

UNMANNED AERIAL VEHICLES AS EDUCATIONAL TECHNOLOGY SYSTEMS IN CONSTRUCTION ENGINEERING EDUCATION

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SUMMARY: *Integrating complex spatio-temporal cognitive tasks such as in-situ planning and trade coordination of job site activities is a continuous challenge to learners in Construction Engineering (CE) courses. Spatial information in this context addresses how physical resources are related to one another at a job site, whereas temporal information defines work sequences and hierarchies that transform physical resources. This paper discusses the impacts of using an innovative learning environment for supporting spatio-temporal cognition in CE education using aerial visualizations from Unmanned Aerial Vehicles (UAVs). Learners experience a unique, ‘birds-eye view’ of the spatio-temporal dynamics of a job site. The effects were on improved abilities to apply, analyze, and synthesize any form of design representation to situations and physical contexts. Our findings demonstrate that participants in the intervention group outperformed the control group on measures of learning and motivation, which underscores the potential of UAVs as an educational technology system in CE education.*

KEYWORDS: *spatio-temporal cognition; unmanned aerial vehicles, aerial image learning; design interpretation; authentic problem learning*

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1. INTRODUCTION

A key challenge in Construction Engineering (CE) education is to support learners in developing critical planning and coordination skills to associate CE designs to unique job site situations and contexts for analysis, decision-making, and problem-solving. Developing these skills using typical representations of project information – e.g., two-dimensional (2D) drawings – is a continuous challenge for CE learners. Extracting meaning from 2D drawings to effectively link them to problems in project management tasks is a highly intensive cognitive process, where learners must select, organize, and integrate new information presented in 2D with knowledge stored in the long-term memory (Wu et al., 2010). The affordances of traditional pedagogical materials (i.e., 2D drawings, videos, images, and building information modeling–BIM) are insufficient to scaffold application, analysis appropriately, and synthesis of design representations to situational and physical contexts (Mutis and Desai, 2019), mainly when the learner is new to this complex cognitive activity. The abundance of variables and the ill-structured nature of conditions in “real-life” construction sites (Jonassen, 2011) impact a learner’s ability to effectively comprehend and manage significant amounts of *spatial* information (how physical resources are related to one another in the 3D CE space) and *temporal* information (the logic of the CE process, such as the sequences and hierarchies of utilizing the resources to accomplish a CE task) (Mutis, 2015; Mutis, 2018). Limited ability to select, organize and integrate spatial and temporal information hinders a learner’s understanding of CE designs and management of the varying local conditions that transpire during construction processes (e.g., changes in the schedule, availability of required materials on the job site, etc.). The effect is that use of existing instructional methods and modalities to support the development of this spatio-temporal cognitive expertise is sub-optimal. The use of traditional instructional materials does not scaffold experiencing the critical properties of the physical context, nor does it adequately support spatial visualization ability that is required to translate 2D drawings to decision-making in a 3D environment (Glick et al., 2012).

Building on the idea that the technological environments can mediate and enhance perception and understanding of the physical world (Shelton, 2003), a system was designed to augment learners’ spatio-temporal cognition by using aerial visualizations that deliberately and systematically integrate complex spatial and temporal information. Each visualization is associated with keywords, categorical topics about CE working problems, and critical construction products and processes. The keywords were used to structure the database and as keys for storage and retrieval of aerial visualizations. Each keyword enables the learner to search, sort, and retrieve aerial visualization according to the categorical topic (e.g., façade).

The categorical topics were the main vocabulary used in the problems, thereby streamlining the retrieval from a database of the aerial visualizations for each case. Each aerial visualization had multiple links or associations to categorical topics. The use of technology and cases enabled us to explore CE scaffolding relative to a) spatio-temporal cognition for problem-solving and b) motivation for engaging in CE problem-solving with and without UAV-afforded aerial visualizations. Using the associated keywords in authentic problem-solving scenarios, the learner inputs a keyword of interest and selects an aerial visualization from the database. The output allows the user to choose the most appropriate video to use during the problem-solving process. In addition, the learning environment provides affordances for the user to control the speed presentation, scale, and resolution and to magnify the aerial visualizations.

Our research and development address this critical issue by introducing a new educational technology system for CE courses – Unmanned Aerial Vehicles (UAV) – as an instructional scaffolding tool to optimize cognitive processing and provide authentic and contextualized meaning to spatial and temporal information (Yoon and Wang, 2014; Yoon et al., 2012). The contributions of the study follow:

- Exploration of an innovative intervention to provide learners the opportunity to develop skills that integrate (Shelton and Hedley, 2004) procedural and configurational knowledge (Wickens and Hollands, 2000).
- Advancement of the CE learners’ understanding of the perception of spatial relations of entities (objects) and dynamic processes, by studying the students’ abilities to process complex information related to CE spatial-temporal configurations, including the comprehension of interdependencies, interactions, and constraints among integrated and specialized engineering systems.
- Conceptualization of scaffolding for the development of individuals’ spatial-temporal cognitive abilities through the observation of real-world construction information through aerial visualizations.

The study discussed in the empirical report addresses two critical gaps in knowledge. First is the exploration of how learners' spatio-temporal cognition can be scaffolded using UAV aerial visualizations to solve authentic CE problems. Second is the investigation of the learners' motivation for authentic CE problem solving with and without UAV aerial visualizations. To examine the role of aerial visualizations in spatio-temporal reasoning in CE education, the authors developed a novel intervention for scaffolding spatio-temporal reasoning during authentic CE problem-solving. The technological innovation consisted of a web-based learning environment that enables learners to explore construction job sites using UAV aerial visualizations. The visualizations represent important instances of spatial-temporal dynamics on actual construction sites that are often difficult or impossible to access in person.

