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Teaching construction hazard recognition through high fidelity augmented reality

Antoine Jean-Pierre Tixier, University of Colorado at Boulder
Mr. Alex Albert, University of Colorado

Alex Albert is a PhD Candidate in the Construction Engineering and Management Program at the University of Colorado at Boulder. He has conducted research for the Construction Industry Institute and ELECTRI International, studying hazard recognition and response. Alex specializes in implementing experimental research methods in engineering education to perform hypothesis testing and draw causal inferences.

Dr. Matthew Ryan Hallowell, University of Colorado

Dr. Matthew Hallowell is an Assistant Professor at the University of Colorado at Boulder. He earned a PhD with a dual focus in Construction Engineering and Management and Occupational Safety and Health from Oregon State University. He also earned a BS and MS in Civil Engineering from Bucknell University. For his efforts in teaching innovations, Dr. Hallowell has received the National Science Foundation CAREER award, Beavers Endowed Faculty Fellowship, John and Mercedes Peebles Innovation in Education Award, the ASCE New Faculty Excellence in Teaching Award, the Department of Civil, Architectural, and Environmental Engineering's Teaching Award, University of Colorado College of Engineering and Applied Science Dean's Performance Award, and the Best Technical Publication Award from the Journal of Safety, Health, and Environmental Research for a paper on a new teaching innovation. He has also selected as an ASCE ExCEEd Teaching Fellow Teaching Mentor and as a President's Teaching and Learning Collaborative Member.

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ABSTRACT

The ability of designers, managers, and workers to identify construction hazards is a fundamental skill that promotes construction safety in practices. Traditionally, construction management programs focus on teaching this topic using the fundamentals of the Occupational Safety and Health Administration and the associated regulations and delivering this material with traditional lecture-based approaches. This study introduces a new method of hazard recognition pedagogy aimed at rapidly improving signal detection and situational awareness. Specifically, a high-fidelity augmented reality software tool built around energy-based cognitive mnemonics (SAVES) that immerses students in a representative environment was created and experimentally tested with a large class. In a series of pre-tests, construction engineering and management students were provided with randomly-selected sets of photographs of construction worksites and were asked to identify the hazards present. In a one-month randomly staged series, students were exposed to SAVES. In SAVES students were asked to identify hazards and the system provided real-time assessment of their performance and feedback for improvement of future iterations. Following this experience, a second series of post-tests was administered. The impact of the augmented reality experience was empirically measured using multiple baseline testing and inferential statistics. The results indicate that students' and workers' abilities to recognize hazards increased, on average, by 21 percent and 26 percent, respectively ($p<0.001$). Qualitative feedback indicates that the approach enhanced intellectual excitement and retention.

Introduction

The aim of Construction Engineering and Management (CEM) education is to equip students with the state of art skills-sets that can empower them to evaluate and respond to critical needs in the construction industry. This is especially challenging given the complex nature of the industry [1] and the accelerated rate at which new knowledge is generated [2]. The role of educators is to facilitate this process and to prepare current students to attain future professional success[3]. Unfortunately, employers have often expressed dissatisfaction with the skill levels of new graduates[4]. In another study by Martin et al. (2005), results indicated that recent graduates were unprepared for practical aspects of their job[5]. Accordingly, engineering graduates may have a good grasp on engineering fundamentals, but they often lack necessary skills in practical situations [6]. More recently, a leading construction educationalist and established researcher was quoted to have said: "we teach too much and our students learn too little" [7]. As a result, institutional educators and instructors are exploring new innovative ways to engage student through active learning processes [8-10] and methods to enhance knowledge retention [11,12].

