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ENHANCING COMPUTATIONAL THINKING IN CONSTRUCTION EDUCATION: THE ROLE OF SENSOR DATA ANALYTICS WITH BLOCK-BASED PROGRAMMING

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***SUMMARY**: The construction industry's shift to data-driven project management has led to the increasing adoption of various sensing technologies. The transition triggers a demand for a workforce skilled in both the technical and analytical aspects of these tools. While sensing technologies and data analytics can support construction processes, the inherent complexity of sensor data processing often exceeds the skill sets of the graduating workforce. Further, integrating sensor-based applications into construction curricula lacks evidence to support effectiveness in training future professionals. Computational thinking-supported data practices can allow construction students to perform sensor data analytics, spanning from data generation to visualization. This pilot study utilizes InerSens, a block programming interface, as a pedagogical tool to develop construction students' computational thinking through sensor-based ergonomic risk assessment. Twenty-six undergraduate students were engaged in instructional units using wearable sensors, data, and InerSens. The effectiveness of the approach was evaluated by examining students' perceived self-efficacy in sensor data analytics skills, task performance and reflections, and technology acceptance. Results show gains in self-efficacy, positive technology acceptance, and satisfactory performance on course assignments. The study contributes to the Learning-for-Use, constructivism, and constructionism frameworks by integrating computational thinking into graphical and interactive programming objects to develop procedural knowledge and by summatively assessing how construction students learn to address challenges with sensor data analytics.*

***KEYWORDS**: sensor, data analytics, computational thinking, construction safety, block programming, construction education.*

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1. INTRODUCTION

The soaring trajectory of data-driven project management in the construction industry has introduced a range of sensing technologies (Arabshahi et al., 2021, Rao et al., 2022). Concurrently, the adoption triggers the demand for a workforce that possesses a comprehensive understanding of these technologies' technical and analytical capabilities, enabling them to impact project outcomes (Khalid et al., 2023a). However, current educational programs largely focus on foundational construction practices, with limited emphasis on sensing technologies and sensor data analytics that are becoming increasingly relevant in modern construction workflows (Ogunseiju et al., 2021). Sensors and data analytics can be applied in construction projects to support practitioners in monitoring site conditions (Shaoa et al., 2023), optimizing resource allocation (Guven and Ergen, 2021), enhancing safety protocols (Hong et al., 2023), tracking project progress (Yi and Qu, 2021), and improving decision-making (Rane et al., 2023). However, the majority of these research initiatives entail complex processes requiring analytical expertise beyond the skills of graduating construction professionals (Nath et al., 2017, Chacón, 2021, Zhu and Hwang, 2024). Particularly, the task of analyzing the vast quantities of data produced by sensors is fraught with multiple challenges. These include the unstructured nature of the data and lack of standardization (Leite et al., 2016, Mezei et al., 2018), the complexity of the analytical workflow (Qolomany et al., 2019), and limitations in data querying and visualization (Martínez-Rojas et al., 2016). Moreover, the limited focus on programming in construction-related disciplines, alongside the reliance on proprietary software for computing (Talaat et al., 2022, Akanmu et al., 2022), restricts students' ability to explore sensor data analytically. As a result, the workforce needs to invest substantial effort before they can derive useful conclusions from the sensor data and implement them on construction job sites (Khalid et al., 2024c). Consequently, the industry exhibits low adoption rates for sensor data analytics, primarily due to a workforce lacking the necessary training (Qi et al., 2020, Mansouri et al., 2020). Addressing these limitations is imperative for enabling a broader segment of the future construction workforce to leverage data-driven decision-making tools effectively.

Developing computational thinking (CT) among students can equip them with essential data-centric skills needed for data-driven industries (Shute et al., 2017). In educational settings, CT can be developed through CT-supported 'Data Practices' (CTDP) (Weintrop et al., 2016), which guides students on how to understand and work with sensor data within their domain-specific investigations (Chakarov et al., 2019). Utilizing CT enables construction students to systematically implement CTDP, engaging in structured practices of sensor data generation, collection, manipulation, analysis, and visualization to derive actionable insights for decision-making (Chakarov et al., 2019). End-user Programming Platforms (EUPs) offer a viable approach for integrating CT-based concepts into interactive objects, allowing construction students to analyze sensor data without advanced programming expertise (Akanmu et al., 2022). Research suggests that Block-based Programming Interfaces (BBPIs), a subset of EUP, can reduce learning barriers and accelerate skill development in complex data-centric areas such as data science, statistics, machine learning, and cybersecurity (Pratidhina et al., 2021, Chen et al., 2021, Tawfik et al., 2022, Barboza et al., 2023). Despite their potential, there is scarce evidence on the effectiveness of BBPIs in equipping construction students with the necessary sensor data analytics skills for safety applications.

To address this gap, this study hypothesizes that a CT framework, coupled with targeted training modules, can significantly enhance the future workforce's ability to process and interpret sensor data. Specifically, the study proposes that pedagogical modules emphasizing structured CT tasks based on construction sensor data practices will improve workforce proficiency in data analytics, resulting in a measurable increase in self-efficacy with satisfactory task performance and favorable technology acceptance. Accordingly, this study integrates CT with sensor-based safety applications. It utilizes a BBPI, named InerSens, designed for construction students to perform sensor data analytics. Through this intervention, students can develop their knowledge and skills in sensor-based ergonomic risk assessment techniques supported by educational data practices (i.e., CTDP). The study employed a summative assessment to evaluate (a) perceived self-efficacy gain of CT-based sensor data analytics skills, (b) performance of analytical tasks and self-reported reflections, and (c) perceived technology acceptance. This approach reveals the intervention's impact on students' higher-order learning of CT concepts and related data practices. This understanding can inform the development of effective learning experiences, broadening construction students' participation in computing through hands-on sensor data analytics. Ultimately, this experience contributes to preparing graduates with the required skills to address real-world construction safety challenges.

2. BACKGROUND

2.1 Integration of computational thinking into construction sensor data analytics

Like fundamental skills such as reading and arithmetic, CT is perceived as one of the most coveted cognitive skills for analytical problem-solving (Shute et al., 2017, Wing, 2006). Research shows that CT includes diverse cognitive constructs applicable beyond programming, extending into broader computing principles. This has led to efforts to enhance CT across various subjects to address specific skill gaps (Mouza et al., 2020, Csizmadia et al., 2015). CT is often viewed as essential for all learners as it enhances technological skills and facilitates advanced problem-solving across fields (Denning, 2009). The integration of core CT skills, such as abstraction, decomposition, algorithm, evaluation, and, generalization into domain-specific tasks can be achieved by incorporating these skills into educational activities to foster relevant abilities (Atmatzidou and Demetriadis, 2016, Martins-Pacheco et al., 2019, Karakasis and Xinogalos, 2020). Furthermore, CTDP provides a structured approach to navigating sensor data, from its creation to the communication of results in educational contexts (Chakarov et al., 2019). In that regard, construction-based sensor data analytics could be viewed as a CT approach employed in analyzing raw sensor data acquired from the sensing technologies on job sites to extract insights and present the resulting models in decision-making formats for operational planning, execution, management, and control (Akanmu et al., 2022, Khalid et al., 2023a, Mansouri et al., 2020). For example, the Inertial Measurement Unit (IMU) as a sensor can be embedded within a CT framework by structuring the computational workflow of IMU data into targeted CT tasks (Ferrier et al., 2022). In construction, wearable IMUs are increasingly used to capture reliable time-series posture data providing insights into potential operational hazards in safety and health applications (Akanmu et al., 2020) without significantly impacting job site productivity (Stefana et al., 2021). Accordingly, the combination of IMU with CT enables end-users or students to engage with core CT practices, such as data decomposition, abstraction, generalization, and, evaluation. This engagement can support end-users to interpret IMU sensor data in a way that is directly relevant to construction industry applications, such as safety risk assessment (Khalid et al., 2024b) and activity recognition (Khalid et al., 2024a). However, integrating sensor data analytics within CT practices typically requires a graphical interface that facilitates tangible interaction (Wu and Chen, 2022). This type of visual medium not only makes complex sensor data more accessible but also enables end-users to experiment with and manipulate data (Chakarov et al., 2019).

2.2 End-user programming for bridging computational thinking with domain skills

EUP is a widely explored approach to meet the growing demand for CT and comparable data analytics skills in both STEM and non-STEM sectors. Particularly in EUP adoption, these sectors share common challenges, such as limited programming capabilities for engaging in data-focused discussions and queries. Offering non-computer science students, EUP platforms where computational concepts are embedded into interactive visual programming objects can facilitate deeper learning experiences. Such EUPs can enable construction students to develop their CT by performing sensor data analytics without the requirement of traditional programming experience (Akanmu et al., 2022). Block-based programming is a visual approach to EUP that simplifies conventional programming in multiple aspects. First, it enables users to create programs using visual programming environments, where they can drag-and-drop blocks available in 'Lego' or 'Puzzle' shapes onto the workspace (Barricelli et al., 2019). This benefits students as they can easily find the needed blocks without memorizing and recalling programming language constructs (Tawfik et al., 2022). Moreover, the distinct shapes and colors of the blocks ensure they only connect in permissible ways. This further reduces the likelihood of syntax errors which is a common obstacle in the learning process of programming. Secondly, these interactive blocks, each symbolizing distinct programming concepts, can be tailored for specific operations and merged to develop applications that meet the user's domain-specific needs (Rough, 2018). As a result, students can prioritize semantics over syntax, enabling users to focus on the logic, structure, and efficiency of their algorithms (Bau et al., 2017).

Tailored for non-programming domains, BBPIs have enabled experimentation of complex data-centric concepts, typically requiring programming skills. They can be particularly effective in facilitating interactive analyses and offering easily communicable media for end-users' decision-making (Khalid et al., 2023b, Weintrop et al., 2017, Barboza et al., 2023, Chakarov et al., 2019). Sarmento et al. (2015) found that students across various academic fields, such as mechanical engineering, electrical engineering, and chemistry, experienced enhanced motivation, attention, relevance, and confidence. They observed these improvements when using BBPI to tackle challenges related to sensors and robots and to develop CT skills. Similarly, Tawfik et al. (2022), investigated a BBPI as a medium to train adult learners on data science skills. The findings indicated that the blocks not only served as useful visual aids for data analysis but also significantly contributed to the learners' ability to comprehend CT principles. In the context of construction education, students often lack formal coding training, limiting their ability to work with unstructured sensor data directly. BPBI-based interventions can address this gap by allowing them to directly create and analyze sensor data for problem-solving in construction without needing advanced programming skills. In this regard, summative assessments can offer a comprehensive view of the end-user perspective and objective performance by incorporating CT-based data practices (Weintrop et al., 2016, Grover, 2017).