2. OVERVIEW OF UAV AFFORDANCES

To be useful, a technology must improve interactions between the individual and the environment (Kaptelinin and Nardi, 2006). The reciprocal relationship between the environment and the individual acting on the environment has been traditionally described as an interaction between the environment's affordances and the individual's abilities (P. D. Antonenko and I. Mutis, 2017). In the context of CE education, learners experience a significant need to be supported as they learn to select, organize, and integrate complex spatio-temporal information as they translate engineering designs to construction implementation at unique job sites. Given this need, Unmanned Aerial Vehicles (UAVs) serve as a promising educational technology because they provide the unique affordance to capture a broad spectrum of spatial and temporal information from the construction job site environment. The UAV data generated by UAVs – aerial visualizations such as videos and images – offer instructional benefits currently unmatched by more traditional learning materials. UAVs enable just-in-time and dynamic visualizations of *in-situ* construction resources, processes, and management of activities as they unfold over time (see FIG. 1).



FIG. 1: UAV Dynamic visualization of construction processes and resources from a construction site.

UAV data provides observers (learners) the opportunity to develop skills that integrate spatial and temporal information by enhancing their understanding of interdependencies, interactions, and constraints among integrated and specialized engineering systems in a construction project. Fundamentally, when a learner observes UAV data, a mediation process occurs. The UAV data, as a representation, serves as a mediation instrument for the interpreter (learner). The UAV dynamically captures *in-situ* contexts (e.g., aerial images that capture multiple physical locations along a flight path), which constitutes a powerful resource for interpreting CE designs. As a mediation instrument, UAV affords experiential observations for awareness, facilitating the development of supporting CE activities, such as planning and goal prioritizing, that are essential for the success of project site activities. UAV visualization provides an important vicarious experience (Conle et al., 2002) that allows the learner to have a powerful feeling of presence at the job site without physically being there. (And there are many important financial, accessibility, and safety reasons why CE students should not visit certain construction sites).

In addition, UAV technology mediates and enhances the human perception of the physical world (see FIG. 2) through its ability to a) record aerial visualizations that integrate spatial and temporal information, b) zoom in on the most relevant aspects of various processes, c) approach and observe a potentially unsafe area of the site from multiple angles, and, importantly, d) replay, pause, review, and discuss aerial visualization recordings to reinforce key concepts and practices.

UAV visualizations allow CE learners to develop skills that integrate (Shelton and Hedley, 2004) procedural and configurational knowledge (Wickens and Hollands, 2000) by enhancing their understanding of interdependencies interactions and constraints among integrated and specialized engineering systems in the construction project. For example, UAV visualizations are interventions that facilitate the association of interdependencies among construction resources (materials, equipment) to follow-up progress on specific job site locations within project

controls. In addition, the UAV output enables interpreters to experience a unique, ‘birds-eye view’ of reality— a perspective that humans would otherwise not be able to observe directly.



FIG. 2: UAV technology mediation and enhancement of human perception of the physical world.

Aerial visualizations serve as a medium for reducing cognitive distance in CE learning. Traditional representations of designs (e.g., 2D drawings, Building Information Modeling) inadequately address the complexities of applying, analyzing, and synthesizing designs to the physical context. The value of static aerial visualizations, compared to the mental reconstruction of a set of separate static images or photographs (Wu et al., 2010) contained in drawings and relevant text passages from construction documents, is that the aerial visualizations integrate spatial information. Aerial visualizations are dynamic and add important temporal information for the observer, thereby enabling the visualizations to serve as a more effective medium for communication and instruction. The images represent an authentic physical context of construction, where multiple pieces of spatial and temporal information related to construction components and processes may be identified. Drawings and virtual models do not enable users to experience the physical context's properties and are, therefore, sub-optimal for CE learning outcomes. On the other hand, virtual 3D models (e.g., Building Information Modeling representations) afford methods for understanding spatial configurations of designs in the construction process but are entirely divorced from the physical world's essential features and properties, causing them to fall short of exposing learners to the wide variety of real-world issues that they can encounter *in-situ* and therefore result in less authentic learning experiences with limited affordances for integrating spatial and temporal information.

Aerial images facilitate observers' awareness when solving authentic CE problems (e.g., space management, which requires planning schedules and activities for potential conflicts). Aerial images can also illustrate the use of materials, identify construction safety issues, and other critical aspects of construction zones. They effectively integrate views of spatial visualizations (Glick et al., 2012) over time to represent and facilitate internalization (Tversky, 2005) of spatio-temporal information.

In CE education, learners are asked to process and integrate complex spatial information from the text- and image-based media provided in textbooks and multimedia presentations. However, their ability to effectively select, organize, and integrate these representations to construct a coherent mental model of a complex construction space along a time continuum is very limited (Glick et al., 2012). This limitation influences a learner's ability to effectively process and internalize the functions and applications of construction objects (e.g., construction materials, equipment, tools) and representations of processes and physical contexts of a project (e.g., engineering designs, drawings) that unfold over time. The ability to process *spatial* and *temporal* information is the spatial-temporal ability (P. Antonenko and I. Mutis, 2017; P. D. Antonenko and I. Mutis, 2017; Mutis, 2018; Mutis and Issa, 2014). The conceptualization of spatial-temporal ability is grounded in understanding spatial cognition and working memory, which considers visual properties of information (shapes, colors) and spatial properties (location and movements). Spatial cognition (The Spatial Intelligence and Learning Center, 2014) frames movements by employing the time dimension, going beyond the core understanding and processing of geometric shapes

(Newcombe et al., 2013; Wai et al., 2009). In the context of CE education, such objects may include construction materials or visualizations and abstract representations (2D drawings and 3D virtual objects) used in teaching. The integration of spatial and temporal information results in the coupling and coordination of both geometric and spatial features (spatial information) with representations defined by logical frameworks related to time. Logical frameworks define the order, sequence, and hierarchies of activities in specific periods. For example, aggregated materials and components required to build an assembly are strictly associated with a time unit (time of day, day number, etc.) at a particular point in the sequence— i.e., one element must go first for a second element to be installed. This specific sequence is the logical framework and the guideline to define tasks in construction.