Construction literature suggests a few solutions that instructors can use to ensure that students acquire skill-sets that are required for professional success. Russell et al. (2007) suggests that instructors need to provide students with field visit opportunities and use real construction environments to provide context-driven education[3]. He further argues that such opportunities would provide students with better prospects to interact with professional engineers and managers on real construction projects that are dealing with real-life challenges. Another solution that is suggested in literature is to establish collaborative partnerships between educational institutes and local construction companies[13]. Although such methods are valuable, they often are not practical because (1) instructors may not gain access to construction projects on a regular basis and during appropriate phases of the project and (2) amidst productivity and safety concerns, it would be disincentive for construction managers to allow access to a large group of students [14].

This paper presents an alternative to traditional field trips and lecture-based teaching: an augmented reality construction safety training system (SAVES) that immerses participants in a realistic and representative construction environment. This module was developed with the intention of providing students with a virtual environment as an alternate method to learn hazard recognition when frequent site visits are unrealistic. Such a module helps students to better understand construciton safety, a key skill that employers find highly desireable[15].

After development of the SAVES system, we empirically tested the effects of a single intervention that included SAVES, an associated training package, and cognitive mnemonics. This test was designed based on the multiple-baseline approach using a series of high resolution photographs and real construction environments as pre-tests and post-tests.

Background on construction safety hazard recognition

In spite of rigorous efforts to reduce injury rates, the construction industry consistently has failed to reduce injury rates to acceptable levels [16,17]. Injury rates recorded by the Bureau of Labor Statistics continue to indicate no significant improvement in safety performance over the last decade. Unfortunately, research continues to validate that construction personnel are more likely to be injured on the job [18-21].

The dynamic nature of construction work and task unpredictability on projects makes hazard recognition difficult [22]. In fact, a study conducted by Carter and Smith[23] indicate a large proportion of hazards as not being identified or assessed on typical projects. As a result, construction personnel are exposed to hazards that they are unaware of [24,25], which increases the risk of injury occurrence. During preconstruction planning, hazard evaluation generally involves predicting task-methods and associated hazards. A risk analysis is then performed to identify appropriate injury prevention techniques. Such approaches are common in research literature. For example, Mitropoulos and Guillama[26] evaluated several high risk practices involving residential framing and suggested risk mitigating strategies and Albert and Hallowell[27] identified hazards for working on Transmission and Distribution (T&D) lines.

Apart from preconstruction safety planning, construction workers use a number of methods to recognize occupational hazards. For example, job safety analysis delves into work-tasks prior to initiating work to recognize relevant hazards[28] and checklists use conventional templates to ensure hazards are recognized [29]. Despite such methods contributing to safer work-places [30], hazards still go unidentified [23]. To improve hazard recognition processes, researchers have extensively studied causal factors of injuries [31-34].

Results of a recent survey of construction injuries indicate that at least 42% of accidents occur as construction personnel lack adequate knowledge [32]. Had they been aware of risk exposure, they would have taken appropriate measures to keep themselves safe [35]. Unfortunately, even engineers and safety professionals lack required hazard recognition skills[36]. Considering the importance of this issue, Construction Engineering and Management (CEM) educators are to take active measures to ingrain hazard recognition competency in students prior to them taking active roles in the industry.

Phase 1: Development of SAVES and training protocol

As mentioned above, despite efforts, injuries are common on construction projects. Research on causal factors attributes inadequate knowledge and awareness as being key factors for such poor performance**.** The evident solution to this problem is to provide individuals with reliable and retainable knowledge for hazard recognition through well-designed training programs. Current forms of training are limited in that they focus on regulatory requirements[33], while not providing contextual learning[6]. Similarly, safety education in the Construction Engineering and Management (CEM) curriculum focuses on OSHA regulatory requirements, rather than providing context-based learning. One prominent solution repeatedly found throughout literature is the use of augmented reality construction safety training systems.