2.3 Assessment methods

Examining success factors in CT interventions often relies on Computational Thinking Self-Efficacy (CTSE) as a key metric (Weese and Feldhausen, 2017). CTSE can help to gauge learners' perceived proficiency in applying CT skills within domain-specific tasks or learning environments (Tsai et al., 2023, Totan and Korucu, 2023, Kasalak and Altun, 2020). Block programming self-efficacy focuses on students' confidence within a visual programming environment, ensuring they can utilize the tools effectively to perform required computational tasks (Kasalak and Altun, 2020). While, self-efficacy in CT encompasses students' abilities to comprehend data, decompose problems into sub-problems, construct algorithms, explore various solutions, define variables, and utilize functions.

Although limited, research suggests extending CT assessment to a broader context outside of strict coding, more in a context-neutral manner (Lai, 2021). Therefore, scales featuring items related to programming languages or constructs may not be as pertinent or meaningful to students in non-computer science fields like construction. Kukul and Karatas (2019) defined four dimensions for assessing students' CTSE, drawn from (Wing, 2006, Wing, 2008) and ISTE & CSTA (Computer Science Teachers Association, 2011): reasoning, abstraction, decomposition, and generalization, focusing on CT's problem-solving facet. Accordingly, Kukul and Karatas (2019) developed and validated a CTSE scale that focuses on the problem-solving aspect of CT. This serves as a useful resource for educators aiming to enhance their students' CT abilities extending beyond the domain of computer science. Additionally, in non-programming contexts, summative assessments can gauge whether learners have acquired adequate content knowledge and can perform effectively after CT instruction, which predominantly relies upon posttest evaluations. However, relying solely on one assessment instrument can lead to incomplete views of CT skills, potentially underrepresenting contexts where CT can be manifested (Lai, 2021). One way to effectively integrate CT concepts in classrooms is by having students directly apply them (Curzon et al., 2014). This can be achieved by mapping CT elements to specific problem-solving and then evaluating the outcomes. This approach involves starting with the purpose behind a learning challenge ('why'), utilizing various CT skills ('how'), and assessing the actual learning outcomes ('what'). These outcomes can be assessed through student-created artifacts, their understanding of the concepts, or their observed behaviors. Hence, combining multiple CT assessment instruments such as pre and post-self-efficacy assessments, graded artifacts, and open-ended qualitative reflections can provide a more comprehensive understanding of learners' targeted skill development. Furthermore, studies show that specific skill development with computer systems is influenced by how users perceive the technology's ease of use (Hackbarth et al., 2003) and usefulness (Koç et al., 2016). Im et al. (2008) further suggested that the perceived risk of information technology can negatively impact both its ease of use and usefulness, ultimately reducing users' behavioral intention to use the system. This highlights the importance of assessing user acceptance of the facilitating technology (i.e., BBPI) in acquiring CT-based sensor data analytics skills.

2.4 Theoretical frameworks

The authors have previously developed InerSens (Khalid et al., 2024b), a BBPI grounded in the four principles of the Learning-for-Use (LfU) framework, as delineated by Edelson (2001). InerSens employs the LfU framework to situate and represent the complexities involved in interpreting and analyzing sensor data to allow students to address construction safety issues. In the context of classroom intervention, constructivism and constructionism are the most widely used theoretical foundations for integrating domain-specific learning objectives through CT (Martins-Pacheco et al., 2019, Fosnot, 2013, Papert and Harel, 1991). Constructivist teaching methods are anticipated to foster skills such as self-reliance, confidence, accountability, and entrepreneurialism (Ambrosio et al., 2014, Dagienė and Futschek, 2019), while constructionism should foster a collaborative culture to construct connections between old and new knowledge through interaction, leading to the creation of socially relevant artifacts for assessment (Ackermann, 2004). Moreover, constructionism is closely linked to the concept inherent to the idea of visual programming languages (i.e., BBPIs), as it underscores that learners develop their knowledge and understanding based on their own experience through ‘experimentation’ and ‘the stimulation of questions and the development of reasoning’ (Begosso et al., 2020). Hence, the construction students' interaction with BBPI where students are assessed on self-efficacy gains corresponds to constructivist principles (Tamilias et al., 2017), while the assessment of students' data practices through the creation of computational artifacts is linked to constructionism (Lodi and Martini, 2021). Collectively, LfU, constructivism, and constructionism promote technology acceptance by enhancing perceived usefulness, increasing engagement, and fostering a supportive learning environment that builds confidence and competence in using new technologies (Edelson, 2001, Tamilias et al., 2017, Lodi and Martini, 2021).

3. METHODOLOGY

This study investigates how a CT intervention, employing a BBPI as the analytical platform, impacts students' self-efficacy, task performance, and technology acceptance during their engagement in construction sensor data analytics (see *Figure 1*). The curriculum includes a problem-solving unit focused on quantifying ergonomic safety risks using IMU sensors and BBPI. Depending on the specific problem chosen, students generate, collect, and analyze sensor data relevant to the construction issues being addressed.

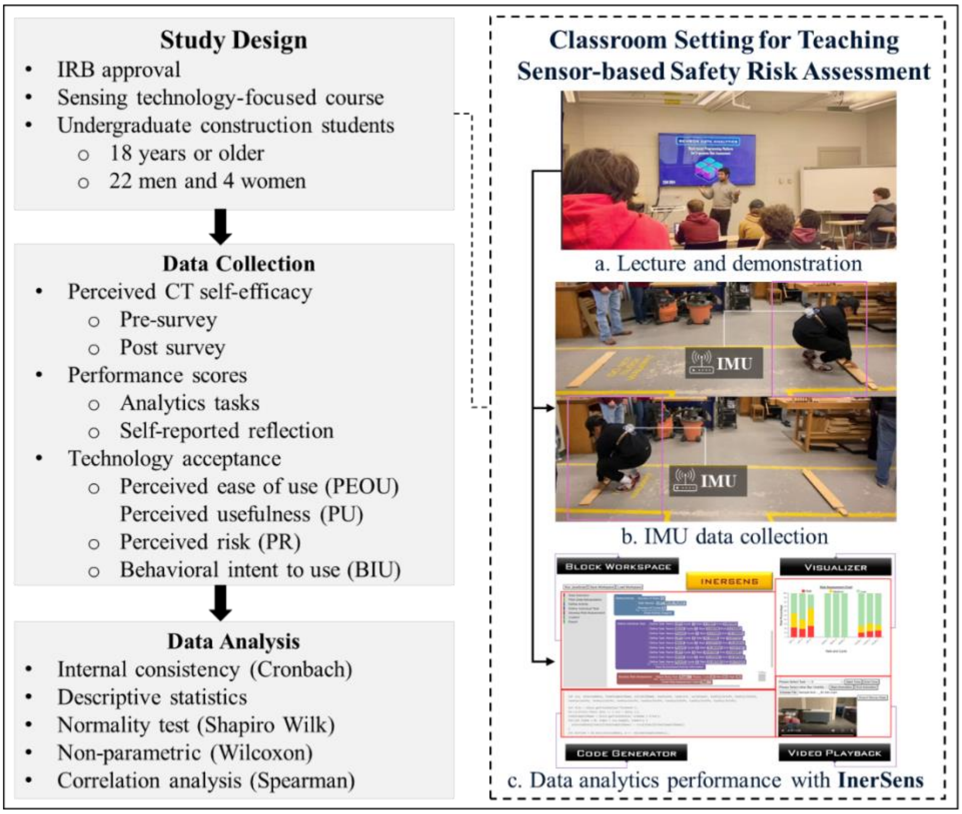

Figure 1: Overview of the research methodology.

3.1 Study design

The study involved a class of 30 undergraduate students majoring in building construction (BC), and construction engineering and management (CEM). Four students were excluded from the analysis and only the data of students who completed all the surveys, assignments, and qualitative responses (N=26) were analyzed. Similar sample sizes have previously been shown to uncover interventions’ effects on learning gains, perceived self-efficacy, and technology acceptance. For example, Jaipal-Jamani and Angeli (2017) examined 21 elementary preservice teachers’ self-efficacy, knowledge of science concepts, and CT skills while engaging them with robotics. The study employed similar data collection methods, including pretests and posttests, questionnaires, and assignments, demonstrating the effectiveness of this sample size in revealing statistically significant findings. Similarly, Schez-

Sobrino et al. (2020) utilized a sample of 12 participants to examine the effect of a CT-based educational intervention. The experiment evaluated the RoboTIC game's impact on programming motivation and interest, utilizing pre- and post-test questionnaires to measure self-efficacy, perceived usefulness, ease of use, and intention to use. The study found a significant positive shift in participants' attitudes toward programming after using the RoboTIC game. Participants reported high intrinsic motivation and perceived ease of use for Augmented Reality tools, indicating enhanced engagement with CT concepts. Accordingly, the final sample of this current study comprised 15.38% of women (N = 4) and men 84.62% (N = 22). Of these, 15.38% were in the BC program (N = 4), while 84.62% were in the CEM program (N = 22). The student sample, aged 18 to 24 years, comprised 80% White, 10% Black or African American, 3.33% Asian, and 6.67% identifying as 'Other' without further specification. The research interventions received approval from the Institutional Review Board (IRB#21-1020).

Students were enrolled in CEM 3154, a course at Virginia Tech focused on equipping students with an understanding of sensing and modeling technologies, demonstrating their applications in construction project planning, job site monitoring, and integrated management. *Figure 2* illustrates the complete timeline of the risk assessment module (M), outlining the implementation stages, including lecture, demonstration, group data collection, and individual data analysis. It also shows when key data collection components, such as graded assignments (A), self-efficacy (SE), and technology acceptance (TA), were introduced throughout the timeframe. The risk assessment module spanned 2 weeks (8th and 9th in a 16-week semester) in alignment with previous studies that utilized comparable timeframes for integrating intervention modules to assess students' CT (Hutchins et al., 2020, Jaipal-Jamani and Angeli, 2017, Weese and Feldhausen, 2017). Overall, the class format for this module involved guided examples through lectures on generating IMU sensor data from construction workers (see M1.1 and M1.2 in *Figure 2*), followed by hands-on data collection (M1.3) and analytics (M1.4 using InerSens) to complete the tasks for risk assessment. It comprised two in-person classes per week, each lasting 1 hour and 15 minutes. In week 1, students' self-reported pre-self-efficacy (SE1) was collected. Week 1 was chosen to obtain these data before any instructional effect on this topic could influence the participants (Atman Uslu, 2023). The module-specific post-survey (SE2) and technology acceptance (TA) surveys were administered upon module completion.

