieved accurate task execution, reflecting the reliability and robustness of their performance.

While our findings suggest a relationship between computational thinking (CT) knowledge, attitude, and skill development, establishing causality remains challenging due to potential confounding variables such as prior experience, individual learning styles, and external educational influences. Among future ventures that could enhance the efficiency of the virtual reality training model, further research should also consider adaptive learning mechanisms that personalize training experience according to user performance feedback. Furthermore, involving much more complicated real-world construction scenarios will strengthen the model applicability to industry settings. Enlarging this model would require collaborative effort with the industry to endorse its effect in varied working environments, along with considering cost-efficient modes of implementation to allow access by different educational institutions and training programs

The current study represents a preliminary, pilot effort involving only five students. While the findings offer initial insights, they should be interpreted with caution due to the small sample size and the absence of assumption checks prior to conducting the correlational analysis. Future studies with larger samples and robust methodological rigor are necessary to validate these findings. This study serves as a foundation for advancing integrated training programs that prepare participants with the cognitive, attitudinal, and practical tools necessary for complex problem-solving in evolving technological landscapes.

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