In our endeavor to respond to this critical need, we developed SAVES (see Figure 1): a high fidelity virtual training environment that integrated virtual and real environment components using the Unreal Development kit (UDK). The purpose of the developed tool was to improve students' and construction personnel's situational-awareness regarding hazards on dynamic construction projects. SAVES was designed based on the principles of mnemonics where cognitive cues in the form of energy sources were provided to trainees. The theory behind providing energy sources as cognitive cues is based on the general understanding that hazards are associated with the inappropriate release of energy. In other words, energy that is required to accomplish work tasks on projects if released inappropriately may cause loss-of-control as a result of which construction personnel may be injured. Table 1 provides the list of the energy-source based cognitive-cues and relevant examples.

In the virtual augmented reality construction environment workers are exposed to real hazards, while not exposing them to any risk. The training protocol begins with educating users on the cognitive energy-source cues. Following the preliminary educational module, users are presented with various work scenarios (virtual) as they navigate through the 3D work-space. The users identify hazards, their associated energy sources, and appropriate severity levels of risks that the hazard poses. In response, SAVES provides verbal feedback on the hazards that were successfully recognized and those that were missed. It is expected that iterative feedback will help improve hazard recognition and retention for future challenges.

Figure 1a: Visual representation of SAVES

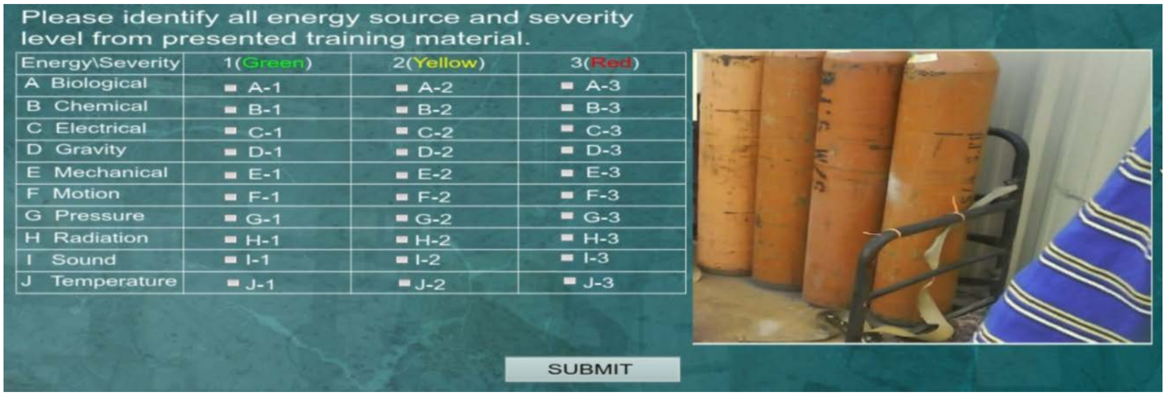

Figure 1b: User input

The development of SAVES began with input from an expert panel of 14 safety professionals. A repository of more than 1000 photographs representing hazards and poor work practice was accumulated. A sub-sample of photographs representing the various energy sources that may be encountered was incorporated into the educational virtual environment module. The virtual environment was built by integrating the photographs into a BIM model of an industrial plant.

Table1: Energy-source based cognitive-cues

Energy source	Examples
Gravity	Falling objects, collapsing roof, and a body tripping or falling
Motion	Vehicle, vessel or equipment movement, flowing water, wind, body positioning: lifting, straining, or bending
Mechanical	Rotating equipment, compressed springs, drive belts, conveyors, motors
Electrical	Power line, transformers, static charge, lightning, energized equipment, wiring, batteries
Pressure	Pressure piping, compressed gas cylinders, control lines, vessels, tanks, hoses, pneumatic and hydraulic equipment
Temperature	Open flame and ignition sources, hot or cold surface, liquids or gases, hot work, friction, general Environmental conditions, steam, extreme and changing weather conditions
Chemical	flammable vapors, reactive hazards, carcinogens or other toxic compounds, corrosives, Pyrophorics, combustibles, inert gas, welding fumes, dusts
Biological	Animals, bacteria, viruses, insects, blood-borne pathogens, improperly handled food, contaminated water
Radiation	Lighting issues, welding arc, X-rays, solar rays, microwaves, naturally occurring radioactive material (NORM) scale, or other non-ionizing sources
Sound	Impact noise, vibration, high-pressure relief, equipment noise

