HAZARD RECOGNITION IN DESIGN: EVALUATING THE EFFECTS OF DESIGN INFORMATION ON HAZARD RECOGNITION PERFORMANCE

by

DYLAN CLEE HARDISON

B.S., East Carolina University, 2010

M.S., East Carolina University, 2012

M.S., University of Colorado Boulder, 2017

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written by Dylan Clee Hardison

has been approved for the Department of Civil, Environmental, and Architectural Engineering

____

Professor Matthew R. Hallowell, Chair

____

Professor Ray L. Littlejohn

____

Professor Paul M. Goodrum

____

Professor Michael Behm

____

Professor Alex Albert

Date_________________________

The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the abovementioned discipline

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ABSTRACT

Dylan C. Hardison (Ph.D., Civil Engineering)

Hazard Recognition in Design: Evaluating the Effects of Design Information on Hazard Recognition

Dissertation directed by: Professor. Matthew R. Hallowell

The construction industry has long been known for its high injury and fatality rate. To combat this, researchers and practitioners have strived to develop new safety management methods to reduce construction safety risks. One of these methods is known as Construction Hazard Prevention through Design (CHPtD). CHPtD theory is founded in recognizing construction safety hazards during the design phase of a project so they may be removed with design solutions. Although this theory has seen substantial research and promotion as an effective safety management practice, the efficacy of the theory remains untested. To test the viability of recognizing safety hazards in design, a series of simulated design for safety reviews with civil engineering students, construction and engineering designers, and construction supervisors were conducted across the United States to explore the effects that different formats of design information had on hazard recognition. Over the course of one year and a half, 117 participants were provided one of three information formats including: two-dimensional (2D) computer aided design (CAD) drawings, three-dimensional (3D) computerized visualizations, and a combination of the two (2D & 3D) through a Latin square experimental design. Participants were asked to explore the design information and identify as many safety hazards as they could for three separate construction work activities. The primary metrics tested include: hazard recognition performance, spatial cognition, and mental workload. This dissertation's primary contributions include the development of an empirical research agenda and an examination of the effects of design information on hazard recognition performance. The results suggest that the format of design information has no effect on hazard recognition performance. Additionally, it was found that mental workload and participants spatial cognition were not related to hazard recognition performance. However, it was found that experience is a key player in predicting hazards during design. These findings suggest that approximately one-half of safety hazards present in the construction phase of a project are identifiable during design. Additionally, the results confirm the necessity for experienced construction professionals' involvement in the CHPtD process to ensure that hazards are recognized, and may therefore be controlled.

DEDICATION

To my dear and beloved wife, Jessica Hardison, for her support, help, patience, and love during this challenging journey. To my parents, Lynn Hill and Rick Hardison, and my grandmother, Marianna Hill for their encouragement throughout my life. To my brother Clay for his encouragement. Additionally, to those whom have lost their lives and have been injured from on-the-job accidents, I dedicate this work to you.

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Chapter 1: Introduction

1.1 Background and Motivation

The construction industry has long been one of the most hazardous of all industrial sectors in the world. Construction accidents come at a great economic cost for both the construction industry and society in general. This includes the direct and indirect costs of accidents coupled with socioeconomic factors associated with construction accidents (Oritz et al. 2009). In response to the many dangers of construction work, researchers and practitioners have developed a plethora of safety management methods and theories to reduce construction safety risks. One of these theories is known as Construction Hazard Prevention through Design (CHPtD). The CHPtD theory is founded in recognizing construction safety hazards during the design phase of a project so they may be removed with design solutions (Gambatese et al., 2008). This theory has been extolled as a superior method of safety risk reduction (Szymberski, 1997; Toole, 2005; Gambatese et al., 2008; Manu et al., 2012) as its central premise, hazard elimination, lies at the top of the well renowned hierarchy of safety controls (Hecker and Gambatese 2003). In the past 20 years, there has been abundant research into CHPtD, which has resulted in a large and dispersed body of literature. Although this literature is rich with many valuable contributions, existing publications have focused heavily on perceptions and conceptual ideas rather than empirical evidence (Hinze and Wiegand, 1992; Szymberski, 1997; Gambatese and Hinze, 1999; Griffith and Phillips, 2001; Huang and Hinze, 2006; Votano and Sunindijo, 2014; Goh and Chua, 2016; Martínez-Aires et al., 2016; Toole et al., 2016). This research has helped to propel CHPtD as a component of government regulation in the United Kingdom and Australia and promotion in the United States. Before political measures are taken, empirical evidence should be collected and an unbiased evaluation of the method's efficacy should be performed.

Hazard Recognition in Construction

In general, safety planning relies on individuals' abilities to foresee and predict construction safety hazards (Albert et al 2014). However, research has shown that construction workers recognize approximately one-half of hazards to which they are exposed to within dynamic construction environments (Carter and Smith, 2006; Bahn, 2013; Lopez del Puerto et al., 2013; Albert et al., 2014). This alarming statistic has become the initiative to improve workers hazard recognition skills by using mnemonics (Albert et al. 2013; Hallowell and Hansen 2016), emotions (Tixier et al 2014; Bhandari 2017), and virtual reality experiences (Hadikusumo and Rowlinson 2004; Tixier et al. 2013; Albert et al. 2014).

Recently, in the context of CHPtD research, Hallowell and Hansen (2016) examined the ability of designers to use Computer Aided Design (CAD) drawings to forecast the presence of downstream construction hazards. They assessed the ability of 17 construction designers to recognize safety hazards for 12 different work activities using actual CAD designs. The safety hazards for each work activity were known from actual work observations and interviews from contractor teams. The results show that designers possess the skill to recognize approximately one-half of safety hazards which are present during design.

Construction Hazard Prevention through Design

Construction Hazard Prevention through Design (CHPtD) involves recognizing, projecting, and removing or controlling design elements that create construction hazards (Behm 2005; Seo and Choi 2008; Driscoll et al. 2008; Ghaderi and Kasirossafar 2011; Hallowell and Hansen 2016). This is often done by reviewing project design information through a CHPtD review process and recognizing hazards relating to construction, maintenance, repair, and demolition (Suraji et al. 2001; WorkCover 2001; Gambatese et al. 2008; Ganah and John 2015; NIOSH 2017). Project design information used in CHPtD processes may include, but is not limited to, the following: two-dimensional computer-aided-design (2D CAD) drawings (Chantawit et al. 2005), material specifications (Brexendale and Jones 2000), three-dimensional building information models (BIM) (Ganah and John 2015 and Zhang et al. 2015), and augmented and virtual reality (AR/VR) (Hadikusumo and Rowlinson 2004 and Sacks et al. 2015). Although many design technologies have evolved over the past 20 years, CAD drawings remain the primary method to convey design intent to construction personnel as they provide the basic technical graphical and textural information needed for construction (Goodrum et al 2016). Some researchers have suggested that CAD and BIM both offer rich opportunity for hazard recognition in design (De Lapp et al. 2004 and Ganah and John 2015), while others have postulated that CAD does not provide an efficient platform for to acquire spatial project information (Collier 1994; Young 1996; and Zhang et al. 2015) nor information relating to the relationships of project constraints, conditions, and trades (Chantawit et al. 2005). Furthermore, some have proposed that BIM offers better opportunities to recognize safety hazards by digitally replicating the physical work environment and aiding in the mental interpretation of spatial constraints and construction sequences (Ku and Mills 2010; Bansal 2011; Ganah & John 2015; and Zhang et al. 2015). These postulations suggest that 3D visualizations of project design information will reduce the mental workload of hazard recognition tasks and improve overall hazard recognition performance.

It is recognized that there is an assumption that the format of construction design information affects peoples' abilities to recognize hazards and affects the level of mental workload of hazard recognition tasks (Ku and Mills 2010; Bansal 2011; Ganah & John 2015; and Zhang et al. 2015). However, these assumptions fail to consider the effects that humans spatial cognitive capabilities have on the mental interpretation of construction designs thereby affecting mental workload. Investigating these effects on hazard recognition performance provides an opportunity to test current assumptions in construction safety literature.

Mental workload and its measurement

The concept of mental workload is based on the premise that there is an upper limit to humans' abilities to process information and generate responses (Hicks and Wierwille 1979; Carswell 2005). Under this premise in the context of construction safety, design information should be designed to require low mental demands for extracting safety information during hazard recognition activities (Dadi et al. 2014a). To date, no research has examined the mental workload associated with hazard recognition tasks stemming from design information. Examining the effects of mental workload during hazard recognition tasks across different formats of design information may discover knowledge to help improve the quality of pre-construction safety plans.

The primary methods of measuring mental workload fall into three distinct categories: physiological, secondary task, and subjective (Hicks and Wierwille 1979; Carswell 2005). Physiological measures include electroencephalogram (Gerjets et al. 2014; Zander & Kothe 2011), magnetic resonance imaging (Whelan 2007), functional near-infrared spectroscopy (Strangman et al. 2002; Coyle et al. 2004), pupillometry (Kuchinke et al. 2007; Jainta and Baccino 2010), and cardiovascular metrics (Mulder 1998 and Martin 2014). Secondary task measurements measure the level of performance of a primary task in conjunction with a secondary task (Hicks and

Wierwille 1979). Lastly, subjective measurements of mental workload assessment employ self-reporting ratings of the difficulties of tasks through the National Aeronautics and Space Administration’s Task Load Index (NASA-TLX) and the Subjective Workload Assessment Technique (SWAT) (Martin 2014). For this study, the NASA-TLX was used as it is nonintrusive and is simple administer (Rubio et al, 2004; Martin 2014). The NASA-TLX is a subjective workload assessment technique that derives an overall mental workload score based on an average rating of six subscales including: mental demand, physical demand, temporal demand, performance, effort, and frustration level. This mental workload assessment method was used to evaluate the variability in mental workload of hazard recognition tasks for the different formats of design information.

The objective of this doctoral dissertation is to address all the aforementioned gaps in the current body of knowledge and further advance the knowledge of CHPtD implementation. This objective will help to ensure that CHPtD advances from merely a theory into a scientifically validated practice with known benefits.

1.2 Current needs for additional research

Considering existing literature, there are several gaps in construction safety literature concerning the efficacy of CHPtD implementation. Although many researchers have extolled CHPtD as a superior method of safety risk reduction (Szymberski, 1997; Toole, 2005; Gambatese et al., 2008; and Manu et al., 2012), little research to date has examined the theories validity with empirical testing. The foremost empirical CHPtD research needs in the construction industry are summarized below:

- Examining the effects of the various formats of design information on hazard recognition during project design stages.
- Examining the relationships between the mental workload of hazard recognition tasks using various formats of design information and hazard recognition performance.
- Examining the relationship of spatial cognition and hazard recognition during design.

Addressing these gaps is the purpose of this doctoral dissertation.

1.3 Dissertation organization

The present document is organized into 5 chapters. The first chapter consists of the introduction where the background, motivation, point of departure, and a summary of each study. This document contains 3 standalone studies developed by the author which address the research needs presented above. These documents are structured in journal paper format with their corresponding abstract, introduction, methodology, results, and conclusions. These 3 studies can be found in chapters 2 – 4. Chapter 5 of this dissertation, presents an overall conclusion with a summary of the contributions to knowledge achieved by the 3 studies. Additionally, future research concerning the nexus of hazard recognition and Construction Hazard Prevention through Design theory is presented.

1.4 Dissertation content and contributions

This section briefly explains the research needs addressed in each paper and the knowledge obtained from each study.

The 1st paper presented in the dissertation can be found in chapter 2 under the title: "*Construction hazard prevention through design: Review of theory and empirical research agenda*." This paper provides a detailed review of Construction Hazard Prevention through Design (CHPtD) literature and a careful distinction between scientific evidence and subjective theory. In this paper, literature is reviewed as it relates to the efficacy of CHPtD, available tools to assist designers with hazard recognition, and use of technology to enable CHPtD. The review contributes to the current literature by uncovering vital knowledge gaps and creating a set of testable hypotheses that define a viable scientific research agenda for the domain. Themes of future empirical research includes understanding hazard recognition during design using available documentation and technological platforms, experimentally testing the efficacy of CHPtD tools, and the lifecycle safety risk assessments of proposed CHPtD solutions. In addition to providing an agenda, this paper may serve as a single resource for researchers and practitioners that summarizes and codifies a large and dispersed body of knowledge. This paper was submitted to *Safety Science* journal in January of 2018.

The 2nd paper presented in the dissertation can be found in chapter 3 under the title: "*Hazard Recognition in Design: A Latin square evaluation of the effects of design information on hazard recognition and prevention through design*." In this paper, a series of simulated design for safety reviews with civil engineering students, construction and engineering designers, and construction supervisors were conducted across the United States to explore the effects that different formats of design information had on hazard recognition performance. In total, 117 participants were provided one of three information formats including: two-dimensional (2D) computer aided design (CAD) drawings, three-dimensional (3D) computerized visualizations, and a combination of the two (2D & 3D) through a Latin square experimental design. Participants were asked to explore the design information and identify as many safety hazards as they could for three separate construction work activities including: rooftop skylight installation, interior soffit drywall installation, and interior metal wall stud framing. This paper's primary contribution centers around the discovering how design information affects peoples' abilities to recognize safety hazards. Statistical analyses include ANOVA and t-test procedures. The results suggest there is no significant effect of design information formats on hazard recognition performance score. It was also discovered that experience has little effect on hazard recognition performance within population groups. However, ANOVA and regression analysis suggests experience does significantly affect hazard recognition performance across population groups. This research challenges the assumption that three-dimensional design information is superior to two-dimensional information and confirms that those involved in Construction Hazard Prevention through Design (CHPtD) processes have construction experience and knowledge to recognize safety hazards in design and thereby implement CHPtD solutions.

The 3rd paper is a continuation of paper #2. Paper #3 contains the same sample of paper #2. However, different hypotheses are tested. This work is separate from paper #2 as it stands alone as written and tests hypotheses relating to mental workload and spatial cognition across the different formats of design information. Specifically, paper #3 aims to determine if subjects' spatial cognition skill and mental workload influenced hazard recognition performance by employing a mixture of two- and three-dimensional construction design information formats. Participants were provided mutually-exclusive arrangements of traditional, two-dimensional computer aided design drawings, three-dimensional computer visualizations, and a combination of the two formats and asked to identify all possible safety hazards from three discrete construction work activities. All safety hazards were known from previously validated research. Participants completed card and cube rotation tests to assess each participants' spatial cognition. Additionally, participants completed a mental workload for via NASA-TLX for each sequential experimental trial. This paper departs from the body of knowledge by evaluating how the format of design information and spatial cognition affect hazard recognition via a simulated pre-construction constructability review. The results suggest that mental workload is not related to hazard recognition performance within and across all design information formats. Additionally, spatial cognition was not found to be related to hazard recognition performance. However, it was found that participants experience in the construction industry does predict hazard recognition performance. This paper is the first attempt in literature to evaluate the mental workload of hazard recognition tasks and validated the importance for those involved in CHPtD processes to have construction experience for effective hazard recognition. Figure 1 below provides a graphic representation of each studies scope, research questions, and key research findings.

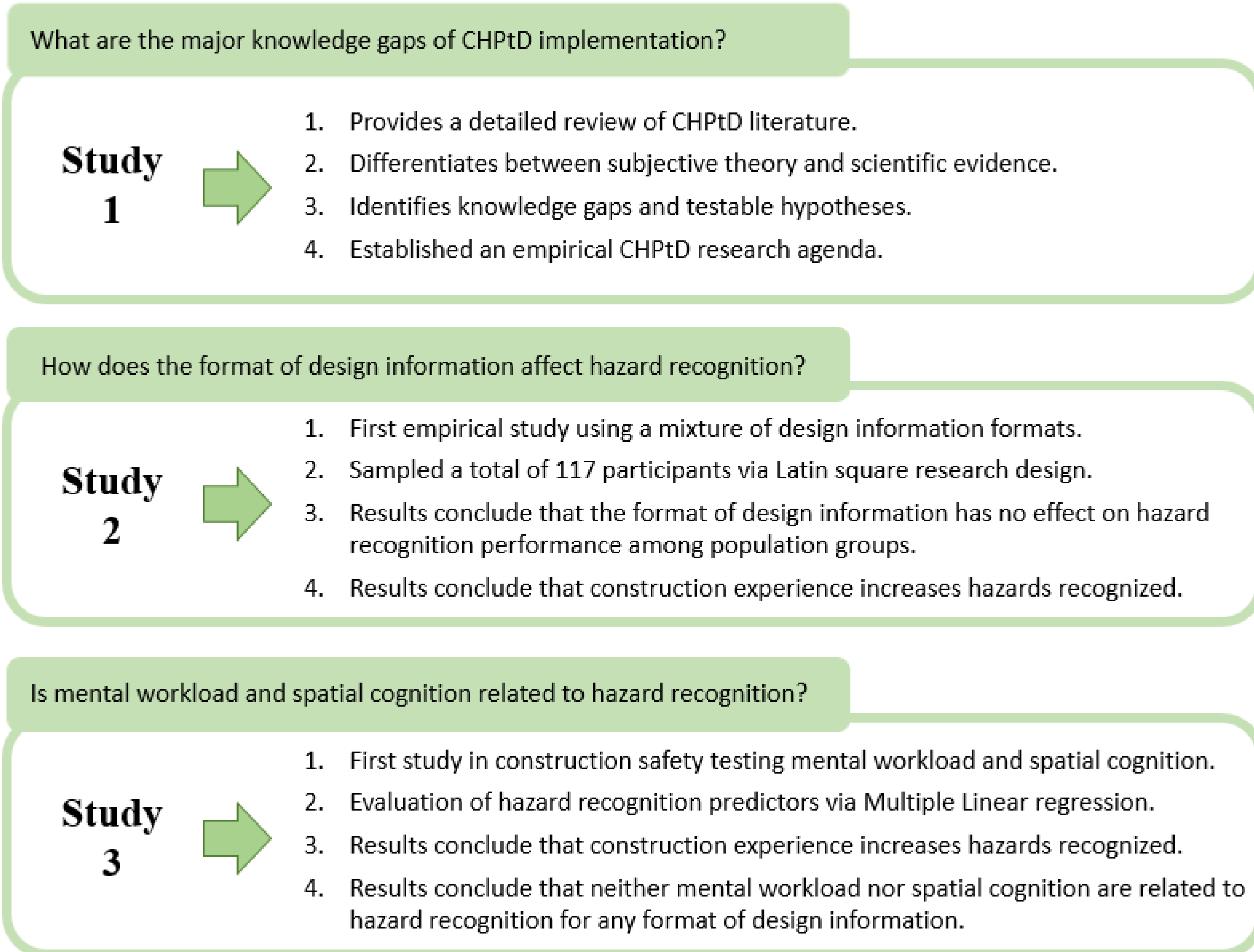

Figure 1: Research questions, scopes, and key findings

1.5 References

Albert, A., Hallowell, M. R., & Kleiner, B. M. (2013). Enhancing construction hazard recognition and communication with energy-based cognitive mnemonics and safety meeting maturity model: Multiple baseline study. Journal of Construction Engineering and Management, 140(2), 04013042.

Albert, A., M. Hallowell, B. Kleiner, A. Chen, and M. Golparvar-Fard. (2014). “Enhancing Construction Hazard Recognition with High-Fidelity Augmented Virtuality.” *Journal of Construction Engineering and Management* 140 (7): 04014024.

Bahn, S. (2013). Workplace hazard identification and management: The case of an underground mining operation. *Safety science*, *57*, 129-137.

Bansal, V. K. (2011). Application of geographic information systems in construction safety planning. *International Journal of Project Management*, *29*(1), 66-77.

Behm, M. (2005). Linking construction fatalities to the design for construction safety concept. *Safety science*, *43*(8), 589-611.

Bhandari, S., & Hallowell, M. R. (2017). Emotional Engagement in Safety Training: Impact of Naturalistic Injury Simulations on the Emotional State of Construction Workers. Journal of Construction Engineering and Management, 143(12), 04017090.

Baxendale, T. and O. Jones (2000). "Construction design and management safety regulations in practice—progress on implementation." International Journal of Project Management 18(1): 33-40.

Carswell, C. M., Clarke, D., & Seales, W. B. (2005). Assessing mental workload during laparoscopic surgery. *Surgical innovation*, *12*(1), 80-90.

Carter, G., & Smith, S. D. (2006). Safety hazard identification on construction projects. *Journal of construction engineering and management*, *132* (2): 197-205.

Chantawit, D., Hadikusumo, B., Charoenngam, C., & Rowlinson, S., (2005),"4DCAD-Safety: visualizing project scheduling and safety planning", Construction Innovation, Vol. 5 Iss 2 pp. 99 – 114

Collier, E. B. 1994. ‘‘Four-dimensional modelling in design and construction.’’ thesis, Stanford Univ., Stanford, Calif.

Coyle, S., Ward, T., Markham, C., & McDarby, G. (2004). On the suitability of near-infrared (NIR) systems for next-generation brain–computer interfaces. *Physiological measurement*, *25*(4), 815.

Dadi, G. B., Goodrum, P. M., Taylor, T. R., & Carswell, C. M. (2014a). Cognitive workload demands using 2D and 3D spatial engineering information formats. Journal of Construction Engineering and Management, 140(5), 04014001.

De Lapp, J. A., Ford, D. N., Bryant, J. A., & Horlen, J. (2004). Impacts of CAD on design realization. Engineering, Construction and Architectural Management, 11(4), 284-291.

Driscoll, T. R., Harrison, J. E., Bradley, C., & Newson, R. S. (2008). The role of design issues in work-related fatal injury in Australia. *Journal of Safety Research*, *39*(2), 209-214.

Gambatese, J. and J. Hinze (1999). "Addressing construction worker safety in the design phase: Designing for construction worker safety." *Automation in Construction*, 8(6), 643-649.

Gambatese, J. A., Behm, M., & Rajendran, S. (2008). Design's role in construction accident causality and prevention: Perspectives from an expert panel. *Safety science*, *46*(4), 675-691.

Ganah, A., & John, G. A. (2015). Integrating building information modeling and health and safety for onsite construction. *Safety and health at work*, *6*(1), 39-45.

G Gerjets, P., Walter, C., Rosenstiel, W., Bogdan, M., & Zander, T. O. (2014). Cognitive state monitoring and the design of adaptive instruction in digital environments: lessons learned from cognitive workload assessment using a passive brain-computer interface approach. Frontiers in Neuroscience, 8, 385

Ghaderi, R., & Kasirossafar, M. (2011). Construction safety in design process. In *AEI 2011: Building Integration Solutions* (pp. 464-471).

Goh, Y. M., & Chua, S. (2016). Knowledge, attitude and practices for design for safety: a study on civil & structural engineers. *Accident Analysis & Prevention*, *93*, 260-266.

Goodrum, P. M., Miller, J., Sweany, J., & Alruwaythi, O. (2016). Influence of the format of engineering information and spatial cognition on craft-worker performance. *Journal of Construction Engineering and Management*, *142*(9), 04016043.

Griffith, A., & Phillips, N. (2001). The influence of the Construction (Design and Management) Regulations 1994 upon the procurement and management of small building works. *Construction Management and Economics*, *19*(5), 533-540.

Hadikusumo, B. and S. Rowlinson (2004). "Capturing Safety Knowledge Using Design-for-Safety-Process Tool." *Journal of Construction Engineering and Management* 130(2): 281-289.

Hallowell, M. R. and D. Hansen (2016). "Measuring and improving designer hazard recognition skill: Critical competency to enable prevention through design." *Safety Science* 82: 254-263.

Hecker, S. and J. Gambatese (2003). "Safety in Design: A Proactive Approach to Construction Worker Safety and Health." Applied Occupational and Environmental Hygiene 18(5): 339-342.

Hicks, T. G., & Wierwille, W. W. (1979). Comparison of five mental workload assessment procedures in a moving-base driving simulator. *Human Factors*, *21*(2), 129-143.

Hinze, J., & Wiegand, F. (1992). Role of designers in construction worker safety. *Journal of construction engineering and management*, *118*(4), 677-684.

Huang, X., & Hinze, J. (2006). Owner's role in construction safety. *Journal of construction engineering and management*, *132*(2), 164-173.

Jainta, S., & Baccino, T. (2010). Analyzing the pupil response due to increased cognitive demand: an independent component analysis study. *International Journal of Psychophysiology*, *77*(1), 1-7.

Ku, K., & Mills, T. (2010). Research needs for building information modeling for construction safety. In *International Proceedings of Associated Schools of Construction 45nd Annual Conference, Boston, MA.*

Kuchinke, L., Võ, M. L., Hofmann, M., & Jacobs, A. M. (2007). Pupillary responses during lexical decisions vary with word frequency but not emotional valence. International Journal of Psychophysiology, 65, 132–140. doi:10.1016/j.ijpsycho.2007.04.004

Lopez del Puerto, C., Clevenger, C. M., Boremann, K., & Gilkey, D. P. (2013). Exploratory study to identify perceptions of safety and risk among residential Latino construction workers as distinct from commercial and heavy civil construction workers. *Journal of Construction Engineering and Management*, *140* (2): 04013048 - 1 – 04013048 - 7.

Manu, P. A., Ankrah, N. A., Proverbs, D. G., & Suresh, S. (2012). Investigating the multi-causal and complex nature of the accident causal influence of construction project features. *Accident Analysis & Prevention*, *48*, 126-133.

Martínez-Aires, M. D., López-Alonso, M., & Martínez-Rojas, M. (2018). Building information modeling and safety management: A systematic review. *Safety Science*, *101*, 11-18.
Martin 2014

NIOSH. (2017). Prevention Through Design. Retrieved August 05, 2017, from https://www.cdc.gov/niosh/topics/ptd/default.html

Ortiz, O., Castells, F., & Sonnemann, G. (2009). Sustainability in the construction industry: A review of recent developments based on LCA. Construction and Building Materials, 23(1), 28-39.

Rubio, S., Díaz, E., Martín, J., & Puente, J. M. (2004). Evaluation of subjective mental workload: A comparison of SWAT, NASA-TLX, and workload profile methods. *Applied Psychology*, *53*(1), 61-86.

Seo, J. W., & Choi, H. H. (2008). Risk-based safety impact assessment methodology for underground construction projects in Korea. *Journal of construction engineering and management*, *134*(1), 72-81.

Sacks, R., J. Whyte, et al. (2015). "Safety by design: dialogues between designers and builders using virtual reality." *Construction Management and Economics* 33(1): 55-72.

Suraji, A., Duff, A. R., & Peckitt, S. J. (2001). Development of causal model of construction accident causation. Journal of construction engineering and management, 127(4), 337-344.

Szymberski, R. (1997). "Construction project safety planning." TAPPI Journal 80(11): 69-74.

Strangman, G., Culver, J. P., Thompson, J. H., & Boas, D. A. (2002). A quantitative comparison of simultaneous BOLD fMRI and NIRS recordings during functional brain activation. *Neuroimage*, *17*(2), 719-731.

Tixier, A., Albert, A., & Hallowell, M. R. (2013). Teaching construction hazard recognition through high fidelity augmented reality. In Proc., 2013 American Society of Engineering Education Annual Conf (pp. 1-23).

Tixier, A. J. P., Hallowell, M. R., Albert, A., van Boven, L., & Kleiner, B. M. (2014). Psychological antecedents of risk-taking behavior in construction. Journal of Construction Engineering and Management, 140(11), 04014052. Chicago

Toole, T. M. (2005). Increasing engineers’ role in construction safety: Opportunities and barriers. Journal of Professional Issues in Engineering Education and Practice, 131(3), 199-207.

Toole, T. M., Gambatese, J. A., & Abowitz, D. A. (2016). Owners’ role in facilitating prevention through design. *Journal of Professional Issues in Engineering Education and Practice*, *143*(1), 04016012.