Associating spatial and temporal information compels mental simulations and spatio-temporal reasoning (Hegarty, 2004). For example, the logical aggregation of materials of an assembly is based on the priority of assembly (Akinici et al., 2002). In the absence of direct observations, reasoning (higher-order cognition) for CE occurs through mental simulation. When observations of CE information occur, their integration with mental simulations facilitates higher-order reasoning by associating observations of *in-situ* information (construction materials and equipment) and representations (engineering designs). However, selection, organization, and integration of spatial and temporal information from multiple media sources (e.g., numerous engineering designs) and learning formats are not straightforward. Working memory can be easily overloaded, especially when the learner is new to the content (Jong, 2010). This condition presents a challenge and an opportunity for educational researchers, and it is the focus of the present study.

2.1 Other applications of UAV in construction

UAV use has exponentially expanded in the last few years with demonstrated applications in the construction industry (Albeaino and Gheisari, 2021; Irizarry and Costa, 2016; Zhou et al., 2018). Fields of application include progress, inspection, structural and health monitoring (Álvares and Costa, 2019; Duque et al., 2018); transportation (Greenwood et al., 2019; Kwon et al., 2017); project control, and site planning (Asadi et al., 2020); disaster management, preservation (Bakirman et al., 2020; Ellenberg et al., 2014); energy efficiency in the built environment (Chen et al., 2021; Ficapal and Mutis, 2019); and earthwork and construction safety (Kim et al., 2019; Liu et al., 2019; Siebert and Teizer, 2014). Although the applications require a human-based post-processing approach— where users process and interpret information collected from UAV—the trend is to use machine learning and robotic applications with higher levels of autonomy (Mutis et al., 2021), thereby reducing required human input in the operations.

3. METHODOLOGY

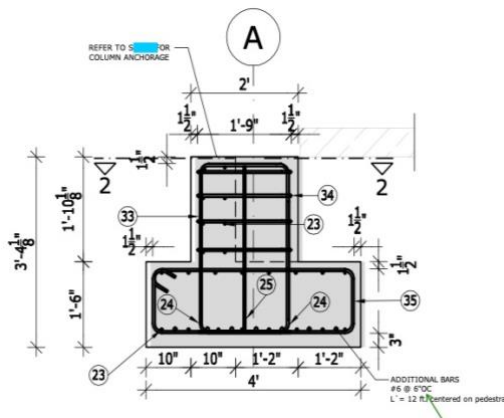
The goal of the study was to enhance CE learning and amplify students' understanding of the dynamic complexity of the CE physical and social contexts through aerial visualizations using UAVs. This approach provided students with authentic, real-world physical and social contextual information through aerial visualizations that immerse learners in situated construction environments. For this purpose, a within- and between-groups quasi-experimental study was designed to address the following research questions:

- RQ1 (focus on cognitive outcomes): How does a UAV-aerial visualization, enhanced-learning environment influence students' spatio-temporal reasoning during authentic CE problem-solving?
- RQ2 (focus on non-cognitive outcomes): To what extent does UAV-supported instruction influence student motivation in a selected CE course?

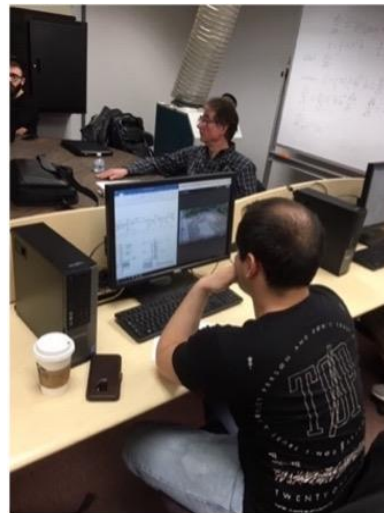
3.1 Participants

The participant pool for the study included students from the Construction Methods and Cost Estimating course, which relies on interpretation of design representations (e.g., 2D drawings and construction documents). The learning goal of the course is to provide knowledge and skills to estimate a construction project's scope of work by teaching students to recognize engineering design components and subsequently quantify materials, labor, equipment, and associated construction methods. The course learning activities demand spatio-temporal reasoning. Learners need to identify: (1) temporal flow using construction products and (2) associated features (e.g., dimensions, location in the building context) that are key to temporal dependencies that define the sequences of construction processes.

Students were invited to partake in the study and receive course credit for their participation. In coordination with the course instructor, two authentic problems were developed about Cost Estimating topics. Each problem was administered separately at an appointed time during the semester. When the problem was administered, participants were asked to work individually to solve the problems within 75 minutes. The experiments took place during a lab section, where participants were randomly assigned to either the treatment or the control group. For the control group, students worked with traditional learning materials (see FIG. 3a). For the treatment group, students worked with the UAV technology intervention (UAV images and videos) and traditional learning materials (see FIG. 3b). Each recruited learner participated in one of the experiments during the course. The experiment was repeated for three consecutive semesters. A total of 61 students ($n=61$) participated in the study over three semesters ($n_{treatment}=32, n_{control}=29$).



(a) 2D representation: Traditional learning materials



(b) Learning with UAV visualizations.

FIG. 3: Treatment and control group learning materials.

3.2 Learning Intervention and Study Procedure

The two authentic problems and their associated assessments (Richard J. Shavelson, 1994) focused on spatial-temporal ability. Each problem covered content related to a particular portion of the Cost Estimating course. Authentic problems are nonroutine problems (e.g., performing an estimation of quantities from a section design of a new project) that reflect authentic practices (e.g., construction engineering management practices), and they go beyond acquiring procedural knowledge (Caleon et al., 2015). Using a representative case allows the authentic problem to be framed as it would be for practitioners encountering the challenge within the complexities of real-world contexts.