Phase 2: Empirical testing of SAVES

After the development of SAVES, we empirically tested the effectiveness of the module in enhancing hazard recognition skills of construction students. The objective at this stage of the research project was to test the null hypothesis that: the use of the *hyper-realistic augmented reality construction safety training system (SAVES) reinforced with the principals of mnemonics, and imparted using andragogical and pedagogical methods will not measurably improve the* *proportion of hazards identified on construction environments.* Further, we wanted to study how differently students performed in recognizing hazards when compared to construction personnel. The following sections describe the research methods and lessons learned from the study.

Research Methods

Several experimental and quasi-experimental methods have been promoted in literature for intervention based studies. Researchers particularly encourage the uses of longitudinal studies [37-39] to enhance reliability, validity and rigor in measuring change over time, which may be induced in the form of an intervention. Among the available longitudinal study methods, the before-and-after (AB) test that gathers data before and after the intervention, and the reversal-design that withdraws the intervention to examine reversal effects were dismissed on methodological grounds. The before-and-after AB design does not provide any control to limit history validly threats [40,41]. Researchers using such techniques cannot claim causality of any kind as confounding variables unrelated to the intervention may have invoked changes. On the other hand, the reversal design requires that the intervention be withdrawn to improve validity of causal inference. This form of research methods is especially unethical when researchers remove an intervention that has positive effects [42,43]. Also in an educational research study, it is impractical to expect participants to unlearn something they have been taught through effective training sessions. Under such circumstance, a highly sensitive method to obtain valid results is the Multiple Baseline Testing (MBT) approach [44]. Thus, we decided to use the MBT design for the purposes of this study.

The MBT design, depicted as Figure 2, is a series of longitudinal before and after A-B studies that is replicated across experimental units (individuals or a group of individuals) within a single study. The intervention is introduced on a staggered basis to each experimental unit. Hence, while one group or subject receives the treatment, the other units perform the role of a control group. Also, the group's performance in the pre-intervention phase provides an additional control for the post-intervention phase and for benchmarking purposes. Hence, if a change is shown to occur only and if only the intervention is introduces, the researcher can infer causality.

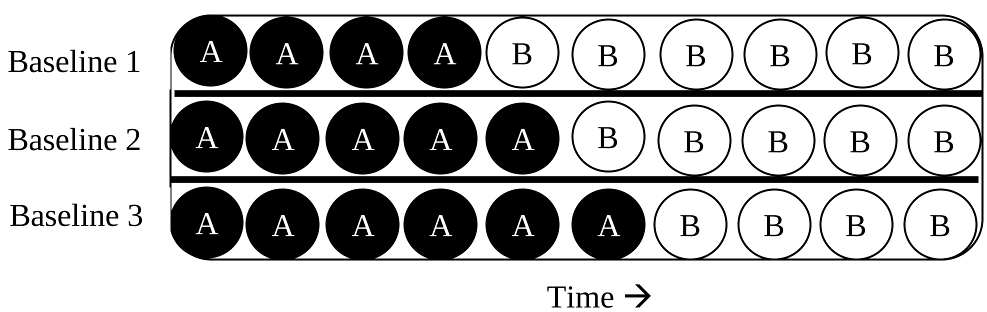

Figure 2: Schematic representation of MBT design

Exchangeability or equivalence of the groups as in other quasi-experimental studies is not a concern as comparisons of effect change is made against the performance of the group in the pre-intervention phase. Such a design also excludes between subjects sources of variability, thus providing better estimates of effect size [45].