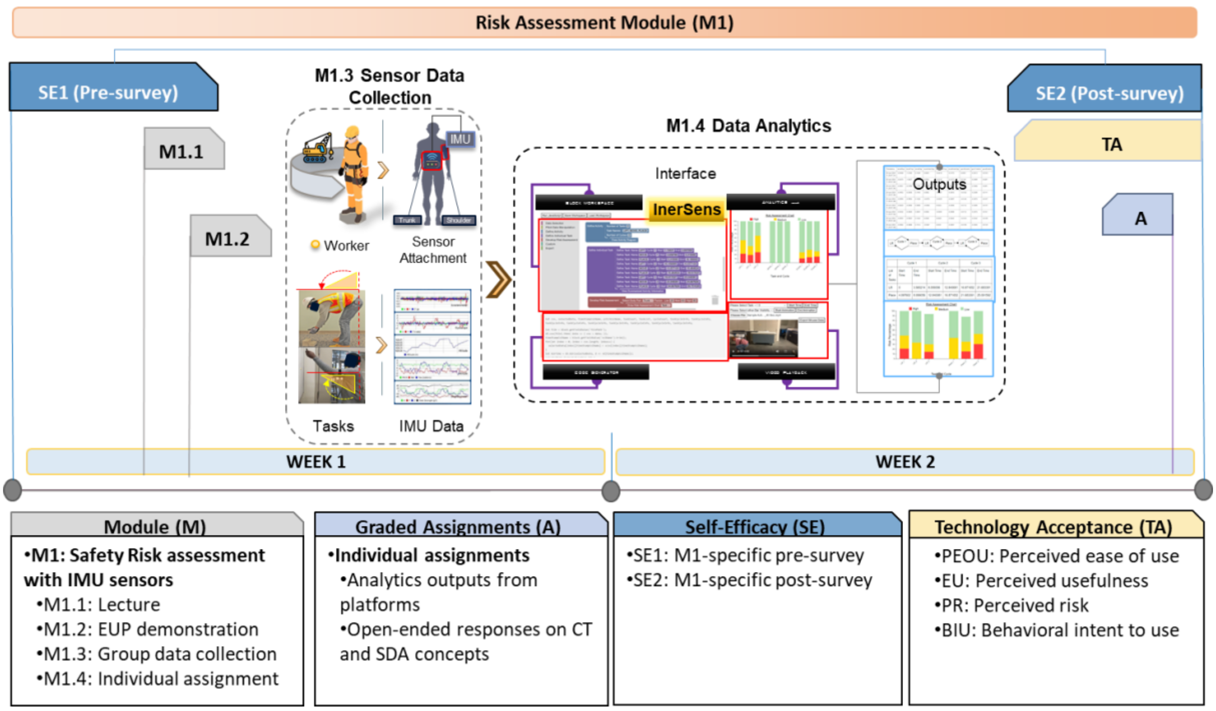

Figure 2: Timeline of CT intervention (icon source: freepik.com).

3.2 Description of the learning environment

3.2.1 Interface design and architecture

InerSens, the BBPI that is utilized as the analytical platform in the current study was built around the Model-View-Controller (MVC) pattern, comprising three key layers: model, view, and controller (see *Figure 3*). The view handles graphical user input or GUI rendering, user inputs, and actions such as sensor data uploads and block interactions. View also presents the analytics outputs (i.e., charts, tables, and diagrams) in the visualizer panel while allowing the import-export functionality. Students can drag the blocks from the menu and drop them into the block workspace to build analytics commands. The code behind the scenes is written in a text-based language (i.e., JavaScript) and displayed in the code generator panel. Cascading Style Sheets (CSS) handle the formatting of this code, while Hypertext Markup Language (HTML) structures the layout. Additionally, HTML enables video playback functionality and enables users to define timestamps on their uploaded videos. A central component (controller) acts as a go-between for the user interface (view) and the data storage (model). When students interact with the interface, the controller uses tools like Blockly and D3 (Data-Driven Documents) to take user inputs and translate them into actual operations. The model manages data created by students, storing it in a MariaDB Server database. It ensures updates are reflected throughout the system via a software layer utilizing the Sequelize API (Application Programming Interface). APIs allow various software systems to communicate and share data with one another.

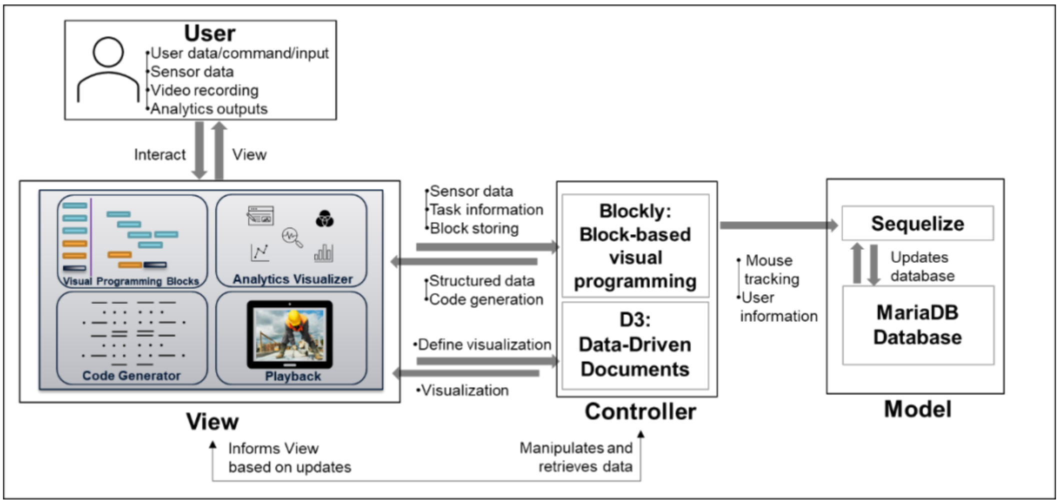

Figure 3: The system architecture of InerSens [adapted from Khalid et al. (2024b)].

3.2.2 Interface affordances to computational thinking

Based on the End User Development (EUD) design framework presented by Barricelli et al. (2023), InerSens incorporates four key elements that encapsulate CT and EUD dimensions characterizing the web-based block programming environment for performing data analytics (see *Figure 4*). For instance, the block selection feature connects to CT's abstraction element, allowing users to pick relevant blocks for data analytics tasks and leveraging EUD's concreteness dimension (Calderon et al., 2022). Construction of block leverages CT's decomposition and EUD's modularity dimension to break down complex problems (D'Alba and Huett, 2017). Additionally, the logical linking of blocks in the system fosters algorithmic thinking and structured solution development (Shute et al., 2017). The analytics visualizer panel enables direct assessment of outcomes, aligning with the testability dimension (CT evaluation) of EUD (Barricelli et al., 2023). Lastly, the system's ability to export results supports reusability (CT generalizability), allowing users to share findings in diverse formats (Shute et al., 2017).

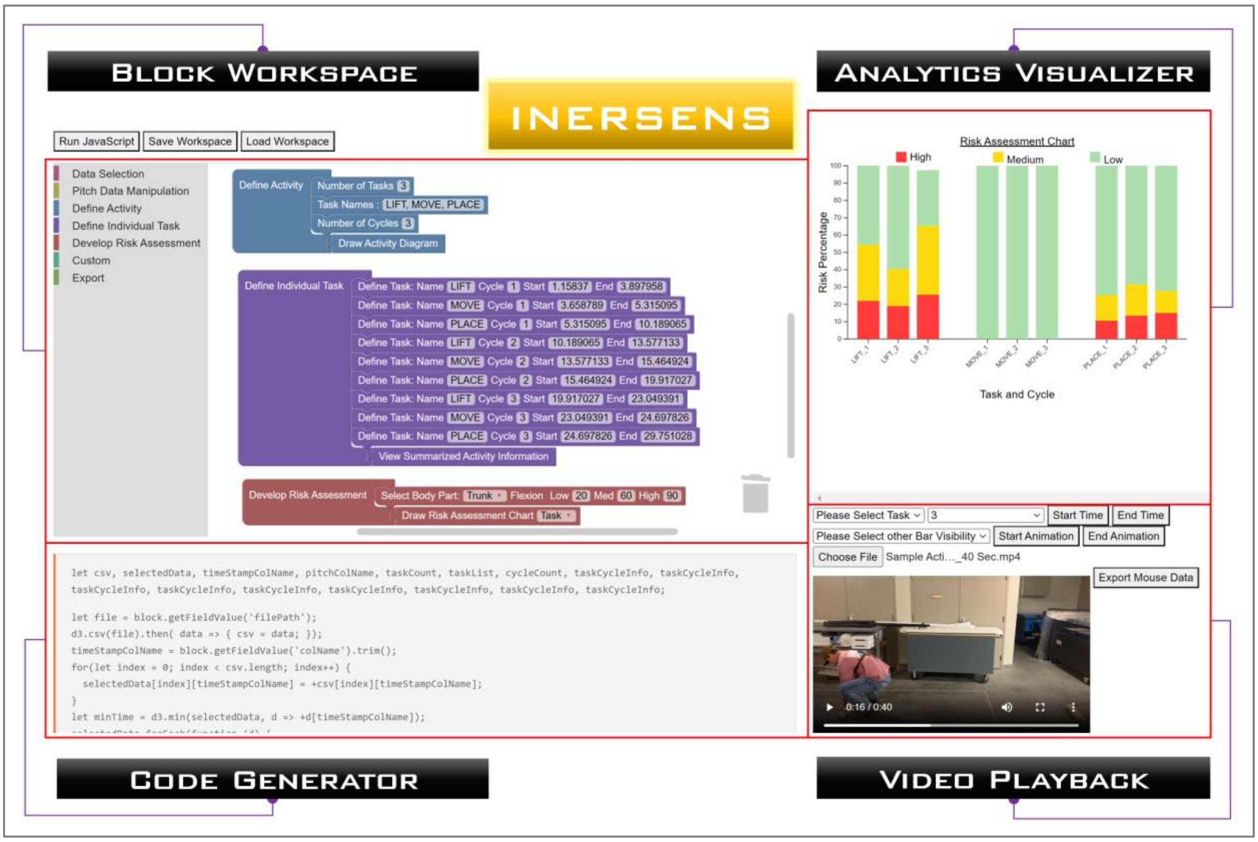

Figure 4: InerSens interface and the key interactive elements [source: (Khalid et al., 2024b)].