At the time each problem was administered, the treatment and control groups worked on the same authentic problem. Participants in both groups were asked to estimate the scope of the work to construct a portion of an engineering design. To arrive at the solution, the participants had to identify the materials used in the construction process for each object in the engineering design and to fill out a template with the quantities of materials to satisfy the process or *estimate the scope of work*. A research assistant supervised the experiment and collected the templates for both groups at the end of the experiment.

Identifying types of construction materials is a critical and first step in defining the scope of the work. Once the types of construction materials are identified, it is possible to quantify the total amount of materials in the construction process.

The assessments of authentic problems were focused on the levels of achievement for spatial and temporal ability problems. Details are shown in Table 1.

TABLE 1: Assessment focuses on levels of achievement for spatial and temporal ability problems

Spatial-Temporal Ability	Experiment Actions for Problem-solving	Assessment Metrics
* Use the learned CEM concepts, methods, and theoretical principles in-context observations.	* Find meanings and apply uses of observed representations of designs, including hidden (no-observable) features.	*Number of design components.
* Breaking down and mapping design parts to understand their functionality within the system design and organizing (orderly fitting parts) into a logical task.	* Aggregate and map design components into categories of a system.	* Number of parts or quantities integrated into a design * Number of parts or quantities integrated into a design

The problem statements for each case, along with the instructors' answers for each problem, are shown in Table 2. The answers represent the two criteria used: recognition (types of construction materials successfully identified) and accuracy (estimated quantities for identified types of construction materials). Table 2 presents the experts' approach to the number of items and the quantities related to the estimation, which was used as a reference to compare the control and the treatment groups. The instrumentation section (following section) elaborates on the rubric created for the assessment.

TABLE 2: Problem statements and experts' solutions

Problem Statement	Type of Construction Material	Estimated Quantity
1) "You are a project engineer from a General Contractor (GC) organization. Your role is to plan and submit a bid for a commercial construction project. As a professional project engineer for this GC firm, you are required to estimate the price of some sections of the construction project. Due to limited time, you are required to execute a quantity estimation for the foundation wall and spread footing of one wall on one side of the building. You are to assume that the job site is flat ground. The job site is near a batch plant."	<ul style="list-style-type: none"> • Excavation • Forms • Keyway • # 5 Rebar • Concrete • Backfill 	<p>55 CY</p> <p>496 SFCA</p> <p>141 LF</p> <p>600 LF</p> <p>24CY</p> <p>34 CY</p>
2) You are a project engineer from a General Contractor (GC) organization. Your role is to plan and submit a bid for a commercial construction project. As a professional project engineer for this GC firm, you are required to estimate the price of some roof sections of the construction project. The roof section inside the parapet walls is 81' 6" by 106' 9" on which you need to perform a materials estimation. Use the section details and plan notes provided".	<ul style="list-style-type: none"> • 5/8" Gypsum • Air Barrier bitumen • 2.5" Polyisocyanurate Insulation • ¼" slope Tapered Insulation • ½" Cover Board • EPDM membrane (rubber) 	<p>8701 SF</p> <p>8701 SF</p> <p>17402 SF</p> <p>8701 SF</p> <p>8701 SF</p> <p>8701 SF</p>

To further illustrate the procedure, consider problem 1 from Table 2. The problem frames a representative case, a *foundation wall and spread footing belonging to one wall that exists on one side of the building*. FIG 4 shows the visual representation (excerpt from drawings) for the representative case. FIG. 4 images are of traditional learning material (2D representations). Students used the given sections of 2D representations of the foundation wall from a sheet of architectural and structural drawings that correspond to the problem. The given sections have the most details to solve problem 1.

Treatment group participants retrieved UAV aerial visualizations using a simple keyword search (e.g., foundation wall, spread footing). The UAV visualization search included the key objects found in the 2D representations of the design. Once retrieved, learners observed an analogous representative case similar to the case of the problem (see FIG. 5). Thus, as learners retrieved and selected cases, the case content was exemplified and amplified by UAV visualizations, which was expected to reinforce learners' case-based reasoning skills (Kolodner, 1993) and their understanding of how unique contexts shape spatio-temporal dynamics of a CE project. Case-based reasoning supports problem-solving by helping learners identify a common structural principle shared among multiple cases.

Case-based reasoning promotes analysis of similarities as well as associations, thereby enhancing the application of the structural principle to the problem and the transfer of learning in other contexts (Mayer and Wittrock, 1996). As the UAV images represent various aspects of the complexity of objects and their relationships in time, learners viewing these images in the context of a CE problem should develop more flexible and adaptable knowledge of how this problem can be addressed in various authentic CE project contexts (i.e., cognitive flexibility theory, Spiro et al. (2003)). This flexibility in cognitive schemas is understood as a mechanism that facilitates the transfer of learning and complex problem solving when learners encounter similar complexities and problems in novel situations. In other words, each case in our learning intervention represented an important aspect of the main schema of a complex authentic CE problem.

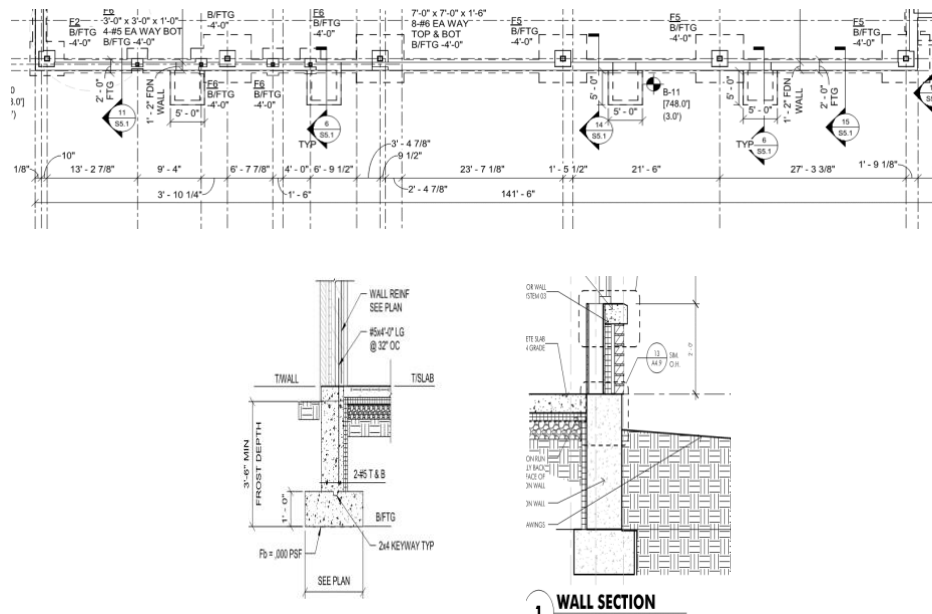


FIG 4: Excerpt of the design of the wall section from working problem: Architectural and structural sections of spread-footing and the wall design.