Empirical testing of the developed intervention

As indicated previously, both construction personnel and construction students were introduced to the combined intervention that included SAVES and energy-based mnemonics. Table 2 provides details on the experimental elements of interest. The dependent variable for the test was the proportion of hazards recognized that was measured longitudinally. In order to reliably measure the dependent variable we developed a relevant metric known as the hazard recognition index (HR index), which was computed as shown in Equation 1.

$$HR = \frac{H_{identified}}{H_{total}} \qquad (1)$$

Where, $H_{identified}$ represents the total number of hazards successfully identified for the given scenario, and H_{total} represents the total number of relevant hazards present in the scenario provided for testing.

Table 2: Experimental element and description

Experimental elements	Description
Unit of analysis	Construction Personnel/ Construction Students
Learning objective	Indentifying hazards in construction environment
Dependent variable	Proportion of hazards identified (HR index)
Intervention	SAVES reinforced with the principles of Mnemonics delivered using androgogical and pedagogical methods
Testing method	*Construction Personnel:* New work environments and different tasks *Construction Students*: High resolution photographs representing construction settings

One important distinction, as indicated in Table 2, was the testing method employed for construction personnel and construction students. Construction personnel were tested on real construction projects and settings, while construction students were tested using high resolution photographs representing real construction tasks and settings. It was impractical for the research team to provide construction students with access to real construction project due to several constraints typically involved with such studies. From our point of view, this was not a serious concern as the aim of the study was not to compare the performance between construction personnel and construction students, but was rather to test if improvements can be achieved using the developed intervention. Nonetheless, important research questions and observations that will need further investigation may be identified through comparisons. Also, testing the intervention on multiple groups and in settings enhances external validity, thereby improving generalizability.

Response of Construction Personnel to the intervention

Data were collected concurrently from three construction crews. Since construction personnel were tested on real construction environments, H_{total} was identified by a site-based panel of 2 safety professionals with a total of 34 years of experience in construction safety and a researcher who recorded operational definitions of the hazards

Figure 3 represents the HR index plotted over time. As shown, the interventions were introduced at t=7, t=8, and t=10 for the baselines 1, 2 and 3, respectively. Visual observations clearly indicate significant improvements after the SAVES and associated protocol was introduced; however, rigorous research requires observational analysis to be supplemented with formal statistical methods. The most intuitive analysis involves analyzing each baseline as an independent AB study, determining effect sizes, and then computing an overall effect size for the entire MBT phase. The mathematical model was used for this purpose. Accordingly, the gathered data can be modeled using equation 2 [46].

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 D_t + \beta_3 SC_t + \varepsilon_t \quad (2)$$

Where, Y_t is the dependent variable at time t; β_0 is the intercept of the regression line at t = 0; β_1 is the slope at the baseline phase; β_2 is the level change measured at time n_1+1; β_3 is the change in slope from the baseline phase to the intervention phase; T_t is the value of the time variable T at time t; Dt is the value of the level-change dummy variable D (0 for the baseline phase and 1 for the intervention phase) at time t; SC_t is the value of the slope-change variable SC defined as [Tt -(n1 + 1)]D; n1 is the number of observations in the baseline phase; ε_t is the error of the process at time t.