Votano, S., & Sunindijo, R. Y. (2014). Client safety roles in small and medium construction projects in Australia. *Journal of Construction Engineering and Management*, *140*(9), 04014045.

Whelan, R. R. (2007). Neuroimaging of cognitive load in instructional multimedia. Educational Research Review, 2, 1–12

Workcover, A. (2001). Construction Hazard Assessment Implication Review–CHAIR.

Young, S. (1996). ‘‘Construction safety: A vision for the future.’’ *J. Manage. Eng.,* 12(4), 33–36.

Zander, T., & Kothe, C. (2011). Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general. Journal of Neural Engineering, 8, 025005.

Zhang, S., Sulankivi, K., Kiviniemi, M., Romo, I., & Eastman, C. (2015). BIM-based fall hazard identification and prevention in construction safety planning. Safety Science, 72, 31-45.

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Chapter 2: Construction hazard prevention through design: Review of theory and empirical research agenda

Dylan Hardison and Matthew Hallowell

2.1 Abstract

Construction Hazard Prevention through Design (CHPtD) is the consideration for worker safety in the design phase of a construction project. The CHPtD theory has seen an abundance of research in recent years, most of which research has been conducted to validate the CHPtD concept using logical argument and subjective evidence. However, there is a dearth of empirical evidence validating the concept and the actual risk reduced via design decisions over a project lifecycle remains unknown. Although CHPtD is supported by many government agencies around the world and has even become legislation in some, empirical validation could serve as a catalyst of implementation. This paper provides a detailed review of CHPtD literature and a careful distinction between scientific evidence and subjective theory. Specifically, literature is reviewed as it relates to the efficacy of CHPtD, available tools to assist designers with hazard recognition, and use of technology to enable CHPtD. The review contributes to the current literature by uncovering vital knowledge gaps and creating a set of testable hypotheses that define a viable scientific research agenda for the domain. Themes of future empirical research include understanding hazard recognition during design using available documentation and technological platforms, experimentally testing the efficacy of CHPtD tools, and the lifecycle safety risk assessments of proposed CHPtD solutions. In addition to providing an agenda, this paper may serve as a single resource for researchers and practitioners that summarizes and codifies a large and dispersed body of knowledge.

2.2 Introduction

Construction work is dangerous because it requires the introduction of energy into work environments. This introduction of energy often creates hazards that expose workers and the public to risk (Hallowell et al., 2017). For this reason, researchers have strived to develop new safety management theories and methods that help practitioners recognize hazards, mitigate risks, and reduce exposures. One of these theories, Construction Hazard Prevention through Design (CHPtD), involves the explicit consideration of worker safety during the design phase of a project. To effectively implement the CHPtD theory and process, hazards are recognized and eliminated or controlled during project design (Gambatese et al., 2008). Often, safety risk mitigation requires adjustment to the final design to protect worker well-being (Rajendran and Gambatese, 2013).

CHPtD is an extension of a broader theory known as Prevention through Design (PtD), which involves the consideration of hazards related to equipment; tools; industry products; new and existing technologies; and work methods, operations, and processes (NIOSH, 2017). The method typically considers the entire lifecycle, including construction, maintenance, repair, and demolition. CHPtD specifically encompasses the efforts of recognizing and removing *construction* safety hazards during the design of the facility. This theory will be the focus of the present paper.

In the past 20 years, there has been abundant research into CHPtD, which has resulted in a large and dispersed body of literature. Although this literature is rich with many valuable contributions, existing publications have focused heavily on perceptions and conceptual ideas rather than empirical evidence (Hinze and Wiegand, 1992; Szymberski, 1997; Gambatese and Hinze, 1999; Griffith and Phillips, 2001; Huang and Hinze, 2006; Votano and Sunindijo, 2014;

Goh and Chua, 2016; Martínez-Aires et al., 2016; Toole et al., 2016). As will be discussed in this critical review, despite the lack of empirical evidence, CHPtD has been extolled as a superior method of safety risk reduction (Szymberski 1997; Toole 2005; Gambatese et al. 2008; and Manu et al. 2012). CHPtD has even become a component of government regulation in the United Kingdom and Australia and promotion in the United States. Before such bold measures are taken, empirical evidence should be collected and an unbiased evaluation of the method's efficacy should be performed.

The purpose of this paper is to provide a scientifically critical review of available CHPtD literature, with emphasis on the distinction between subjective and empirical evidence. The aim is to review the large and dispersed body of CHPtD literature, provide the scientific community with a true state of scientific knowledge, and highlight opportunities for future research and scientific debate. This review makes a strong and potentially controversial distinction between theoretical and empirical knowledge akin to those made in other scientific fields (e.g., theoretical physics and experimental physics). It is our argument, that to promote safety as a science, we must not only create concepts, models, hypotheses, and propositions, but also seek to prove them false with empirical evidence. It is not our position that empirical evidence is more important than theory; rather, we adopt the position that both are important for scientific discourse. A stronger scientific debate and more stringent testing of theory may help to advance the practical implementation of CHPtD, especially given the strong political and contractual barriers that the method faces in a fragmented construction industry. Simply, the translation of CHPtD as a "good idea" to scientifically tested strategy with known benefits may transition the method from scientific theory into legislation or industry standard practice.

2.3 Research Objectives and Point of Departure

The specific goals of this study were to: (1) provide an overview of the CHPtD literature; (2) differentiate theoretical, subjective, and empirical evidence; (3) identify the overall strengths and limitations in the current body of knowledge; and (4) propose the future needs of CHPtD research that will bridge identified gaps. To date, there is no research that examines the totality of CHPtD literature or attempts to provide such distinction. This is also the first known scientific review of a specific safety strategy. It is recognized that this paper may be controversial in nature as it criticizes the aggregate CHPtD literature for a lack of empirical evidence. However, the authors have written the paper to catalyze debate and new inquiry.

2.4 Review Methodology

The first step of this analysis was to perform a comprehensive review of CHPtD literature published in peer-reviewed journals. *Google Scholar* and *Web of Science* were used as a search databases and the key search phrases were "Design for Safety," "Design for Construction Safety," "Safety through Design," "Prevention through Design," "Construction Safety," "Construction Hazard Prevention through Design," and "Hierarchy of Safety Controls." The reference sections of papers identified from this search were then used to locate additional relevant literature. Conference proceedings were not included in this review for two reasons: the peer-review process and standards for publication are highly variable and difficult to measure and the inclusion of only journal articles provides a quality standard and proper scope for this review.

Once papers were identified and reviewed, they were each categorized into 3 publication types based upon the sources of information they report: (1) theoretical papers that focus on the formulation of an idea to explain, predict, and understand the CHPtD theory based upon logical argument; (2) subjective studies that report evidence based on personal opinions, interpretations, emotions, and personal judgments; and (3) empirical studies that source evidence founded in experimentation, analysis, measurement, and observations of actual phenomena. These studies are indicated as “theoretical, subjective, and empirical,” accordingly. Some papers present ideas and concepts based upon logical argument while others test a hypothesis via a controlled experiment. Most research fits into a more nebulous group where the results are based upon the subjective perceptions of experts. The definitions of the 3 research categories are provided in Table 1. It is important to note that the research category classification depends largely upon the context of the paper. For example, if one were to study the risk reduced by various CHPtD strategies using opinions from expert groups, the paper would be classified as subjective research. However, if one were to study designers’ perceptions of CHPtD acceptance in practice via a questionnaire of designers, the study would be classified as empirical. This is a subtle yet important distinction made in the review.

Table 1: Categorization of literature based upon reported

Research Category	**Criteria**
Theoretical	The formulation of an idea to explain, predict, and understand the CHPtD theory based upon logical argument.
Subjective	Research with evidence based on personal opinions, interpretations, emotions, and personal judgments.
Empirical	Research and evidence founded in experimentation, analysis, measurement, and observations of actual phenomena.

The literature search yielded a total of 85 academic journal papers published in 30 different journals.

Each paper was reviewed to make the determination of publication type and research category using the classification in Table 1. Once the papers were reviewed and classified, they were summarized in chronological order in accordance with their topic area within CHPtD. Interestingly, the literature organized into three primary topic areas: (1) viability of CHPtD to prevent injuries and fatalities; (2) methods for implementing CHPtD during the project delivery process; and (3) tools that enable the recognition of hazards and selection of alternative designs to reduce risk.

2.5 Viability of CHPtD to prevent injuries and fatalities

CHPtD researchers have adopted the general position that CHPtD reduces injuries through the mitigation of risk during design. For example, in an early study Behm (2005) examined the viability of CHPtD to prevent injuries and fatalities by developing an objective model using predetermined criteria to determine if accidents were linked to construction design features. The panel analyzed approximately 224 reports from the National Institute of Occupational Safety and Health’s Fatality Assessment and Control Evaluation (NIOSH FACE) program. Participants were asked to review each report and indicate the extent to which a design change would have prevented the fatality. In this review, experts linked 42% of fatalities reviewed to some aspect of project design. This paper serves as the argument that most authors use for the viability of CHPtD. Since the study builds upon the general theory of CHPtD and leverages the opinions of experts, the authors classified it as subjective research.

Literature soon built upon the work of Behm (2005) using the same methodology of reviewing past incidents and establishing if the incident could have been prevented with a design change. First, Seo and Choi (2008) performed a qualitative retrospective analysis of accident data for underground construction projects and identified 203 design elements that had a direct link to construction accidents. The authors specifically identified design features that contributed to safety incidents that, if addressed in design, would have reduced or eliminated the risk (Seo and Choi 2008). Second, Driscoll et al. (2008) investigated the relationship between 210 Australian worker fatalities and design by using qualitative assessments performed by the authors to determine if the accidents could have been prevented via CHPtD. The results show that there was a perception that many design issues including a lack of machine guarding, electrical grounds, and fall protection systems contributed to accidents. They believed that 77 (37%) of the 210 workplace deaths "*definitely or probably*" had design-related issues involved. Third, Ghaderi and Kasirossafar (2011) randomly selected a series of 100 accident reports from Iran and distributed them to three subject matter experts. They found that experts believed that design alterations that incorporate safety consideration could have reduced safety risks that contributed to injuries (Ghaderi and Kasirossafar 2011).

More recently, Lingard et al. (2012) examined four scenarios of the construction of a food processing plant to investigate the feasibility of designing for safety using site observations and project stakeholder interviews. Data were collected using site observations, interviews with project stakeholders, and worksite inspections. They employed actor-network theory (ANT) to identify ways in which design decisions unfolded to incorporate CHPtD alterations into project design. By employing ANT, Lingard et al. (2012) applied a more robust methodology to examine the effects that decision making processes had on CHPtD initiatives. This research provides evidence of discrete building design changes that have the potential to reduce construction risks.

Later research by Lingard (2013) suggests that many of the referenced CHPtD solutions found in literature refer to the change in the ways that construction operations are designed, rather than discrete building elements themselves. Lingard et al. (2015) reconfirmed these findings by examining the relationships between the timing of risk controls and the quality of safety strategy outcomes on 23 live construction projects from the United States and Australia. Through a series of 288 qualitative interviews with project stakeholders, they found that when a greater proportion of risk controls are selected during the pre-construction stages of a project, better site safety performance can be obtained. The strength in this approach lies in the prospective use of leading indicators rather than the retrospective analysis of past accident data. By focusing on actual live construction projects, Lingard et al. (2015) investigated the extent to which the consideration of safety during design can deliver improved safety performance in subsequent project stages.

The aforementioned research has been heavily referenced. For example, Behm (2005) has been cited over 350 times at the time that this paper was written and many of these references are made to justify the need for their research in CHPtD (e.g., Cooke et al. 2008; Driscoll et al. 2008; Dharmapalan et al. 2014; Gibb et al. 2014; and Zhao et al. 2016). The early work by Behm (2005) was critical for understanding possible links between CHPtD and incidents. However, although never suggested in the paper, Behm's (2005) study was used by others to advance the theory of CHPtD as being factual while it remained an untested theory. The citation to this past work has even begun to yield governmental policy development. For example, the National Institute of Occupational Safety and Health (NIOSH) and the United States Occupational Safety and Health Administration (OSHA) have cited the linkage to accidents identified by Behm (2005) to provide evidence that construction injuries and fatalities could be avoided through safer design (NIOSH

2017 and OSHA 2017a). The promulgation of the CHPtD theory is not limited to the work of Behm (2005). The work of Seo and Choi (2008) has also been cited to provide evidence of the validity of the theory for underground construction work (Zou and Li 2010; Fang et al. 2011; Ding and Zhou et al. 2013; and Yu et al. 2014) and hazard recognition and risk assessment (Casanovas et al. 2013 and Perlman et al. 2014).

The categorization of the research that has been studied or has been referenced to promote the viability of the CHPtD is provided in Table 2. As will be discussed later, scientific exploration to objectively test CHPtD provides a rich opportunity for the advancement of construction safety research.

Table 2: Comprehensive literature review results

Reference (Chronological)	**Method**	**Key Results**	**Research Category**
Szymberski 1997	Developed theory concerning effectiveness of safety strategies over time.	Argues that the ability to influence safety is greatest during design and exponentially decreases over a projects lifecycle.	Theoretical
Behm 2005	Developed a model to determine if construction fatalities were linked to the construction design for safety concept.	The results show that 42% of 224 fatality cases reviewed were linked to design and the associated risk contributing to the fatality would have been reduced or eliminated with safe design.	Subjective
Seo and Choi 2008	Qualitative assessment of design features.	Design elements and features played a role in accident causation.	Subjective
Driscoll et al. 2008	Qualitative assessment of design features.	77 (37%) of the 210 workplace deaths investigated "*definitely or probably*" had design-related issues involved.	Subjective
Ghaderi and Kasirossafar 2011	Qualitative assessment of 100 accident reports by three subject matter experts.	Design alterations that incorporate safety consideration could have reduced safety risks that contributed to injuries.	Subjective
Lingard et al. 2012	Site observations, interviews with project stakeholders, and worksite inspections analyzed with actor-network theory.	Design for Safety initiatives could have reduced safety risks to construction workers.	Subjective
Fonseca et al. 2014	Observations of 3 Brazilian construction sites to understand the roles of communication in hazard recognition from project design until work execution.	25 cases provide evidence suggesting that hazard recognition during design can improve safety. Additionally, communication increases the ability to recognize safety hazards during and after design.	Theoretical and Subjective
Lingard et al. 2015	288 qualitative interviews with project stakeholders of "live" construction projects	Better site safety performance can be obtained when a greater proportion of risk controls is selected during the pre-construction stages of a project.	Subjective

As the reader may note, the studies supporting CHPtD are similar in structure because they are mostly retrospective analyses of project conditions or injury reports made by the authors or expert groups. These reviewers use their knowledge and logic to ascertain whether a design change could have prevented the injury or fatality. Thus, this body of knowledge can be classified as largely subjective as the viability of CHPtD largely remains a theory rather than an empirically-supported principle. From a scientific perspective, the following hypothesis remains untested: *design changes do not cause reductions in injuries and fatalities.* One will note that, using scientific convention, the hypothesis is stated in the negative. This is done purposely to acknowledge that theory or perception should be continuously tested and, if it cannot be proven false via empirical data or experimentation, it remains the prevailing theory.

Performing an experiment or collecting empirical data to test a fundamental CHPtD hypothesis is likely to be a difficult task, which may explain why the research community has relied heavily on retrospective analyses and expert perception. However, the authors suggest that the research community (1) acknowledge the true state of knowledge by citing CHPtD as a theory based on prevailing opinion rather than fact and (2) make serious efforts to test hypotheses empirically rather than replicating opinion-based studies.

2.6 Processes of implementing CHPtD

A great deal of literature has focused on how to implement the CHPtD process in practice. As will be discussed, processes have been developed and tested; however, there has been no comparison or experimental testing to determine the extent to which the process achieves the desired outcomes or if one process is superior to another in typical contexts.

Although there is no consensus or empirical evidence on how CHPtD can be optimally implemented, most researchers and practitioners agree that CHPtD should be a part of the constructability review process (Emerson 1962; Francis et al. 1999; Lam et al. 2006; Lam et al. 2015; and Ganah and John 2015). This argument was supported by 111 internet surveys of industry practitioners who felt that CHPtD can be best performed by: 1) coordinating drawings and specifications, 2) performing site investigations, 3) inspecting underground conditions, 4) sequencing trades, and 5) updating of specifications and removal of ambiguities (Lam et al., 2015). Additionally, Lam et al. (2006) found a common perception that a lack of consideration of constructability issues such as access restrictions, work area congestion, and construction task complexity can manifest in inefficient construction procedures. For this reason, they suggest that multiple stakeholders be involved in the design review process.

Perhaps the most widely recognized method for CHPtD is the Construction Hazard Assessment Implication Review (CHAIR) process introduced by the Australian Council of Building Design Professions and the Royal Australian Institute of Architects (WorkCover 2001). CHAIR is a process that was developed to convene designers, constructors, clients, and other key stakeholders and assist them with forecasting safety issues associated with design. Safety hazards are intended to be identified through a series of constructability reviews of plans, drawings, and project specifications. Using the CHAIR process, reviewers evaluate individual building elements to understand the safety hazards associated with the lifecycle risks of building designs. CHAIR was designed to consider the lifecycle of a facility to ensure that safety risks are as low as reasonable practicable across the facility’s lifecycle. This allows for safety hazards to be recognized early in design and removed where feasible. The process also places emphasis on identifying safety management strategies for hazards not removable with CHPtD solutions (WorkCover 2001). CHAIR is a well-designed and logical process for CHPtD that has few identifiable limitations. Nevertheless, it is important that the process be empirically examined, redesigned where necessary, and retested before it is promoted as a standardized process that produces optimal results.

2.7 Hazard recognition in design

For effective CHPtD implementation, designers must be able to recognize safety hazards during the design phase. Although the CHPtD process should include the input of safety professionals, trade contractors, and other stakeholders (Suraji et al. 2001), designers should be able to recognize construction safety hazards and rely on stakeholder input for more complex work procedures that require advanced technical expertise. Recently, Hallowell and Hansen (2016) examined the extent to which designers can use design information to forecast the presence of construction hazards. Hallowell and Hansen (2016) assessed the ability of 17 construction designers to recognized safety hazards for 12 different work modules each consisting of individual work activities and two-dimensional design documents. The hazards were known from actual work observations and interviews from the project team. The results show that designers recognize roughly half of safety hazards present during design. Although there is only one study in this domain, it is an example of empirical evidence upon which procedures and tools can be built.

2.8 Tools designed to enable CHPtD

In theory, CHPtD tools have the capability of enabling designers to better recognize and address construction hazards associated with their designs with automated processes, checklists, and standardized procedures (Ku and Mills 2010). The review revealed that a great deal of literature has focused on building, implementing, and describing these tools. These tools range from collections of expert judgments that provide suggestions for commonly-encountered situations (subjective) to computer software that automatically checks plans and specifications for conditions that have caused previous injuries (empirical).

Subjective tools

The first CHPtD tool was created by Gambatese et al. (1997) who interviewed owners, designers, and constructors to identify safety solutions for commonly-encountered situations in building designs (e.g., pipe clearance, parapet walls near roof edges, and height of window sills). A total of 430 suggestions were compiled and used as a database for the *Design for Safety ToolBox*. The *Design for Safety ToolBox* took the form of a computerized checklist where specific building components could be selected and design suggestions were automatically provided to the user.

Eleven years later, Cooke et al. (2008) developed *ToolSHeD*, a decision support tool to help designers recognize hazards. The web-based tool reproduces the reasoning used by CHPtD experts in assessing the risk of falling from the roofs of buildings during maintenance work. *ToolSHeD* is smaller in scope than the *Design for Safety ToolBox* because it only covers fall hazard from roof top work. Although smaller in scope, *ToolSHeD* is more sophisticated because it uses 'if-then' rule checks to customize design suggestions for specific configurations based on expert experience. The *ToolSHeD* goes a step further by enabling designers to place textual notes into the tool for all design elements as a method to convey information to construction and maintenance workers (Cooke et al. 2008).

Later, Dewlaney and Hallowell (2012) created a subjective tool to aid in injury prevention for *Leadership in Energy and Environmental Design* (LEED) construction projects that uses the LEED v2.2 checklist as the user interface. Dewlaney and Hallowell 2012 expanded on the *Design for Safety ToolBox* by providing specific suggestions to mitigate LEED safety risks identified by Rajendran et al. (2009) and Fortunato et al. (2011). To operate the tool, the user selects the applicable LEED credits in the interface and, once selected, the tool provides a risk report and mitigation strategies intended to reduce risk.

Both the *Design for Safety ToolBox* and the *ToolSHeD* provide suggestions to a designer based upon the aggregate knowledge of experts. The authors hypothesize that these tools will enable designers to create safer designs that reduce safety risk over the project lifecycle. The true effectiveness of the tool lies in three distinct areas: (1) the input of safety experts used as the repository for CHPtD solutions; (2) the change in holistic safety risk levels because of design alterations; and (3) the use of safety risk data output in decision-making processes.

Relying on the input of safety expertise as the foundation of a safety design tool presents three major challenges: (1) safety experts may fail to recognize high risk areas in designs due to unfamiliarity of the design itself; (2) a design solution in one environment may not be an optimal design solution in another; (3) a design change that may be optimal in one context may shuffle risk to other locations, phases, exposures, and tasks thereby inadvertently increasing lifecycle risk through sub-optimization. For example, subjective tools are created by collecting and storing expertise for specific design scenarios. Although the design suggestions in these tools cover broad range of situations, the tools may result in the sub-optimization of lifecycle safety risks. For example, a designer may elect to increase pipe clearance that reduces the chance that an employee may strike their head but this change may require more work at height and in congested spaces increasing safety risks. That is, a potential pitfall of using most subjective CHPtD tools is that mitigating a hazard using a design suggestion may simply move that hazard from one phase, location, or task to another (i.e., risk shuffling). Thus, empirical lifecycle safety risk assessments of design changes are needed to more objectively forecast potential effects. To date, no study has been conducted to evaluate the effects that CHPtD solution have on lifecycle safety risks.

Objective tools

Many different information technologies have been used in construction for the purposes of improving safety performance. The use of technology has been successful for integrating empirical safety data into systems that have been shown to be useful for many safety applications (Hallowell et al. 2016). Among these, a prominent use of technology for safety in design is hazard recognition and control by using Building Information Modeling (BIM) software. BIM is more than a three-dimensional design tool; it is a virtual process that encompasses all aspects, disciplines, and building systems within a single, virtual model, and allows all project stakeholders to collaborate accurately and efficiently during construction design (Azhar 2011). A completed model in BIM can contain the precise geometry and relevant data needed to support the design, procurement, fabrication, and construction activities required to transform design intent into finished projects (Azhar 2011). It is because of the ability to be rich in information that BIM is a useful tool for safety planning and hazard recognition during construction design (Hallowell et al. 2016).

BIM does not address construction safety directly. Rather, it provides a visual and data driven system that can be used by practitioners as a method to recognize safety hazards during design and pre-project planning (Qi et al. 2011). Kasirossafar and Shahbodaghlou (2012) conducted survey based research to identify the features of BIM that can be used to improve construction safety. The researchers presented surveys to 62 professional engineers and construction academics with BIM experience. The results show that incorporating various levels of detail into BIM allows users to visualize many aspects of construction equipment that relate to safety. Additionally, it is suggested that BIM allows better communication among team members, the integration of safety prevention strategies into BIM, and promotes better hazard recognition among designers (Kasirossafar and Shahbodaghlou 2012; Ganah and John 2015; and Martinez-Aires et al 2018). It is because of this that BIM has been a central focus of CHPtD research employing objective CHPtD tools.

Since BIM is an information-rich design technology that can be used as a tool for safety management in many construction phases, it has seen much attention. BIM technologies have been used to link safety information including site schedule sequencing, product information, and safety precautions to individual design elements (Akinci et al 2002; Jordani 2008; Howard and Björk 2008; Goedert and Meadati 2008). BIM has been paired with localization and tracking technologies such as Radio Frequency Identification, Ultra-Wide Band, Global Positioning Systems, and Geographic Information Systems to develop sensing-warning systems to alert workers when they enter hazardous zones (Chae and Yoshida 2008; Fullerton et al. 2009; Costin et al. 2014). Additionally, BIM has been used for safety planning and training (Kim et al. 2014), emergency planning (Ruppel and Abolghasemzadeh 2009 and Li et al. 2014), and has been extended into virtual and augmented reality (Hadikusumo and Rowlinson 2002; Sacks et al. 2013; and Albert et al. 2014).

Researchers have begun to objectively explore the use of BIM to improve safety performance during the design and planning phase by developing tools to supplement designers hazard recognition skills. Many of the tools have been developed to employ rule-checking software that evaluates the spatial configuration of 3D designs within BIM systems (Hadikusumo and Rowlinson 2002; Qi et al. 2011; Zhang et al. 2013; Zhang et al. 2014; Cheng and Teizer 2014; Kim and Teizer 2014; and Zhang et al. 2015). In addition to this, BIM tools have been developed to automatically generate CHPtD suggestion checklists relating to design configurations (Qi et al. 2011; Zhang et al. 2013; Zhang et al. 2014; Cheng and Teizer 2014; Kim and Teizer 2014; and Zhang et al. 2015) and even automatically generate protective systems directly into the 3D design within BIM software (Zhang et al. 2013; Zhang et al. 2014; Cheng and Teizer 2014; Kim and Teizer 2014; and Zhang et al. 2015). These tools have been applied to fall hazards in construction (Qi et al. 2011; Melzner et al 2013; Zhang et al. 2013; and Zhang et al. 2015), exterior scaffolding systems (Kim and Teizer 2014), tower crane placement (Cheng and Teizer 2014), and underground construction (Zhang et al. 2014). More advanced tools can generate schedules of materials (Kim and Teizer 2014), suggest design alternatives (Qi et al. 2011), calculate probabilities of injuries from subjective data (Zhang et al. 2014), and provide color coded outputs for risk locations within BIM software allowing the visual communication of safety risks during design (Zhang et al. 2014).

The research reported in this section reveals that BIM-related CHPtD research tends to be objective, providing empirical evidence or methods for improving safety applications. As can be seen in Table 3 below, 12 empirical studies focused on supplementing designers' hazard recognition skills with BIM safety applications. Only the empirical BIM-related studies included are reported. Within these 12 studies, 7 developed rule-checking software that enables BIM systems to automatically identify safety hazards in BIM. However, only 6 of these tools provide any safety suggestions as others only identify the hazard without reporting any corrective procedure for risk reduction. Furthermore, 5 of the systems that report corrective actions automatically generate the protective system into BIM. None of these systems empirically evaluate the safety risk levels of design attributes, elements, or potential safety solutions. Further, these objective tools, although sophisticated, still do not address the potential for risk shuffling.

Both subjective and objective tools present their own potential benefits. Subjective tools are built using professional expertise and may apply to a broad range of safety applications. These tools allow researchers to use many construction industry resources to compile CHPtD suggestions that can be used to facilitate safer designs. Additionally, subjective tools can address a wide variety of design configurations and construction site hazards and are not limited to any one operational scope (Gambatese et al. 1997). Alternatively, objective tools provide more automated processed that supplement human decision making when performing hazard recognition and design tasks (Kim and Teizer 2014). Both subjective and objective tools provide the opportunity for hazard recognition and CHPtD implementation. However, they fail to address the effects that CHPtD suggestions have on lifecycle safety risks. For this reason, research is still needed in understanding how design changes affect risk shuffling. Quantifying lifecycle safety risks of design changes would allow the construction industry implement CHPtD while accomplishing the intended goal of holistic risk reduction.