3.2.3 Sensor-based ergonomic safety risk quantification with InerSens

The pedagogical goal of InerSens is to enable students to learn how to translate the requirements of industry stakeholders into a series of computational tasks and extract valuable insights from extensive raw sensor data. The analytics platform embeds an ergonomic risk assessment framework to analyze posture angles and identify motion-related risks in construction (Gonsalves et al., 2021). This methodology targets repetitive subtasks and dynamic postures, following postural risk classification (i.e., low, medium, and high) (Chander and Cavatorta, 2017). *Figure 5* illustrates the analytics framework for the sensor-based safety risk quantification process with InerSens.

The capabilities of the existing sensor system (i.e., IMU) and the analytical tasks (within InerSens) primarily correspond to CTDP (Weintrop et al., 2016). Chakarov et al. (2019) reported that CTDP allows for a practical classroom intervention. It enables students to utilize sensor systems, collect and manipulate data to display relevant information, analyze data to address research questions and create visualizations to communicate analysis results. *Table 1* presents students' active involvement in CTDP and corresponding to CT dimensions (CTD) to build procedural knowledge aimed at achieving specific ergonomic-related safety objectives. The tasks were structured to lead students to apply CT approaches through incremental objectives (i.e., structured data, tables, or visuals) that collectively contribute to the overall final outcomes (i.e., risk chart/distribution) (Curzon et al., 2014). These tasks can be classified as closed-ended, signifying that they have clear and specific outcomes and are particularly well-suited for CT assessment practices in academic settings (Zhong et al., 2016).

In the sensor data collection phase, students identified construction-related ergonomic safety issues that could be captured using the IMU sensor (via the SensorPlay app on smartphones). IMUs could be strapped to various target body parts (i.e., trunk, elbow, or shoulder). For instance, a manual lifting activity could involve three subtasks (lifting, moving, placing) across multiple cycles. Collected data included time-stamped acceleration, angular rotation, pitch, and external video from a secondary device. After collecting data, students could load them into the InerSens platform for immediate visualization. The time-stamped sensor data could be aligned with video footage to verify and extract specific subtask timing and cycle count details with milliseconds precision. For subsequent analysis, the pitch data and its corresponding timestamps could be abstracted away from the entire data set. Manipulation tasks ensured data accuracy and preparedness for further analysis. This included adjusting the orientation of the neutral plane, converting units, and handling negative values. The students could then progress to organizing data based on construction tasks and cycles. This involved defining each task with precise start and end times and simultaneously visualizing these through activity diagrams and new data frames. Here, students broke down the entire activity into individual tasks, leveraging their knowledge of construction ergonomics and associated safety risks. Students could define thresholds for ergonomic risks, classifying angles into low, medium, and high-risk categories. This demonstrated their understanding of safety risk thresholds. Students could then obtain the cumulative risk levels for each task through a risk assessment chart or table which relied on frequency distribution as a percentage of task duration. By analyzing the chart or table, students could compare tasks and cycles, gaining insights into how task design choices influence the associated ergonomic risks.

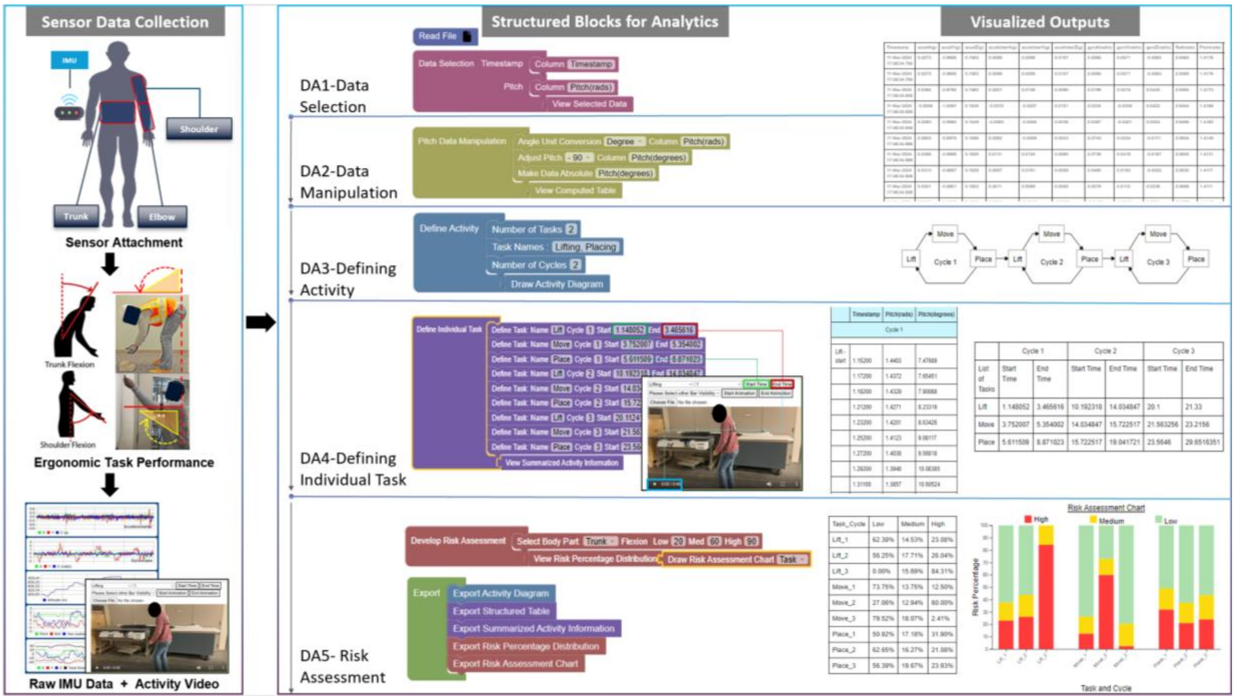

Figure 5: Sensor-based safety risk quantification workflow using InerSens.

3.3 Data collection

The study aimed to investigate construction students' perceived skills in applying CT practices to sensor data analytics, their platform-based analytical performance, and their acceptance of the technology platform. This involved conducting self-efficacy surveys to gauge students' confidence in various CT dimensions, assignment-based performance evaluations to measure their practical application of CT skills, and technology acceptance surveys to assess their views on the usability and utility of the technology platform. To mitigate any power relationship, the study incorporated several measures in data collection, reviewed by participants before the survey. These included voluntary participation with assurances that responses would not impact grades, and data analysis scheduled only after grades were released. Additionally, data was de-identified with random participant IDs (e.g., 1 to 26), and identifiable information was securely stored and retained for up to three years before destruction.

Table 1: Details of classroom activities and their relation to CTD and CTDP (Chakarov et al., 2019, Weintrop et al., 2016).

Task Workflow	Description	CTD and CTDP
DC1-Sensor data and activity video creation, collection, and load-up	• Identify an ergonomic safety problem that can be addressed with the IMU sensor • Identify resources that can provide information to accomplish a task • Target body part prone to risk (i.e., trunk, shoulder, or elbow) to the activity • Attach sensor on target and set video recording • Mimic a construction activity • Record sensor and activity video data • Import, open, and review raw IMU data from the local drive on the analytics visualizer • Import, play, and review video recording of the construction activity into video playback display	• CTD-Reasoning • CTDP-Data creation • CTDP-Data collection
DA1-Data selection	• Identify necessary data and blocks for the ergonomic quantification solution • Delete and only retain required data columns (i.e., retain timestamp and pitch data columns)	• CTD-Abstraction • CTDP-Data manipulation • CTDP-Data visualization
DA2-Data manipulation	• Convert pitch unit (from Radian to Degrees) • Identify the neutral plane and adjust the orientation (if needed) • Convert all pitch data to absolute (if negative values are identified) • Create and view the pitch data in a new data frame before entering them into the subsequent computation	• CTD-Decomposition • CTDP-Data manipulation • CTDP-Data visualization
DA3-Defining activity	• Define data based on construction activity information (i.e., number of different tasks and cycles) • Create and view an activity diagram capturing all the tasks and cycles in the appropriate order	• CTD-Decomposition • CTDP-Data analysis • CTDP-Data visualization
DA4-Defining individual tasks	• Systematically define specific sub-tasks based on ground truth to categorize data • Utilize video-playback tool to view and register the precise start and end times of all tasks • Create and view a table of summarized task-related information (i.e., task name, cycle, start and end times)	• CTD-Decomposition • CTDP-Data analysis • CTDP-Data visualization
DA5-Development of risk assessment	• Select the body part affected • Define bin values as thresholds for different levels of ergonomic risks (i.e., <20°: Low risk, 20-60°: Medium risk; >60°: High risk for trunk) • Develop stacked bar columns showing different risk levels associated with the corresponding tasks • Sort the data by different criteria to answer questions about the dataset (i.e., show data by tasks or by cycles) • Select a specific task to view the dynamic visualization of the chart simultaneously with the video; evaluate the correctness of the analytics inputs and contributing data sources (i.e., check if a task that should pose a high risk is actually reflecting high-risk after the analytics)	• CTD-Abstraction • CTD-Decomposition • CTD- Generalization • CTDP-Data analysis • CTDP-Data visualization

3.3.1 Technology acceptance surveys

A separate survey was developed and incorporated to evaluate participants' perceptions regarding the acceptance of technology focused on perceived ease of use (PEOU), perceived usefulness (PU), perceived risk (PR), and behavioral intent to use (BIU). This aimed to measure students' acceptance of the BBPI in facilitating their task performance (Seraj et al., 2019, Tzafilkou and Protogeros, 2017). In that regard, PU is the user's expectation that using the platform will enhance job performance, while PEOU is the extent to which the system is anticipated to be free of effort. According to the technology acceptance model or TAM, BIU is influenced by both PU and PEOU. However, an emerging factor in new technology adoption is the impact of PR on individuals' decision confidence (Im et al., 2008). PR can influence PU and PEOU, particularly in scenarios where outcomes are uncertain to end-users due to unknown outcomes of the target system. In the current study, PU, PEOU, and BIU were adapted from standard TAM and UTAUT questions (Davis, 1989, Venkatesh and Davis, 1996), while PR measurements were adapted from Im et al. (2008).

3.3.2 Assignment-based performance scores

Student performance was assessed based on an individual assignment, a widely used approach for summatively assessing CT in classrooms (Zhong et al., 2016, Brennan and Resnick, 2012, Weintrop et al., 2016). Students were asked to develop the deliverables including an exported structured table, activity diagram, summarized activity information, risk percentage distribution, and a risk assessment chart that allowed instructors to allocate scores by evaluating these artifacts. The indicators of completion and points allocation are detailed in *Table 2*. Moreover, students had to submit a screenshot of their block-based workspace for correctness evaluation according to the deliverables. All deliverables were submitted in the identical format as exported from the InerSens platform, adhering to specific submission guidelines for file naming and packaging.