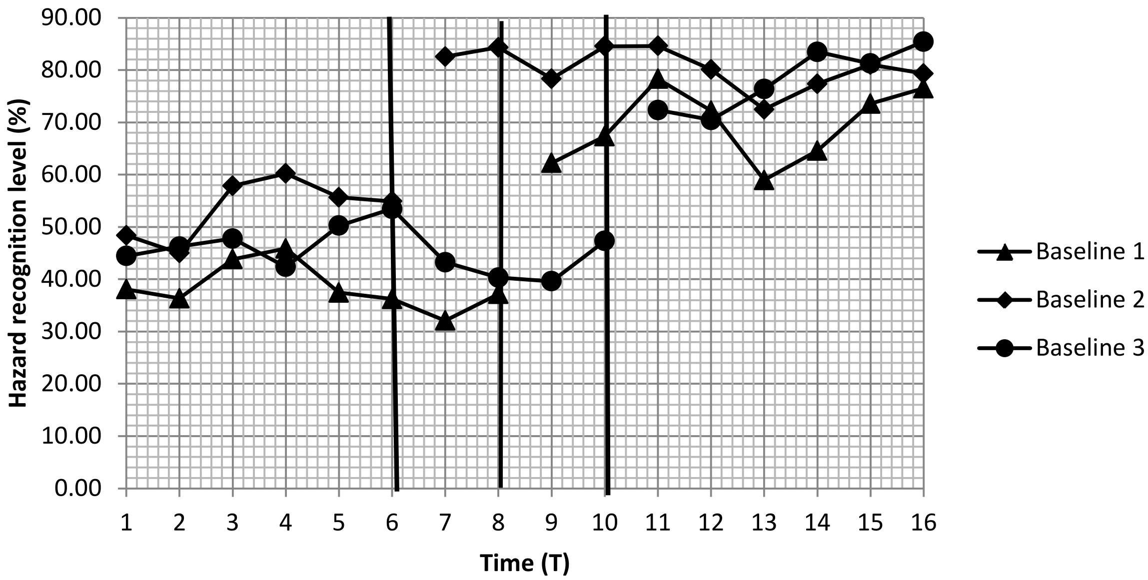

Figure 3: Response to the intervention

As evident from Equation 2, the effect sizes that will be reported would include level change, which is the immediate or sudden jump (either positive or negative) in percent performance and the slope change, which refers to the gradual improvement with elapsed time. After computation of these effect changes for each baseline, the overall effect size in level change was determined using equation 3. Similarly, the overall slope change was computed in the same way by substituting in equation 3, the corresponding variables for slope change from each baseline data.

$$LC_{overall} = \frac{\sum_{j=1}^{J} \frac{1}{\sigma_j^2} b_{LC_j}}{\sum_{j=1}^{J} \frac{1}{\sigma_j^2}} \quad (3)$$

Where J is the nmber of crews; b_{LC_j} is the level change coefficent estimated for the jth crew; σ_j^2 is the estimated standard error for the jth level change coefficient

Inferential statistical results

The results of the statistical analysis are presented in Table 3. The analysis began with the testing of the underlying assumptions required to perform regression analysis. The Levene's test for homoscedasticty of error variance and the Anderson –Darling test for normality of errors with $\alpha = 0.05$. The Durban-Watson test indicated no evidence of autocorrelation. Hence, equation 2 can be used to make valid inferences. It is important to note that if the data violated the assumption of independent errors, equation 2 would yield erroneous results. Methods to incorporate the effect of autocorrelation are presented elsewhere [47]. From Table 3, baseline 1 exhibited a level change improvement of 22.78% (p=0), which is clear evidence indicating statistically significant improvement. This represents that difference between the predicted value of HR index had the intervention not been introduced based on the pre-intervention regression line and the post-intervention regression equation for t=7. In other words, the projected baseline data for the seventh observation is 60.35% (b_0+b_1 (T)), while the expected value of the post-intervention regression line for the seventh observation is 83.14% (b_0 + b_1 (T) + b_2 (D) + b_3 (SC)). The difference between the two values represents the significant level change improvement: 22.78% (83.14% - 60.35). Similarly, baseline 2 and 3 indicated a significant level change improvement of 30.80% (p=0) and 26.95% (p=0), respectively. The overall level change improvement was 26.28% using equation 3.

The effect size associated with slope for baseline 1 (-2.504) signifies the change in slope between the pre-intervention and post-intervention phase. This indicates that the slope in the post-intervention stage is -0.59 (p=0.04), which may have occurred by chance alone assuming α = 0.05. While baseline 1 indicates a gradual decline of HR indices by 0.59% with each subsequent observation, baseline 1 and 2 suggest a gradual increase of 1% (p=0.237) and 3% (p=0.009 : statistically significant change) with each subsequent observation, respectively. Hence, overall there is significant increase in hazard recognition as a result of using the developed intervention.