Table 3: Empirical Studies Using BIM to enable CHPtD

References	**Research Contributions**			
	Supplement Designers Hazard Recognition Skills	Use Rule-Checking for Automated Hazard Identification	Provide CHPtD Suggestions	Automatically Generate Safety Systems into BIM
Li et al. 2003	x			
Hadikusumo and Rowlinson 2004	x			
Navon and Kolton 2006	x			
Teizer et al. 2005	x			
Bansal 2011	x			
Hadikusumo and Rowlinson 2002	x	x		
Qi et al. 2011	x	x	x	
Zhang et al. 2013	x	x	x	x
Zhang et al. 2014	x	x	x	x
Cheng and Teizer 2014	x	x	x	x
Kim and Teizer 2014	x	x	x	x
Zhang et al., 2015	x	x	x	x

2.9 Proposed empirical research agenda for CHPtD

The research community has made incremental advances in the science of CHPtD. However, more objective hypothesis testing is needed if the community aims to advance unbiased, valid, and reliable knowledge. The large body of literature has solidified strong consensus that CHPtD is effective in preventing injuries, CHPtD tools can enable hazard recognition and communication in design, and new technologies like BIM offer opportunities for integration of reliable data.

The consensus in theory provides ample opportunity to build and test hypotheses that add scientific rigor to the CHPtD discourse, which is presently lacking. We use the results of the structured review of literature to identify key knowledge gaps, create scientifically testable hypotheses, and justify those hypotheses with the current state of knowledge. The aggregate represents a research agenda that represents the primary contribution of this paper. The primary motivation for creating this research agenda is the momentum that CHPtD has as a theory in the academic and professional communities, the recent creation of broad and impactful legislation in some areas of the world (e.g., the UK and Australia), and the resistance that some practitioners, especially designers, impose on the advancement of the method. We believe that strong and balanced scientific exploration of the topic will help to address the reasonable criticism that CHPtD remains merely a ‘good idea’ supported by the opinion of experts and not a stanch scientific principle.

The research agenda below is organized as a set of testable hypotheses, each stated in the negative per scientific custom. Each hypothesis is supported by the literature review previously described and would add significant validity to a core area of CHPtD work.

Ho1: CHPtD design solutions do not reduce lifecycle safety risks.

One of the major gaps in CHPtD literature is the lack of evidence that the method reduces risks and prevents injuries and fatalities over a projects lifecycle. Although experts believe that injuries could have been prevented through design changes, there is no scientific evidence that a specific design change reduces risk. That is, a design change may logically decrease risk in one location at one specific time but increase risks in other locations and in other time periods.

The United States Occupational Safety and Health Administration (OSHA 2015), National Institute for Occupational Safety and Health (NIOSH 2013), and Gambatese et al. (1997) provide design suggestions for specific types of work (e.g., increase the height of parapet walls). OSHA (2015), for example, claims that the suggested design alteration "*protects against the risk of serious falls from roofs or platforms during construction, maintenance, and demolition activities over the life of a building.*" This assumption is founded in OSHA's belief that "*all safety professionals know that it is much more effective to design safety into a process than it is to try to manage safety within a process that is inherently unsafe* (OSHA 2015)." Despite the beliefs of OSHA, NIOSH, and the experts in the Gambatese et al. (1997) study, one fact remains: there is no empirical evidence that the suggested design alternative reduces safety risk throughout the project lifecycle. Opponents of CHPtD can easily cite this gap in knowledge as a reason that CHPtD should not promulgate into legislation or industry standard practice. However, closing said knowledge gap could provide the method with the scientific backing needed for advancements. Although potentially challenging, testing this hypothesis is now in reach with recent advancements in and validation of empirical safety risk analysis (Tixier et al. 2016), artificial intelligence for safety (Zhang et al. 2013; Cheng and Teizer 2014; Kim and Teizer 2014; Zhang et al. 2014: and Zhang et al., 2015), and predictive analytics (Esmalili et al. 2015 and Alexander et al. 2017).

Ho2: Risk-based approaches cannot be used to select design alternatives that optimize lifecycle safety.

Many risk assessment methodologies have been developed to forecast occupational safety and health risks. These include, but are not limited to, hazard loss prevention (Fine, 1975), workers compensation classification risk scores (Knab 1978), risk and uncertainty modelling (Hertz and Thomas 1983), influence diagrams (Howard 1984), analytic decision hierarchy process (Saaty 1990), probability and severity matrices (DoD 2012), safety cost modelling (Aminbakhsh et al. 2013), predictive analytics (Salas and Hallowell 2016 and Alexander et al. 2017), and safety attribute based modelling (Tixier et al. 2017). However, no research to date has examined the validity of applying quantitative risk assessment methodologies for lifecycle safety risk reduction. Research has focused on integrating subjective data as CHPtD solutions (Gambatese et al. 1997; Cooke et al. 2008; Dewlaney and Hallowell 2012) but no research has investigated if empirically founded and quantitative risk assessment methodologies can be applied during CHPtD to reduce life cycle safety risks.

One method to address this gap in literature would be to integrate empirical safety risk quantification methodologies into BIM systems to automatically evaluate the physical attributes (i.e. work at height, work in confined spaces, use of tools and equipment, access restriction, etc.) for both pre-CHPtD and post-CHPtD solution integration (Hallowell et al. 2016). By incorporated this type of data into BIM system, users could have automated risk-based feedback to select the optimum CHPtD solution to reduce safety risks over a projects entire life cycle. Although building upon current BIM-based CHPtD tools and integrating risk-based attribute data may be a challenging endeavor, future research is needed that focuses on integrating safety attribute data into BIM systems to investigate how the physical attributes of construction and maintenance work will affect the project from a lifecycle perspective. Such developments in safety technology within BIM may help to perpetuate BIM's use for safety planning and CHPtD implementation (Hallowell et al. 2016) and build on current risk assessment methodologies during project design.

Ho3: Not all construction safety hazards are recognizable during design phases.

Recently, research conducted by Hallowell and Hansen (2016) found that the average designer can recognize approximately one-half of all safety hazards from construction design documents, which increased by an average of 27% with energy-based mnemonic training. Additionally, the hazard recognition skills of designers with construction field experience was, on average, 45% higher than designers with no construction field experience. These are important findings that must be further investigated because the premise of CHPtD is that designers are to recognize and mitigate hazards in design. Despite the general premise of CHPtD, the research suggests that some hazards are recognizable but others may remain unrecognizable during construction design phases. Understanding, through controlled experimentation, what types of hazards are recognizable and when they emerge in the project delivery process could provide key information for setting reasonable expectations and bounds for CHPtD implementation. Further, understanding which hazards are recognizable in specific phases of design development and project delivery could enable a more efficient and targeted safety review process. This evidence would also be useful as BIM and other technologies are used to check rules and automatically design safety interventions.

Ho4: CHPtD tools do not affect hazard recognition or the selection of optimal design solutions.

Many tools, both subjective and objective, have been developed to supplement designers' hazard recognition skills (Gambatese et al. 1997; Li et al. 2003; Hadikusumo and Rowlinson 2004; and Navon and Kolton 2006; Cooke et al. 2008; and Dewlaney and Hallowell 2012). Much research has been devoted to discussions relating to tool development and their uses during construction design (Gambatese et al. 1997; Ku and Mills 2010; Zhou et al. 2012; and Zhou et al. 2013). However, the efficacy of these tools remains nebulous. Although the current tools may provide a viable platform for hazard recognition during design, no research has investigated the extent to which various tools enable hazard recognition and the selection of optimal design alternatives. At present, the tools remain an untested guide that is based on the best available theory and expert opinion. Testing the efficacy of the tools through controlled experimentation could help to showcase strengths and identify weaknesses where future research and development is needed. Furthermore, testing such tools could help to uncover the specific mechanisms that enable improved performance so the design of future tools is more effective. This hypothesis is a good example where the safety science community owes society a duty to test the efficacy of practicable and new ideas.

Ho5: The modality of design information does not affect hazard recognition and removal during design.

Construction safety literature has discussed many of the benefits of using a variety of design information to improve safety (Chantawit et al. 2005; Ganah and John 2015; Zhang et al. 2015). These include two-dimensional Computer Aided Drawings (CAD) (Chantawit et al. 2005), three-dimensional Building Information Modeling (BIM) software (Ganah and John 2015 and

Zhang et al., 2015), and augmented and virtual reality (AR/VR) (Hadikusumo and Rowlinson 2004). These technology applications have been found to be a useful addition to the strategies commonly used for safety management tasks. However, although much research has focused on developing BIM and AR/VR tools that can be used to improve safety though constructability reviews, design suggestions (Gambatese et al. 1997 and Cooke et al. 2008), and the automation of safety systems (Zhang et al. 2013; Cheng and Teizer 2014; Kim and Teizer 2014; Zhang et al. 2014: and Zhang et al., 2015); research has yet to understand how different modes of design information stimuli (e.g. CAD, BIM, AR/VR, etc.) affect hazard recognition performance during design. By addressing this gap in literature, the construction industry can understand how design information affects hazard recognition of specific work tasks and will allow for the identification of design attributes that aid in hazard recognition tasks. From there, research can begin to evaluate the cognitive workload and focal attention of hazard recognition tasks that require the visual search of design information for safety hazards and can begin to understand why certain design stimulus modalities may yield variability in hazard recognition performance.

Ho6: The risks reduced by the various levels of the hierarchy of controls are not equal.

The United States Department of Defense, NIOSH, and OSHA have recognized the hierarchy of safety controls as being a viable theory for successful safety and health management practices (DoD 2012; NIOSH 2015; and OSHA 2015). Additionally, OSHA has used the hierarchy when developing industrial regulations (OSHA 2008 and 2017) and the hierarchy has become a focus of NIOSH's national occupational research agenda (NIOSH 2012). This is in part due to hazard elimination, the central premise of CHPtD, lying at the top of the hierarchy (Hecker and

Gambatese 2003). However, scientific literature and empirical evidence indicating the variability of risk reduction levels through the application of the different levels of the hierarchy is sparse.

As suggested by Barnett and Brickman (1986), although the hierarchy provides an important tool for improving worker safety, the hierarchy is not founded in scientific law via experimental observations. Rather, the hierarchy is founded in consensus and its general validity stands to be tested with numerous counterexamples (Barnett and Brickman 1986). However, no research to date tests the assumption that the quantity of safety risk reduction varies among the different levels of the hierarchy of safety controls, and that eliminating safety hazards with CHPtD solutions is optimal. Although case study research has shown that it is possible to eliminate safety hazards through the implementation of CHPtD solutions (Lingard et al. 2012; Zhang et al. 2013; Fonesca et al. 2014; Zhang et al. 2014; Cheng and Teizer 2014; Kim and Teizer 2014; and Zhang et al. 2015), research has yet to address how the effects of risk shuffling and CHPtD design solutions may affect other aspects of lifecycle safety. Future research is needed to investigate the risk reduction levels of eliminating safety hazards through CHPtD solutions as compared to lower order safety controls over the lifecycle of projects. With this research, the industry can better understand the feasibility of implementing hazard elimination through CHPtD solutions to reduce hazardous energy exposures which may vary in energy magnitude and exposure duration. This research is paramount for the perpetuation of the consensus that higher order safety controls are potentially more effective and protective than those that lie at the bottom of the hierarchy.

2.10 Conclusions

The purpose of this paper was to assess the current state of CHPtD research and to identify current trends and experimental hypotheses for future empirical research. This paper departs from current literature by presenting a conceptual framework for the advancement of the CHPtD research agenda through empirical hypothesis testing. This paper has discussed research trends relating to improving worker safety during project design phases, the tools to assist designers with hazard recognition, and potential hypotheses for moving the CHPtD process forward with empirical research. Additionally, a distinction between theoretical, subjective, and empirical research has been presented.

CHPtD has seen abundant research in the last 20 years. Much of the research reviewed in this paper falls into two categories: subjective and empirical research. The reviewed subjective research tends to focus on perceptions and conceptual ideas (Hinze and Wiegand, 1992; Szymberski, 1997; Gambatese and Hinze 1999; Griffith and Phillips, 2001; Huang and Hinze, 2006; Votano and Sunindijo 2014; Goa and Chua 2016; Martínez-Aires et al. 2016; Toole et al. 2016) rather than empirical evidence and has employed retrospective analyses of past accident data to test the viability of risk mitigation via CHPtD strategies (Behm 2005; Seo and Choi 2008; Driscoll et al. 2008; Ghaderi and Kasirossafar 2011; and Lingard et al. 2012). Other publications use case studies to subjectively determine the effects of hazard recognition and risk control during project design (Fonseca et al. 2014 and Lingard et al. 2015). Additionally, subjective research has been used to develop CHPtD tools that aid with hazard recognition in design. These systems provide designers with automated processes, checklists, and standardized procedures that can be used to supplement designers hazard recognition skills (Ku and Mills 2010).

Empirical research tends to focus on objective CHPtD tool development and implementation (see Table 3) and has been used to objectively test designers hazard recognition skills (Hallowell and Hansen 2016). The review revealed that objective CHPtD tools employ rule-checking computer software that evaluates the spatial conditions within building information modeling software to automate the hazard identification process. Furthermore, some objective tools have the capability of automatically providing CHPtD suggestions and generating safety systems into building information modeling software (see Table 3). Both subjective and objective CHPtD tools provide much promise. A great deal of literature has focused on building, implementing, and describing these tools and how they can be used in design. However, no research to date has tested the efficacy of using the tools for CHPtD implementation.

The consensus in CHPtD theory provides ample opportunity to build and test new empirical research hypotheses. In this paper, we used the results of a structured literature review to identify key knowledge gaps, create scientifically testable hypotheses, and justify those hypotheses with the current state of knowledge. The primary motivation for creating testable hypotheses is the momentum that CHPtD has as a theory in the academic and professional communities. A strong and balanced scientific exploration of the topic may help advance CHPtD from merely a ‘good idea’ into a scientifically-supported safety management strategy. The hypotheses included in this paper are listed below, each stated in the negative per scientific custom. Each hypothesis is supported by the literature review and would add significant validity to a core area of CHPtD research.

Ho1: CHPtD design solutions do not reduce lifecycle safety risks.

Ho2: Risk-based approaches cannot be used to select design alternatives that optimize lifecycle safety.

Ho3: Not all construction safety hazards are recognizable during design phases.

Ho4: CHPtD tools do not affect hazard recognition or the selection of optimal design solutions.

Ho5: The modality of design information does not affect hazard recognition and removal during design.

Ho6: The risks reduced by the various levels of the hierarchy of controls are not equal.

The hypotheses listed above focus on lifecycle safety risks (*Ho1, and Ho2*), hazard recognition in design (*Ho3, Ho4, and Ho5*), and the hierarchy of safety controls (*Ho6*). Lifecycle safety risk analysis can be used to understand the effects that CHPtD solutions have on holistic project risks. One of the major gaps in CHPtD literature is the lack of evidence that CHPtD reduces risks and prevents injuries and fatalities over a projects lifecycle. To date, there is no scientific evidence to suggest that a specific design change reduces lifecycle safety risks. Additionally, there is no evidence suggesting which types of safety hazards are recognizable during design and how the modality of design information and current CHPtD tools affect hazard recognition performance. Investigating the types of hazards identifiable by designers could help to identify knowledge gaps which can be filled with various types of safety training and hazard recognition methods. Lastly, there is no evidence to suggest that the risks reduced by the various levels of the hierarchy of controls are equal. However, the United States Department of Defense, NIOSH, and OSHA have recognized the hierarchy of safety controls as being a viable theory for successful safety and health management practices (DoD 2012; NIOSH 2015; and OSHA 2015). Research is needed that tests the assumption that risk reduction varies among the different levels of the hierarchy of safety controls and that eliminating safety hazards with CHPtD solutions is optimal.

This paper has assessed the current state of CHPtD research and has identified potential empirical hypotheses for future research. Although many valuable contributions have been made to the body of CHPtD knowledge, the research community needs to begin to shift its attention to evidence-based methods that test current assumptions and address the many gaps in CHPtD research. It is of the upmost importance that the scientific community remains steadfast in rigorous and empirical research in construction safety.

2.11 References

Akinci, B., Fischer, M., & Kunz, J. (2002). Automated generation of work spaces required by construction activities. *Journal of construction engineering and management*, *128*(4), 306-315.

Albert, A., M. Hallowell, B. Kleiner, A. Chen, and M. Golparvar-Fard. 2014. "Enhancing Construction Hazard Recognition with High-Fidelity Augmented Virtuality." *Journal of Construction Engineering and Management* 140 (7): 04014024.

Alexander, D., Hallowell, M., & Gambatese, J. (2017). Precursors of Construction Fatalities. II: Predictive Modeling and Empirical Validation. *Journal of Construction Engineering and Management*, *143*(7), 04017024.

Aminbakhsh, S., Gunduz, M., & Sonmez, R. (2013). Safety risk assessment using analytic hierarchy process (AHP) during planning and budgeting of construction projects. *Journal of safety research*, *46*, 99-105.

Azhar, S. (2011). Building information modeling (BIM): Trends, benefits, risks, and challenges for the AEC industry. *Leadership and management in engineering*, *11*(3), 241-252.

Bansal, V. K. (2011). Application of geographic information systems in construction safety planning. *International Journal of Project Management*, *29*(1), 66-77.

Barnett, R. L., & Brickman, D. B. (1986). Safety hierarchy. *Journal of Safety Research*, *17*(2), 49-55.

Casanovas, M. D. M., Armengou, J., & Ramos, G. (2013). Occupational risk index for assessment of risk in construction work by activity. *Journal of Construction Engineering and Management*, *140*(1), 04013035.

Chantawit, D., Hadikusumo, B. H., Charoenngam, C., & Rowlinson, S. (2005). 4DCAD-Safety: visualizing project scheduling and safety planning. *Construction Innovation*, 5(2), 99-114.

Chae, Soungho, and Tomohiro Yoshida. 2008. “A Study of Safety Management Using Working Area Information on Construction Site.” *Proceedings of the 25th International Symposium on Automation and Robotics in Construction*, June, 292–99.

Cheng, T., & Teizer, J. (2012). Modeling tower crane operator visibility to minimize the risk of limited situational awareness. *Journal of Computing in Civil Engineering*, *28*(3), 04014004.

Coble, R. J., & Blatter, R. L. (1999). Concerns with safety in design/build process. *Journal of Architectural Engineering*, *5*(2), 44-48.

Cooke, T., Lingard, H., Blismas, N., & Stranieri, A. (2008). ToolSHeDTM: the development and evaluation of a decision support tool for health and safety in construction design. *Engineering, Construction and Architectural Management*, *15*(4), 336-351.

Costin, Aaron, Nipesh Pradhananga, and Jochen Teizer. 2014. “Passive RFID and BIM for Real-Time Visualization and Location Tracking.” In *Construction Research Congress 2014*, 169–78. American Society of Civil Engineers.

Dewlaney, K. S., Hallowell, M. R., & Fortunato III, B. R. (2011). Safety risk quantification for high performance sustainable building construction. *Journal of Construction Engineering and Management*, *138*(8), 964-971.

Dewlaney, K. S., & Hallowell, M. (2012). Prevention through design and construction safety management strategies for high performance sustainable building construction. *Construction Management and Economics*, *30*(2), 165-177.

Dharmapalan, V., Gambatese, J. A., Fradella, J., & Moghaddam Vahed, A. (2014). Quantification and assessment of safety risk in the design of multistory buildings. *Journal of Construction Engineering and Management*, *141*(4), 04014090.

Ding, L. Y., & Zhou, C. (2013). Development of web-based system for safety risk early warning in urban metro construction. *Automation in Construction*, *34*, 45-55.

DoD. (2012). MIL-STD-882E. Retrieved December 3, 2017, from http://www.system-safety.org/Documents/MIL-STD-882E.pdf

Emerson. (1962). Surveys of the Problems Before the Construction lndustry: a report prepared for the MinisQ of Works. HMSO, London, 1962

Esmaeili, B., Hallowell, M. R., & Rajagopalan, B. (2015). Attribute-based safety risk assessment. II: Predicting safety outcomes using generalized linear models. *Journal of construction engineering and management*, *141*(8), 04015022.

Fang, Q., Zhang, D., & Wong, L. N. Y. (2011). Environmental risk management for a cross interchange subway station construction in China. *Tunnelling and Underground Space Technology*, *26*(6), 750-763.

Fine, W. T. (1975). *A Management Approach in Accident Prevention* (No. NSWC/WOL/TR-75-104). NAVAL SURFACE WEAPONS CENTER WHITE OAK LAB SILVER SPRING MD.

Fonseca, E. D., Lima, F. P., & Duarte, F. (2014). From construction site to design: The different accident prevention levels in the building industry. *Safety science*, *70*, 406-418.

Francis, V. E., Chen, S. E., Mehrtens, V. M., Sidwell, A. C., & McGeorge, W. D. (1999). Constructability strategy for improved project performance. *Architectural Science Review*, 42(2), 133-138.

Fullerton, C. E., Allread, B. S., & Teizer, J. (2009). Pro-active-real-time personnel warning system. In *Construction Research Congress 2009: Building a Sustainable Future* (pp. 31-40).

Gambatese, J. A., Hinze, J. W., & Haas, C. T. (1997). Tool to design for construction worker safety. *Journal of Architectural Engineering*, *3*(1), 32-41.

Gambatese, J. and J. Hinze (1999). "Addressing construction worker safety in the design phase: Designing for construction worker safety." *Automation in Construction,* 8(6), 643-649.

Gambatese, J. A., Behm, M., & Rajendran, S. (2008). Design's role in construction accident causality and prevention: Perspectives from an expert panel. *Safety science*, *46*(4), 675-691.

Ganah, A., & John, G. A. (2015). Integrating building information modeling and health and safety for onsite construction. *Safety and health at work*, *6*(1), 39-45.

Ghaderi, R., & Kasirossafar, M. (2011). Construction safety in design process. In *AEI 2011: Building Integration Solutions* (pp. 464-471).

Gibb, A., Lingard, H., Behm, M., & Cooke, T. (2014). Construction accident causality: learning from different countries and differing consequences. *Construction Management and Economics*, *32*(5), 446-459.

Goedert, J., and P. Meadati. 2008. "Integrating Construction Process Documentation into Building Information Modeling." *Journal of Construction Engineering and Management* 134 (7): 509–16.

Goh, Y. M., & Chua, S. (2016). Knowledge, attitude and practices for design for safety: a study on civil & structural engineers. *Accident Analysis & Prevention, 93*, 260-266.

Griffith, A., & Phillips, N. (2001). The influence of the Construction (Design and Management) Regulations 1994 upon the procurement and management of small building works. *Construction Management and Economics, 19*(5), 533-540.

Hadikusumo, B. H. W., & Rowlinson, S. (2002). Integration of virtually real construction model and design-for-safety-process database. *Automation in Construction, 11*(5), 501-509.

Hadikusumo, B. H. W., & Rowlinson, S. (2004). Capturing safety knowledge using design-for-safety-process tool. *Journal of construction engineering and management*, *130*(2), 281-289.

Hallowell, M. R., Hardison, D., & Desvignes, M. (2016). Information technology and safety: Integrating empirical safety risk data with building information modeling, sensing, and visualization technologies. *Construction Innovation*, *16*(3), 323-347.

Hallowell, M. R., Alexander, D., & Gambatese, J. A. (2017). Energy-based safety risk assessment: does magnitude and intensity of energy predict injury severity? *Construction Management and Economics*, *35*(1-2), 64-77.

Hertz, D. B., & Thomas, H. (1983). *Risk analysis and its applications* (pp. 11-15).

Howard, R. A. (1984). Readings on the Principles and Applications of Decision Analysis: Professional Collection (Vol. 2). Strategic Decisions Group.

Howard, Rob, and Bo-Christer Björk. 2008. "Building Information Modelling – Experts' Views on Standardisation and Industry Deployment." *Advanced Engineering Informatics*, Network methods in engineering, 22 (2): 271–80.

Hinze, J., & Wiegand, F. (1992). Role of designers in construction worker safety. *Journal of construction engineering and management*, *118*(4), 677-684.

Huang, X., & Hinze, J. (2006). Owner's role in construction safety. *Journal of construction engineering and management*, *132*(2), 164-173.

Hwang, S. (2012). Ultra-wide band technology experiments for real-time prevention of tower crane collisions. *Automation in Construction*, *22*, 545-553.

Johnson, N., Creasy, T., & Fan, Y. (2016). Recent Trends in Theory Use and Application within the Project Management Discipline. *Journal of Engineering, Project, and Production Management*, *6*(1), 25.

Jordani, David. 2008. "BIM: A Healthy Disruption to a Fragmented and Broken Process." *Journal of Building Information Modelling* 2 (2): 24–26.

Kasirossafar, M., & Shahbodaghlou, F. (2013). Building Information Modeling or construction Safety Planning. In *ICSDEC 2012: Developing the Frontier of Sustainable Design, Engineering, and Construction* (pp. 1017-1024).

Kim, H., H. Lee, M. Park, B. Chung, and S. Hwang. 2014. "Information Retrieval Framework for Hazard Identification in Construction." *Journal of Computing in Civil Engineering* 0 (0): 04014052.

Kim, K., & Teizer, J. (2014). Automatic design and planning of scaffolding systems using building information modeling. *Advanced Engineering Informatics*, *28*(1), 66-80.

Knab, L. I. (1978). Numerical aid to reduce construction injury losses. *Journal of the Construction Division*, *104*(4), 437-445.

Ku, K., & Mills, T. (2010). Research needs for building information modeling for construction safety. In *International Proceedings of Associated Schools of Construction 45nd Annual Conference, Boston, MA*.

Lam, P. T., Wong, F. W., & Chan, A. P. (2006). Contributions of designers to improving buildability and constructability. *Design Studies*, *27*(4), 457-479. Lingard, H. (2013). Occupational health and safety in the construction industry. *Construction management and economics*, *31*(6), 505-514.

Li, H., Ma, Z., Shen, Q., & Kong, S. (2003). Virtual experiment of innovative construction operations. *Automation in Construction*, *12*(5), 561-575.

Li, N., Becerik-Gerber, B., Krishnamachari, B., & Soibelman, L. (2014). A BIM centered indoor localization algorithm to support building fire emergency response operations. *Automation in Construction*, 42, 78-89.

Lingard, H., & Holmes, N. (2001). Understandings of occupational health and safety risk control in small business construction firms: barriers to implementing technological controls. *Construction Management & Economics*, *19*(2), 217-226.

Lingard, H. (2013). Occupational health and safety in the construction industry. *Construction management and economics*, *31*(6), 505-514.

Martínez-Aires, M. D., Rubio Gámez, M. C., & Gibb, A. (2016). The impact of occupational health and safety regulations on prevention through design in construction projects: Perspectives from Spain and the United Kingdom. *Work*, *53*(1), 181-191.

Manu, P. A., Ankrah, N. A., Proverbs, D. G., & Suresh, S. (2012). Investigating the multi-causal and complex nature of the accident causal influence of construction project features. *Accident Analysis & Prevention*, *48*, 126-133.

Martínez-Aires, M. D., López-Alonso, M., & Martínez-Rojas, M. (2018). Building information modeling and safety management: A systematic review. *Safety Science*, *101*, 11-18.

Melzner, J., Zhang, S., Teizer, J., & Bargstädt, H. J. (2013). A case study on automated safety compliance checking to assist fall protection design and planning in building information models. *Construction Management and Economics*, *31*(6), 661-674.

NIOSH. (2012). PREVENTION THROUGH DESIGN. Retrieved December 3, 2017, from https://www.cdc.gov/niosh/programs/ptdesign/nora.html

NIOSH. (2013). Preventing Falls through the Design of Roof Parapets. Retrieved June 11, 2017, from https://www.cdc.gov/niosh/docs/2014-108/pdfs/2014-108.pdf

NIOSH. (2015). Hierarchy of Controls. Retrieved December 3, 2017, from https://www.cdc.gov/niosh/topics/hierarchy/default.html

NIOSH. (2017). Prevention Through Design. Retrieved August 05, 2017, from https://www.cdc.gov/niosh/topics/ptd/default.html

Oloufa, A. A., Ikeda, M., & Oda, H. (2003). Situational awareness of construction equipment using GPS, wireless and web technologies. *Automation in Construction*, *12*(6), 737-748.