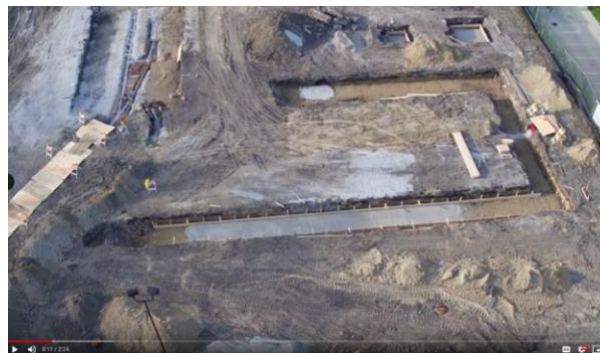


FIG. 5: Analogous case to the case of the problem (analogous objects between the design and the UAV image: a spread-footing of another project).

3.3 Instrumentation: Authentic Assessments of Problem-Solving Ability

Because the task measured problem-solving ability in unique CE contexts, the authentic assessment (Montgomery, 2002) measured CE learners' proficiency in the skill of identifying relevant spatial and temporal information—or, the ability to recognize how physical resources related to one another (space) and the logic for their construction during the CE process (time). For example, because key features were missing from the observed geometrical representation, the assessment measured the students' level of proficiency in identifying and associating existing design components to one another, including linking them into a logic of a construction process. As it often happens in real life, the engineering design representations either lack critical features in their geometry or features

of the design components are difficult to find, as they are disparately located within design documents (set of 2D drawings), thereby making the task for learners to recognize all objects in the design difficult. This results in a demand for significant effort, on the part of the learner, to identify objects and their associated type of construction materials used into the construction process. Thus, the students needed to use spatial and temporal information to successfully arrive at the solutions. Table 3 shows a summary of the authentic assessment criteria used in the rubrics.

TABLE 3: Assessments, level of achievement, and assessment metrics.

CE Course	Authentic Problems for Topics of the	Case	Problem-solving Skill	Level of Achievement (with Spatial-temporal Ability)	Assessment Metrics
Construction Methods and Cost Estimating	(1) Foundations	Quantity estimation for the foundation	Spatial and temporal ability: the ability to associate spatial and temporal information	Ability to recognize the number of components involved in estimating a foundation section	Identification of components
	Estimation of small commercial building	wall and spread footing of one wall of one side of the building			
	(2) Estimation of materials in roof construction for small commercial building	Quantity estimation for the roof section inside the parapet walls			Quantification of the components

The authors designed a problem-solving rubric for the experiment in collaboration with the course instructor (see Table 4). Two criteria were used in the rubric (see Table 4). The first criterion was the recognition of the of construction materials required to estimate the scope of the work (e.g., for problem 1, they were: excavated soil, forms, keyway, rebar, concrete, backfill; for problem 2, they were: 5/8" gypsum, air barrier bitumen, 2.5" polyisocyanurate insulation, 1/4" slope tapered insulation, 1/2" cover board, EPDM membrane). A structure based on levels was used to analyze this criterion—the number of correctly identified construction materials defined each level—i.e., recognition level. There were four levels within the structure for this criterion: (1) at least 4 out of 6 possible material types; (2) at least 3 out of 6 possible material types; (3) at least 2 out of 6 possible material types; and (4) at least 1 out of 6 possible material types. The number of types of construction materials was recognized as an indicator of the learners' ability to retrieve from memory cognitive schemas as conceptualizations of the observed patterns of shapes—i.e., learner's ability to identify the observed elements from the engineering design. The second criterion was accuracy of the estimated quantities of recognized material types. The learners' ability to estimate quantities informs on their understanding of the required amounts of materials to construct the observed engineering design. Based on the expert's (instructor's) input with respect to the level of difficulty of the designs in the problem, an upper and lower range of 25% from the experts' solution was defined as an acceptable answer (i.e., if the learner's answer was no more than 25% higher or no less than 25% lower than the instructor's solution, the learner's answer was considered acceptable). Since there were 6 possible material types, there were 6 possible acceptable or not acceptable answers for each type of construction material. For the analysis of the accuracy criterion, a structure that was based on levels was used (see Table 4).

TABLE 4: Rubric.

Case (Criteria)	Correct	Partially Correct	Minimally Incorrect	Partially Incorrect	Incorrect
Level of Recognition (Recognized type of construction materials)	At least 4 out of 6 (>= 66.66 %)	3 out of 6 (50 %)	2 out of 6 (33.33%)	1 out of 6 (16.66%)	0%
Level of Accuracy (Acceptable answers of estimated quantities for each type of construction materials)	At least 4 out of 6 (>=66.66%)	At least 3 out of 6 (50%)	At least 3 out of 6 (33.33%)	At least 1out of 6 (16.66%)	0%



The number of acceptable quantities defined each level—i.e., accuracy level. There were four possible levels: (1) at least 4 out of 6; (2) at least 3 out of 6; (3) at least 2 out of 6, and (4) at least 1 out of 6 of acceptable answers for the estimated quantities of each type of construction materials. These criteria represent the two major steps to estimate the scope of work and to solve problems related to CE cost estimating—problems where learners have to effectively integrate spatio-temporal information in order to provide a solution.