Table 3: Results of construction personnel response to intervention

Predictor	Coefficient	Std. Error	t value	p value
Construction Personnel Baseline 1				
Constant	46.984	3.884	12.097	0.000
Time	1.910	0.997	1.915	0.080
D	22.782	4.593	4.960	0.000
SC	-2.504	1.098	-2.281	0.042
Construction Personnel Baseline 2				
Constant	41.528	4.632	8.996	0.000
Time	-0.701	0.917	-0.764	0.460
D	30.798	6.015	5.120	0.000
SC	1.613	1.297	1.224	0.237
Construction Personnel Baseline3				

Constant	47.225	2.747	17.191	0.000
Time	-0.314	0.443	-0.708	0.492
D	26.949	4.002	6.734	0.000
SC	3.309	1.058	3.127	0.009

Response of Construction Students to the intervention

As discussed previously, students were tested using high resolution photographs to measure the effects of introducing the intervention. ***The same protocol described above was used for the student group.*** Associated hazards in the photographs were identified by a 14 member construction expert team. To conduct the study efficiently, 39 random students were assigned to two different groups and the intervention was provided separately on a staggered basis. It is important to note that each student was assigned individual tests. Students were assigned to two groups only to utilize the benefits and rigor of the MBT design. Unlike some experimental design methods such as the Pretest-posttest control group design, where the researcher needs to ensure equivalence of the two different groups, the MBT method excludes between groups variability as comparisons are made within each baseline. In other words, effect size is computed by comparing a single subject's performance in the pre-intervention phase and the post-intervention phase.

Statistical analysis involved the same steps as was performed with the construction personnel. After testing the underlying assumptions, equation 2 parameters were estimated by regressing the dependent variable on the predictor variables. Tables 4 and 5 summarize the results of construction student response to the intervention. In the table B_2 corresponds to the level change improvement in hazard recognition for a particular student, B_3 corresponds to the slope change improvement in hazard recognition performance for each student, and the p-value indicates the statistical significance of the change.

As can be observed from the p-values, 62% of students exhibited a statistically significant level-change improvement and 38% of students exhibited no statistically significant change in performance. However, the overall MTB study illustrated a statistically significant level change improvement of 21% ($p = 0$), which was computed using Equation 3. The results of the study do not reveal the presence of an overall slope change.

Table 4: Results of construction student response to intervention (Student Group 1)

Student	B_2	p-value	B_3	p-value
1	25.183918	0.046599	5.4984954	0.0696854
2	31.558197	0.0063425	0.7412186	0.7518473
3	9.149857	0.4457604	2.7935344	0.3427928
4	24.832205	0.0327014	1.8738484	0.4651401
5	26.316917	0.0726581	1.5881687	0.632494
6	2.2764656	0.8443964	-5.0983492	0.0916382
7	17.39571	0.1645352	-1.7991709	0.5400258
8	50.085614	0.0099606	3.8102186	0.3524869
9	13.491639	0.2666123	-6.4694689	0.0417182
10	22.154732	0.0286444	0.0927813	0.9662567
11	30.047955	0.0043949	1.3550348	0.5221815
12	1.9602373	0.8575789	-3.4014259	0.2172282
13	12.826337	0.0993856	-5.5816073	0.0082235
14	29.114819	0.0394666	2.6075758	0.4086817
15	42.00424	0.0007712	3.4410137	0.1504571
16	30.136726	0.0123775	3.6074318	0.1701513
17	6.5151588	0.5467437	0.8210888	0.7536573
18	39.983787	0.0295854	-2.1791887	0.5872689
19	28.797469	0.0087492	1.9774945	0.3890009
20	17.590765	0.0785685	-2.4457019	0.2919233
21	10.148555	0.5544045	-0.5588261	0.8928354
22	23.399758	0.0364517	-1.617032	0.5132793
23	12.794563	0.3457771	-3.6758438	0.269818

Table 5 - Results of construction student response to intervention (Student Group 2)