OSHA. (2008). Occupational Noise Exposure. Retrieved December 3, 2017, from https://www.osha.gov/pls/oshaweb/owadisp.show_document?p_table=standards&p_id=9735

OSHA. (2015). Design for Construction Safety: Instructors Guide. Retrieved June 11, 2017, from https://www.osha.gov/dte/library/DfCSInstructorGuide.pdf

OSHA. (2017a). Commonly Used Statistics. Retrieved June 11, 2017, from https://www.osha.gov/oshstats/commonstats.html

OSHA. (2017b). Small Entity Compliance Guide for the Respirable Crystalline Silica Standard for Construction. Retrieved December 3, 2017, from https://www.osha.gov/Publications/OSHA3902.pdf

Perlman, A., Sacks, R., & Barak, R. (2014). Hazard recognition and risk perception in construction. *Safety science*, *64*, 22-31.

Pink, S., Morgan, J., & Dainty, A. (2014). Safety in movement: Mobile workers, mobile media. *Mobile Media & Communication*, *2*(3), 335-351.

Qi, J., Issa, R. R. A., Hinze, J., & Olbina, S. (2011). Integration of safety in design through the use of building information modeling. In *Computing in Civil Engineering (2011)* (pp. 698-705).

Rajendran, S., Gambatese, J. A., & Behm, M. G. (2009). Impact of green building design and construction on worker safety and health. *Journal of Construction engineering and Management*, *135*(10), 1058-1066.

Rajendran, S. and J. A. Gambatese (2013). "Risk and Financial Impacts of Prevention through Design Solutions." *Practice Periodical on Structural Design and Construction*, 18(1): 67-72.

Ruppel, U., and P. Abolghasemzadeh. 2009. "BIM-Based Immersive Evacuation Simulations." In *18th International Conference on the Application of Computer Science and Mathematics in Architecture and Civil Engineering.* Weimar, Germany.

Saaty, T. L. (1990). How to make a decision: the analytic hierarchy process. *European journal of operational research*, 48(1), 9-26.

Sacks, R., Perlman, A., & Barak, R. (2013). Construction safety training using immersive virtual reality. *Construction Management and Economics*, *31*(9), 1005-1017.

Sacks, R., Whyte, J., Swissa, D., Raviv, G., Zhou, W., & Shapira, A. (2015). Safety by design: dialogues between designers and builders using virtual reality. *Construction Management and Economics*, *33*(1), 55-72.

Salas, R., & Hallowell, M. (2016). Predictive validity of safety leading indicators: Empirical assessment in the oil and gas sector. *Journal of Construction Engineering and Management*, 142(10), 04016052.

Seo, J. W., & Choi, H. H. (2008). Risk-based safety impact assessment methodology for underground construction projects in Korea. *Journal of construction engineering and management*, *134*(1), 72-81.

Suraji, A., Duff, A. R., & Peckitt, S. J. (2001). Development of causal model of construction accident causation. *Journal of construction engineering and management*, *127*(4), 337-344.

Teizer, J., Kim, C., Haas, C., Liapi, K., & Caldas, C. (2005). Framework for real-time three-dimensional modeling of infrastructure. *Transportation Research Record: Journal of the Transportation Research Board*, (1913), 177-186.

Tixier, J., Dusserre, G., Salvi, O., & Gaston, D. (2002). Review of 62 risk analysis methodologies of industrial plants. *Journal of Loss Prevention in the process industries*, *15*(4), 291-303.

Tixier, A. J. P., Hallowell, M. R., Rajagopalan, B., & Bowman, D. (2016). Application of machine learning to construction injury prediction. *Automation in construction*, *69*, 102-114.

Tixier, A. J. P., Hallowell, M. R., & Rajagopalan, B. (2017). Construction safety risk modeling and simulation. *Risk analysis*, 37, 1917-1935.

Toole, T. M. (2005). Increasing engineers' role in construction safety: Opportunities and barriers. *Journal of Professional Issues in Engineering Education and Practice*, *131*(3), 199-207.

Toole, T. M. (2011). Internal impediments to ASCE's vision 2025. *Leadership and Management in Engineering*, *11*(2), 197-207.

Toole, T. M., Gambatese, J. A., & Abowitz, D. A. (2016). Owners' role in facilitating prevention through design. *Journal of Professional Issues in Engineering Education and Practice*, *143*(1), 04016012.

Votano, S., & Sunindijo, R. Y. (2014). Client safety roles in small and medium construction projects in Australia. *Journal of Construction Engineering and Management*, *140*(9), 04014045.

Walter, L., & Styhre, A. (2013). The role of organizational objects in construction projects: the case of the collapse and restoration of the Tjörn Bridge. *Construction management and economics*, *31*(12), 1172-1185.

Wang, X., & Dunston, P. S. (2008). User perspectives on mixed reality tabletop visualization for face-to-face collaborative design review. *Automation in construction*, *17*(4), 399-412.

Yu, Q. Z., Ding, L. Y., Zhou, C., & Luo, H. B. (2014). Analysis of factors influencing safety management for metro construction in China. *Accident Analysis & Prevention*, *68*, 131-138.

Zhang, C., Hammad, A., & Rodriguez, S. (2011). Crane pose estimation using UWB real-time location system. *Journal of Computing in Civil Engineering*, *26*(5), 625-637.

Zhang, S., Teizer, J., Lee, J. K., Eastman, C. M., & Venugopal, M. (2013). Building information modeling (BIM) and safety: Automatic safety checking of construction models and schedules. *Automation in Construction*, *29*, 183-195.

Zhang, L., Wu, X., Ding, L., Skibniewski, M. J., & Lu, Y. (2014). Bim-based risk identification system in tunnel construction. *Journal of Civil Engineering and Management*, *22*(4), 529-539.

Zhang, S., Sulankivi, K., Kiviniemi, M., Romo, I., Eastman, C. M., & Teizer, J. (2015). BIM-based fall hazard identification and prevention in construction safety planning. *Safety science*, *72*, 31-45.

Zhao, D., McCoy, A. P., Kleiner, B. M., Mills, T. H., & Lingard, H. (2016). Stakeholder perceptions of risk in construction. *Safety science*, *82*, 111-119.

Zhou, W., Whyte, J., & Sacks, R. (2012). Construction safety and digital design: A review. *Automation in Construction*, 22, 102-111.

Zhou, Z., Irizarry, J., & Li, Q. (2013). Applying advanced technology to improve safety management in the construction industry: a literature review. *Construction Management and Economics*, *31*(6), 606-622.

Zou, P. X., & Li, J. (2010). Risk identification and assessment in subway projects: case study of Nanjing Subway Line 2. *Construction Management and Economics*, *28*(12), 1219-1238.

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Chapter 3: Hazard Recognition in Design: A Latin square evaluation of the effects of design information on hazard recognition skill and prevention through design decisions

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Dylan Hardison, Matthew Hallowell, and Ray Littlejohn

3.1 Abstract

A series of simulated design for safety reviews with civil engineering students, construction and engineering designers, and construction supervisors were conducted across the United States to explore the effects that different formats of design information had on hazard recognition performance. In total, 117 participants were provided one of three information formats including: two-dimensional (2D) computer aided design (CAD) drawings, three-dimensional (3D) computerized visualizations, and a combination of the two (2D & 3D) through a Latin square experimental design. Participants were asked to explore the design information and identify as many safety hazards as they could for three separate construction work activities including: rooftop skylight installation, interior soffit drywall installation, and interior metal wall stud framing. This paper's primary contribution centers around the discovering how design information affects different population groups hazard recognition performance. Mean and dispersion tests suggest that the incorporation of design information as an intervention had no significant effects for any of the population groups in the study. Additionally, ANOVA analysis suggests that the is no significant effect of design information formats on hazard recognition. It was also discovered that experience has little effect on hazard recognition performance within population groups. However, ANOVA and regression analysis suggests experience does significantly affect hazard recognition performance across population groups. This research challenges the assumption that three-dimensional design information is superior to two-dimensional information and confirms that

those involved in Construction Hazard Prevention through Design (CHPtD) processes have construction experience and knowledge to recognize safety hazards in design and thereby implement CHPtD solutions.

3.2 Introduction

It is recognized that the construction industry is one of the most hazardous industries worldwide (Esmaeili and Hallowell 2012; Zhang and Fang 2013). Given the nature of construction work, a plethora of hazards must be managed to prevent accidents while transforming design intent into finished facilities. One method to reduce injuries is to recognize and respond to hazards before they are encountered in construction. Although hazard recognition can occur at any stage in a project lifecycle (Hecker and Gambatese 2003), researchers have strived to understand how construction safety hazards can be recognized and controlled during design, a process known as Construction Hazard Prevention through Design (CHPtD) (Behm 2005; Seo and Choi 2008; Driscoll et al. 2008; Ghaderi and Kasirossafar 2011; and Lingard et al. 2012).

CHPtD has been praised as being a superior method of safety risk reduction as the central premise (i.e., hazard elimination) lies at the top of the hierarchy of safety controls (Szymberski, 1997; Toole, 2005; Gambatese et al., 2008; and Manu et al., 2012). One method for CHPtD implementation is to use design information in its various forms to forecast the emergence of hazards during construction. This design information may range from two-dimensional computer aided drawings (CAD) to three-dimensional building information models (BIM) (Goodrum et al. 2016). Researchers have stressed the importance of design information for hazard recognition tasks (Ku and Mills 2010; Bansal 2011; Kasirossafar and Shahbodaghlou 2012; Ganah & John 2015;

Zhang et al. 2015; and Martinez-Aires et al 2018) and have begun to study the effects that design information has on hazard recognition (Hallowell and Hansen 2016). Researchers have implicitly assumed that three-dimensional (3D) design information formats will enable improved hazard recognition skill compared with traditional two-dimensional (2D) formats (Ku and Mills 2010; Bansal 2011; Ganah & John 2015; and Zhang et al. 2015). However, this assumption remains untested.

The objective of this study is to explore the impact of various forms of design information on hazard recognition performance and CHPtD decision making. Such inquiry tests a fundamental assumption propagated in literature using a controlled experimental procedure and adds rigor to the growing field of CHPtD.

3.3 Literature Review

Construction Hazard Prevention through Design (CHPtD)

Construction Hazard Prevention through Design (CHPtD) is a theory that involves the consideration of worker safety during the design phase of a project (Gambatese et al. 2008 and NIOSH 2013). Specifically, CHPtD involves recognizing, projecting, and removing or controlling design elements that create construction hazards (Behm 2005; Seo and Choi 2008; Driscoll et al. 2008; Ghaderi and Kasirossafar 2011; Hallowell and Hansen 2016). This is often achieved by reviewing project design information in a formal review process and addressing hazards relating to construction, maintenance, repair, and demolition (Suraji et al. 2001; WorkCover 2001; Gambatese et al. 2008; Ganah and John 2015; NIOSH 2017).

Several researchers have used subjective research techniques to provide evidence that design characteristics are related to construction accidents (Behm 2005; Seo and Choi 2008; Driscoll et al. 2008; Ghaderi and Kasirossafar 2011) and case study research has shown that it is possible to eliminate safety hazards through the implementation of CHPtD design solutions (Cheng and Teizer 2012; Lingard et al. 2012; Zhang et al. 2013; Fonesca et al. 2014; Zhang et al. 2014; Kim and Teizer 2014; Zhang et al. 2015). Additionally, CHPtD theory has been employed in design through automated processes, checklists, and standardized procedures (Gambatese et al. 1997; Cooke et al. 2008; Dewlaney and Hallowell 2012) and has been extended into technology applications within BIM software (Li et al. 2003; Hadikusumo and Rowlinson 2004; Navon and Kolton 2006; Teizer et al. 2005; Bansal 2011; Hadikusumo and Rowlinson 2002; Qi et al. 2011; Cheng and Teizer 2012; Zhang et al. 2013; Zhang et al. 2014; Kim and Teizer 2014; Zhang et al., 2015).

In the past 20 years, the CHPtD research field has grown, resulting in a large and dispersed body of literature. However, it is still unclear what types of safety hazards are recognizable in design and how different formats of design information affect hazard recognition skill. Research in this domain would provide a rich opportunity for the advancement of CHPtD in research and in practice.

Hazard Recognition in Construction

Safety planning relies on the ability to forecast and prevent construction safety hazards (Albert et al. 2014). Unfortunately, research has shown that construction workers recognize approximately one-half of hazards to which they are exposed and individuals are unable to recognize safety hazards in dynamic construction environments (Carter and Smith, 2006; Bahn, 2013; Lopez del Puerto et al., 2013; Albert et al., 2014). This statistic has become the focus of many studies seeking to use mnemonics (Albert et al. 2013; Hallowell and Hansen 2016), emotions (Tixier et al 2014; Bhandari 2017), and virtual reality experiences (Hadikusumo and Rowlinson 2004; Tixier et al. 2013; Albert et al. 2014) to improve worker's hazard recognition skills.

Although hazard recognition research has emerged, there has been comparatively little inquiry into hazard recognition during the design phase. In a sole study, Hallowell and Hansen (2016) empirically examined the extent to which designers use CAD drawings to forecast construction hazards. They assessed the ability of 17 construction designers to recognize safety hazards for 12 different work activities using actual CAD designs. The safety hazards for each work activity were known from work observations and interviews from contractor teams. The results show that designers recognize approximately one-half of safety hazards present during design. Although this is the first research in this domain, there is a lack of evidence suggesting what types of safety hazards and hazardous energy sources are recognizable during design.

Using Design Information for Construction Safety Planning

Pre-construction safety planning is an activity that involves gathering safety details from design information, which may include 2D computer-aided-design (2D CAD) drawings (Chantawit et al. 2005), material specifications (Brexendale and Jones 2000), 3D building information models (BIM) (Ganah and John 2015 and Zhang et al. 2015), and augmented and virtual reality (AR/VR) (Hadikusumo and Rowlinson 2004 and Sacks et al. 2015). In the construction industry, 2D CAD drawings remain the primary method to convey design intent to site personnel as they provide the basic technical graphical and textural information needed to create construction installations (Goodrum et al. 2016).

Although some researchers contend that 2D CAD and BIM both offer rich opportunity for hazard recognition in design (De Lapp et al. 2004 and Ganah and John 2015), others suggest CAD does not provide an efficient platform for to acquire spatial project information (Collier 1994; Young 1996; and Zhang et al. 2015) nor information relating to the relationships of project constraints, conditions, and trades (Chantawit et al. 2005). It is postulated that these limitations lead to poor safety planning and awareness among workers (Chantawit et al. 2005). On the other hand, researchers propose that BIM offers enhanced opportunities to recognize safety hazards by digitally replicating the physical work environment and aiding in the mental interpretation of spatial constraints and construction sequences (Ku and Mills 2010; Bansal 2011; Ganah & John 2015; and Zhang et al. 2015). Researchers have also proposed that BIM should promote higher situational awareness among workers since it allows them to visualize objects in their environment as it relates to safety in greater accuracy than CAD designs (Kasirossafar and Shahbodaghlou 2012; Ganah and John 2015; Martinez-Aires et al. 2018). Although these propositions are consistently made in literature, they have not been empirically tested. This provides an opportunity for experimental validation to enable CHPtD maturity.

3.4 Research Objectives and Point of Departure

The aim of this study is to investigate the extent to which different formats of design information affect hazard recognition during the design phase of a construction project. Specifically, the objective of this research was to measure the variability of hazard recognition performance across three formats of design information (3D visualizations, 2D CAD, and a combination of the two) and a control group. The corresponding alternative hypotheses are as follows:

Ha1: Provision of design information in general does affect hazard recognition performance.

Ha2: The format of design information does affect hazard recognition performance.

Ha3: Years of construction experience does predict hazard recognition performance.

This is the first attempt in research to conduct experimental research to examine variability of hazard recognition performance via a controlled and simulated CHPtD review process. By addressing this gap in literature, the research community can better understand how to better improve the efficacy of CHPtD processes.

3.5 Research Methods

Selection of Work Activities

The first step of the research was to obtain actual information about construction hazards faced on a real construction project. Because construction projects involve many different construction activities and design elements, the research team selected three discrete building components (i.e., modules). To maintain consistency with existing research, three of the twelve modules studied in Hallowell and Hansen (2016) were selected. Specifically, skylight installation, soffit drywall installation, and interior wall stud installation were selected because they were from the same project, complete plans and specifications for the facility were made available by the project team, the activities involve a strong dispersion of work attributes, and the work was independent of adjacent activities when performed. Additionally, as described in Hallowell and Hansen (2016), the actual construction hazards faced by the work crews were identified and documented through field observations and interviews. Table 4 and 5 below includes the work activity descriptions and associated safety hazards for three work activities (Hallowell and Hansen 2016).

Table 4: Work Activities and Descriptions

Construction Activity	Activity Description
Skylight Installation	This work involves the construction of a skylight. The framing for the skylight and original roof has previously been demolished and opened. A temporary cover was installed. Includes: removal of temporary cover and installation of new skylight. Does not include removal of debris or materials.
Soffit Drywall Installation	This work involves the construction of a drywall soffit. Includes: all preparatory work and setup, and installation of soffit and wall drywall.
Interior Wall Stud Installation	This work involves the construction of an interior wall. Includes: vertical members of metal stud framing.

Table5: Safety Hazards and Hazardous Energy Sources for Each Activity (from Hallowell and Hansen 2016)

Skylight Installation	**Soffit Drywall Installation**	**Interior Wall Stud Installation**
Electrical Cords and Tools (Electrical)	Electrical Cords and Tools (Electrical)	Ascending and Descending Scaffold (Gravity)
Flying Debris (Motion)	Flying Debris (Motion)	Electrical Cords and Tools (Electrical)
Hand Tools (Motion)	Hand Tools (Motion	Flying Debris (Motion)
Heat Stress and Sun Exposure (Temperature / Radiation)	Moving Man Lift (Motion)	Hand Tools (Motion)
Positioning Heavy Material (Motion)	Positioning Heavy Material (Motion)	Heat Stress and Sun Exposure (Temperature / Radiation)
Noise (Sound)	Noise (Sound)	Moving Man Lift (Motion)
Objects and Tools at Height (Gravity)	Objects and Tools at Height (Gravity)	Positioning Heavy Material (Motion)
Trip Hazards (Gravity)	Trip Hazards (Gravity)	Noise (Sound)
Cuts on Razor Knife (Motion)	Cuts on Razor Knife (Motion)	Objects and Tools at Height (Gravity)
Open Flame (Temperature)	Sharp Metal Trim (Motion)	Trip Hazards (Gravity)
Pinch Points (Motion)	Small Particles (Chemical)	Sharp Blade on Saw (Motion)
Pressurized Propane Tank (Pressure)	Work Overhead (Gravity)	Hot Work and Sparks (Temperature)
Protruding Nails/Sharps (Motion)	Work at Height (Gravity)	Sharp Steel (Motion)
Small Particles (Chemical)		Uneven Work Surface (Gravity)
Flashing Cement (Chemical)		Work Overhead (Gravity)
Work at Height (Gravity)		Work at Height (Gravity)

Developing 3D Visualizations

The plans and specifications provided by the project team provided direct information that could be used in the experiment. However, 3D BIM was not used on the project and, thus, needed to be created from the plans and specifications. Thus, the relevant design elements from the 2D CAD drawings obtained by Hallowell and Hansen (2016) were transformed into 3D visualizations. The 3D visualizations were designed to a #350 Level of Development (L.O.D.) ensuring design elements were modeled to "rough dimensions" (BIMForum 2017). Additionally, the L.O.D. #350 was chosen to represent a mature design in the design process as a mature design is considered here to be more appropriate for hazard searches than conceptual designs. A total of 27 screenshots of the 3D BIM environment captured all building elements associated with the work activities and were assembled into a portable document file (PDF). Screenshot angles were carefully selected to ensure that all attributes of the BIM environment were included in the PDF.

The authors considered providing participants with the design in BIM software during the experiment; however, variability in experience with BIM was felt to be a strong confounding factor that would have been introduced by the software. Thus, the team elected to provide easy-to-navigate screenshots of the software to promote internal validity at the expense of some ecological validity. This process also better mirrors how a safety design review would be conducted with a multi-disciplinary team with varying experience with and exposure to BIM. Sample images are provided in Figure 2.

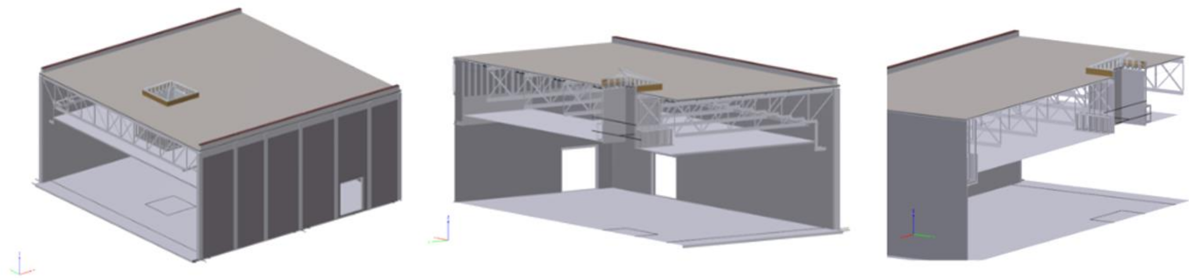

Figure 2. Example 3D Visualizations detailed to #350 Level of Detail

Selection of Human Subjects

A total of 117 participants from Colorado, North Carolina, and Wisconsin participated in the study. To enhance the practical contributions, three population groups (N = 39 each) were solicited, including: construction design professionals, construction supervisors; and civil engineering students. Construction design professionals were included only if they perform design-related activities in their current employment such as architectural design, drafting, BIM development, virtual design and construction, and clash detection. Construction supervisors were included only if they actively supervise construction personnel and processes on an active site. Lastly, civil engineering students were included only if they had formal classroom training in CAD and BIM. The population groups demographics are shown in table 6. Additional demographic information is shown in appendix tables 4 and 5.

Table 6: Salient Participant Demographics

	Age			Years of Industry Experience	
Population Group	**Mean**	**St. Dev.**	**Range**	**Mean**	**St. Dev.**
Construction Designers	40.43	13.10	22 - 64	16.24	11.44
Construction Supervisors	39.33	10.98	21 - 65	17.33	11.60
Civil Engineering Students	22.17	1.98	20 - 31	0.70	0.60

Population Treatment and Control Groups

Within each population group, participants were randomly assigned to each treatment group or the control group. Specifically, the groups included: skylight installation, soffit drywall installation, and interior wall stud framing.

1. Control Group: Provided with a description of the work activity but not provided with any specific design information (see Table 1).
2. 2D CAD Treatment Group: Provided with 2D plans and a description of the work activity
3. 3D Visualization Treatment Group: Provided with a 3D representation of the BIM model and a description of the work activity
4. Combination Treatment Group: Provided with the 2D CAD, 3D visualization, and a description of the work.

An ANOVA sample size calculation ($\alpha = 0.05$), yielded an $N = 27$ required for each treatment group and a MEANS sample size calculation using the same α yielded a required $N = 12$ for the control group. The selection and order of the design modules and the format of design information for each module was assigned using a Latin square design.

Latin Square Experimental Design

To study the effects of design information format on hazard recognition performance, a Latin square experimental design was used. A Latin square design is an experimental design that controls for the negative effects of multiple variable interactions by blocking the treatment and independent variables. Within Latin square designs, the number of levels of independent variables must equal the number of levels of the treatment factor. This creates an (n x n) matrix in which no one treatment and independent variable combination can occur more than once in the design. These designs cross the treatment factors with the independent variables in a counterbalanced order to ensure that the negative effects of repeated observations are minimized during the research trials (Edwards 1951; McNemar 1951). More specifically, this design allows researchers to assess the variation in data of an independent variable for a single population group over a series of sequential research trials (Edwards 1951 and McNemar 1951). Latin square has been used in a wide variety of research including agriculture (Mead et al 2003), metallurgy (Peng et al. 2016), and psychology (Edwards 1951; McNemar 1951; Birney 2006; Baracz et al. 2016; Daniel 2016).

A 3x3 Latin square design (see Table 7) was employed to cross the 3 treatment factors (i.e., construction activities) with the 3 independent variables (i.e., design information formats). The construction activities include skylight, soffit drywall, and metal wall stud installation. The design information formats include CAD, 3D visualizations, and a combination of the two. Finally, the dependent variable is hazard recognition performance of each of the treatment variables crossed with the independent variables.

Table 7: 3X3 Latin Square Design

		Design Information Format		
		3D Visualization	2D CAD	Combination of 2D and 3D
Construction Activity	Skylight Installation	**A-1**	**C-3**	**B-2**
	Soffit Drywall Installation	**B-3**	**A-2**	**C-1**
	Interior Wall Stud Framing	**C-2**	**B-1**	**A-3**

As can be seen in the 3x3 matrix in Table 7, there were three variations in experimental arrangements consistent of the order in which the treatment variable is crossed with the independent variable. The variations in the experimental arrangements are represented by the letters “A,” “B,” and “C,” respectively. Each letter is its own arrangement that consists of 3 independent and sequential trials. Additionally, the order in which the experimental arrangements are presented to participants is indicated by the ordering number. For example, one variation is presented here as experimental arrangement “A”. This arrangement first employs the 3D visualization format for the skylight construction activity (i.e., A-1). Secondly, the arrangement employs the CAD format for the soffit drywall construction activity (i.e., A-2). Lastly, the combination of CAD and 3D visualization with the interior wall stud framing construction activity (i.e., A-3) is presented. As required by the Latin square research design, each experimental arrangement appears an equal number of times within and for all population groups. This design allows evaluation of variability in means for all arrangements using an analysis of variance (ANOVA) statistical techniques (Edwards 1951; McNemar 1951). The design also mitigates the potential impact of a learning curve or interactions among treatment types. If this design were not selected, confounding effects due to the sequence of design information format or construction work activity may have presented a potential confound in the results. The Latin square nullifies these confounds and learning curves through a counterbalanced design.

Additional benefits of this design are that it: (1) allows for the nullification of any learning curve that is attained during the sequential research trials; (2) allows the assessment of variability of means within the independent variable; and (3) ensures that the variability in performance is truly attributable to the independent variables by counterbalancing procedures (Edwards 1951 and McNemar 1951).

Conducting Experimental Research Trials

Data collected for construction designers and supervisors' population groups were collected on actual construction jobsites and construction office headquarters. Once a participant was randomly selected and assigned to one of the experimental assignments, participants were briefed about the research process. Each participant was provided a copy of the work activity description (see table 1) associated with the appropriate research arrangement (i.e., A-1). Participants were treated in a consistent manner to minimize researcher influence and bias. Distractions were kept to a minimum where feasible and all research trials were conducted between the primary investigator and subject with no outside human interaction. This was done to strengthen internal validity of the study by ensuring participants had consistent information regarding construction activities. Participants were allowed an unrestricted amount of time to review work activity descriptions, and were then presented with the appropriate experimental arrangement. The 2D CAD drawings which provide the technical and annotated design information were printed on 24” X 18” paper. Participants were provided the 3D visualizations via a PDF displayed on a 17” laptop monitor. When assigned to the combination treatment group, participants were instructed to use both 3D visualizations and CAD as desired. The control group was provided only with the activity descriptions in Table 1.

During the research trial, participants were instructed to “review the design information and identify as many safety hazards as you can.” Safety hazards were identified for the participants as “a source of energy that, if released, and results in exposure, could cause injury or death.” Participants were asked to identify “ways that workers could become injured, ill, or be killed in the work situation” and were asked to “disregard citing infractions of safety and health regulations.” When identifying a hazard, participants were asked to verbally narrate their response. All hazards were transcribed during the experiments by the lead researcher. No part of the experimental process was time-restricted.