3.4 Instrumentation: Course Interest Survey

Course Interest Survey (Keller, 2010) was used to explore the potential effects of UAV-supported instruction on student motivation. As a situational instrument, the CIS is not intended to measure students' generalized levels of motivation toward learning. This instrument helped determine how motivated students were or expected to be by a particular activity or course. The CIS was administered to all participants twice once in the pre-test format and once in the post-test format. The pre-test occurred two weeks before the unit on estimating façade scaffolding, and then two weeks after the conclusion of this unit, participants responded to the post-test. The CIS consists of 34 items that measure each of the four components of the ARCS model of learner motivation: attention, relevance, confidence, and satisfaction (Keller, 1987). The following is an example of an item on the construct of relevance: “The things I am learning in this course will be useful to me”. Participants rated statements using a Likert scale ranging from Not True (1) to Very True (5). A total motivation score was calculated from these ratings and a score for each of the ARCS components. Cronbach’s reliability estimates were calculated for responses to the pre-CIS: attention ($\alpha = .78$), relevance ($\alpha = .73$), confidence ($\alpha = .64$), satisfaction ($\alpha = .81$), and total score ($\alpha = .90$); as well as for the post-CIS: attention ($\alpha = .79$), relevance ($\alpha = .74$), confidence ($\alpha = .62$), satisfaction ($\alpha = .77$), and total score ($\alpha = .91$) (α coefficient of reliability ranges from 0 to 1). Cronbach’s reliability informed the internal consistency of the given test items—measuring the strength of the consistency as a measure of a concept. Results demonstrated that scale has reasonably strong α coefficients, ranging from the recommended neighborhood of 0.65 to 0.90 (less than 0.5 is not acceptable and higher than 0.95 indicates redundancy issues (Cortina, 1993)), meaning that the items indeed tap into the underlying constructs of attention, relevance, confidence, and satisfaction.

4. DATA ANALYSIS AND RESULTS

4.1 Learning Outcomes

Results showed that participants have lower recognition of the type of construction materials when they used a given portion of the 2D drawings (i.e., traditional learning materials) to solve the problems ($M = 40.78$, $SD = 28$, $N = 94$ on a 1-100 scale) as compared to those who use both the technology intervention and given portion of the 2D drawings ($M = 54.17$, $SD = 29.63$, $N = 32$). In this summary, M is the mean and SD is the standard deviation. Learners of the treatment condition were better able to process spatial-temporal information in comparison with those of the control group. Implementation of the treatment condition led to a higher awareness of the type of construction materials required for use in the construction process of the problem, along with appropriate scaffolding. Results also demonstrated that participants who used traditional 2D representation learning material had a lower level of accuracy of the estimated quantities for each type of construction material ($M = 25.29$, $SD = 26.58$, $N = 29$ on a scale of 1-100) when compared with those who used both the technology intervention and the given portion of the 2D drawings ($M = 33.32$, $SD = 32.23$, $N = 32$). Mann-Whitney U test—a nonparametric alternative to the independent t -test—was conducted since each group (dependent variable) showed a significant pattern from normal distribution after plotting histogram and obtaining results from the Shapiro-Wilk test (see Table 5). The Mann-Whitney U test determined whether there is a difference in the levels of recognition of materials between control and treatment participant design groups (treatment vs. control), see Table 5.

The Mann-Whitney U test for the case of the level of recognition at 0.1 level of significance, there was a statistically significant difference in engagement scores between control and treatment groups, ($U = 580.5$, $z = 1.710$, $p = 0.087$), using an exact sampling distribution for U (Dineen & Blakesley, 1973). Although there is a minor difference among the groups, the U test results indicate the treatment group has a higher ability to process spatial and temporal information than the control group. After conducting the Mann-Whitney U test for the case of level of accuracy at the 0.1 significance level, there was not a statistically significant difference in engagement scores between control and treatment groups ($U = 522$, $z = 0.858$, $p = 0.391$), using an exact sampling distribution for U (Dineen and Blakesley, 1973).

TABLE 5: Summary Statistics for learning outcomes.

Test	Case	Condition	Results	N
Shapiro-Wilk	Recognition of Materials	Control	(W(29) = 0.951, p = 0.193)	29
		Treatment	(W(32) = 0.869, p = 0.01)	32
	Level of Accuracy	Control	(W(29) = 0.850, p = 0.001)	29
		Treatment	(W(32) = 0.855, p = 0.001)	32
Mann-Whitney U	Recognition of Materials	Control and Treatment	(U = 580.5, z = 1.710, p = 0.087)	61
		Control and Treatment	(U = 522, z = 0.858, p = 0.391)	61

The experiments demonstrated that the aerial images incorporated more effective affordances than traditional learning materials after the investigators’ observations and interpretation of results. The case of the level of accuracy reinforces the idea that the control and treatment group had the same abilities when performing high-cognitive tasks—incorporating acquired CEM knowledge for problem-solving operations to calculate the correct quantitative units on identified materials. The core component to realize the case of the level of accuracy demands retrieval of CEM knowledge of methods to perform quantification of already identified materials either from traditional or aerial images.

4.2 Non-cognitive attribute outcomes

Non-cognitive outcomes included personality traits with measures that addressed student motivation constructs based on the ARCS model of motivational design (Keller, 2010): Attention, Relevance, Confidence, and Satisfaction. As a result of the estimation activity, overall interest increased for both groups. Still, the increase was greater for the treatment group that used the UAV-supported online learning environment (see Table 6 for descriptive statistics). A repeated-measures ANOVA demonstrated that the treatment group exhibited a significantly higher improvement in overall CIS scores ($F_{1,43} = 42.70, p < .0001, \eta^2 = .49$). The partial *eta squared* value (a measure of effect size) indicates that the between-subjects factor “condition” accounted for almost half of the variance in the pre-test and post-test change in the score. A repeated measures ANCOVA analysis was also performed with Gender and Ethnicity as covariates. Still, these variables significantly interacted with the within-subjects variable, that is, CIS score change between the pre-test and post-test.

