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# NSF ITEST: Advancing Computational Thinking in STEM K-12 for Exposure to Built Environment Careers

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## Abstract

The construction industry plays a vital role in shaping the built environment and contributes significantly to the US economy. Yet it continues to face persistent workforce shortages and widening skills gaps in adopting digital technologies. With the introduction of data-sensing technologies, such as drones and laser scanners, there is an increasing demand for a workforce capable of collecting, interpreting, and applying sensor data to improve project planning, safety, and sustainability. However, these data-driven applications are rarely introduced at the K–12 level, limiting early awareness of emerging STEM career pathways in the construction and built environment fields. Funded by the National Science Foundation's Innovative Technology Experiences for Students and Teachers (ITEST) program, this research examines how embodied interaction and the data-sensing modules within Data Sensing Learning Tool (DASLET), a virtual reality (VR)-based learning environment, influence middle school computational thinking (CT), interest, and career awareness. By situating learning within realistic construction contexts, the project aims to make abstract computational concepts more tangible and relevant to students' experiences. This paper focuses on early formative evaluations conducted with educators and students to assess CT and cognitive workload using DASLET. Results indicate that the system effectively supported task completion while keeping cognitive load manageable. This study suggests that immersive learning environments can play a meaningful role in supporting K–12 students' understanding of construction-related STEM concepts while broadening awareness of construction careers and pathways that are often underrepresented in traditional school curricula.



## Keywords

Virtual Reality, Construction Education, K-12, Computational Thinking


## Introduction and Background

The construction industry faces a persistent workforce shortage due to a lack of interest in construction careers among younger generations, an aging workforce, and demand for workers exceeding the supply [1], [2]. Compounding this challenge is a limited awareness among K–12 students of the range of career pathways within the industry [3]. This lack of early exposure is consequential, as interest in STEM fields often develops before middle school, and career preferences formed in early high school strongly influence long-term career persistence [4], [5], [6]. As a result, many students fail to recognize construction as a technology-driven and innovation-oriented profession, further constraining the future workforce pipeline. The industry also faces a growing digital skills gap as it adopts data-driven, technology-enabled practices, such as robotics, that require proficiency in digital tools and data interpretation [7]. Sensing technologies show strong potential to enhance real-time monitoring, quality, safety, and productivity, highlighting the need for targeted educational interventions to prepare the future construction workforce [8].

Computational thinking (CT) is a structured problem-solving approach that encompasses the decomposition of complex tasks, the recognition of patterns and relationships, the abstraction of generalizable principles, and the design and refinement of algorithmic solutions, a foundational competency for 21st-century STEM learners [9]. Block-based programming tools provide an accessible visual entry point for middle schoolers to develop these skills [10], [11]. Virtual reality (VR) supports CT skills by creating immersive, contextualized learning environments where abstract concepts become tangible. Research shows that VR positively impacts K–12 STEM learning by increasing engagement, comprehension, and motivation, while enabling interactive simulations and exposing students to workplace contexts for career exploration [12], [13], [14].

This study draws on Cognitive Apprenticeship Theory and the Social Cognitive Career Theory (SCCT). Cognitive Apprenticeship Theory emphasizes situated learning through modeling and scaffolding in authentic contexts [15], which the Data Sensing Learning Tool (DASLET) applies by embedding computational tasks within construction scenarios. SCCT suggests that self-efficacy, outcome expectations, and career interests interact to shape educational choices [16], [17], [18]. However, there is limited empirical research on VR for construction-focused CT learning in K-12; therefore, this study reports on formative assessments of DASLET to evaluate self-reported CT and cognitive load imposed by the learning environment and to examine the potential for integrating VR into the middle school classroom.

## Research Design and Methods

Figure 1 presents the research framework guiding the development, assessment, and deployment of DASLET with construction educators and students. While the overall framework supports iterative development and deployment, this paper focuses specifically on the formative assessment phase and associated data collection, evaluating self-reported CT and cognitive load.