3.6 Results and Analysis

Calculating the Hazard Recognition Index

After the research trial concluded, the researcher computed the dependent variable, i.e., the proportion of correct hazard identifications for each module. The Hazard Recognition index (HR_{index}) was adopted from Carter and Smith (2006) and Albert et al. (2014), which results in proportion data. The numerator in the index is the total number of hazards correctly recognized by the participant for the construction activity. The denominator is the total number of safety hazards for each construction activity (HR_{index}) [Eq. (1)]:

$$[1]\ \mathrm{HR}_{index} = \frac{\mathrm{H\ recognized}}{\mathrm{H\ total}}$$

The resulting HR_{index} data compare closely to previous research. For example, Albert et al. 2013 employed a multiple baseline testing procedure and found that workers were able to recognize and communicate approximately 38% of the safety hazard prior to the intervention of energy based mnemonics, which were found to increase overall hazard recognition skill by 31%. Additionally, Albert et al 2014 employed a high-fidelity augmented virtual environment system for hazard recognition and found that workers were able to recognize approximately 50% of the hazards from the system. Furthermore, research by Hallowell and Hansen 2016 found that construction designers were able to recognize approximately 50% of safety hazards using nly 2D CAD drawings. These studies suggest that the findings of the present work are closely aligned with previous research findings. The overall range of hazard recognition performance ranged from 6.3% for the civil engineering students control group to the highest of 84.6% for the construction supervisor treatment group. Overall, the construction supervisors outperformed the construction designers, who outperformed the civil engineering students. The HR_{index} values for each population group, format of design information, and construction work activities can be seen in tables 8, 9, and 10 below.

Table 8: Population Groups and HR_{index} Range Values

Population Group	HR_{index} Values (All Activities)			
	Mean	**Low**	**High**	**Delta**
Construction Supervisor - Treatment	45.3%	12.5%	76.9%	64.4%
Construction Supervisor - Control	44.4%	18.7%	84.6%	65.9%
Construction Designer - Treatment	37.9%	12.5%	81.2%	68.7%
Construction Designer - Control	41.4%	23.0%	76.9%	53.9%
Civil Engineering Students - Treatment	27.8%	6.2%	69.2%	63.0%
Civil Engineering Students - Control	33.7%	6.2%	62.5%	56.3%

Table 9: Treatment Groups and HR_{index} by Format of Design Information

		Design Information Format			Total
		2D CAD	**3D BIM**	**Combination**	
Population Treatment Groups	**Construction Designers**	HR Index (μ) = 39.5% n = 27	HR Index (μ) = 39.0% n = 27	HR Index (μ) = 35.2% n = 27	**HR Index (μ) = 37.9% n = 81**
	Construction Supervisors	HR Index (μ) = 44.9% n = 27	HR Index (μ) = 44.3% n = 27	HR Index (μ) = 46.7% n = 27	**HR Index (μ) = 45.3% n = 81**
	Civil Engineering Students	HR Index (μ) = 29.2% n = 27	HR Index (μ) = 26.1% n = 27	HR Index (μ) = 25.9% n = 27	**HR Index (μ) = 27.1% n = 81**
		HR Index (μ) = 37.9% n = 81	**HR Index (μ) = 36.5% n = 81**	**HR Index (μ) = 35.9% n = 81**	

Table 10: Population Groups and HR$_{index}$ by Construction Work Activity

		Design Information Format			Total
		Skylight Installation	**Soffit Drywall Installation**	**Interior Wall Stud Framing**	
Population Treatment Groups	**Construction Designers**	HR Index (µ) = 30.3% n = 27	HR Index (µ) = 46.2% n = 27	HR Index (µ) = 37.3% n = 27	**HR Index (µ) = 37.9% n = 81**
	Construction Supervisors	HR Index (µ) = 35.9% n = 27	HR Index (µ) = 54.4% n = 27	HR Index (µ) = 45.6% n = 27	**HR Index (µ) = 45.3% n = 81**
	Civil Engineering Students	HR Index (µ) = 24.3% n = 27	HR Index (µ) = 33.3% n = 27	HR Index (µ) = 23.6% n = 27	**HR Index (µ) = 27.1% n = 81**
Population Control Groups	**Construction Designers**	HR Index (µ) = 36.5% n = 12	HR Index (µ) = 50.0% n = 12	HR Index (µ) = 38.0% n = 12	**HR Index (µ) = 41.5% n = 36**
	Construction Supervisors	HR Index (µ) = 42.7% n = 12	HR Index (µ) = 48.0% n = 12	HR Index (µ) = 42.7% n = 12	**HR Index (µ) = 44.5% n = 36**
	Civil Engineering Students	HR Index (µ) = 29.7% n = 12	HR Index (µ) = 37.8% n = 12	HR Index (µ) = 33.9% n = 12	**HR Index (µ) = 33.8% n = 36**
		HR Index (µ) = 33.2% n = 117	**HR Index (µ) = 45.0% n = 117**	**HR Index (µ) = 36.9% n = 117**	

N = number of observations; µ = HR_{index}

Examine the Effects of Design Information using Mean and Dispersion Tests

The first hypothesis Ha1: "*Design information does affect hazard recognition performance*," was tested independent of design information format. The HR_{index} was calculated for all population groups and categories for each construction activity. All HR_{index} data were found to be normally distributed with equal of variances except for the treatment group of the student population (skewness $p = 0.007$). A Two-Sample Independent Mean and Dispersion test resulted in t-test values of statistical significance for each combination of population group and construction activity. Table 11 provides the sample size, mean, and standard deviation for each construction activity for both the treatment and control population categories of each population group. Additionally, the test results of statistical significance (i.e., *t* and *p*) are presented for each two-sample mean and dispersion test independent of activity for each population group. The results suggest there is no statistically significant difference in the HR_{index} between the treatment groups (some form of design information) and the control group (no design information) for practitioners. Therefore, the authors fail to reject the null hypothesis H01 and conclude that "*Design information does not affect hazard recognition performance*" as evaluated by the HR_{index}. This was a very surprising finding, as the implication is that the design information provides no additional benefit in the hazard recognition performance and that a practitioner can perform equally as well by simply thinking about the work activity in abstraction. It should be noted that a significant difference does exist for civil engineering students who have relatively little experience but the direction of the difference indicates that the control group performed slightly better than the treatment group.

Table 11: Descriptive Statistics and Two-Sample Independent Mean and Dispersion Test Results

Population	Population Category	Sample Size	Mean (HR_{index})	Total (HR_{index})	t	p
Designer	Treatment	81	37.92%	39.70%	-0.091	0.928
	Control	36	41.49%			
Supervisor	Treatment	81	45.30%	44.90%	0.264	0.792
	Control	36	44.50%			
Student	Treatment	81	27.08%	30.44%	-2.504	0.017*
	Control	36	33.79%			

Note: t = variance of the group mean; p indicates significance.

Asterisk (*) = Statistically significant difference beyond 95% confidence.

Analysis of Variance of Design Information Format HR Scores

The next step in data analysis was to test hypothesis Ha2: "*The format of design information does affect hazard recognition skill*" by examining the variability of hazard recognition performance of the independent variables (i.e., design information format) crossed with the treatment factors/dependent variables (i.e., construction activity) using analysis of variance (ANOVA). The ANOVA statistical test determines whether there is a difference between means of independent variables (Dielman 2005; Fellows and Liu 2008). This test estimates statistically significant differences between the means using an *F* value while measuring the variability of the dependent variable that is explained by the independent variable (Dielman 2005; and Fellows and Liu 2008). The control groups were removed from this analysis as they received no design information and are thus not needed for testing hypothesis (Ha2). Table 12 below provides the sample size, sample mean HR_{index}, overall HR_{index}, *F*, an p values of ANOVA analysis of design information format by population group. This analysis is independent of construction work activity and order of research trial as these variables were blocked in the Latin square design, thereby controlling for their effects.

Table 12: Design Information format ANOVA Results by Population Group

Population	Design Information Format	Sample Size	Mean (HR_{index})	Total (HR_{index})	F	p
Designer	2D CAD	27	39.51%	37.91%	0.818	0.445
	3D Visualization	27	39.04%			
	Combination	27	35.18%			
Supervisor	2D CAD	27	44.88%	45.29%	0.259	0.773
	3D Visualization	27	44.26%			
	Combination	27	46.74%			
Student	2D CAD	27	29.23%	27.08%	0.599	0.552
	3D Visualization	27	26.12%			
	Combination	27	25.89%			

Note: F = variance of the group mean; p = significance.

Asterisk (*) = Statistically significant difference beyond 95% confidence.

Surprisingly, the results suggest that there is no significant difference in the proportion of safety hazards recognized across the three independent variables (i.e., design information formats). The ANOVA analysis suggests that no statistical significance exists to reject null hypothesis Ho2 for any population group (All p values > α (0.05)). Therefore, the results suggest failure to reject null hypothesis (Ho2).

Determine if Experience Improves HR Scores

The participants came from a wide range of construction experience. To determine if years of construction experience played a significant role in hazard recognition performance, a one-way analysis of variance (ANOVA) was applied within each treatment and control group to test hypothesis Ha3: “Years of construction experience does predict hazard recognition performance.” (Ha3). For the treatment and control groups within each population, a median split of construction experience was conducted to dichotomize the variable into “high” and “low” experience levels, where ‘high’ included all participants whose years of experience exceeded the median and ‘low’ were all participants whose experience was less than the median. A one-way ANOVA was used to compare these two groups. Table 13 below provides the population and categories, mean HR_{index}values, overall HR_{index}value, F, and p statistics.

Table 13: Construction Experience Statistics on HR_{index} by Population Groups and Categories

Population	Population Category	Experience Level	Sample Size	Mean (HR_{index})	Total (HR_{index})	F	p
All Combined Groups	Treatment	High	123	42.89%	36.69%	56.89	0.000*
		Low	120	30.48%			
	Control	High	54	43.93%	39.64%	8.869	0.004*
		Low	54	35.34%			
Designer	Treatment	High	39	37.49%	37.89%	0.069	0.794
		Low	42	38.30%			
	Control	High	18	43.37%	41.49%	0.704	0.409
		Low	18	39.61%			
Supervisor	Treatment	High	39	46.82%	45.35%	1.004	0.320
		Low	42	43.88%			
	Control	High	18	42.97%	44.89%	0.475	0.496
		Low	18	46.81%			
Student	Treatment	High	33	30.66%	27.64%	3.504	0.065
		Low	48	24.62%			
	Control	High	18	33.30%	33.78%	0.042	0.839
		Low	18	34.26%			

Note: F = variance of the group mean; p = significance.

Asterisk (*) = Statistically significant difference beyond 95% confidence.

As can be seen in Table 13, there is no significant effect of years of construction experience on hazard recognition performance *within* any of the population treatment or control groups (All p values > α (0.05)). However, the results suggest that construction experience does have a significant effect on hazard recognition performance when all treatment and control groups are aggregated. In total, 117 participants yielded 351 observations. Of these 351 observations, participants who had "*high*" experience levels did significantly better than those whom had "*low*" experience levels in both the treatment ($F_{1,235}$ = 56.890, p = 0.000) and control group ($F_{1,104}$ = 9.941, p = 0.004).

To validate these results, a multiple regression analysis was applied to each treatment and control group (Pedhazur 1997). Multiple regression was used to evaluate the extent to which variability in hazard recognition performance can be predicted by years of professional experience. As can be seen in Table 11 below, there was no significant relationship for any treatment or control group but, again, there was a significant effect of (t = 5.504, p = 0.000*) for the treatment and (t = 2.293, p = 0.023*) for the control when all groups were aggregated. This result is a result of the variability between the students population group and construction design and supervision practitioners. The students, in both the treatment and control groups, have both low levels of construction experience combined with low HR_{index} scores. Alternatively, construction design and supervision practitioners had more years of construction experience and higher HR_{index} scores. Therefore, there is a relationship between construction experience and hazard recognition performance. These findings support the ANOVA results. Therefore, null hypothesis Ho3 is rejected as the aggregate of data shows that experience significantly affects hazard recognition performance with both ANOVA and regression analysis. Tables 14 and Figure 2 below shows the results of the regression analysis. Specifically, the adjusted R squared, *t*, and p statistics are shown. Figure 3 below provides the scatterplots for the years of construction experience and hazard recognition performance *across* all populations and *within* each population treatment group. The scatterplots for the control groups can be found in Appendix Figure 1.

Table 14: Linear Regression Results for Experience and HR_{index}

Population	Population Category	Number of Observations	R^2	Adjusted R^2	DF	*F*	*t*	p
All Combined Groups	Treatment	243	0.111	0.108	1 & 241	30.29	5.504	0.000*
	Control	81	0.047	0.038	1 &106	5.258	2.293	0.023*
Designer	Treatment	81	0.013	0.000	1 & 79	1.044	1.022	0.310
	Control	36	0.002	-0.027	1 & 34	-0.081	-0.285	0.778
Supervisor	Treatment	81	0.026	0.014	1 & 79	2.143	1.464	0.147
	Control	36	0.001	-0.030	1 & 32	0.042	0.206	0.838
Student	Treatment	81	0.033	0.021	1 & 79	2.769	1.664	0.100
	Control	36	0.036	0.007	1 & 34	-1.279	-1.131	0.266

Note: t = variance of the group mean; p = significance.

Asterisk (*) = Statistically significant difference beyond 95% confidence.

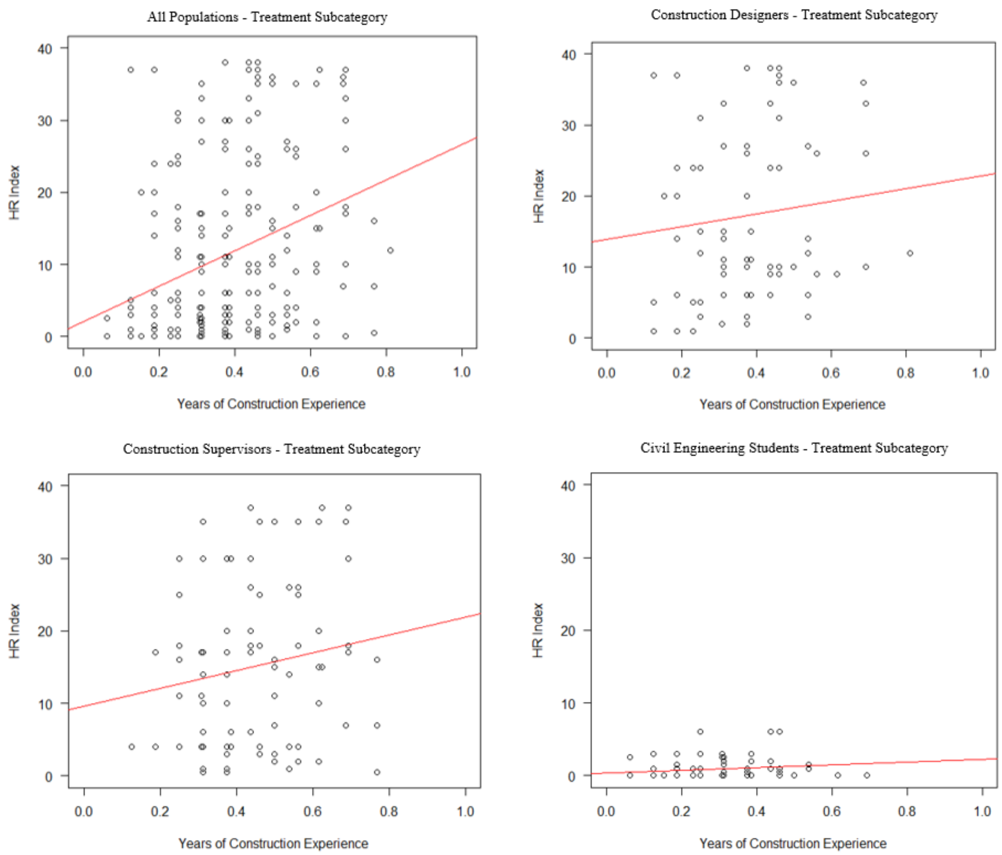

Figure 3: Scatterplot of HR_{index} and Years of Construction Experience Across and Within all Population Treatment Groups

3.7 Conclusions

The Construction Hazard Prevention through Design (CHPtD) theory has seen an abundance of research in recent years. This research has been useful in advancing the theories development and has strived to validate its use with subjective research methods. Several researchers have used subjective research techniques to provide evidence that construction accidents have been related to design characteristics (Behm 2005; Seo and Choi 2008; Driscoll et al. 2008; Ghaderi and Kasirossafar 2011) and case study research has shown that it is possible to eliminate safety hazards with CHPtD solutions (Cheng and Teizer 2012; Lingard et al. 2012; Zhang et al. 2013; Fonesca et al. 2014; Zhang et al. 2014; Kim and Teizer 2014; Zhang et al. 2015).

Through this research, the CHPtD theory has been promoted as a valuable safety management strategy. Although this literature is rich with many valuable contributions, there is a dearth of empirical evidence validating it use for risk reduction in practical construction settings (Hardison et al. In press).

Within existing literature, there are two key assumptions that provided the inspiration for this research. First, researchers suggest that both two-dimensional computer aided design (CAD) drawings and BIM both provide a rich opportunity for hazard recognition in design (De Lapp et al. 2004 and Ganah and John 2015). Researchers have suggested that the use of design information will enhance the ability to recognize hazards stemming from downstream construction work, and therefore it is assumed that the use of design information increases the efficacy of hazard recognition in design (De Lapp et al. 2004; Chantawit et al. 2005; Ku and Mills 2010; Bansal 2011; Kasirossafar and Shahbodaghlou 2012; Ganah and John 2015; Martinez-Aires et al. 2018). Second, it is assumed that the format of design information affects hazard recognition performance during design. Researchers suggest CAD alone is insufficient as a platform for hazard recognition in design as it limits the ability to acquire spatial project information (Collier 1994; Young 1996; Zhang et al. 2015) and information relating to the relationships of project constraints, conditions, and trades (Chantawit et al. 2005). Conversely, researchers suggest that BIM offers enhanced opportunities to recognize safety hazards by digitally replicating the physical work environment and aiding in the mental interpretation of spatial constraints and construction sequences (Ku and Mills 2010; Bansal 2011; Ganah & John 2015; and Zhang et al. 2015). This is thought to increase situational awareness through easier visualization of the work environment than 2D CAD alone (Kasirossafar and Shahbodaghlou 2012; Ganah and John 2015; Martinez-Aires et al. 2018).

Although these propositions are consistently made in literature, they have not been empirically tested and provided the inspiration for this research.

This work tested 117 subjects hazard recognition skills using 3 formats of design information (i.e., 2D CAD, 3D visualizations, and a combination of the two) crossed with 3 treatment variables (i.e., construction activities) via a Latin square experimental design to determine the effects of design information formats on subjects' hazard recognition skill. This papers primary contribution to the body knowledge is the identification of how design information, and the different formats of design information, affect hazard recognition performance during project design phases. Subjects' performed a simulated Construction Hazard Prevention through Design (CHPtD) safety review of one construction design, presented in 3 different information formats, and were asked to identify potential safety hazards arising from 3 separate construction activities. The following hypotheses were tested:

Ho1: Provision of design information in general does not affect hazard recognition performance.
Ho2: The format of design information does not affect hazard recognition performance.
Ho3: Years of construction experience does not predict hazard recognition performance.

To test (Ho1), the hazard recognition performance between all populations treatment and control groups were examined using mean and dispersion t-test procedures. The treatment groups of the study were provided a mixture of three formats of design information for three independent construction activities. The control group was not provided any design information. Both treatment and control groups were provided descriptions of the construction work activities and asked to identify all safety hazards associated with the construction work activity. Overall, the results suggest that the provision of design information does not increase the ability to recognize safety hazards when the scope of the construction work activity is known. This was a very surprising finding, as the implication is that the design information provides no additional benefit in the the HR_{index} and that a practitioner can perform equally as well by simply thinking about the work activity in abstraction. Therefore, the authors fail to reject research hypothesis (Ho1).

To test Ho2, analysis of variance (ANOVA) was used to examine the variability of hazard recognition performance of the independent variables (i.e., design information format) crossed with the treatment factors/dependent variables (i.e., construction activity) within all populations treatment groups. The control groups were not included in the analysis as they did not receive any design information. Surprisingly, the results suggest that there is no significant difference in the proportion of safety hazards identified across the three independent variables (i.e., design information formats). The ANOVA analysis suggests that no statistical significance exists to reject the null hypotheses for any population group. Therefore, the results suggest failure to reject null hypothesis (Ho2).

Lastly, to determine if years of construction experience played a significant role in hazard recognition performance, both one-way analysis of variance (ANOVA) and Multiple Linear regression were applied within each treatment and control group to test hypothesis (Ho3). The ANOVA analysis suggests that there was no significant effect of the years of construction experience within each population group. However, the results suggest that construction experience does have a significant effect on hazard recognition performance across the aggregate of all data. These results were confirmed with MLR analysis. Although MLR analysis suggests that construction experience does not predict hazard recognition performance within groups, the results do reconfirm the ANOVA as experience does predict performance when the data are aggregated across all population groups.

Overall, the results of this study are contrary to current assumptions in construction safety literature. First, as this study suggests, it may not be true that design information is useful for recognizing safety hazards in design. Future research is needed to discover which types of safety hazard are recognizable during design phases and which ones remain latent until construction. The overall premise of CHPtD is to recognize safety hazards in design so they may be eliminated or managed prior to construction (Hecker and Gambatese 2003; Gambatese et al 2008). Understanding which types of construction hazards are recognizable in various project delivery phases will be beneficial for the advancement of CHPtD theory into commercial practice.

Secondly, it was found that the format of design information had no effect on the HR_{index}. This is an interesting find since the prevailing literature assumes that 3D visualizations will yield higher hazard recognition performance than CAD alone (Kasirossafar and Shahbodaghlou 2012; Ganah and John 2015; and Martinez-Aires et al. 2018). The assumption that one format is superior to another is thereby rejected, and if cannot be proven false with additional research, stands to be tested. This is an important finding in the domain of construction safety as it suggests that various formats of design information will fail to yield variability in hazard recognition performance during design stages. Coupled with the last finding of this study, which suggests that construction experience predicts hazard recognition, it is here proposed that a multi-disciplinary team consisting of experienced professionals is more important for hazard recognition than the format of design information used for CHPtD review processes. If findings of this type continue to hold true in future research, there will be strong practical implications on CHPtD theory and implementation.

3.8 Limitations

This study has two notable limitations. First, although the authors suggest there is no difference among the format of design information, more complex 3D visualizations presented in actual BIM software may yield different hazard recognition scores across for 3D design information formats. Additionally, the level of design complexity, level of detail, and amount and quality of data within the BIM environment may affect the number of visual ques that participants can use for recognizing safety hazards. In this study, the BIM environment contained no mechanical electrical, or plumbing design elements and all elements were designed to resemble "rough dimensions." However, these design elements were also removed from the 2D drawings to maintain consistency with the 3D visualizations. More CHPtD research of this type, using actual design of varying complexities and known construction safety hazards, could be used to better understand how the different levels design complexity and completion affect hazard recognition. Therefore, the following null research hypothesis is presented: "Varying levels of design complexity and Level of Detail do not affect hazard recognition."

Secondly, although Care was taken to ensure that that the results are generalizable to the commercial high-rise construction, all study participants were native to Colorado, North Carolina, and Wisconsin within the United States. Further samples of construction industry practitioners are needed to further generalize these research findings to a broader audience. For this reason, the results of this research may not be generalizable to countries outside of the United States. Although a diverse population of construction workers and designers were solicited for participation; the results may not hold consistency for those outside of the scope of commercial high-rise construction. For this reason, future research is needed to test the hypotheses in this study across populations outside those involved in commercial high-rise construction. Additionally, the authors believe this research process can be expanded into different phases of project lifecycles such as occupancy, maintenance, and demolition. Although these limitations are humbly recognized, the authors believe the strength of this study lies in the actual work observations and associated comprehensive safety hazard lists, complete counterbalanced Latin square design, sample size, and diverse population groups.

3.9 Acknowledgements

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3.10 References

Albert, A., Hallowell, M. R., & Kleiner, B. M. (2013). Enhancing construction hazard recognition and communication with energy-based cognitive mnemonics and safety meeting maturity model: Multiple baseline study. Journal of Construction Engineering and Management, 140(2), 04013042.

Albert, A., M. Hallowell, B. Kleiner, A. Chen, and M. Golparvar-Fard. (2014). "Enhancing Construction Hazard Recognition with High-Fidelity Augmented Virtuality." Journal of Construction Engineering and Management 140 (7): 04014024.

Bahn, S. (2013). Workplace hazard identification and management: The case of an underground mining operation. Safety science, 57, 129-137.

Bansal, V. K. (2011). Application of geographic information systems in construction safety planning. International Journal of Project Management, 29(1), 66-77.

Baracz, S. J., Everett, N. A., McGregor, I. S., & Cornish, J. L. (2016). Oxytocin in the nucleus accumbens core reduces reinstatement of methamphetamine-seeking behaviour in rats. Addiction biology, 21(2), 316-325.

Baxendale, T., & Jones, O. (2000). Construction design and management safety regulations in practice—progress on implementation. International Journal of Project Management, 18(1), 33-40.

Behm, M. (2005). Linking construction fatalities to the design for construction safety concept. Safety science, 43(8), 589-611.

Bhandari, S., & Hallowell, M. R. (2017). Emotional Engagement in Safety Training: Impact of Naturalistic Injury Simulations on the Emotional State of Construction Workers. Journal of Construction Engineering and Management, 143(12), 04017090.

BIMForum. (2017). Level of Development Specification. Retrieved February 18, 2018, from http://bimforum.org/wp-content/uploads/2017/11/LOD-Spec-2017-Part-I-2017-11-07-1.pdf

Birney, D. P., Halford, G. S., & Andrews, G. (2006). Measuring the influence of complexity on relational reasoning: The development of the Latin Square Task. Educational and Psychological Measurement, 66(1), 146-171.

Carter, G., & Smith, S. D. (2006). Safety hazard identification on construction projects. Journal of construction engineering and management, 132 (2): 197-205.

Chantawit, D., Hadikusumo, B., Charoenngam, C., & Rowlinson, S., (2005),"4DCAD-Safety: visualizing project scheduling and safety planning", Construction Innovation, Vol. 5 Iss 2 pp. 99 – 114

Cheng, T., & Teizer, J. (2012). Modeling tower crane operator visibility to minimize the risk of limited situational awareness. Journal of Computing in Civil Engineering, 28(3), 04014004.

Collier, E. B. 1994. ‘‘Four-dimensional modelling in design and construction.’’ thesis, Stanford Univ., Stanford, Calif.

Cooke, T., Lingard, H., Blismas, N., & Stranieri, A. (2008). ToolSHeDTM: the development and evaluation of a decision support tool for health and safety in construction design. Engineering, Construction and Architectural Management, 15(4), 336-351.

Daniel, E. (2016). Motivational and cognitive correlates of avoidance of ambiguity: The role of values and relational complexity. Personality and Individual Differences, 102, 149-152.

De Lapp, J. A., Ford, D. N., Bryant, J. A., & Horlen, J. (2004). Impacts of CAD on design realization. Engineering, Construction and Architectural Management, 11(4), 284-291.

Dewlaney, K. S., Hallowell, M. R., & Fortunato III, B. R. (2011). Safety risk quantification for high performance sustainable building construction. Journal of Construction Engineering and Management, 138(8), 964-971.

Dielman, TE. (2005). Applied Regression Analysis: a Second Course in Business and Economic Statistics 4th ed. Mason, OH: South-Western Cengage Learning.

Driscoll, T. R., Harrison, J. E., Bradley, C., & Newson, R. S. (2008). The role of design issues in work-related fatal injury in Australia. Journal of Safety Research, 39(2), 209-214.