TABLE 6: Descriptive statistics for Course Interest Survey pre-test and post-test scores by condition.

	Condition	Mean	Std. Deviation	N
CIS Total Pre-test Scores	Control	75.23	20.61	22
	Treatment	77.43	23.99	23
	Total	76.36	22.18	45
CIS Total Post-tests Scores	Control	75.73	16.24	22
	Treatment	97.39	14.95	23
	Total	86.80	18.91	45

Regarding the individual CIS subconstructs, scores increased to a greater degree for the treatment group for each individual variable: Attention ($F_{1,43} = 8.61, p = .005, \eta^2 = .17$), Relevance ($F_{1,43} = 48.46, p < .0001, \eta^2 = .53$), Confidence ($F_{1,43} = 29.10, p < .0001, \eta^2 = .40$), and Satisfaction ($F_{1,43} = 27.07, p < .0001, \eta^2 = .38$). The large partial *eta-squared* values indicate that the difference in condition accounted for a large percent in the change in the score between the pre-test and the post-test.

5. DISCUSSION

This paper reports on the impact and effects of using aerial images and videos from UAV as the main intervention to understand spatial and temporal information. The presented exploratory quasi-experimental study provided evidence of the promise of UAV-supported instruction in CE curricula. Experiments revealed how to influence students’ abilities to process complex information and develop important knowledge related to CE spatial-temporal configurations. The study explored the effects of how the CE students learn when using the intervention, thereby opening opportunities to enhance the design of learning-material using UAV technology.

Results showed how UAV technology-enabled learners to expand their repertoires of actionable possibilities for contextual awareness of construction tasks to solve CE problems. The investigation revealed that the UAV visualizations provide a unique technological affordance for learning and knowledge-building scaffolds for CE education. The mediating power of UAV visualizations enhanced learners' spatial and temporal information processing ability as used when solving CE problems. The effects were on improved abilities to effectively apply, analyze, and synthesize any form of design representation or construction resource to situations and physical contexts— in other words, the UAV mediation brings robust benefit to their spatial-temporal cognitive ability development as used in CE activities. Without such visualizations, the users' awareness of project complexities would have proved more challenging. Users had a high degree of control over the aerial visualizations by changing the coverage areas of the construction site. This is possible as the recorded visualizations cover all areas of the construction site following pre-established UAV paths— a defining reference for the UAV camera orientation, position, and elevation position for the recorded visualizations. The flight path enables observations of target objects and the objects' details (e.g., type of construction materials) that might be found in designs of the problems.

The UAV visualizations, however, have technology factors that impact their quality and, thereby, their effectiveness as an intervention. For example, UAV visualizations over the construction area have arbitrary orientations and angle views with reference to points on the ground in the image, and UAV footage coverage areas depend on pre-established UAV paths that define UAV camera orientation, position, and elevation. These factors make it challenging to efficiently locate objects or areas of interest on the images. The elevations (i.e., height above ground level (AGL)) create issues when the distribution of objects of interest within the image area is dense and major scale variations exist. Still, the advantages of using UAV images supersedes their limitations. The UAV's affordance to present a large set of cases effectively facilitates observations of multiple areas and framing multiple cases—i.e., the UAV demonstrates several situations and contexts in job site environments.

Cognitive outcomes (RQ1). The quasi-experimental design focused on how the main intervention impacts pedagogical tasks in processing spatial and temporal information. The design included the following quantitative aspects: (1) the effect of using UAV real-world aerial visualizations as a training method has on users' spatial-temporal skills and problem-solving; (2) the effect that the intervention has on users' knowledge acquisition and achievement of learning objectives specific to CE training.

The authors framed the problems from a CE course as representative cases. Cases refer to previous experiences of a situation or problem to indicate situations and conditions where the design elements were used. The cases addressed the learners' challenges on the perception of spatial-temporal information related to the subject of the CE course. The design allowed the researchers to assess the level of effort to process spatial and temporal information required in each case. The cases represent the complexity of an authentic problem. Learners adapt previous experiences to the complexities of the new situation presented in each problem Field (Kolodner, 1993), enabling them to understand situations and conditions. Adapting previous experiences to a new experience is possible using analogical reasoning. Learners associated other experiences to understand new observations in the problem— by encountering similar features in the problem.

When framing problems to cases, the authors considered the unique nature of construction projects and their contexts that characterize CE solutions. To a large extent, the solutions were based on personal experience and the experts' exposure to various situations. Building cases serve as a methodology to frame in-situ scenarios with observed problems from personal experiences. When used as a mediating mechanism, UAV visualizations operate as an affordance tool to experience multiple cases of an authentic problem. The mediating mechanics enable using analogical reasoning that is both the end and the means to learning for problem-solving. UAV visualizations allowed observations of one or multiple cases with analogous complexity of the authentic problem. For example, when observing similarities on the aerial image with the objects of the design of the given problem, learners tended to remember and recall pieces of spatial and temporal information that scaffold steps for problem-solving.

The experimentations were based on the effectiveness of estimating the scope of the work by quantification of the acceptable range of quantities based on the experts' (instructors) estimates. The recognition demonstrated how learners could associate design components to one another (i.e., spatial information), such as how formwork and a keyway are associated with rebar and concrete. The experiments demonstrated that learners in the treatment group could process temporal information more efficiently since they more efficiently recognized the required components for the quantity estimation and the associated scope of the work. For example, by recognizing the type of construction materials, the treatment group noticed how an excavation precedes installing forms and keyways

and how rebar is placed before concrete and a required backfill. Learners from the treatment group were able to interpret spatial and temporal information more efficiently. For example, when the 2D representation of the building section of the authentic problem had missing information related to materials used in the construction process (formwork), the treatment group could identify such construction materials more efficiently than the control group.