Student	B_2	p-value	B_3	p-value
1	36.445277	0.0303921	1.1563479	0.7787772
2	19.047518	0.025256	0.3859371	0.8510135
3	14.161905	0.3356985	2.6857143	0.5171887
4	32.348642	0.0048495	0.3350966	0.8926885
5	35.563298	0.0203207	-3.4329245	0.3596316
6	58.81214	0.0046575	7.314055	0.1306302
7	18.913397	0.3473241	2.045904	0.7161862
8	26.362764	0.015321	2.7484342	0.2964889
9	21.230652	0.0372547	0.6861726	0.7856739
10	11.482192	0.4390227	2.1870807	0.6032186
11	29.87153	0.0372349	2.3770024	0.5082253
12	16.594088	0.0376121	0.7794206	0.6941897
13	6.4041514	0.6169649	-0.5099948	0.8886674
14	30.994587	0.0949553	-0.2710551	0.9553637
15	19.056943	0.027389	-1.1449979	0.5880275
16	12.185059	0.6089497	-3.0719278	0.6521834

Discussion of Results

Apart from showing the effectiveness of using SAVES and associated protocol as a training tool to improve hazard recognition skills, several other observations were made during the study. First, the research provided strong evidence suggesting that construction personnel and construction students lack adequate hazard recognition skills. This finding, in fact corroborates already established research indicating that workers are often exposed to unperceived risks on dynamic construction projects [23]. Although, a review of method statements from three construction projects indicated hazard recognition levels that ranged between 66.5% to 89.9%[23], this research indicates that construction personnel hazard identification capability ranged between 32% to 60%. This is not surprising given that this previous study benchmarked performance with construction publications and risk logs rather than direct observations in dynamic environments.

In this study, construction students were tested based on high-resolution photographs rather than on construction projects. This approach does not require skills associated with predicting construction tasks and procedures that will be undertaken in the near future. Yet, construction students, during the pre-intervention phase, performed rather poorly when compared to construction personnel. The HR_{index} for construction students ranged between 7% and 50% with an average of 23%, where construction personnel scored between 32% and 60% with an average of 45%. On exploring the reason for this difference, observations indicated that construction students with no field experience could not recognize construction processes and aspects of construction equipments used on projects. For example, one student requested extra information on what was a simple welding screen. The student had never seen a welding screen before and wanted help with its application. In several other instance, students inaccurately identified gas operated tools as being operated on electricity. Such ignorance on equipment and construction processes could yield dangerously inappropriate responses to mitigate risk. To resolve such lack in knowledge, field visits to construction projects must be made a part of regular university curriculum. Although augmented safety training systems may help in educating students on construction processes, their focus is on educating students on safety issues.

We also observed that construction students navigated with more ease in the virtual environment. This was evident from the fact that construction students on average navigated 28 work-scenarios in a given hour while construction personnel completed only about 21 work scenarios. Although this may be attributed to the difference in exposure to such technology between generation X and Y learners, it is surprising that construction personnel improved by 26% as opposed to 21% after the training session. We believe this is because construction personnel are more knowledgeable about construction processes and methods than are construction students.

Conclusion

The role of educators is to equip students with skill-sets required for their professional success. Unfortunately, researchers have shown that graduating students often do not have adequate skills to apply acquired theory in practice. Educators in the construction field have suggested frequent field visits to enhance student's practical knowledge. Obtaining such frequent access to industry projects are often a challenge and impractical at other situations. In this study we developed an augmented reality construction safety training system (SAVES) to immerse participants in a hyper-realistic construction environment to develop hazard recognition skills. Tests with construction personnel and construction students reveal a significant improvement in hazard recognition skills. Thus, augmented reality provides a feasible and highly potential alternative to construction educationalists to help students recognize hazards, when frequent access to dynamic construction projects is unrealistic. Further, this research reveals that the use of augmented virtual environments in construction education enhances intellectual excitement and retention.

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