Edwards, A. L. (1951). Balanced Latin-square designs in psychological research. The American journal of psychology, 64(4), 598-603.

Esmaeili, B., and Hallowell, M. R. (2012). “Diffusion of safety innovations in the construction industry.” J. Constr. Eng. Manage., 10.1061/(ASCE)CO.1943-7862.0000499, 955–963.

Fellows, R, & Liu, A. (2008). Research Methods for Construction (3rd ed.). Malden, MA: Wiley-Blackwell Publishing.

Fonseca, E. D., Lima, F. P., & Duarte, F. (2014). From construction site to design: The different accident prevention levels in the building industry. Safety science, 70, 406-418.

Gambatese, J. A., Hinze, J. W., & Haas, C. T. (1997). Tool to design for construction worker safety. Journal of Architectural Engineering, 3(1), 32-41.

Gambatese, J. A., Behm, M., & Rajendran, S. (2008). Design’s role in construction accident causality and prevention: Perspectives from an expert panel. Safety science, 46(4), 675-691.

Ganah, A., & John, G. A. (2015). Integrating building information modeling and health and safety for onsite construction. Safety and health at work, 6(1), 39-45.

Ghaderi, R., & Kasirossafar, M. (2011). Construction safety in design process. In AEI 2011: Building Integration Solutions (pp. 464-471).

Goodrum, P. M., Miller, J., Sweany, J., & Alruwaythi, O. (2016). Influence of the format of engineering information and spatial cognition on craft-worker performance. Journal of Construction Engineering and Management, 142(9), 04016043.

Hadikusumo, B. H. W., & Rowlinson, S. (2002). Integration of virtually real construction model and design-for-safety-process database. Automation in Construction, 11(5), 501-509.

Hadikusumo, B. and S. Rowlinson (2004). "Capturing Safety Knowledge Using Design-for-Safety-Process Tool." Journal of Construction Engineering and Management 130(2): 281-289.

Hallowell, M. R. and D. Hansen (2016). "Measuring and improving designer hazard recognition skill: Critical competency to enable prevention through design." Safety Science 82: 254-263.

Hecker, S. and J. Gambatese (2003). "Safety in Design: A Proactive Approach to Construction Worker Safety and Health." Applied Occupational and Environmental Hygiene 18(5): 339-342.

Kasirossafar, M., & Shahbodaghlou, F. (2013). Building Information Modeling or construction Safety Planning. In ICSDEC 2012: Developing the Frontier of Sustainable Design, Engineering, and Construction (pp. 1017-1024).

Kim, K., & Teizer, J. (2014). Automatic design and planning of scaffolding systems using building information modeling. Advanced Engineering Informatics, 28(1), 66-80.

Ku, K., & Mills, T. (2010). Research needs for building information modeling for construction safety. In International Proceedings of Associated Schools of Construction 45nd Annual Conference, Boston, MA.

Li, H., Ma, Z., Shen, Q., & Kong, S. (2003). Virtual experiment of innovative construction operations. Automation in Construction, 12(5), 561-575.

Lingard, H. C., Cooke, T., & Blismas, N. (2012). Designing for construction workers' occupational health and safety: a case study of socio-material complexity. Construction Management and Economics, 30(5), 367-382.

Lopez del Puerto, C., Clevenger, C. M., Boremann, K., & Gilkey, D. P. (2013). Exploratory study to identify perceptions of safety and risk among residential Latino construction workers as distinct from commercial and heavy civil construction workers. Journal of Construction Engineering and Management, 140 (2): 04013048 - 1 – 04013048 - 7.

Manu, P. A., Ankrah, N. A., Proverbs, D. G., & Suresh, S. (2012). Investigating the multi-causal and complex nature of the accident causal influence of construction project features. Accident Analysis & Prevention, 48, 126-133.

Martínez-Aires, M. D., López-Alonso, M., & Martínez-Rojas, M. (2018). Building information modeling and safety management: A systematic review. Safety Science, 101, 11-18.

McNemar, Q. (1951). On the use of Latin squares in psychology. Psychological bulletin, 48(5), 398.

Mead, R., R.N. Curnow, and A.M. Hasted. 2003. Statistical methods in agriculture and experimental biology. Chapman and Hall/CRC, Boca Raton, FL.

Navon, R. and O. Kolton (2006). "Model for Automated Monitoring of Fall Hazards in Building Construction." Journal of Construction Engineering and Management 132(7): 733-740.

NIOSH. (2013). Preventing Falls through the Design of Roof Parapets. Retrieved June 11, 2017, from
https://www.cdc.gov/niosh/docs/2014-108/pdfs/2014-108.pdf

NIOSH. (2017). Prevention Through Design. Retrieved August 05, 2017, from https://www.cdc.gov/niosh/topics/ptd/default.html

Pedhazur, E. (1997). Multiple Regression in Behavioral Research: Explanation and Prediction. Holt, Rinehart and Winston.

Peng, Y. H., Lee, C. H., Popuri, S. R., & Kumar, K. S. (2016). Preparation of High-Purity Ultrafine Copper Powder in Mass-Production by Chemical Reduction Method: Taguchi Robust Design Optimization. Powder Metallurgy and Metal Ceramics, 55(7-8), 386-396.

Qi, J., Issa, R. R. A., Hinze, J., & Olbina, S. (2011). Integration of safety in design through the use of building information modeling. In Computing in Civil Engineering (2011) (pp. 698-705).

Seo, J. W., & Choi, H. H. (2008). Risk-based safety impact assessment methodology for underground construction projects in Korea. Journal of construction engineering and management, 134(1), 72-81.

Sacks, R., J. Whyte, et al. (2015). "Safety by design: dialogues between designers and builders using virtual reality." Construction Management and Economics 33(1): 55-72.

Suraji, A., Duff, A. R., & Peckitt, S. J. (2001). Development of causal model of construction accident causation. Journal of construction engineering and management, 127(4), 337-344.

Szymberski, R. (1997). "Construction project safety planning." TAPPI Journal 80(11): 69-74.

Teizer, J., Kim, C., Haas, C., Liapi, K., & Caldas, C. (2005). Framework for real-time three-dimensional modeling of infrastructure. Transportation Research Record: Journal of the Transportation Research Board, (1913), 177-186.

Tixier, A., Albert, A., & Hallowell, M. R. (2013). Teaching construction hazard recognition through high fidelity augmented reality. In Proc., 2013 American Society of Engineering Education Annual Conf (pp. 1-23).

Tixier, A. J. P., Hallowell, M. R., Albert, A., van Boven, L., & Kleiner, B. M. (2014). Psychological antecedents of risk-taking behavior in construction. Journal of Construction Engineering and Management, 140(11), 04014052. Chicago

Toole, T. M. (2005). Increasing engineers' role in construction safety: Opportunities and barriers. Journal of Professional Issues in Engineering Education and Practice, 131(3), 199-207.

Workcover, A. (2001). Construction Hazard Assessment Implication Review–CHAIR.

Young, S. (1996). ''Construction safety: A vision for the future.'' J. Manage. Eng., 12(4), 33–36.

Zhang, M., and Fang, D. (2013). "A continuous behavior-based safety strategy for persistent safety improvement in construction industry." J. Autom. Constr., 34(1), 101–107.

Zhang, S., Teizer, J., Lee, J. K., Eastman, C. M., & Venugopal, M. (2013). Building information modeling (BIM) and safety: Automatic safety checking of construction models and schedules. Automation in Construction, 29, 183-195.

Zhang, L., Wu, X., Ding, L., Skibniewski, M. J., & Lu, Y. (2014). Bim-based risk identification system in tunnel construction. Journal of Civil Engineering and Management, 22(4), 529-539.

Zhang, S., Sulankivi, K., Kiviniemi, M., Romo, I., & Eastman, C. (2015). BIM-based fall hazard identification and prevention in construction safety planning. Safety Science, 72, 31-45.

Chapter 4: Relationships among Mental Workload, Spatial Cognition, and Hazard Recognition Performance in Construction Hazard Prevention through Design Tasks

Dylan C. Hardison; Matthew Hallowell; and Ray Littlejohn

4.1 Abstract

Construction Hazard Prevention through Design (CHPtD) is promoted as a superior method of injury prevention that is achieved by reviewing design information to identify and mitigate hazards before they are encountered in construction. Unfortunately, it remains unknown if demographics, the format of design information, or cognitive ability affects hazard recognition skill in design reviews. Therefore, a series of experimental trials were conducted to determine if spatial cognitive capabilities and mental workload associated with various formats of design information influence hazard recognition performance during CHPtD tasks. Participants were provided mutually-exclusive arrangements of traditional two-dimensional computer aided design drawings, three-dimensional computer visualizations, and a combination of the two formats and asked to identify all possible safety hazards associated with three discrete construction work activities. Prior to the task, participants completed card and cube rotation tests to assess pre-existing personal spatial cognitive capability. After each task, participants completed the NASA task load index questionnaire to assess the mental workload (i.e., mental demand) of each hazard recognition task. Multiple Linear Regression was used to measure the association among these variables. Contrary to theoretical evidence, the results indicate that there is no association between spatial cognitive ability, mental workload, or hazard recognition performance. The results conflict with the prevailing belief that 3D visualizations are superior to 2D visualizations in terms of promoting hazard recognition. However, a demographic analysis revealed that construction

experience and the total time spent in the hazard recognition trials predicts hazard recognition performance across all experimental trials. The implication is that an experienced individual who spends more time than average on a CHPtD task will perform better in a CHPtD task, even if the individual has low spatial cognitive abilities or if the task has relatively high mental demands. Simply, skill in a CHPtD task depends more on the experience and diligence of the practitioner rather than the format of the design information, task demand, or cognitive ability.

4.2 Introduction

Due to the ever present high injury and fatality rates of the construction industry, researchers have strived to identify methods that reduce the occurrence and severity of safety accidents. One prominent method is Construction Hazard Prevention through Design (CHPtD), which involves recognizing and mitigating hazards during project design before they manifest in construction. Research has shown that prevailing opinion is that CHPtD provides an opportunity to make changes that would have prevented serious injuries and fatalities (Behm 2005; Seo and Choi 2008; Driscoll et al. 2008; Ghaderi and Kasirossafar 2011; Lingard et al. 2012: Hallowell and Hansen 2016). Despite consensus, there is relatively little empirical research or validation. In fact, to date, only a few researchers have attempted to empirically examine practitioner ability to recognize hazards during design (Hallowell and Hansen 2016; Hardison et al. *in press*).

Some have theorized that three-dimensional (3D) design information provides a more effective visual platform than two-dimensional (2D) and, therefore, enhances hazard recognition skill and requires less mental effort to process (Ku and Mills 2010; Bansal 2011; Kasirossafar and Shahbodaghlou 2012; Ganah & John 2015; Zhang et al. 2015; Martinez-Aires et al 2018).

However, these assumptions remain untested. Therefore, there is a rich opportunity to investigate the extent to which various formats of design information and spatial cognitive ability relate to hazard recognition performance in design.

This paper focus on the nexus of spatial cognition and the mental workload of hazard recognition tasks. Spatial cognition is considered a personal condition that precedes any activity and that is relatively stable. Mental workload, however, relates to an individual's cognitive processing of a stimulus and is affected by both pre-existing cognitive ability and the lucidity of the information. Thus, the format of design information was experimentally manipulated in the study via Latin square design. Specifically, the authors designed a simulated CHPtD field study with 117 participants including designers, construction supervisors, and civil engineering students. The experiment was designed to test whether mental workload varies across format of design information (i.e., 2D, 3D, and a combination of both) and whether spatial cognitive abilities predict hazard recognition performance. Incidentally, the influence of demographics like experience were also explored independent of the primary hypothesis.

4.3 Literature Review

This section describes literature that defines and connects hazard recognition, mental workload, spatial cognition in the context of CHPtD theory. This section helps to define the context in which this study has been performed and provides necessary background to establish the authors' epistemological positioning for each of the variables under investigation.

Construction Hazard Prevention through Design

Construction Hazard Prevention through Design (CHPtD) is the consideration for worker safety in the design phase of a construction project (Gambatese 2008). The central premise of CHPtD implementation lies in *hazard elimination*, as only those hazards recognizable during design can be eliminated or controlled with CHPtD solutions. In the past 20 years, CHPtD has seen an abundance of research, which has resulted in a large and dispersed body of literature. This body of knowledge has made valuable advances in construction safety research. However, considering limited empirical evidence CHPtD has been extolled as a superior safety management strategy (Szymberski, 1997; Toole, 2005; Gambatese et al., 2008; and Manu et al., 2012). Subjective research has linked design elements to safety accidents (Behm 2005; Driscoll et al. 2008; Seo and Choi 2008; Ghaderi and Kasirossafar 2011) and has used case studies to suggest that design changes may affect safety risks during construction (Lingard 2013 and Lingard 2015). However, a lack of formal empirical data which tests the efficacy of CHPtD processes indicates the need for a more robust understanding of the role of design information format during CHPtD implementation.

CHPtD has seen research in theory development (Szymberski 1997), linkage of accident data to design characteristics (Behm 2005; Seo and Choi 2008; Ghaderi and Kasirossafar 2011) case study research (Lingard 2013; Lingard 2015; Fonesca et al. 2014); and many technology applications including BIM (Hadikusumo and Rowlinson 2002; Qi et al. 2011; Zhang et al. 2013; Zhang et al. 2014; Cheng and Teizer 2014; Kim and Teizer 2014; and Zhang et al. 2015) and augmented and virtual reality (Hadikusumo and Rowlinson 2002; Sacks et al. 2013; and Albert et al. 2014). Although, this research and technology application provide valuable knowledge and practical CHPtD implementation tools, little is known about their efficacy in design. For example, no research to date examines the cognitive processes of employing theses design tools and theoretical concepts. It is unknown if designers and construction practitioners possess the inherent skills to recognize the hazards that the CHPtD theory and technology applications aim to control. Additionally, it is unknown what visual cues existing in design information can be used for hazard recognition. For this reason, more investigation into the cognitive processes and visual search patterns of CHPtD implementation are needed.

Role of Design Information in CHPtD

The design process ultimately yields plans, specifications, and other contract documents. This design information is developed to convey intent for the delivery of a facility and other projects (Goodrum et al. 2016). The format of such information may include 2D computer aided drawings (2D CAD) (Goodrum et al. 2016); 3D building information models (3D BIM) (Zhang et al. 2015), material specifications (Dadi et al. 2014b), and even virtual reality (Hadikusumo and Rowlinson 2004; Sacks et al. 2015). Although 3D design technologies have emerged as a practical option for some practitioners, traditional 2D drawings remain the pervasive method of conveying design information (Emmitt and Gorse 2003; Chantawit et al. 2005; Bowden et al. 2006; Goodrum and Miller 2015).

Although researchers propose that design information can be used for pre-construction safety planning, others have suggested that 2D design information does not permit simple conceptualization of future physical and environmental conditions, which may lead to the misunderstanding of project design information (Collier 1994; Young 1996; Chantawit et al. 2005;

Zhang et al. 2015) Alternatively, it has been proposed that 3D visualizations of design information enable hazard recognition because the information is believed to be easier to understand and interpret (Ku and Mills 2010; Bansal 2011; Kasirossafar and Shahbodaghlou 2012; Ganah & John 2015; Zhang et al. 2015; Martinez-Aires et al 2018). These postulations suggest that the mental demands of hazard recognition tasks are reduced using 3D visualizations; however, these assumptions have not been empirically tested and they fail to consider the effects that humans spatial cognitive capabilities that ultimately drive the interpretation of information (e.g., facility design). Thus, there is a clear need to understand not only the effects of design format on hazard recognition skill but also how the format affects the mental workload of a hazard recognition task and the mediating role of spatial cognition.

Mental Workload

The concept of mental workload is based on the premise that there is an upper limit to human ability to process information and generate responses (Hicks and Wierwille 1979; Carswell 2005). Under this premise, mental workload is the ratio of mental resources required for an activity as compared to the total available resources at any given point in time (Carswell 2005). Therefore, it is understood that design information plays an important role in end user's mental workload (Hicks and Wierwille 1979; Dadi et al. 2014a). Ideally, the most effective design information should reduce the mental workload requirements while allowing the necessary information to be conveyed (Dadi et al. 2014a). Building on Dadi et al. (2014a), in the context of construction safety, design information should be developed to require low mental demands for extracting safety information during hazard recognition activities. Experiments that measure the mental workload of hazard recognition tasks across different formats of design information may discover knowledge that improves the quality of pre-construction safety plans.

Assessing the mental workload of hazard recognition tasks using design information as a visual stimulus for identifying hazards is an area of construction safety research that has yet to receive attention. Taken from the context of mental workload research in aviation, *mental workload of CHPtD tasks,* is the interaction between the requirements of a hazard recognition task; the circumstances surrounding performing the task; and the skills, behaviors, and perceptions of those involved in CHPtD tasks (Borghini et al. 2012). There has been much human behavior research into the mental workloads of performance of various tasks. This includes driver impairment (De Waard 1996); driver performance (Lenne et al. 1997; Nilsson et al. 1997; Thiffault and Bergeron 2003; Leung and Starmer. 2005; Ng Boyle et al. 2008; Rakauskas et al. 2008; Verwey and Zaidel 1999); nursing (Kim et al. 2018; Tubbs-Cooley et al. 2018); and aviation (Svensson et al. 1993; Wilson 2002; Borghini et al. 2012; Grassman et al. 2017) to name a few. Past research in driving and aviation, has shown that an increase in mental demand is required when the complexity of vehicle and aircraft cock pits increases. Due to the increase in complexity of the instrumentation, more attentional demand is required for task performance and therefore increases the overall mental workload of task performance (Borghini et al. 2012). This finding may hold true for a variety of tasks outside of driving and aviation which require the use of various visual stimulus for tasks performance. Understanding how the complexity of design information affects the mental workload of hazard recognition tasks may lead to the optimal design of CHPtD technologies to ensure that the circumstances surrounding hazard recognition tasks make the hazard recognition process as easy as possible for those involved in CHPtD processes and thereby increase its efficacy.

Methods of Measuring Mental Workload

The primary methods of measuring mental workload fall into three distinct categories: physiological, secondary task, and subjective (Hicks and Wierwille 1979; Carswell 2005). Physiological assessment techniques evaluate the relationships between cognitive activity and the autonomic nervous system (Wilson and Fisher 1991). These measures include electroencephalogram (Gerjets et al. 2014; Zander & Kothe 2011), magnetic resonance imaging (Whelan 2007), functional near-infrared spectroscopy (Strangman et al. 2002; Coyle et al. 2004), pupillometry (Kuchinke et al. 2007; Jainta and Baccino 2010), and cardiovascular metrics (Mulder 1998 and Martin 2014). Secondary task measurements include the addition of a secondary task to assess the attentional demands of primary tasks (Hicks and Wierwille 1979; Carswell 2005). The premise of secondary task measurement is that, when the mental workload of the primary task increases, the performance of the secondary task will diminish (Hicks and Wierwille 1979). Finally, subjective methods of mental workload assessments employ self-reporting ratings of the difficulties of tasks to be used as an evaluation metric of mental workload (Martin 2014). These methods include the National Aeronautics and Space Administration's Task Load Index (NASA-TLX) and the Subjective Workload Assessment Technique (SWAT) (Martin 2014). For this study, the NASA-TLX was used as it is has been found to be preferred over the SWAT (Battiste and Bortolussi 1988; Hill et al. 1992) and is best suited for detecting smaller differences in mental workload (Nygren 1991; Rubio et al, 2004). The subjective methods are also preferred when maintaining ecological validity, such as conducting an experiment or when technology could confound the relationships among variables.

Measuring Mental Workload via the NASA-TLX

The NASA-TLX is a subjective workload assessment technique that relies on a multidimensional construct to derive an overall mental workload score based on an average rating of six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration level. These six subscales are used to compute an overall mental workload score (Hart & Staveland 1988). The NASA-TLX has also been found to be highly correlated with other measures of mental workload (Battiste & Bortolussi 1988; Hill et al. 1992). However, as suggested by Argyris (1976), research participants may not accurately self-report the true level of mental workload from research trials during post-task questionnaires and interviews. Table 15 below provides a description of the NASA-TLX factors and the associated measurement scales.

Table 15. NASA-TLX Factors and Descriptions

NASA-TLX Factors	Rating Scale	Description
Mental Demand	1-20 (low-high)	How mentally demanding was this task?
Physical Demand	1-20 (low-high)	How physically demanding was this task?
Temporal Demand	1-20 (low-high)	How hurried or rushed was the pace of this task?
Performance	1-20 (low-high)	How successful were you at accomplishing what you were asked to do?
Effort	1-20 (low-high)	How hard did you have to work to accomplish your level of performance?
Frustration	1-20 (low-high)	How insecure, discouraged, irritated, stressed, and annoyed were you?

Principles of Spatial Cognition

Spatial cognition, another variable of interest in this study, is defined as the ability to retain, manipulate, and generate precise visual images (Lohman 1979). Construction designs, which are typically presented via 2D paper-based drawings (Collier 1994; Young 1996; Chantawit et al. 2005; Gould and Joyce 2013; Goodrum et al 2916), are complex documents that require workers to use spatial orientation to mentally manipulate the design information to generate an understanding of the construction design (Goodrum et al. 2016). The process of spatial orientation includes encoding, remembering, transforming, and matching design information (Lohman 1979) and has been found to lead to omissions and ambiguities of information (Rieber 1995). Understanding that there is an upper cognitive limit to human ability to understand and interpret information (Ekstron 1976; Hicks and Wierwille 1979), it is suggested that design information should be presented in a way that is easy for workers to understand (Dadi et al. 2014b). This is inferred to aid in retention, manipulation, and generation of precise visual images from construction design that can be used to recognize construction safety hazards (Lohman 1979).

Methods of Measuring Spatial Cognition

Numerous studies have shown that spatial ability is positively related to problem solving ability as well as success in geometry and mathematics (Fennema and Sherman 1977; Battista et al. 1982; Fennema and Tartre 1985; Moses 1977). Studies attempting to measure and improve people's spatial reasoning and cognition abilities stem back to the 1920's (Gagnon 1985). For example, several studies have attempted to measure and improve subjects' spatial cognition using mechanical aptitude skill assessment (Seashore and McCollom 1932); film and television (Daily and Neyman 1967; Moses 1979); classroom training (Ball & Bogatz, 1970); engineering and mechanical drawings (Saloman 1979); videogames (Small and Small 1982; Gagnon 1985); and dynamic geometry software (Travis and lennon 1997; Guven and Temel 2008).

Paper and pencil spatial assessment methodologies have also been developed to assess users' spatial skills. For example, the Purdue Spatial Visualization Test (PSVT) was developed to assess humans' abilities to visualize the rotation of three-dimensional objects. The PSVT test has been used to test the growth of intellectual abilities (McGee and Mark 1979); the effects of gender differences on spatial cognitive ability (Voyer et al. 1995; Maeda and Yoon 2013); and used to develop spatial skills through classroom training (Sorby and Baartmans 1996). Additionally, the Educational Testing Service developed two tests to measure spatial cognition associated with a task (Ekstrom 1976). The card rotation test measures the ability to interpret the transformation of a 2D shape. The test presents the subject with a 2D image, which is then manipulated by rotating or flipping. The participant is asked to compare the image against the modification and correctly identify if the image is rotated or flipped and rotated. Alternatively, 3D spatial cognition is measured using the cube rotation test. The participant is presented with two cubes of equal size and dimensions but with different labels on each face. The participant is asked to distinguish whether the first cube could be logically rotated to match the second cube. The participant's skill with this distinction represents their 3D spatial cognition. The card and cube rotation tests were used in this study as it has been validated by providing strong evidence to evaluate human's spatial abilities (Huttenlocher and Presson 1979; Presson 1982; Wraga et al. 2000; Kozhevnikov and Hegarty 2001). Additionally, these tests were used as the technology could confound the relationships among variables.

Relationships between Spatial Cognition, Mental Workload, and Work Performance

Spatial cognition has been found to play a significant role in construction craft productivity. Recent research by Goodrum et al. (2016) tested the influence of spatial cognition on model assembly tasks. They presented 54 participants with a mixture of design information formats (i.e., 2D isometric drawings, 3D visual displays, and a 3D physical scale model) and found that both design information format and spatial cognition significantly affected participants abilities to assemble a replicate model (Goodrum et al. 2016). Additionally, Dadi et al. (2014b) performed a similar study in which 77 participants constructed a physical model using a randomized and counterbalanced assignment of one of three design information formats: 2D drawing set, 3D computer model, and a 3D scale physical model. The results show that participants who used the 3D scale physical model outperformed others in completion times and direct work rates and resulted in lower mental workload levels (Dadi et al. 2014b).

Research Objectives and Point of Departure

The two goals of this study are (1) to determine if the mental workload of hazard recognition tasks and the format of design information are related; and (2) to determine if spatial cognition and the hazard recognition performance of design information formats are related. The four primary steps conducted to achieve these goals included the following: (1) assessing spatial cognition, (2) performing experimental hazard recognition testing by manipulating the design format, (3) measuring the variability of hazard recognition performance for three modes of design information (3D BIM, 2D CAD, and a combination of the two), and (4) examining the relationships of spatial cognition and mental workload on hazard recognition task performance. This review explains the research relevant to the creation of hypotheses that are relevant to the current scientific discourse but have yet to be tested. The alternative research hypotheses are presented below:

Ha1: The mental workload of hazard recognition tasks is related to design information format.

Ha2: Spatial cognition is related to design information format and hazard recognition performance.

Ha3: Design information reduces mental workload of hazard recognition tasks.

Ha4: Time of hazard recognition trial is related to hazard recognition performance.

4.4 Research Methods

This study involved collecting empirical field data through a series of three sequential hazard recognition experimental trials, coupled with mental workload measurements and two tests to measure spatial cognitive capabilities. These tests and the experimental design are described below. Prior to any tests, the subjects were introduced to the study, consent was obtained, and a demographic questionnaire that asked for participants age, gender, education level, years of construction experience, job position, and spatial cognition through card and cube rotation tests as administered per the human subjects' plan.

Latin Square Experimental Design

A Latin square experimental design was used to measure the effects of the format of design information on hazard recognition performance and mental workload. The Latin square design controls for the negative effects of multiple variable interactions by blocking the treatment and independent variables. Latin square designs create an (*n x n*) matrix of an equal number of levels of independent variables and treatment factors (ex., 3x3 or 4x4). These designs cross the treatment factors with the independent variables in a counterbalanced order to ensure that the negative effects of repeated observations are minimized (Edwards 1951; McNemar 1951). This counterbalancing allows researchers to assess the variability of data for the independent variable over a series of sequential research trials (Edwards 1951; McNemar 1951).

A 3x3 Latin square design was developed to cross the 3 treatment factors (i.e., construction activities) with the 3 independent variables (i.e., design information formats). The construction activities include skylight installation, soffit drywall installation, and interior metal wall stud framing. The design information formats include 2D CAD, 3D visualizations, and a combination 2D and 3D. Finally, the dependent variable is hazard recognition performance of each of the treatment variables crossed with the independent variables. This design controls for any learning curve that is attained through repeated observations. Additionally, this design ensures that the variability in performance is truly attributable to the independent variables by counterbalancing procedures (Edwards 1951; McNemar 1951). A description of the deliverables presented to participants via the Latin square experimental design can be seen below in Table 6.

Selection of Human Subjects

In total, 117 participants from Colorado, North Carolina, and Wisconsin participated in the study. To enhance the practical contributions, three population groups (N = 39 each) were solicited, including: construction design professionals; construction supervisors; and civil engineering students. Construction design professionals were included only if they perform design-related activities in design software such as BIM and CAD. Construction supervisors were included only if they actively supervise construction personnel and processes. The last population group, civil engineering students, were included only if they had classroom training in CAD and BIM. The population groups demographics are shown in table 16.