Observations of UAV outputs from a construction project's operations enable opportunities to improve CE pedagogy by increasing the perception of construction project complexity. The UAV visualization added new affordances for scaffolding the processing of spatial and temporal information.

Non-cognitive outcomes (RQ2). Students in the treatment group provided significantly higher ratings of motivation and its four ARCS subconstructs. Although the number of subjects was small, the emergence evidence generated by this study suggests that UAV-supported instruction helps create situational motivation, improves student self-efficacy for learning CE, and results in better perceptions of the relevance of learning and instruction. The evidence of positive outcomes on situational motivation, self-efficacy, and perceptions of the relevance of learning and instruction does not seem to be affected by a slightly significant difference in findings on measures in problem-solving among treatment and control groups. Regarding the idea that the combination of perseverance and passion may heighten an individual's immersion into a performance domain—or the intensity of focus that the learner experiences—the evidence suggests that the potential exists to promote higher performance levels.

This exploratory quasi-experimental study provides evidence of the promise of UAV-supported instruction in CE curricula. In this study's particular example, students in the treatment group provided significantly higher ratings of motivation and its four ARCS subconstructs. Despite finding a minor difference among the treatment and control groups with respect to the measure of learning, the tentative evidence generated by this study suggests that UAV-supported instruction helps create situational motivation, improves student self-efficacy for learning CE, and results in better perceptions of the relevance of learning and instruction. Empirical studies with larger samples and contexts other than construction estimation will demonstrate whether these effects persist and what specific instructional manipulations result in enhanced learning outcomes.

6. CONCLUSIONS, LIMITATIONS, AND FUTURE WORK

The traditional medium used to represent designs (e.g., 2D drawings) inadequately presents the complexity of a design for a construction system—this shortfall results in learners facing difficulties in interpreting, analyzing, and synthesizing designs. The difficulties limit project engineers, project personnel, and CE learners' abilities to process complex spatial and temporal information. 2D drawings are static images. Their affordances do not enable CE learners to effectively develop experiences in the association of spatial and temporal information, thereby limiting an individual's understanding of the construction process.

The study presented herein showed that UAV visualizations (image and videos) adequately offer a context for CE learners by (1) capturing images from construction job site environments and integrating real-world spatial-temporal features; and (2) enabling the contextual analysis of construction processes. The use of UAV visualizations provided unique technological affordances by enhancing the processing of real-world contexts. As shown in the experimentation, the UAV output afforded learning to spatially and temporally distributed information, which served as a scaffold for the development of spatial and temporal ability. This ability is critical in CE education. Learners capitalized on the advantages of UAV technologies, which by focusing on capturing images from active construction job site environments (Hou et al., 2013; Yabuki et al., 2011), enabled the learners to integrate real-world spatial-temporal features and participate in a contextual analysis of construction tasks and resources (Chen and Huang, 2013; Park and Kim, 2013).

The intervention (UAV visualization) served as a scaffold of individuals' development of their spatial-temporal cognitive abilities by facilitating the perception of spatial relations of entities (objects) (Montello, 1998) and dynamic processes. The experiments demonstrated an impact on the students' abilities to process complex information from the treatment compared with the control group. The treatment group brought opportunities for the students' development of critical knowledge related to CE spatial-temporal configurations.

The learners' observation of the UAV visualizations created a set of experiences that enriched their personal experiences and knowledge about real construction site information (e.g., in-situ organizations of a project's layout). Observations of the UAV visualizations facilitated the understanding of the complexity of problems from

the CE course content. The result provided evidence that the use of UAV aerial images and video of analogous physical context contributes to informative experiences related to design interpretation.

This study has some limitations worth noting. First, the number of subjects (CE learners) that participated in the experiments for the selected course (Construction Methods and Cost Estimating) was not large. Although typically, the selected course had a good number of students during the academic semester, the study was not designed as an actual assessment of the CE learners' course. The experiment activities demand a high degree of control—requiring active supervision from graduate students and instructors in a computer lab at different class times and locations from regular course instruction hours. The authors implemented a strategy to recruit students based on offering extra credit as an incentive for their participation. Despite the authors' efforts, the strategy offered limited motivations for the students' participation. The sample used in this study may have been significantly limited, which may have under-estimated the strength of relationships between the dependent and independent variables (i.e., higher level of significance). Second, all data used is from only two problems. This focus limited the generalizability of the findings since it was not possible to compare differences and variabilities among problems. Future research is encouraged to incorporate an ample repertoire of concepts and practices into cases relevant to CE problems to address this limitation. Third, the study did not include testing a priori exposure of subjects to real-world scenarios analogous to each problem. Discriminating the level of exposure (exposure allows learners to code experiences in memory) will help to determine more accurate levels of analysis. The level of exposure might influence the students' ability to retrieve and use spatial-temporal information and might have effects on the dependent variables. Further research should incorporate tests for a priori experience to determine the direct and indirect effect on the dependent variables. Fourth, the course-interest survey took place using an online data collection method. However, not all students responded to the course-interest survey, reducing the authors' ability to make a paired comparison to analyze the cognitive and non-cognitive outcomes. Future research should consider more effective motivating mechanisms to improve and seize the opportunity to compare cognitive (learning) and non-cognitive outcomes.

Future research should also develop interventions with more sophisticated functionalities. For example, the technology should incorporate intelligent search and retrieval techniques, which would empower learners to facilitate finding and navigating among a library of analogy cases (i.e., a library of UAV-labelled videos and images for search and retrieval). These types of technology functionalities should incorporate functions that allow retrieving individual past solutions that are generally compatible and analogous with a new aspect of the problem (target case), facilitating case-based learning with technology—a transition that should be promoted to advance CE learning and the investigation of learning processes, thereby contributing to the critical need for developing spatial-temporal abilities.

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