Reflection reports were collected to assess the methods students employ during the task performance (Zhong et al., 2016), integral to assessing students' CT practices (Curzon et al., 2014). The study adopted the 'Assessing Development of Computational Practices' instrument to measure students' proficiency in CT practices and categorize their open-ended self-reported responses into low, medium, or high levels (Martin et al., 2014, Harvard Graduate School of Education, n.d.). The questions prompted students to explain their use of the InerSens platform for understanding sensor data through abstracting problems, decomposing tasks, building block algorithms, evaluating analyses, and contemplating solution reuse. *Table 3* shows the point allocation for each CT dimension (one question per dimension).

Table 2: Performance assessment criteria for analytical artifacts.

Indicators	Points
Data selection	20
Data manipulation	20
Define activity	20
Define individual task	20
Risk chart/distribution	20
Possible points allocation	100

a. 50% = Correctness of blocks and user inputs
b. 50% = Accuracy with respect to ground-truth

Table 3: Performance assessment criteria for reflection reports.

CT Dimension	Points
Reasoning	15
Abstraction	15
Decomposition	15
Algorithmic thinking	15
Evaluation	15
Generalization	15
Possible points	90

a. 5 = Low proficiency
b. 10 = Medium proficiency
c. 15 = High proficiency

3.4 Data analysis

Data pertaining to students' self-efficacy, performance scores, and technology acceptance were collected (refer to *Figure 1)*. The internal consistency of the survey instruments was assessed using Cronbach's alpha (Tavakol and Dennick, 2011). The self-efficacy survey demonstrated excellent internal consistency with a Cronbach's alpha of 0.9409. The technology acceptance survey demonstrated good internal consistency, with an average score of 0.8192 across the four constructs. The scores for each construct were PU at 0.8672, PEOU at 0.8765, PR at 0.7791, and BIU at 0.7539. Descriptive statistics were employed to extract means, counts, percentages, and standard deviations from the sample, providing insights into data distribution and central tendencies. The survey responses, encompassing self-efficacy and technology perception, were categorical variables, while performance scores were treated as continuous. Normality testing using the Shapiro-Wilk test in JMP Pro 17 indicated a non-normal distribution ($p<0.05$) of the data. Due to this non-normality, as indicated by the Shapiro-Wilk test outcomes, Wilcoxon Signed-Ranks Tests (WSRT) were employed to assess statistically significant differences and effect sizes (r) between paired observations of pre- and post-surveys for self-efficacy. Additionally, non-parametric Spearman correlation analysis was conducted among key CT constructs using JMP Pro 17's multivariate feature, which explores correlations among multiple numeric variables (pre- and post-survey). Rubrics utilized for scoring students' analytical artifacts and self-reported assignments are detailed in *Tables 2 and 3*. Descriptive statistics were employed to report performance scores derived from these rubrics. Regarding the technology acceptance survey, descriptive statistics were utilized to present findings, and non-parametric Spearman correlation analysis was conducted to explore correlations among key constructs such as PU, PEOU, PR, and BIU. Further non-parametric correlation tests were conducted to examine the effects of performance scores on perceived self-efficacy and technology acceptance.

4. RESULTS

This results section presents detailed findings from the pilot study in terms of the CT-based intervention's impact on construction students' self-efficacy in sensor data analytics, performance, and perceived acceptance of the InerSens. Additionally, it explores the relationships between performance, self-efficacy, and usability perceptions.

4.1 Self-efficacy of CT-based data analytics

A comparison between pre- and post-surveys was conducted descriptively to assess changes in perceived self-efficacy following the risk assessment module (see *Figure 6*). The results showed improvements across all constructs of the self-efficacy scale. Specifically, the highest improvement in terms of mean rating difference was observed in two data reasoning items (SER-Q4 and Q2), followed by abstraction (SEA-Q8).

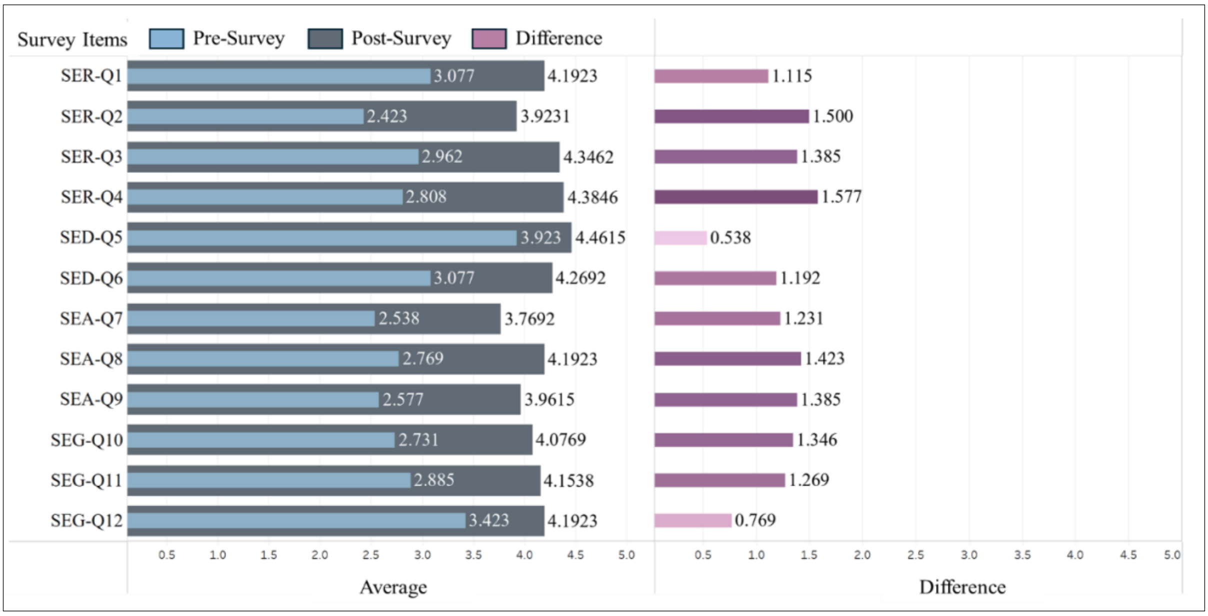

Figure 6: Comparison of mean rating between pre- and post-self-efficacy on CT sub-dimensions.

Table 4: *Statistical comparison of self-efficacy survey items (bolded*: statistical significance at p-value<0.05).*

Questions	Intervention	SD	Z-Score	Effect Size (r)	P-Value
SER-Q1	Pre	1.071	3.8008	0.597	**0.0001***
	Post	0.482			
SER-Q2	Pre	1.080	4.652	0.674	**<.0001***
	Post	0.615			
SER-Q3	Pre	1.160	4.238	0.639	**<.0001***
	Post	0.551			
SER-Q4	Pre	1.241	4.332	0.647	**<.0001***
	Post	0.560			
SED-Q5	Pre	0.874	2.323	0.414	**0.0201***
	Post	0.499			
SED-Q6	Pre	1.071	4.051	0.622	**<.0001***
	Post	0.523			
SEA-Q7	Pre	1.046	3.859	0.603	**0.0001***
	Post	0.890			
SEA-Q8	Pre	1.120	4.059	0.622	**<.0001***
	Post	0.962			
SEA-Q9	Pre	0.968	4.421	0.655	**<.0001***
	Post	0.854			
SEG-Q10	Pre	1.058	4.327	0.647	**<.0001***
	Post	0.675			
SEG-Q11	Pre	1.187	3.926	0.612	**<.0001***
	Post	0.533			
SEG-Q12	Pre	1.044	3.022	0.509	**0.0025***
	Post	0.482			

WSRT revealed statistically significant improvements across all self-efficacy scale items from pre- to post-intervention (see *Table 4*). Statistically significant improvements were observed across all self-efficacy reasoning (SER) items ($p \leq .0001$*), all decomposition (SED) items such as SED-Q5 ($p = 0.0201$*) and SED-Q6 ($p < .0001$*), all abstraction (SEA) items ($p \leq .0001$*), and all generalization (SEG) items ($p \leq .0025$*). These findings indicate a consistent and positive effect of the intervention on enhancing students' self-efficacy in CT across these dimensions. Although the WSRT does not use Z-scores directly, its statistic can be converted into an effect size (r) measure. This effect size (r) is calculated by dividing the Z-score by the square root of the sample size. The statistically significant difference was corroborated by the large effect sizes (r) observed. Effect sizes of 0.01, 0.06, and 0.14 are categorized as small, medium, and large, respectively (Tomczak and Tomczak, 2014).

Consolidating these CT efficacy items into respective dimensions (see *Figure 7*), the highest improvement (51.19%) was observed in abstraction, closely followed by data reasoning, which showed a 49.48 % improvement from the pre- to the post-intervention. Generalization had a 37.42% improvement, and the lowest improvement was observed in decomposition, with a 24.71% increase.

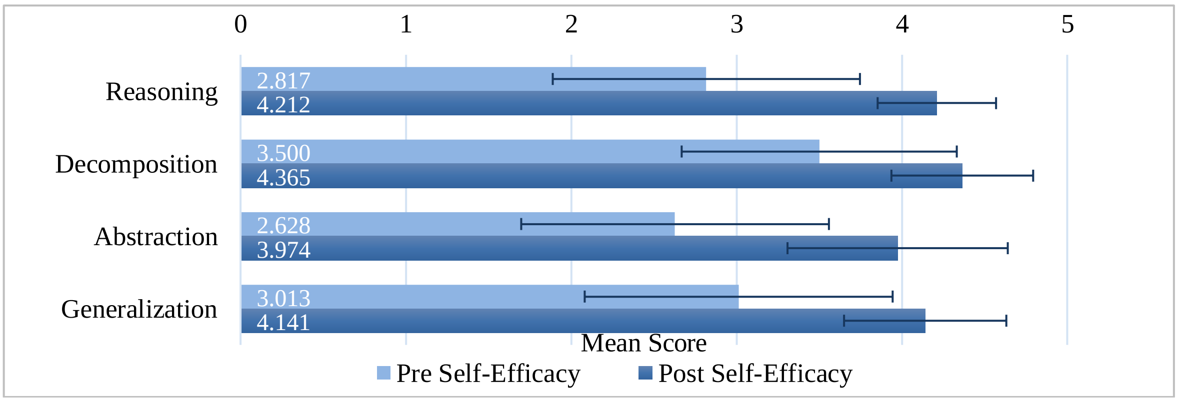

Figure 7: Comparison of mean rating between pre- and post-self-efficacy on CT dimensions.