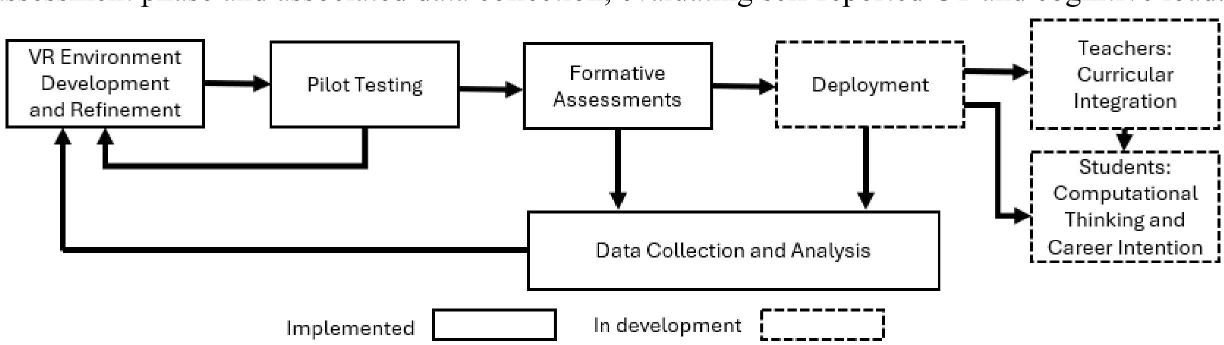


**Figure 1.** Conceptual research framework illustrating the iterative development, implementation, and evaluation of DASLET with construction educators and students.

DASLET features a virtual construction site developed in Unity 3D (version 2022.3.6f1) to simulate authentic site conditions, equipment, and workflows relevant to construction operations. The environment was designed to balance realism, interactivity, and usability while remaining accessible to learners with varying levels of construction experience. Environmental assets were sourced from the Unity Asset Store and supplemented with custom-built models to enhance fidelity. Following the initial development of the VR environment and pilot testing, DASLET was evaluated through external formative assessments conducted with educators and students. Self-reported CT skills were also assessed using a modified version of a previously validated instrument [19]. Modifications were made to ensure alignment with DASLET. Content validity of the adapted instrument was reviewed by subject-matter experts prior to deployment. Cognitive workload was measured using the validated NASA Task Load Index (NASA-TLX) [20].

Participants completed realistic, scenario-based tasks (e.g., site monitoring and drone-based inspection) that incorporated data-sensing technologies, such as laser scanning, drone flight, a robodog, and a global positioning system (GPS) within authentic construction contexts. The immersive environment was delivered using an HTC VIVE Pro head-mounted display and a PlayStation 4 (PS4) controller to support embodied interaction during drone simulations [19]. Participants navigated the environment at their own pace in a single 45-minute session. Prior to participation, they were briefed on the study purpose and IRB-approved procedures and they received standardized training on the VR equipment to minimize novelty effects and extraneous cognitive load.

Within the VR environment, participants accessed a central interface that guided them through four instructional modules (Figure 2): (1) Activity exploration to observe construction activities on the jobsite; (2) Sensor tutorial to expose users to various data sensing devices in construction; (3) Sensor and site activity interactions; and (4) Activity sequencing to model activities using block-based programming to assess CT skills.

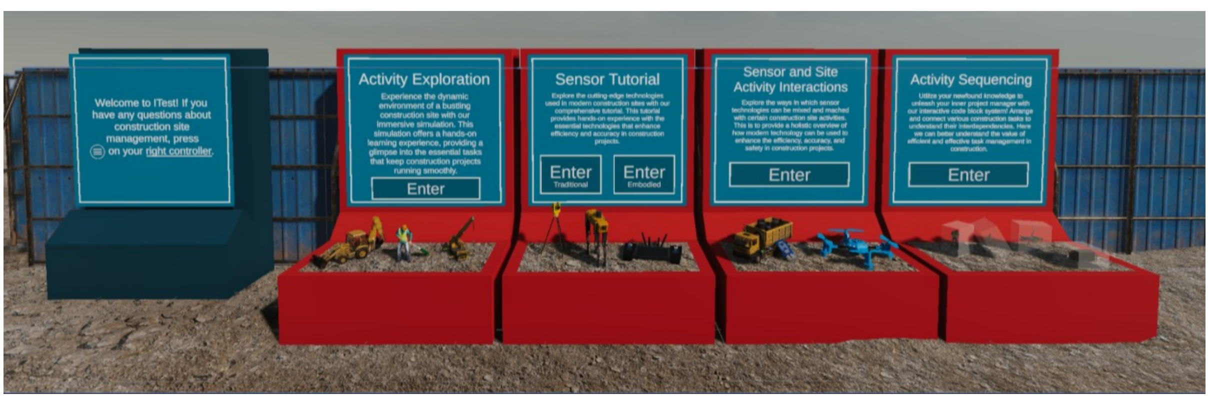


**Figure 2.** Scene from DASLET showing the welcome screen and four interactive modules

All participants completed each module and post-experience surveys administered through Qualtrics. To assess CT, participants completed a task of building a wall. Their performance, based on task completion using the four pillars of CT, was also assessed. Self-reported CT skills were assessed using a modified version of a previously validated instrument on a five-point scale (strongly disagree to strongly agree) [20]. Modifications were made to ensure alignment with DASLET. Content validity of the adapted instrument was reviewed by subject-matter experts prior to deployment. Cognitive workload was measured using the validated NASA Task Load Index (NASA-TLX) on a ten-point scale (very low to very high) [21]. Twenty-one participants were involved in this study, comprising 11 students (8 high school and 3 middle school) and 10 educators (3 middle school teachers, 4 researchers, and 3 professors). 90.5% used VR before and 85.7% were comfortable using the VR headset during the experiment.