Table 16: Salient Participant Demographics

Demographic Metrics		Designers	Construction Supervisors	Civil Engineering Students
Age	**Mean**	40.4	39.3	22.1
	St. Dev	13.1	10.9	1.9
	Range	22 – 64	21 - 65	20 - 31
Years of Industry Experience	**Mean**	16.2	17.3	0.7
	St. Dev	11.4	11.6	0.6

Sample Size Calculation

Sample size calculations were conducted in MVP Stats statistical software to ensure that adequate sample size was gathered to test research hypotheses. An ANOVA sample size calculation ($\alpha = 0.05$, $\beta = 0.10$, effect = 1 standard deviation from mean), yielded an N = 27 required within each independent variable (i.e., design information formats). Thus, within each population group (i.e., designers), 27 participants were assigned to a treatment group and 12 were assigned to a control group. An additional control group was included in the sample to test the variability of mental workload between the treatment and control groups. A MEANS sample size calculation ($\alpha = 0.05$, $\beta = 0.10$, effect = 1 standard deviation from mean) yielded a required N = 12 for the control group. Sample size calculations were performed to ensure adequate data to make correct rejection decisions for research hypotheses.

Selection of Work Activities

To enhance the practical contributions of the study, information regarding construction hazards faced on a real construction project was obtained from previous research conducted by Hallowell and Hansen (2016). The research team selected three discrete building construction work activities from that study. Additionally, the actual construction hazards faced by the work crews were identified and documented through field observations and interviews and were taken directly from Hallowell and Hansen (2016). Specifically, skylight installation, soffit drywall installation, and interior wall stud installation were selected because: they were from the same construction project; complete 2D CAD drawings were provided by the project team; attributes of the work were dispersed by activity; and each activity was independent of adjacent construction work. The activities provided include: skylight installation, soffit drywall installation, and interior wall stud installation. Skylight installation was described as "*This work involves the construction of a skylight. The framing for the skylight and original roof has previously been demolished and opened. A temporary cover was installed. Includes: removal of temporary cover and installation of new skylight. Does not include removal of debris or materials*." Additionally, soffit drywall installation was described as "*This work involves the construction of a drywall soffit. Includes: all preparatory work and setup, and installation of soffit and wall drywall*." And lastly, interior wall stud framing was described as "*This work involves the construction of an interior wall. Includes: vertical members of metal stud framing*" (Hallowell and Hansen 2016). Table 17 below shows the three work activity descriptions and associated safety hazards.

Table 17: Documented Safety Hazards and Hazardous Energy Exposures for Each Activity (adapted from Hallowell and Hansen 2016)

Hazards for All Activities	Skylight Installation	Soffit Drywall Installation	Interior Wall Stud Installation
Ascending and Descending Scaffold (Gravity)			X
Cuts on Razor Knife (Motion)	X	X	
Electrical Cords and Tools (Electrical)	X	X	X
Flashing Cement (Chemical)	X		
Flying Debris (Motion)	X	X	X
Hand Tools (Motion)	X	X	X
Heat Stress and Sun Exposure (Temperature / Radiation)	X		X
Hot Work and Sparks (Temperature)			X
Moving Man Lift (Motion)		X	X
Noise (Sound)	X	X	X
Objects and Tools at Height (Gravity)	X	X	X
Open Flame (Temperature)	X		
Pinch Points (Motion)	X		
Positioning Heavy Material (Motion)	X	X	X
Pressurized Propane Tank (Pressure)	X		
Protruding Nails/Sharps (Motion)	X		
Sharp Blade on Saw (Motion)			X
Sharp Steel (Motion)		X	X
Small Particles (Chemical)	X	X	
Trip Hazards (Gravity)	X	X	X
Uneven Work Surface (Gravity)			X
Work at Height (Gravity)	X	X	X
Work Overhead (Gravity)		X	X

Developing 3D Visualizations

Although much literature advocates incorporating safety into design using 3D software such as BIM (Ku and Mills 2010; Bansal 2011; Kasirossafar and Shahbodaghlou 2012; Ganah & John 2015; Zhang et al. 2015), this research adopts 3D visualizations rather than traditional BIM designs. Modeling the information directly in a BIM platform and using this software in the experimental design was considered; however, variability in experience with BIM was felt to be a strong confounding factor that would have been introduced by a specific software platform. To reduce this confound, the team elected to provide easy-to-navigate static screenshots of the software via portable document file (i.e., pdf) to promote internal validity at the expense of some ecological validity. The relevant 2D CAD design information obtained by Hallowell and Hansen (2016) was transformed from into 3D visualizations with BIM software. The 3D visualizations were designed to a #350 Level of Development (L.O.D.) ensuring design elements were modeled to "*rough dimensions*." (BIMForum 2017). A total of 27 screenshots of the 3D BIM environment captured all building elements associated with the work activities and were assembled into a PDF. Screenshot angles were carefully selected to ensure that all attributes of the BIM environment were included in the PDF. This process also reflects how a design for safety review could be conducted with a multi-disciplinary team possessing a variety of BIM experience. Sample images of the 3D visualizations and 2D CAD are provided in Figures 1 and 2 below.

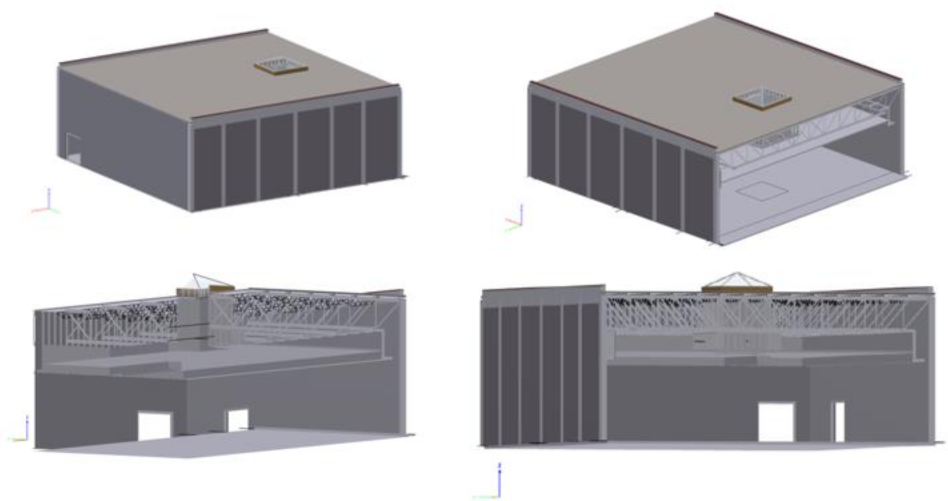

Figure 1. Example 3D Visualizations detailed to #350 Level of Detail

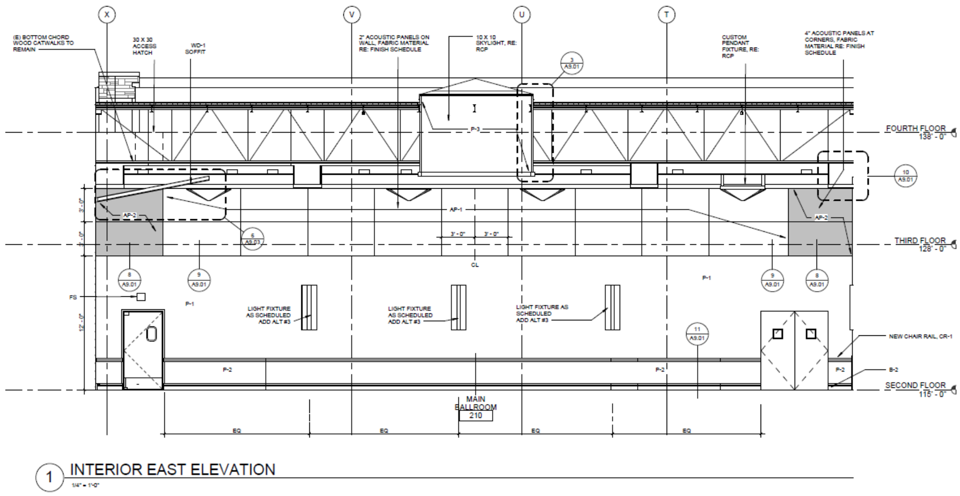

Figure 2. Example 2D CAD detail

Experimental Arrangements of the Latin Square

As can be seen in the 3x3 matrix in Table 6, there were three variations in experimental arrangements based on the order in which the work activities are crossed with the independent variable. The variations in the experimental arrangements are represented by the letters “*A*,” “*B*,” and “*C*,” respectively. Each letter is its own arrangement that consists of 3 independent and sequential trials. Additionally, the order in which the experimental arrangements are presented to participants is indicated by the ordering number. Each experimental arrangement containing a specific combination of one design information format and construction work activity is indicated by the ordering of sequential research trials in table 18 below.

Table 18: Experimental arrangements by Order, Format, and Activity for all Treatment Groups.

Experimental Arrangement Identifier	Research Trial Sequence	Design Information Format	Construction Work Activity
A	1	3D Visualization	Skylight Installation
A	2	2D CAD	Soffit Drywall Installation
A	3	Combination of 2D and 3D	Interior Wall Stud Framing
B	1	2D CAD	Interior Wall Stud Framing
B	2	Combination of 2D and 3D	Skylight Installation
B	3	3D Visualization	Soffit Drywall Installation
C	1	Combination of 2D and 3D	Soffit Drywall Installation
C	2	3D Visualization	Interior Wall Stud Framing
C	3	2D CAD	Skylight Installation

Population Treatment and Control Groups

Within each population group (N=39), 27 participants were randomly assigned to each populations treatment group and 12 were randomly assigned to each populations control group. Each group was then provided deliverables for each research trial as indicated by the letter “X” as shown in Table 19 below:

Table 19: Experimental Deliverables by Population Treatment and Control Group

Experimental Deliverables	Control Groups	Treatment Groups (Latin square)		
		2D CAD	3D Visualization	Combination
Work Activity Descriptions (See table xx)	X	X	X	X
2D CAD Design Documents	n/a	X	n/a	X
3D Visualizations	n/a	n/a	X	X

Conducting Experimental Research Trials

The experimental trials for professionals (i.e., designers and construction supervisors) were collected on actual construction jobsites or offices. All research trials were conducted with the primary investigator and subject with no outside human interaction. This was done to strengthen internal validity of the study by ensuring participants had consistent information regarding construction activities. Once a participant was randomly selected and assigned to one of the population treatment or control groups, they were briefed about the research process. After administering the two spatial cognition tests, participants were provided a copy of the work activity description (see table 4) associated with the appropriate research trial (i.e. condition “A”). This was done to strengthen internal validity of the study by ensuring participants had consistent descriptions of the work to be assessed for safety hazards. Participants were allowed an unrestricted amount of time to review work activity descriptions and the design information provided in the appropriate format. The 3D visualizations were displayed on a 17” laptop computer and the CAD drawings were printed on 24” X 18” paper. The participants were instructed to use both CAD and 3D formats for the combination when dictated by the experimental arrangement.

When presented with work activity descriptions and design information, participants were asked to "*Review the design information and identify as many safety hazards as you can.*" Participants were asked to verbally narrate safety hazards as they were recognized. All hazards were transcribed during the experiment by the lead researcher. For the purposes of this study, safety hazards were identified as "*a source of energy that, if released, and results in exposure, could cause injury or death*." Participants were asked to identify "*ways that workers could become injured, ill, or be killed in the work situation*" and were asked to "*disregard citing infractions of safety and health regulations.*" This was done to ensure that the true intent of the hazard narration was captured rather than capturing data related to safety regulations.

Once participants completed each sequential hazard recognition task, they were asked to complete the NASA-TLX subjective mental workload questionnaire. This questionnaire included six subscales of mental workload that may be used to quantify the mental workload of hazard recognition trials. These include, *mental demand, temporal demand, Physical demand, performance, effort,* and *frustration*. *Physical demand* was excluded from the mental workload assessment as this variable was not relevant as there was no physical task. Participants were asked to rate each of these subscales on a 0 - 20 scale for each of the hazard recognition trials.

Results

Hazard Recognition Performance

Hazard recognition performance was examined for each research trial for all participants. The Hazard Recognition index (HR_{index}), which was initially used as the Hazard Identification Index by Carter and Smith (2006) and later adopted by Albert et al. (2014) as the Hazard

Recognition index, results in proportion data where the numerator contains the total number of hazards that participants correctly recognized while the denominator contains the total number of safety hazards present for each work activity (HR_{index}) [Eq. (1)]:

$$[1]\ \mathrm{HR}_{index} = \frac{\mathrm{H\ recognized}}{\mathrm{H\ total}}$$

The next step was to calculate the mental workload sum of hazard recognition tasks from each NASA-TLX administered. To calculate the mental workload scores, the five subscales in the NASA-TLX were considered for overall mental workload. A sum of subscales resulted in a mental workload sum of each research trial (MW Sum) [Eq. (2)]. The HR_{index} scores and MW Sums for each population groups treatment subcategory crossed with design information format can be seen in Table 20 below.

Table 20: The HR_{index} and MW Sums for all treatment population subcategories

		Design Information Format			
		2D CAD	**3D BIM**	**Combination**	**Total**
Population Treatment Groups	**Designers**	HR Index (μ) = 39.51% MW Sum (μ) = 40.22 n = 27	HR Index (μ) = 39.04% MW Sum (μ) = 37.92 n = 27	HR Index (μ) = 35.18% MW Sum (μ) = 38.51 n = 27	**HR Index** **(μ) = 37.91%** **MW Sum** **(μ) = 38.88** **n = 81**
	Construction Supervisors	HR Index (μ) = 44.88% MW Sum (μ) = 37.74 n = 27	HR Index (μ) = 44.26% MW Sum (μ) = 39.77 n = 27	HR Index (μ) = 46.74% MW Sum (μ) = 37.11 n = 27	**HR Index** **(μ) = 45.29%** **MW Sum** **(μ) = 38.20** **n = 81**
	Civil Engineering Students	HR Index (μ) = 29.23% MW Sum (μ) = 38.92 n = 27	HR Index (μ) = 26.12% MW Sum (μ) = 35.62 n = 27	HR Index (μ) = 25.89% MW Sum (μ) = 38.59 n = 27	**HR Index** **(μ) = 27.08%** **MW Sum** **(μ) = 37.71** **n = 81**
		HR Index **(μ) = 37.87%** **MW Sum** **(μ) = 38.96** **n = 81**	**HR Index** **(μ) = 36.47%** **MW Sum** **(μ) = 37.77** **n = 81**	**HR Index** **(μ) = 35.93%** **MW Sum** **(μ) = 38.07** **n = 81**	

Next, each participants' overall spatial cognition score was calculated by generating the mean of the card rotation test scores and cube rotation test scores of each participant. This results in proportion data which is hereby considered the (Man SC) [Eq. (3)]. The descriptive statistics of participants Mean SC scores and population group sample sizes can be seen in Table 21 below:

$$[3]\ \text{Mean SC} = \frac{\text{Card Rotation Test Score} + \text{Cube Rotation Test Score}}{2}$$

Table 21: SC_{index} Descriptive Statistics Across and Within All Population Groups

Population	Population Category	Sample Size	Mean SC	Percent Difference	t	p
All Participants	Treatment	81	38.26%	1.28%	1.445	0.149
	Control	36	38.75%			
Designer	Treatment	27	38.88%	2.30%	0.700	0.485
	Control	12	39.80%			
Supervisor	Treatment	27	38.20%	5.96%	5.379	0.000
	Control	12	36.05%			
Student	Treatment	27	37.71%	7.15%	-1.696	0.093
	Control	12	40.41%			

Multiple Linear Regression

Multiple Linear Regression (MLR) was used to test hypothesis Ha1 and Ha2 relating to participants spatial cognition and mental workload scores of independent research trials. MLR analysis is a method for measuring the variability of one variable explained by variability in more than one other variable. (Tam and Fung 1998). An MLR model is an extension of the simple linear regression model for data when multiple predictor variables explain the variability in a response variable (Eberly 2007, pp. 166). Generally, regression techniques strive to model the relationships among multiple variables by quantifying the magnitude that a response variable is related to a set of predictor variables (Eberly 2007). The output of the linear regression model can be used as a forecasting tool to evaluate the effects of various predictor variables on the response variable (Goh and Teo 2000; Eberly 2007, pp. 166). The multiple linear regression equation for which all models in this paper were built is provided in [Eq. (4)].

$$[4]\ Y\ (HR_{index}) \sim \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n$$

Y = Response Variable

β_0 = Intercept

β_n = Regression Coefficient

X_n = Independent Variable

The response variable under investigation was HR_{index}. HR_{index} was used as the response variable/dependent variable as the purpose of the research is to see the effects of mental workload, spatial cognition, total time of trial, and years of experience on hazard recognition performance. The independent variables including MW Sum and Mean SC were chosen as they are the primary effects of investigation. Additionally, total time of research trials and participants years of construction experience were selected to determine their effect on HR_{index}.

One of the common threats to the validity and usefulness of regression models is overfitting the dataset by having too many predictor variables present in any MLR model (Wilks 1995). The concept of overfitting is based in the number of observations in a data set that creates an upper limit of model complexity in which the model may fail to replicate in future samples (Babyak 2004). To ensure the number of predictor variables are not overfitted the model, the maximum number of predictor variables was set to N = 6 to allocate a minimum of 15 observations per predictor variable as recommended by Babyak (2004).

Examining Mental Workload and Spatial Cognition Across Design Information Formats

To test if spatial cognition and mental workload are related to hazard recognition performance across all formats of design information and population treatment groups, 5 predictor variables were selected for MLR analysis by investigating the effects of the variables of interest and their effects on the MLR model. The correlation matrix of these predictor variables can be seen in Tables 22 below. All MLR analysis were conducted in the open-source statistical package R. The response variable of interest was hazard recognition performance denoted as HR_{index}. The model equation [Eq. (5)], predictor variables, and MLR results can be seen below in Table 23.

Table 22: Correlation Matrices Across All Design Information Formats

Variables	HR Index	MW Sum	Mean SC	Total Time
HR Index	1.0			
MW Sum	0.0046	1.0		
Mean SC	-0.0117	0.0479	1.0	
Total Time	0.3053*	0.1851*	-0.0931	1.0
Years of Industry Experience	0.3342*	-0.1448*	-0.1608*	0.2601*

Items left blank as they are the table inverse of correlations thus not represented.
Asterisk (*) = Statistically significant difference beyond 95% confidence.

As can be seen from the MLR results in Table 12 below, mental workload, spatial cognition, and the interaction between the two did not predict the HR_{index} (all $p > 0.05$). However, years of construction experience ($t = 3.765$, $F = 14.1752$, and $p = 0.0002$*) and total time of research trial ($t = 3.779$, $F = 14.2808$, and $p = 0.0001$*) are significant. These are the only two predictor variables with statistical significance, which was surprising and counter to prevailing research. With MLR, the output generally provides t and p values for each predictor variable. Here, F is also provided as t^2 for explanation (Judd et al. 2004, pp.64). Additionally, the overall model output verifies significance ($F = 8.596$, $p = 0.000$), and the Adjusted R^2, which is the goodness-of-fit of the model (Eberly 2007, pp. 166), explains 15.85% of the variability of hazard recognition performance across all design information formats for all treatment population groups. Within the model, the coefficients of β_3 (i.e. Years of Industry Experience) and β_4 (i.e. Total Time of Trial (Minutes)) are represented as $\beta_3 = 0.0055$ and $\beta_4 = 0.0287$ respectively. These coefficients indicate that each year of industry experience will yield a 0.5% increase in the HR_{Index}. In other words, the results suggest that an increase of 10 years of industry experience will yield a 5% increase in the HR_{Index}. Additionally, the coefficients suggest that each minute spent in the hazard recognition trial will increase the HR_{Index} by 2.8%. Figures 4 below show the scatterplots for HR_{index} in association with Years of Construction Experience and Total Time of Research Trial (Seconds).

Table 23: Linear Regression Model for HR_{index} Across All Design Information Formats and Population Treatment Groups

Across All Design Information Formats Model Equation [Eq. (5)]:		$Y (HR_{index}) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6$					
Variables		**Coefficients** β_n	**Estimate** X_n	**Std. Error**	***t***	**F**	***P***
Intercept		β_0	0.3461	0.1196	2.893	8.3694	0.0042
Predictor Variables	Mental Workload Average (X1)	β_1	-0.0017	0.0155	-1.107	-1.2254	0.2693
	Spatial Cognition Average (X2)	β_2	-0.1114	0.1566	-0.711	-0.5055	0.4776
	Years of Industry Experience (X3)	β_3	0.0055	0.0014	3.765	14.1752	0.0002*
	Total Time of Trial (Minutes) (X4)	β_4	0.0287	0.0076	3.779	14.2808	0.0001*
	Total Time of Trial (Minutes): Experience (X6)	β_5	-0.000	0.000	-1.640	-2.6896	0.1023
	Mental Workload Average: Spatial Cognition Average (X5)	β_6	0.0228	0.0211	1.085	1.1772	0.2789

Note: *t*, *F* = variance of the group mean; p = significance.

Asterisk (*) = Statistically significant difference beyond 95% confidence.

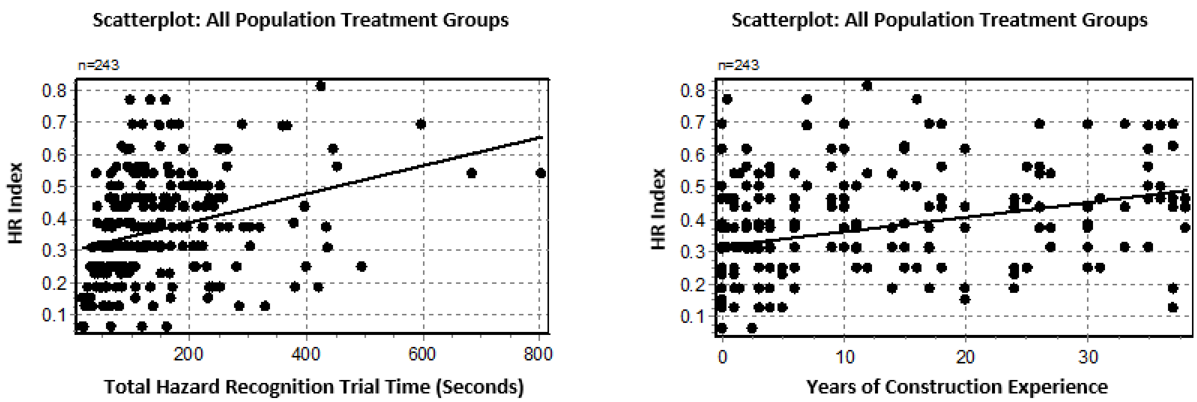

Figure 4: Scatterplots for HR Index and Time (Seconds) for All Population Treatment Groups

Examining Mental Workload and Spatial Cognition Within Design Information Formats

To test if spatial cognition and mental workload are related to hazard recognition performance ***within independent design information formats***, the same 5 predictor variables were selected for MLR analysis. The correlation matrices for each of the predictor variables within each model and design information format are presented in Table 24. The model equation [Eq. (6)], predictor variables, and MLR results for each regression model within design information format can be seen below in Table 25. Additionally, Table 26 provides the overall regression model output for all independent design information formats.

Table 24: Correlation Matrices Within Design Information Formats

Design Information Format Correlation Matrix					
		HR Index	**MW Sum**	**Mean SC**	**Total Time**
2D CAD	**HR Index**	1.0			
	MW Sum	-0.0054	1.0		
	Mean SC	-0.0115	0.0341	1.0	
	Total Time	0.0726	0.2270*	-0.1225	1.0
	Years of Industry Experience	0.2179	-0.1328	-0.1608	0.2854*
3D Visualization	**HR Index**	1.0			
	MW Sum	0.0324	1.0		
	Mean SC	-0.054	0.0098	1.0	
	Total Time	0.4021*	0.2996*	-0.0641	1.0
	Years of Industry Experience	0.4370*	-0.1222	-0.1608	0.2475*
Combination	**HR Index**	1.0			
	MW Sum	-0.0185	1.0		
	Mean SC	0.0297	0.1042	1.0	
	Total Time	0.4677*	0.0735	-0.0927	1.0
	Years of Industry Experience	0.3655*	-0.1832	-0.1608	0.2619*

Items left blank as they are the table inverse of correlations thus not represented.

Asterisk (*) = Statistically significant difference beyond 95% confidence.

Table 25: Linear Regression Model for HR_{index} for the Each Design Information Format

Within Independent Design Information Format Model Equation [Eq. (6)]:		$Y (HR_{index}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6$					
Predictor Variables		**Coefficients** β_n	**Estimate** X_n	**Std. Error**	***t***	**F**	***P***
Intercept (**2D CAD Format**)		β_0	0.3846	0.2545	1.512	2.2861	0.1349
2D CAD Format Predictor Variables	Mental Workload Average (X1)	β_1	-0.0031	0.0064	-0.495	-0.2450	0.6218
	Spatial Cognition Average (X2)	β_2	-0.1420	0.3303	-0.430	-0.1849	0.6685
	Years of Industry Experience (X3)	β_3	0.0073	0.0033	2.202	4.8488	0.0308*
	Total Time of Trial (Minutes) (X4)	β_4	0.0003	0.0002	1.172	1.3735	0.2451
	Total Time of Trial (Minutes): Experience (X5)	β_5	-0.0000	0.0000	-1.551	-1.3342	0.1252
	Mental Workload Average: Spatial Cognition Average (X6)	β_6	0.0049	0.0088	0.561	0.3147	0.5762
Intercept (**3D Visualization Format**)		β_0	0.1925	0.1866	1.032	1.065	0.3056
3D Visualization Format Predictor Variables	Mental Workload Average (X1)	β_1	0.0006	0.0046	0.150	0.022	0.8811
	Spatial Cognition Average (X2)	β_2	0.0700	0.2389	0.293	0.085	0.7701
	Years of Industry Experience (X3)	β_3	0.0054	0.0032	1.669	2.785	0.0993
	Total Time of Trial (Minutes) (X4)	β_4	0.0006	0.0002	2.149	4.618	0.0349*
	Total Time of Trial (Minutes): Experience (X5)	β_5	-0.0000	0.0000	-0.252	-0.063	0.8014
	Mental Workload Average: Spatial Cognition Average (X6)	β_6	-0.0014	0.0062	-0.225	-0.050	0.8227
Intercept (**Combination Format**)		β_0	0.3860	0.2023	1.908	3.640	0.0602
Combination Format Predictor Variables	Mental Workload Average (X1)	β_1	-0.0058	0.0056	-1.040	-1.081	0.3018
	Spatial Cognition Average (X2)	β_2	-0.1764	0.2658	-0.664	-0.440	0.5083
	Years of Industry Experience (X3)	β_3	0.0036	0.0020	1.746	3.048	0.0849
	Total Time of Trial (Minutes) (X4)	β_4	0.0004	0.0001	3.002	9.012	0.0036*
	Total Time of Trial (Minutes): Experience (X5)	β_5	0.0078	0.0074	1.050	1.102	0.2973
	Mental Workload Average: Spatial Cognition Average (X6)	β_6	-0.0000	0.0000	-0.230	-0.052	0.8184

Note: *t*, *F* = variance of the group mean; p = significance.

Asterisk (*) = Statistically significant difference beyond 95% confidence.

Table 26: Overall Linear Regression Model Output for the 2D CAD Design Information Format

Information format of MLR Model	RSE	*F*	DF	R^2	Adj. R^2	*P*
2D CAD	0.1733	1.1840	6 & 74	0.0876	0.0135	0.3245
3D Visualization	0.1354	4.915	6 & 74	0.2849	0.2270	0.000*
Combination	0.1358	5.406	6 & 74	0.3048	0.2484	0.000*

As can be seen from the MLR results in table 25 above, mental workload, spatial cognition, and the interactions between them were not significant in the prediction of the HR_{index} (all $p > 0.05$) within any design information format. Years of construction experience was found to be significant within the 2D CAD MLR model (t = 2.202, F = 4.8488, and p = 0.0308*). Within the 2D CAD design information format, mental workload, spatial cognition, experience, and the total time spent in the hazard recognition trial are all insignificant (all $p > 0.05$). Model comparisons of MLR analysis constructed through an automated forward stepwise model generation procedure across and within all design information formats can be seen in Appendix 5.