To explore the relationships between these CT dimensions, the primary components of the self-efficacy scale underwent Spearman correlation analysis, revealing significant positive correlations (see *Table 5*). Decomposition showed a moderate correlation with the reasoning dimension (ρ = 0.6847, p = 0.0001*), as did abstraction with reasoning (ρ = 0.6617, p = 0.0002*) and decomposition (ρ = 0.6583, p = 0.0003*). Additionally, generalization exhibited moderate positive correlations with reasoning (ρ = 0.6231, p = 0.0007*), abstraction (ρ = 0.6161, p = 0.0008*), and decomposition (ρ = 0.5055, p = 0.0084*).

Table 5: Spearman's correlation between CT self-efficacy dimensions.

Variable	by Variable	Spearman ρ	P-Value
Decomposition	Reasoning	0.6847	**0.0001***
Abstraction	Reasoning	0.6617	**0.0002***
Abstraction	Decomposition	0.6583	**0.0003***
Generalization	Reasoning	0.6231	**0.0007***
Generalization	Abstraction	0.6161	**0.0008***
Generalization	Decomposition	0.5055	**0.0084***

(bolded*: statistical significance at p-value<0.05) (Green: Strong correlation, ρ = 0.7 – 0.9; Blue: Moderate correlation, ρ = 0.4 – 0.69; Orange: Weak correlation, ρ = 0.1 – 0.39)

4.2 Summative Assessment of Performance Score

Table 6 outlines participants' performance assessed objectively across two sections: analytics and self-report. In the analytics section, participants demonstrated strong proficiency in the 'Define Activity' task, achieving a perfect score of 20.00 with no variability (SD of 0.00). Students also demonstrated high performance in 'Data Selection' and 'Data Manipulation,' scoring averages of 19.231 and 16.923, respectively. Students showed comparatively lower performance in 'Risk Chart/Distribution,' where some students struggled with the accuracy of representing the risk or percentage distribution. For instance, some displayed high-risk scenarios for ergonomic postures that should have been categorized as low or medium risk. This resulted in an average score of 12.692 for this criterion. Overall, the analytics section yielded an average score of 85.00 out of 100 (SD = 16.467). In the self-report section, participants' scores were more varied. While in 'Generalization' students demonstrated the highest average score of 12.884 (out of 15), 'Algorithmic Design' had the lowest average score of 8.653. The overall average for the self-report section was 63.076 out of 90 (SD = 15.132). Combining scores from both sections, participants achieved an average total score of 77.94 out of 100, factoring from a total possible score of 190 (SD = 0.127).

Table 6: Summary of summative assessments on student performance with descriptive statistics across individual sections and total score.

	Performance Criteria	SD	Mean
Analytics Section	Data selection	3.846	19.231
	Data manipulation	6.661	16.923
	Define activity	0.00	20.00
	Define individual task	5.601	16.153
	Risk chart/distribution	7.624	12.692
	Total (100 points)	*16.467*	*85.00*
Self-report Section	Data reasoning	4.161	10.00
	Abstraction	4.385	10.00
	Decomposition	4.317	10.769
	Algorithmic design	4.287	8.653
	Evaluation	3.308	10.769
	Generalization	3.445	12.884
	Total (90 points)	*15.132*	*63.076*
	Grand Total = 190 (factored to 100)	0.127	77.94

Table 7 presents the performance groups (i.e., low, moderate, and high) categorized and the distribution of the overall class scores.

Table 7: Categorized performance groups and class score distribution.

Performance Groups	Score Distribution	
	Number of Students	Percentage of Students
Low (50 - 70)	5	19.23%
Moderate (70 - 80)	11	42.31%
High (80 - 100)	10	38.46%

4.3 Perceived Technology Acceptance of InerSens

The usability survey results indicate positive perceptions of the BBPI tool across the dimensions of PU, PEOU, PR, and BIU. In *Figure 8*, orange represents scores below 3, indicating negative perceptions, while blue denotes scores above 3, reflecting positive perceptions. On the measure of PU, students generally exhibited positive perceptions with a mean rating ranging from approximately 3.885 to 4.154. Specifically, PU4 and PU5 were recorded with the highest mean rating, indicating a strong agreement among students regarding its utility. Similarly, the ease of use (PEOU) was well-received, with mean scores above 4 (i.e., agree). In terms of perceived risk (PR), the scores were relatively low, ranging from 2.192 to 2.538, suggesting a general consensus among students that the InerSens system posed minimal risks. Among the BIU measures, ratings varied between 3.385 and 3.731, indicating a moderate agreement of intent to continue utilizing InerSens for sensor data analytics.

Overall, a majority of participants perceived the tool as useful (PU), with 58% agreeing and 23% strongly agreeing (see *Figure 9*). In terms of PEOU, positive responses were also dominant, ranging from 59% agreement and 29% strong agreement. Regarding PR, most participants indicated that the BBPI platform presented minimal risks. Specifically, 41% expressed disagreement and 13% strongly disagreed with the notion of any potential risks associated with the BBPI platform, while 36% of students provided neutral responses. Lastly, 55% of the participants agreed to use the tool in the future with 6% strongly agreeing. These findings suggest a generally favorable reception of the InerSens BBPI among participants, highlighting its perceived utility, ease of use, low-risk profile, and potential utilization intent.

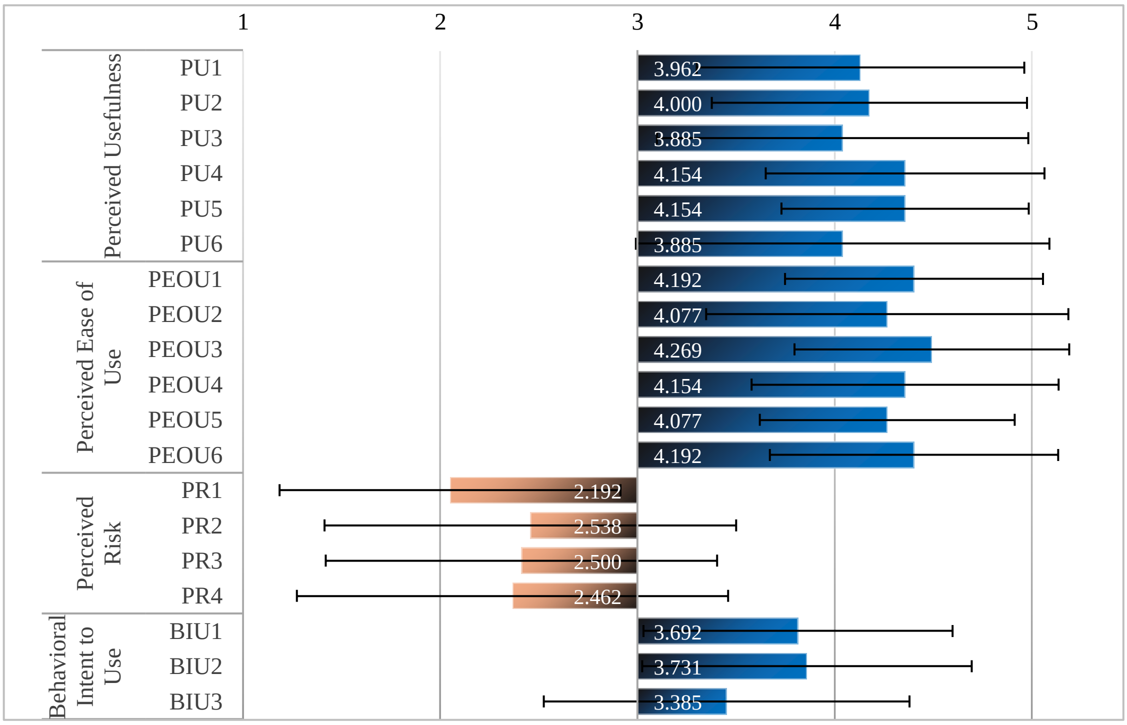

Figure 8: Mean ratings of technology acceptance dimensions (PU, PEOU, PR, BIU).

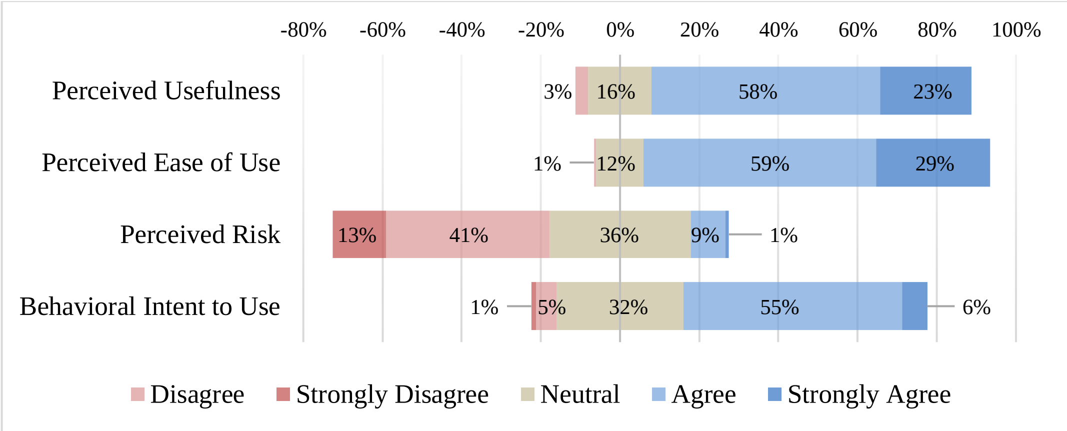

Figure 9: Percentage distribution of students' ratings on technology acceptance constructs.

Aligned with prior research, PU and PEOU are core TAM constructs indicating system acceptance, while PR influences them, affecting BIU (Im et al., 2008). Given this framework, the constructs were examined using Spearman's correlation to explore their interrelationships and their collective influence on users' intention to adopt and continue using the educational system. *Table 8* indicates a moderate positive correlation between PU and PEOU (Spearman ρ = 0.6684, p = 0.0002*). PU (Spearman ρ = 0.3505, p = 0.0792) and PEOU (Spearman ρ = 0.1296, p = 0.5282) showed weak correlations with BIU that did not reach statistical significance, indicating a less direct influence on behavioral intent. Similarly, PR demonstrated a weak negative correlation directly with BIU (Spearman ρ = -0.1505, p = 0.4632). The results indicate a moderate negative correlation between PEOU (Spearman ρ = -0.4206, p = 0.0324*) and PU (Spearman ρ = -0.5525, p = 0.0034*), both reaching statistical significance highlighting that perception of the system-related risk significantly diminishes PU and PEOU. This further suggests and corroborates the study by Im et al. (2008) that PR of new technology has a stronger influence on PU and PEOU rather than directly on BIU.