**Results and Discussion**

Participants reported high perceptions across the four CT dimensions, although students' mean ratings were lower than educators' (Figure 3). Decomposition received an overall mean of 3.80 (SD = 0.69), indicating moderate perceived support. Pattern recognition achieved an overall mean of 3.97 (SD = 0.65), suggesting participants found the system reasonably effective in scaffolding this dimension. Abstraction yielded an overall mean of 4.06 (SD = 0.68), reflecting balanced system support across CT tasks. Algorithm design received an overall mean of 3.98 (SD = 0.64), indicating that participants perceived the system as effective in supporting implementation and procedural thinking.

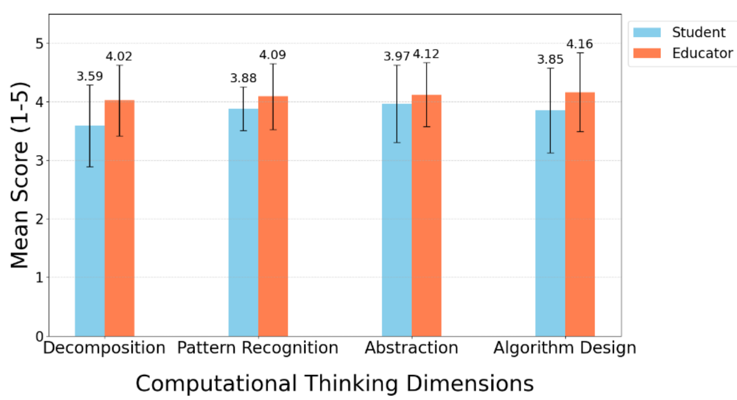


**Figure 3.** Assessment of the dimensions of computational thinking in students and educators

Overall, abstraction emerged as the most prominent CT factor, followed closely by algorithm design and pattern recognition. CT ratings were consistently favorable across all subgroups. Differences between groups were not assessed during the development phase due to the small sample size, but will be assessed during the classroom implementation phase.

In assessing the cognitive load demand, the descriptive analysis of self-reported workload factors across all participants indicated generally moderate mental demand and relatively low frustration (Figure 4). Mental demand received an overall mean of 4.43 (SD = 2.44), indicating moderate cognitive engagement. Physical demand yielded substantially lower mean ratings of 2.05 (SD =

2.46), suggesting minimal physical effort. Temporal demand averaged 3.38 (SD = 2.67), indicating moderate time pressure. Performance ratings were highest across dimensions, with an overall mean of 7.33 (SD = 2.10), indicating strong perceived effectiveness. Overall, effort averaged 4.05 (SD = 2.72), and frustration level had the lowest mean at 3.24 (SD = 2.83), suggesting positive user experiences with minimal frustration. The workload profile shows that participants performed well, with moderate cognitive engagement, low physical demand, and minimal frustration, indicating that the system effectively supported task completion with manageable cognitive load. For both assessments, the differences between groups were not assessed for statistical significance; the descriptive data are presented to illustrate CT confidence and cognitive load patterns across participant types.

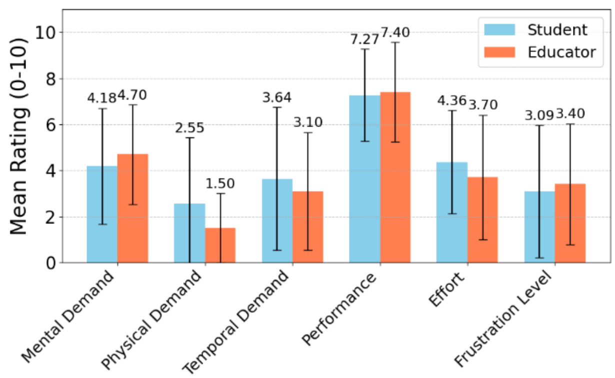


**Figure 4.** Assessment of cognitive load demand using the NASA TLX constructs

## Conclusion

This study conducted a formative evaluation of DASLET, assessing CT and cognitive workload for potential integration into middle school classrooms. The study found that across the CT constructs, abstraction had the highest overall mean and the participants were able to generalize solutions and work with conceptual representations independent of specific implementations within DASLET. Participants were able to complete the tasks with manageable cognitive demand. The limitations of this study include the small sample size and heterogeneity of the groups, given that this was a formative assessment. Also, the assessment is based on self-reported measures. Future work will expand formative assessments to larger groups of middle school students and assess CT skills using self-reported measures and performance-based task assessments.

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