Table 8: Spearman's correlation between constructs of technology acceptance.

Variable	By Variable	Spearman ρ	p-value
PEOU	PU	0.6684	**0.0002***
BIU	PU	0.3505	0.0792
BIU	PEOU	0.1296	0.5282
BIU	PR	-0.1505	0.4632
PR	PEOU	-0.4206	**0.0324***
PR	PU	-0.5525	**0.0034***

(bolded: statistical significance at p-value<0.05) (Blue: Moderate correlation, ρ = 0.4 – 0.69; Orange: Weak correlation, ρ = 0.1 – 0.39)

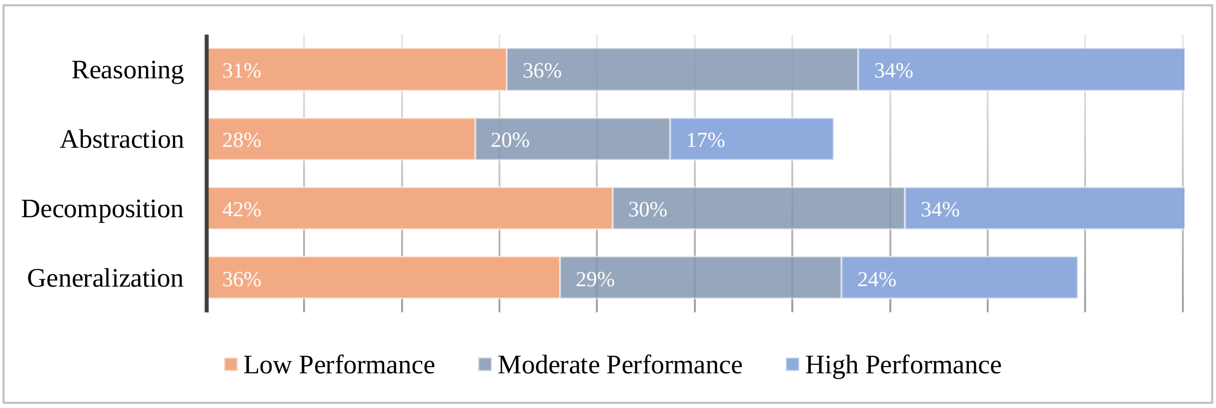

Figure 10: Percentage improvement from pre- to post-self-efficacy survey.

4.4 Relationship between Performance, Perceived Self-Efficacy, and Usability

The self-efficacy improvement percentages of students in CT across different performance levels were descriptively studied. *Figure 10* indicates that students with low performance demonstrated the highest improvement in decomposition dimension at 42%, followed by generalization at 36%, reasoning at 31%, and abstraction at 28%. Those with moderate performance showed a similar trend, with the most improvement in reasoning (36%), followed by decomposition (30%), and generalization (29%), and the least improvement in abstraction (20%). Students with high performance exhibited the highest improvement in reasoning and decomposition, both at 34%, while generalization showed a 24% improvement, and abstraction showed the least improvement at 17%.

Table 9: Spearman's correlation between students' performance and self-efficacy.

Performance	Self-Efficacy Indicators	Spearman ρ	p-value
Performance Scores	SER-Q1	0.1296	0.528
	SEA-Q8	0.1278	0.5339
	SER-Q3	0.1226	0.5507
	SEG-Q10	-0.0338	0.8696
	SED-Q5	-0.0611	0.767
	SEA-Q7	-0.0624	0.762
	SER-Q2	-0.0712	0.7296
	SER-Q4	-0.0929	0.6517
	SEG-Q12	-0.1828	0.3714
	SED-Q6	-0.2754	0.1732
	SEA-Q9	-0.3076	0.1264
	SEG-Q11	-0.3298	0.0999

(bolded: statistical significance at p-value<0.05) (Orange: Weak correlation, ρ = 0.1 – 0.39)

The analysis of the correlation between students' performance scores and self-efficacy indicators revealed weak associations across all measures (see *Table 9*). None of the correlations reached statistical significance, as indicated by the p-values being greater than 0.05. These findings suggest a limited relationship between students' perceived self-efficacy and their actual performance scores.

Students' perceptions of technological acceptance were descriptively analyzed across three performance categories: low, moderate, and high performers (see *Figure 11*). Students in the moderate performance category reported the highest mean ratings for both PU and PEOU, as well as BIU, and perceived the least risk of using InerSens. Conversely, low performers perceived the risk to be higher compared to other groups with a mean rating of 2.75 while showing the lowest PU, PEOU, and BIU. Furthermore, the ratings of high performers for PU, PEOU, PR, and BIU constructs were situated between those of low and moderate performers.

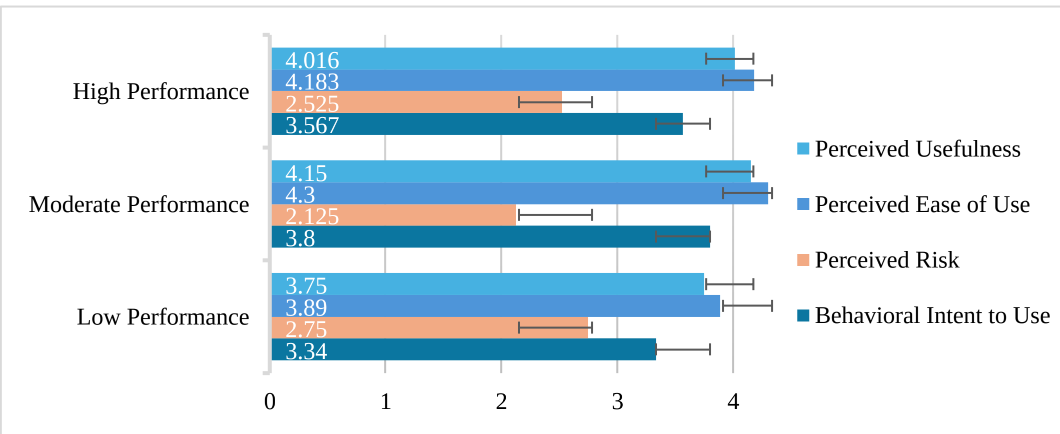

Figure 11: Comparison of mean perceived usability ratings categorized by performance groups.

Based on these findings, correlations between performance scores and usability constructs were examined. *Table 10* indicates a weak correlation between students' performance levels and their perceptions of platform acceptance. The highest positive correlation was observed between performance scores and PEOU6, and the highest negative correlation between performance and PR1.

Table 10: Spearman's correlation between students' performance and usability indicators.

Variable	By Variable	Spearman ρ	P-Value
Performance Scores	PEOU6	0.3417	0.0876
	PU1	0.2878	0.154
	BIU2	0.2741	0.1754
	PEOU3	0.2173	0.2863
	BIU1	0.1802	0.3785
	PR3	0.1373	0.5035
	PU2	0.1282	0.5326
	PEOU5	0.1207	0.557
	PU4	0.1184	0.5644
	PU5	0.0746	0.7171
	PR4	0.064	0.756
	PEOU1	0.0605	0.7691
	PEOU2	0.0595	0.7729
	PR2	0.0174	0.9327
	PU3	-0.0026	0.99
	PEOU4	-0.0743	0.7182
	BIU3	-0.1796	0.3799
	PU6	-0.1825	0.3723
	PR1	-0.2109	0.3011

(bolded: statistical significance at p-value<0.05) (Orange: Weak correlation, ρ = 0.1 – 0.39)

5. DISCUSSION

The findings demonstrate that undergraduate construction students' engagement with BBPI for learning CT concepts and performing sensor data analytics resulted in increased self-efficacy of perceived abilities, satisfactory performance scores, and favorable technology acceptance. These findings are discussed within the unique scope of construction education and in comparison to existing literature, highlighting implications, and suggesting potential areas for future research.

5.1 Perceived self-efficacy

All self-efficacy items in the questionnaire exhibited significant differences between pre- and post-responses, indicating that the intervention improved construction students' perceived confidence in performing sensor data analytics to address ergonomic safety risks with BBPI. Significant improvements were observed in the data reasoning dimension of CT, focusing on students' perceived ability to understand IMU sensor data and its relevance to quantifying awkward and repetitive postures. Specifically, two questions from the survey showed a high increment in mean scores and large effect sizes. The question SER-Q4: *'I have the skills and knowledge to understand how to implement/deploy/equip/attach the sensor with respect to the orientation of the specific/target body part (e.g., trunk) in order to correctly capture the IMU's pitch angle'* demonstrated the highest mean-variance (2.808 to 4.3846 = 1.577) and a large effect size (r = 0.647). While, SER-Q2: '*I have the skills and knowledge to understand the data produced by the IMU's accelerometer, gyroscope, and magnetometer and how these data translated into pitch, roll, and yaw are utilized for the quantification of ergonomic risk*.' exhibited the second highest mean increase from 2.423 to 3.931 (a difference of 1.50) and a large effect size of 0.674. Both highlight the shift in construction students' perceptions from disagreement to agreement. In the decomposition section, statements assessed student efficacy in defining subtasks (SED-Q5) and structuring IMU data (SED-Q6). Higher improvement was observed for SED-Q6, leading to a 24.71% increase in the overall decomposition constructs' mean rating at the post-efficacy level. The modest improvement in pre-survey self-efficacy (mean = 3.5) might be partially explained by students initially overestimating their confidence. Research suggests that some individuals tend to have inflated self-perceptions compared to their actual skill levels due to unawareness (Kruger and Dunning, 1999). Additionally, interventions may have a smaller effect when initial self-efficacy is high, leaving less room for improvement (Bandura et al., 1999). Hence, this score, the highest among all pre-intervention surveys, already positioned participants slightly above neutral or leaning towards agreement, leaving less room for significant changes. The abstraction dimension of CT can be traced in multiple activities including the abstraction of raw IMU data (i.e., by removing unnecessary detail) through data practices (i.e., data manipulation and data visualization) allowing students to focus on data only integral for analytics. In this dimension, students' perception of self-efficacy showed statistically significant improvement across all items, each accompanied by a large effect size ($r > 0.6$). This led to a consolidated enhancement of 51.19% in the abstraction dimension, marking the most substantial improvement among the four CT dimensions surveyed. The generalization dimension aimed to gauge students' perceived self-efficacy in developing workflows for addressing ergonomic risks with IMU data, applying concepts to different risks, and understanding implications for construction activities, including prevention strategies. Within this dimension, each item exhibited statistically significant improvement, resulting in an overall 37.42% improvement.

All the CT efficacy dimensions were found to be moderately correlated with each other (p-value < 0.05) suggesting that perceived improvement in one CT dimension is likely to correspond with enhancements in others. The statistically significant p-values further validate these relationships, confirming their unlikely occurrence by coincidence. These findings which indicate that engagement with BBPI increased the self-efficacy of construction students in learning CT-based sensor data analytics concepts align with results presented by Lédeczi et al. (2019). In their study involving 24 students, they reported that when students engaged in BBPI activities to learn sensor-based cyber-security concepts integrated into a short 1-week course, students' self-efficacy in CT increased.

5.2 Analytical performance

The summative assessment required students to showcase proficiency in two modes: constructing analytical outputs and providing reflective self-reports on describing decision-making processes with the InerSens platform. In the analytics part, all students achieving a perfect score (i.e., 20) in the first criteria (i.e., defining activity) underscores their comprehension of the construction activity, including decomposing it with accurate task sequencing and involved cycles. This was determined by students' submission of the activity diagram as analytics output (see DA3 in ***Figure 5***). The successful completion of this activity was possibly influenced by students' practical involvement in performing construction tasks, identifying safety issues, and collecting sensor data. Similarly, students exhibited proficiency in tasks such as data selection (mean score = 19.231), followed by data manipulation (mean score =16.923), defining individual tasks (mean score =16.153), and risk chart/distribution (mean score = 12.692). These variations in performance scores offer fresh insights into challenges for construction students in accurately quantifying ergonomic risks using the platform, signaling areas for analytical precision improvement. Although InerSens links data representations (e.g., structured data tables, risk distribution, task timing, dynamic risk visual, and video review) to support simultaneous data modeling and visualization practices (Weintrop et al., 2016) as well as accuracy verification, errors were still more pronounced in developing accurate risk charts compared to other criteria. The analytics task's significance lies in its focus on accuracy and correctness. If the ergonomic construction risk classification is incorrect, it could lead to erroneous assessments of potential hazards, which may result in inappropriate safety measures being implemented or critical risks being undermined (Prakash and Lokeeshvar, 2023). This could ultimately expose the safety of construction workers and impact project timelines and costs due to accidents or injuries. In this regard, the findings indicate an opportunity to improve learning outcomes by motivating analytical accuracy and communicating its impact on translating raw sensor data into meaningful insights implementable to improve project performance. Possible methods could be providing additional interactive features in the BBPI for exploring data visualization and integrated feedback systems to notify students of inaccuracies, highlighting risks associated with incorrect quantification.

In the self-report part, the high mean score in generalization indicates students' strong understanding of extrapolating attempted sensor-based analytical solutions (i.e., ergonomics safety) to broader concepts (e.g., equipment safety), while other dimensions also scored highly, reflecting consistent understanding among students. However, the algorithmic design had the lowest mean score (8.653) in student performance indicating a relatively weaker articulation of this concept compared to others. When combining scores from both parts, a significant proportion of students fall within the moderate (42.31%) and high range (38.46%), with fewer students achieving low scores (19.23%).

Therefore, the majority of the students' ability to generate analytical outputs via BBPI, representing real-world construction safety applications, and articulate adopted methodologies in self-reports, highlights the intervention's effectiveness in instilling concepts of CT-based sensor data analytics. This aligns with Wilkerson-Jerde (2014), who adopted Categorizer, a JavaScript-based interactive gallery for students to engage in CT. The findings showed that CT-based educational tools can effectively develop students' CT through the creation of computational artifacts. These outcomes then can be measured to gauge learners' gain. This also aligns with Jiang and Kahn (2020), who found that students gain new knowledge through computational activities involving unstructured data that simulate real-world problems. This suggests that the BBPI platform, by encouraging students to work with sensor data (unstructured), might offer similar benefits in terms of knowledge acquisition during CT activities. Vartiainen et al. (2020) further support this notion, indicating that working with unstructured data affords students the opportunity to employ various cognitive processes of CT to make data-driven decisions.

5.3 Technological acceptance of InerSens

Students' perceptions across four key dimensions of technology acceptance were assessed for InerSens. The findings indicated positive views on its usefulness (PU) and ease of use (PEOU). Additionally, students perceived low risks (PR) associated with using the platform and expressed a favorable intention (BIU) to continue using it. These factors, according to Schez-Sobrino et al. (2020), Guedes et al. (2019), Jung et al. (2021), are key influences on students' overall acceptance and adoption of educational technologies. The current study also reveals statistically significant correlations, suggesting that PR moderates the effects of PU and PEOU on the intention to use (BIU) the system. This finding aligns with Im et al. (2008), whose research also identified the influence of system-related risk on intended usage. They found that users' perception of risk can impact their perception of a system's usefulness and ease of use, ultimately affecting their willingness to continue using it. PR, as described by Jacoby and Kaplan (1972), Yap and Hii (2009) entails the subjective belief in encountering technology-related risks (i.e., financial, performance, physical, psychological, and social risks) during the pursuit of desired outcomes. This is particularly significant in education, given that students invest time and money in college education to learn concepts expecting tangible value gained through interacting with such pedagogical platforms. Hence, this assessment can guide practitioners to prioritize each construct in the adoption of BBPI aligning with recommendations by Im et al. (2008). It suggests emphasizing ease of use when introducing a technology perceived as risky and shifting focus to communicate its usefulness when users perceive significantly low risk.

5.4 Performance and perception

In terms of links between the self-efficacy improvement in CT across different performance levels, students with low performance demonstrated the highest improvement in the decomposition dimension, followed by generalization, reasoning, and abstraction. Conversely, students with high performance exhibited the highest improvement in reasoning and decomposition, followed by generalization and abstraction. These findings suggest that self-efficacy improvement may vary across different dimensions of CT and performance levels, with certain dimensions showing greater improvement for students with varying performance levels. The correlation analysis between students' performance scores and self-efficacy indicators revealed weak associations across all measures. None of the correlations reached statistical significance (p-values>0.05) for any self-efficacy indicators. This suggests a limited relationship exists between students' perceived self-efficacy in CT and their actual performance scores. This aligns with the work of Wei et al. (2021) who found a weak correlation between CT performance with a BBPI and students' self-efficacy. However, these results differ from the study by Román-González et al. (2018), who found significant positive correlations between CT performance and programming self-efficacy. The present study concentrated on applying CT skills to analyze sensor data for risk assessment, contrasting with Román-González et al. (2018), whose focus was on traditional programming learning. This suggests that the types of CT skills exercised in academic settings might influence the self-efficacy-performance relationship. Moreover, Schunk et al. (2014) highlighted that self-efficacy may only be a single factor influencing academic performance. Task complexity, motivational factors, opportunities to practice and even instructional strategies can also play a significant role in performance, as emphasized by Bearneza (2020).

Another key observation is the increasing trend in ratings for PU and PEOU among high and moderate-performance groups. This implies that as students' academic performance improves, they may find the BBPI easier to navigate or integrate into their learning processes. Moreover, the weak yet highest positive correlation between performance levels and PEOU6 implies that students who perform better find the tool easier to use and more aligned with their learning requirements. Numerous studies indicate that perceived usefulness is positively related to learners' performance in technology-based learning (Hassanein et al., 2010, Vogel et al., 2007). Moderate performers show a stronger inclination to use tools like InerSens in the future compared to low and high performers, indicating varying levels of behavioral intent across performance groups. The theory of self-determination suggests that individuals are more motivated to use educational tools when they feel they can make progress (Deci and Ryan, 2012). It is possible that moderate performers may see BBPI as a useful tool for future usage, while high performers, with strong CT skills and learning strategies, might find it less effective for their academic success. Furthermore, the higher perceived risk among low-performing students may reflect their apprehensions or uncertainties about using BBPI. Their negative experiences (i.e., low-performance scores) likely lead to concerns about its effectiveness in supporting their learning (Im et al., 2008). For instance, PR1 exhibits a weak yet the highest negative correlation with performance scores, suggesting that individuals who score lower tend to perceive more performance-related risks associated with InerSens.

6. CONCLUSIONS, LIMITATIONS AND FUTURE WORKS

The current study provides evidence of the effectiveness of a CT-based sensor data analytics intervention in a construction sensing technology-related course, over a 2-week duration. Findings indicate that, in addition to fostering sensor data analytics learning gains among construction students, the pedagogical approach of mapping such data practices within BBPI led to improvements in perceived CT-related data analytics skills with favorable technological acceptance. This was accomplished by immersing construction students in a holistic process of sensor data analytics including the creation and collection of data with physical sensors, simultaneous manipulation, analysis, and visualization with a BBPI, and guiding them through the CTDP to enhance their fundamental computational thinking abilities. Upon transitioning into the workforce, with an understanding of sensor capabilities and the data's relevance to construction challenges, skilled students are primed to identify opportunities where sensor-based analytical strategies can effectively extract practical insights. This may extend to contributing to the design and development of analytical tools or customizing existing platforms based on specific requirements that can address challenges recognized by construction companies. The findings also highlight that students' intent to use an educational tool can be influenced by their academic performance with it. Therefore, prioritizing the integration of tools into environments where students have confidence in their utility and perceive reduced risks is significantly important when designing and implementing similar educational technologies. This study sets precedence for educators and researchers in exploring the connection between visual programming, CTDP, and CT empirically which all signify the students' capacity to understand, analyze, and learn from extensive data sets. This study contributes to the body of knowledge on effective pedagogical practices, informing the design of sensor-related modules supported by BBPI to effectively integrate CT into construction technology classrooms. It further extends the current literature on the effect of BBPI on developing CT skills by reporting on a different population (i.e., construction students) and a different context (i.e., sensor-based ergonomic risk assessment).

In terms of limitations, this study had a small sample size (N=26), which may limit the generalization of findings to a broader population. Future research will address this by including a larger and more diverse sample, while also examining demographic factors (e.g., gender, age, programming, and data analytics experience) and types of educational settings to explore potential influences of individual differences. Additionally, future research will evaluate the effectiveness of the BBPI platform in other applications, such as machine learning for ergonomic activity recognition, offering students exposure to leveraging artificial intelligence for construction sensor data analytics. Additional objective measures such as interaction analysis using students' mouse-tracking data will also be employed.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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