Although the MLR model is insignificant within the 2D CAD design information format, there was a significant effect of the Total Time of Research Trial on the HR_{index} in both the 3D visualization and combination design information formats. Within the 3D visualization Format, Total Time of Trial was found to be significant (t = 2.149 F = 4.618, and p = 0.0349*). The overall 3D visualization model output verifies model significance (F = 4.915, p = 0.000*), and the Adjusted R^2 explains 22.70% of the variability of hazard recognition performance within the 3D visualization design information format. Additionally, the Total Time of Trial was also found to be significant (t = 3.002 F = 9.012, and p = 0.003*) within the combination design information format. This overall model was found to be significant (F = 5.406, p = 0.000*), and the Adjusted R^2 explains 24.84% of the variability of HR_{Index}in the model within the combination design information format. A scatterplot of HR_{index} and Total Time of Trial can be seen for both 3D visualization and combination design information formats in Figure 5 below.

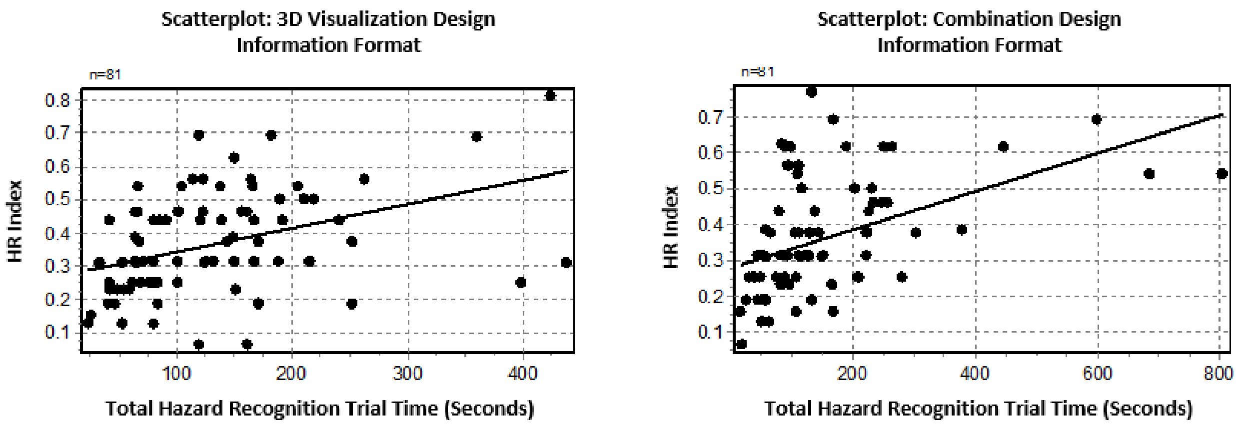

Figure 5: Scatterplots of HR_{index} and Total Time of Trial

The MLR results in this paper suggest that neither mental workload or spatial cognition predict HR_{index} between or within all formats of design information. Since there was no relationship between either MW Sum and Mean SC for any format of design information, the authors fail to reject null hypotheses Ho1 and Ho2. Therefore, the authors conclude that "*The mental workload of hazard recognition tasks is not related to design information format*" and that "*Spatial cognition is not related to design information format*." However, the *Total Time of Trial* for hazard recognition tasks was found to be significant and therefore related to the HR_{index}. Therefore, the authors reject null hypothesis Ho4 and conclude that the time spent in hazard recognition trials does predict the HR_{index}.

Examining the Effects of Design Information on Mental Workload

An Analysis of Variance (i.e., ANOVA) statistical approach was used to test Ha3: *Design information reduces mental workload of hazard recognition tasks*. Specifically, ANOVA analysis was applied to examine the variability of MW sums of the independent variables (i.e., design information format). The ANOVA statistical test determines whether there is a difference between means of independent variables (Dielman 2005; Fellows and Liu 2008). This test estimates statistically significant differences between the means using an F value while measuring the variability of the dependent variable that is explained by the independent variable (Dielman 2005; and Fellows and Liu 2008). The control groups are removed from this analysis as they received no design information and are thus not needed for testing hypothesis (Ho3). Table 27 below provides the sample size, sample MW Sums, F, and p values of ANOVA analysis of mental workload for each design information format across and within all population treatment groups. This analysis is independent of construction work activity and order of research trial as these variables were blocked in the Latin square design and their effects controlled.

Table 27: ANOVA results for total MW Sums across and within all treatment groups

Population Treatment	Design Information Format	Sample Size	Mean (MW Sum)	*F*	p
All	2D CAD	81	38.96	0.203	0.816
	3D Visualization	81	37.77		
	Combination	81	38.07		
Designer	2D CAD	27	40.22	0.214	0.808
	3D Visualization	27	37.93		
	Combination	27	38.52		
Supervisor	2D CAD	27	37.74	0.286	0.752
	3D Visualization	27	39.77		
	Combination	27	37.11		
Student	2D CAD	27	38.92	0.790	0.457
	3D Visualization	27	35.62		
	Combination	27	38.59		

Note: *F* = variance of the group mean; p = significance.

Asterisk (*) = Statistically significant difference beyond 95% confidence.

Surprisingly, the results of the MLR and ANOVA analysis suggest there is no significant difference in the total mental workload sum for the three design information formats across and within all population treatment groups. From the ANOVA results in Table 17 above, the mean values of MW Sum were found to be insignificant for the three design information format groups across all populations ($F = 0.203$ and $p = 0.816$). Additionally, the means of the MW Sum values for the different information formats within each of the three population treatment groups were also found to be insignificant (all $p > 0.05$).

To better understand the effects of design information on mental workload of hazard recognition trials, a mean and dispersion t-test was performed to evaluate the differences of mental workload between the treatment and control subcategory of each population group. Specifically, t-test were used to examine the differences in means for the treatment and control subcategories of the aggregate of all subjects across and within population groups. Table 28 below provides the population groups and sample sizes, mean MW Sum, and *F*, and *p* values.

Table 28: Overall MWS within Groups Two-Sample Independent Mean and Dispersion Test Results

Population	Population Category	Sample Size	Mean (MW Sum)	Percent Difference	t	p
All Samples	Treatment	81	38.26	1.20%	-0.333	0.739
	Control	36	38.75			
Designer	Treatment	27	38.88	2.36%	-0.356	0.722
	Control	12	39.80			
Supervisor	Treatment	27	38.20	5.96%	0.783	0.435
	Control	12	36.05			
Student	Treatment	27	37.71	7.15%	-1.192	0.236
	Control	12	40.41			

As can be seen from table 18 above, the pairwise t-test results suggest there is no significant differences in the MW Sums for the treatment and control groups across and within all population groups (all $p > 0.05$). Due to these results, it is suggested that the employment of design information does not reduce the overall mental workload of hazard recognition tasks. Therefore, the authors fail to reject null hypothesis Ho3 and conclude that design information does not affect the mental workload of hazards recognition tasks.

Conclusions

The Construction Hazard Prevention through Design (CHPtD) theory has seen much research over the last 20 years. The central premise the theory, recognizing safety hazards in design so they may be eliminated or managed with CHPtD solutions, is founded in the ability to recognize safety hazards in design. Within literature, two knowledge gaps provided the initiative for this research. First, it has been assumed that the level of mental workload required to use construction design information for hazard recognition varies among different formats of design information (Ku and Mills 2010; Bansal 2011; Kasirossafar and Shahbodaghlou 2012; Ganah & John 2015; Zhang et al. 2015). It has been postulated that BIM and other 3D visualization technologies provide greater efficacy of CHPtD processes as they decrease the required mental workload to interpret the physical work environment (Ku and Mills 2010; Bansal 2011; Kasirossafar and Shahbodaghlou 2012; Ganah & John 2015; Zhang et al. 2015; Martinez-Aires et al 2018). However, this assumption lacks empirical evidence. Secondly, the concept of spatial cognition, which is considered as the ability to retain, manipulate, and generate precise visual images (Lohman 1979), has been tested in construction research and has been found to be related to construction craft productivity (Dadi et al. 2014b; Goodrum et al. 2016). However, no research to date has explored whether a person's spatial cognitive capabilities predict hazard recognition performance for various formats of design information. These knowledge gaps provided the inspiration for this research.

In this study, 117 participants were presented with a construction design in three formats through a Latin square experimental design. Participants were asked to explore the design information and identify as many safety hazards as they could for three separate construction work activities. The mental workload of each hazard recognition trial was assessed using the NASA TLX subjective mental workload assessment sheet. Additionally, each participants' spatial cognitive capabilities were tested using card and cube rotation tests. The alternative research hypotheses are presented below:

Ha1: The mental workload of hazard recognition tasks is related to design information format.

Ha2: Spatial cognition is related to design information format and hazard recognition performance.

Ha3: Design information reduces mental workload of hazard recognition tasks.

Ha4: Time of hazard recognition trial is related to hazard recognition performance.

Hypotheses (Ha1 and Ha2) were the primary research hypotheses and were tested using Multiple Linear Regression (MLR) Analysis. The MLR results suggest that participants mental workload of hazard recognition tasks nor spatial cognitive capabilities predict the HR_{index} when examined across all population or within population groups. Therefore, the authors fail to reject null hypotheses (Ho1) and (Ho2) and conclude that mental workload and spatial cognition do not predict the HR_{index}. Hypothesis (Ha3) was tested using analysis of variance (i.e., ANOVA) analysis. The ANOVA analysis suggests that there is no statistically significant difference for mental workload levels for hazard recognition tasks when examined across all population and within population groups. Lastly, hypothesis (Ha4) was tested using MLR. Through MLR analysis, it was found that the time spent in hazard recognition trials did increase the HR_{index}. Therefore, the authors fail to reject null hypotheses (Ho1, Ho2, and Ho3). However, the authors do find statistical significance to reject null hypothesis (Ho4) and conclude that time spent in CHPtD processes predicts the HR_{index}. Additionally, it was found that construction experience is a key predictor.

The results of this research are contrary to the assumptions made in construction safety literature. There has been much discourse in construction safety literature which attempts to use logic to suggest that 3D visualization technologies such as BIM will permit improved hazard recognition during design. These postulations are made suggesting that the 3D interface of BIM environments will allow users to easily orient themselves into the simulated work environment. Which is considered to be more difficult in 2D technologies such as CAD as 2D technologies will require more mental workload and cognitive processes that 3D (Ku and Mills 2010; Bansal 2011; Kasirossafar and Shahbodaghlou 2012; Ganah & John 2015; Zhang et al. 2015). However, the results of this research suggest that there is no statistically significant variability between the levels of mental workload across the formats of design information used. Additionally, it was found that spatial cognition nor mental workload predict the HR_{index}. However, the results suggest that construction experience and time spent in the hazard recognition experience are predictors of performance. For this reason, the authors suggest that a multi-disciplinary team of construction industry professionals with experience be included in CHPtD processes. This will help to increase situational awareness and overall hazard recognition performance. It is concluded from this research, that having an experienced panel of practitioners for hazard recognition in design is more important than the format of design used.

Limitations

This study has two notable limitations. First, care was taken to ensure that that the results are generalizable to the commercial high-rise construction. However, all study participants were native to Colorado, North Carolina, and Wisconsin. Due to this limited geographical representation, further samples from the construction industry are needed to increase the external validity of this study to a broader construction audience. Although a diverse population of construction industry practitioners were solicited for participation; the results may not hold consistency for those outside of the scope of commercial high-rise construction. Additionally, this research included no data outside the United States and therefore may not be externally generalizable on a global scale.

Second, although the authors suggest there is no difference among the format of design information, more complex designs in both 2D and 3D visualizations may affect hazard recognition and mental workload across various formats of design information. Additionally, the industrial sector, level of design complexity, level of design detail, and amount and quality of data within designs may affect the number of visual ques that participants can use for recognizing safety hazards. More CHPtD research of this type, using actual design of varying complexities and known construction safety hazards, could be used to better understand how the different levels design complexity and completion affect hazard recognition. Therefore, the following null research hypothesis is presented: "*Varying levels of design complexity and Level of Detail do not affect the mental workload of hazard recognition tasks*." Although these limitations are humbly recognized, the authors believe the strength of this study lies in the actual work observations and associated comprehensive safety hazard lists, complete counterbalanced Latin square design, sample size, and diverse population groups.

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References

Akintoye, A., and Skitmore, M. (1994). “Models of UK private sector quarterly construction demand.” J. Constr. Manage. Econ., 12(1), 3–13

Albert, A., M. Hallowell, B. Kleiner, A. Chen, and M. Golparvar-Fard. (2014). “Enhancing Construction Hazard Recognition with High-Fidelity Augmented Virtuality.” *Journal of Construction Engineering and Management* 140 (7): 04014024.

Argyris, C. (1976). Theories of action that inhibit individual learning. *American Psychologist*, *31*(9), 638.

Babyak, M. A. (2004). What you see may not be what you get: a brief, nontechnical introduction to overfitting in regression-type models. Psychosomatic medicine, 66(3), 411-421.

Bahn, S. (2013). Workplace hazard identification and management: The case of an underground mining operation. *Safety science*, *57*, 129-137.

Ball, S., & Bogatz, G. A. (1970). The first years of sesame street: An evaluation. Princeton, N.J.: Educational Testing Service.

Battiste, V., & Bortolussi, M. (1988, October). Transport pilot workload: A comparison of two subjective techniques. In *Proceedings of the Human Factors Society Annual Meeting* (Vol. 32, No. 2, pp. 150-154). Sage CA: Los Angeles, CA: SAGE Publications.

Behm, M. (2005). Linking construction fatalities to the design for construction safety concept. *Safety science*, *43*(8), 589-611.

Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., & Babiloni, F. (2014). Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. Neuroscience & Biobehavioral Reviews, 44, 58-75.

Bowden, S., Dorr, A., Thorpe, A., Anumba, C. (2006). “Mobile ICT Support for Construction Process Improvement”. *Automation in Construction* Vol. 15 (5). 664–676.

Cao, A., Chintamani, K. K., Pandya, A. K., & Ellis, R. D. (2009). NASA-TLX: Software for assessing subjective mental workload. Behavior research methods, 41(1), 113-117.

Carswell, C. M., Clarke, D., & Seales, W. B. (2005). Assessing mental workload during laparoscopic surgery. *Surgical innovation*, *12*(1), 80-90.

Carter, G., & Smith, S. D. (2006). Safety hazard identification on construction projects. *Journal of construction engineering and management*, *132* (2): 197-205.

Chantawit, D., Hadikusumo, B., Charoenngam, C., & Rowlinson, S., (2005),"4DCAD-Safety: visualizing project scheduling and safety planning", Construction Innovation, Vol. 5 Iss 2 pp. 99 – 114

Cheng, T., & Teizer, J. (2012). Modeling tower crane operator visibility to minimize the risk of limited situational awareness. Journal of Computing in Civil Engineering, 28(3), 04014004.

Cooper, M. D., & Phillips, R. A. (2004). Exploratory analysis of the safety climate and safety behavior relationship. Journal of safety research, 35(5), 497-512.

Coyle, S., Ward, T., Markham, C., & McDarby, G. (2004). On the suitability of near-infrared (NIR) systems for next-generation brain–computer interfaces. *Physiological measurement*, *25*(4), 815.

Dadi, G. B., Goodrum, P. M., Taylor, T. R., & Carswell, C. M. (2014a). Cognitive workload demands using 2D and 3D spatial engineering information formats. Journal of Construction Engineering and Management, 140(5), 04014001.

Dadi, G. B., Goodrum, P. M., Taylor, T. R., & Maloney, W. F. (2014b). Effectiveness of communication of spatial engineering information through 3D CAD and 3D printed models. *Visualization in Engineering*, *2*(1), 9.

Daily, J. T., & Neyman, C. A. (1967). Development of a curriculum and materials for teaching basic vocational talents. Final report for Office of Education, contract No. OE-5085-023. Washington, D.C.: George Washington University, Education Research Project.

De Waard, D., 1996. The measurement of drivers' mental workload. Ph.D. Thesis. Traffic Research Centre, University of Groningen, Haren, The Netherlands.

Driscoll, T. R., Harrison, J. E., Bradley, C., & Newson, R. S. (2008). The role of design issues in work-related fatal injury in Australia. *Journal of Safety Research*, *39*(2), 209-214.

Eberly L.E. (2007) Multiple Linear Regression. In: Ambrosius W.T. (eds) Topics in Biostatistics. Methods in Molecular Biology™, vol 404. Humana Press

Ekstrom, R. B., French, J. W., Harman, H. H., and Dermen, D. (1976). "Manual for kit of factor-referenced cognitive tests." Educational Testing Service, Princeton, NJ.

Emmitt, S., and Gorse, C. (2003). Construction communication, Blackwell, Oxford, U.K.

Esmaeili, B., Hallowell, M. R., & Rajagopalan, B. (2015). Attribute-based safety risk assessment. II: Predicting safety outcomes using generalized linear models. Journal of construction engineering and management, 141(8), 04015022.

Fang, D. P., Huang, X. Y., & Hinze, J. (2004). Benchmarking studies on construction safety management in China. Journal of Construction Engineering and Management, 130(3), 424-432.

Fennema, E. & Sherman, J. (1977). Sex - related differences in mathematical achievement, spatial visualization and affection factors. Am. Educational Research Journal 4: 51-71.

Fonseca, E. D., Lima, F. P., & Duarte, F. (2014). From construction site to design: The different accident prevention levels in the building industry. Safety science, 70, 406-418.

Gagnon, D. (1985). Videogames and spatial skills: An exploratory study. *ECTJ, 33*(4), 263-275.

Gerjets, P., Walter, C., Rosenstiel, W., Bogdan, M., & Zander, T. O. (2014). Cognitive state monitoring and the design of adaptive instruction in digital environments: lessons learned from cognitive workload assessment using a passive brain-computer interface approach. Frontiers in Neuroscience, 8, 385

Ghaderi, R., & Kasirossafar, M. (2011). Construction safety in design process. In *AEI 2011: Building Integration Solutions* (pp. 464-471).

Goh, B. H. (1999). “An evaluation of the accuracy of the multiple regression approach in forecasting sectoral construction demand in Singapore.” J. Constr. Manage. Econ., 17(2), 231–241.

Goh, B. H., and Teo, H. P. (2000). “Forecasting construction industry demand, price and productivity in Singapore: the Box–Jenkins approach.” J. Constr. Manage. Econ., 18(5), 607–618.

Goodrum, P. M., and Miller, J. M. (2015). “Innovative delivery methods of information to the crafts.
Construction Industry Institute”, *Univ. of Texas at Austin*, Austin, TX. RT 327.

Goodrum, P. M., Miller, J., Sweany, J., & Alruwaythi, O. (2016). Influence of the format of engineering information and spatial cognition on craft-worker performance. *Journal of Construction Engineering and Management*, *142*(9), 04016043.

Gould, F, & Joyce, N. (2013). Construction Project Management (4th ed.). New Jersey: Prentice Hall.

Grassmann, M., Vlemincx, E., von Leupoldt, A., & Van den Bergh, O. (2017). Individual differences in cardiorespiratory measures of mental workload: An investigation of negative affectivity and cognitive avoidant coping in pilot candidates. Applied ergonomics, 59, 274-282.

Güven, B., & Temel, K. O. S. A. (2008). The effect of dynamic geometry software on student mathematics teachers' spatial visualization skills. *TOJET: The Turkish Online Journal of Educational Technology*, *7*(4).

Hadikusumo, B. H. W., & Rowlinson, S. (2002). Integration of virtually real construction model and design-for-safety-process database. Automation in Construction, 11(5), 501-509.

Hadikusumo, B. and S. Rowlinson (2004). "Capturing Safety Knowledge Using Design-for-Safety-Process Tool." *Journal of Construction Engineering and Management* 130(2): 281-289.

Hallowell, M. R. and D. Hansen (2016). "Measuring and improving designer hazard recognition skill: Critical competency to enable prevention through design." *Safety Science* 82: 254-263.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. *Advances in psychology*, *52*, 139-183.

Hicks, T. G., & Wierwille, W. W. (1979). Comparison of five mental workload assessment procedures in a moving-base driving simulator. *Human Factors*, *21*(2), 129-143.

Hill, S. G., Iavecchia, H. P., Byers, J. C., Bittner Jr, A. C., Zaklade, A. L., & Christ, R. E. (1992). Comparison of four subjective workload rating scales. *Human factors*, *34*(4), 429-439.

Huttenlocher, J., & Presson, C. C. (1979). The coding and transformation of spatial information. Cognitive Psychology, 11, 375-394.

Jainta, S., & Baccino, T. (2010). Analyzing the pupil response due to increased cognitive demand: an independent component analysis study. *International Journal of Psychophysiology*, *77*(1), 1-7.

Judd, C. M., McClelland, G. H., & Ryan, C. S. (2011). Data analysis: A model comparison approach. Routledge.

Kim, J. H., Parameshwara, N., Guo, W., & Pasupathy, K. S. (2018). The Impact of Interrupting Nurses on Mental Workload in Emergency Departments. International Journal of Human–Computer Interaction, 1-12.

Kozhevnikov, M., & Hegarty, M. (2001). A dissociation between object manipulation spatial ability and spatial orientation ability. *Memory & Cognition*, *29*(5), 745-756.

Kuchinke, L., Võ, M. L., Hofmann, M., & Jacobs, A. M. (2007). Pupillary responses during lexical decisions vary with word frequency but not emotional valence. International Journal of Psychophysiology, 65, 132–140. doi:10.1016/j.ijpsycho.2007.04.004

Lenné, M., Triggs, T.J., Redman, J.R., 1997. Time of day variations in driving performance. Accident Analysis and Prevention 29, 431–437.

Leung, S., Starmer, G., 2005. Gap acceptance and risk-taking by young and mature drivers, both sober and alcohol-intoxicated, in a simulated driving task. Accident Analysis and Prevention 37, 1056–1065.

Liberda, M., Ruwanpura, J., & Jergeas, G. (2003). “Construction Productivity Improvement: A Study of Human, Management and External Issues”. ASCE. *Construction Research Congress*. 1–8. 10.1061/40671(2003)5

Lingard, H. C., Cooke, T., & Blismas, N. (2012). Designing for construction workers' occupational health and safety: a case study of socio-material complexity. *Construction Management and Economics*, *30*(5), 367-382.

Lingard, H. (2013). Occupational health and safety in the construction industry. Construction management and economics, 31(6), 505-514.

Lohman, D. F. (1979). "Spatial ability: A review and reanalysis of the correlational literature". Rep. No. ADA075972, U.S. Office of Naval Research, Arlington, VA.

Lopez del Puerto, C., Clevenger, C. M., Boremann, K., & Gilkey, D. P. (2013). Exploratory study to identify perceptions of safety and risk among residential Latino construction workers as distinct from commercial and heavy civil construction workers. *Journal of Construction Engineering and Management*, *140* (2): 04013048 - 1 – 04013048 - 7.

Maeda, Y., & Yoon, S. Y. (2013). A meta-analysis on gender differences in mental rotation ability measured by the Purdue spatial visualization tests: Visualization of rotations (PSVT: R). Educational Psychology Review, 25(1), 69-94.

Martin, S. (2014). Measuring cognitive load and cognition: metrics for technology-enhanced learning. *Educational Research and Evaluation*, *20*(7-8), 592-621.

McGee, M. G. (1979). Human spatial abilities: Psychometric studies and environmental, genetic, hormonal, and neurological influences. Psychological bulletin, 86(5), 889.

Moses, B. E. (1977). The nature of spatial ability and its relationship to mathematical problem-solving. Dissertation Abstracts International. 38(8), 4640A. (University Microfilms No. AAG7730309)

Mulder, L. J. M. (1988). Assessment of cardiovascular reactivity by means of spectral analysis.

Nilsson, T., Nelson, T.M., Carlson, D., 1997. Development of fatigue symptoms during simulated driving. Accident Analysis and Prevention 29, 479–488.

Ng Boyle, L., Tippin, J., Paul, A., Rizzo, M., 2008. Driver performance in the moments surrounding a microsleep. Transportation Research Part F 11, 126–136.

Park, H. K., Han, S. H., and Russell, J. S. (2005). "Cash flow forecasting model for general contractors using moving weights of cost categories." J. Manage. Eng., 4(164), 164–172.

Presson, C. C. (1982). Strategies in spatial reasoning. Journal of Experimental Psychology: Learning,Memory, & Cognition, 8, 243-251.

Qi, J., Issa, R. R. A., Hinze, J., & Olbina, S. (2011). Integration of safety in design through the use of building information modeling. In Computing in Civil Engineering (2011) (pp. 698-705).

Rakauskas, M.E., Ward, N.J., Boer, E.R., Bernat, E.M., Cadwallader, M., Patrick, C.J., 2008. Combined effects of alcohol and distraction on driving performance. Accident Analysis and Prevention 40, 1742–1749.

Rubio, S., Díaz, E., Martín, J., & Puente, J. M. (2004). Evaluation of subjective mental workload: A comparison of SWAT, NASA-TLX, and workload profile methods. *Applied Psychology*, *53*(1), 61-86.

Sacks, R., J. Whyte, et al. (2015). "Safety by design: dialogues between designers and builders using virtual reality." *Construction Management and Economics* 33(1): 55-72.

Seashore, R. H., & McCollom, I. N. (1932). Studies in Motor and Mechanical Skills. Science, 75(1944), 358-359.

Seo, J. W., & Choi, H. H. (2008). Risk-based safety impact assessment methodology for underground construction projects in Korea. *Journal of construction engineering and management*, *134*(1), 72-81.

Small, D. & Small, S. (1982). The experts' guide to beating Asteroids, Battlezone, Galazian Ripoff and Space Invaders. Creative Computing, I8(1), 18-33.

Salomon, G. (1979). Interaction of Media Cognition and Learning. San Francisco: Jossey-Bass.

Sorby, S. A., & Baartmans, B. J. (1996). A Course for the Development of 3-D Spatial Visualization Skills. *Engineering Design Graphics Journal*, *60*(1), 13-20.

Strangman, G., Culver, J. P., Thompson, J. H., & Boas, D. A. (2002). A quantitative comparison of simultaneous BOLD fMRI and NIRS recordings during functional brain activation. *Neuroimage*, *17*(2), 719-731.

Svensson, E., Angelborg-Thanderz, M., & Sjöberg, L. (1993). Mission challenge, mental workload and performance in military aviation. Aviation, space, and environmental medicine.

Sweany, J., Goodrum, P., Miller, J. (2016). "Analysis of empirical data on the effects of the format of engineering deliverables on craft performance". *Automation in Construction*, Volume 69. (2016) 59-67

Szymberski, R. (1997). "Construction project safety planning." TAPPI Journal 80(11): 69-74.

Tang, J. C. S., Karasudhi, P., and Tachopiyagoon, P. (1990). "Thai construction industry: Demand and projection." J. Constr. Manage. Econ., 8(3), 249–257

Tam, C. M., & Fung IV, I. W. (1998). Effectiveness of safety management strategies on safety performance in Hong Kong. Construction Management & Economics, 16(1), 49-55.

Thiffault, P., Bergeron, J., 2003. Monotony of road environment and driver fatigue: a simulator study. Accident Analysis and Prevention 35, 381–391.

Travis, B., Lennon, E., (1997). Spatial skills and computer-enhanced instruction in calculus. Journal of Computers in Mathematics and Science Teaching. 16(4), 467-475

Tubbs-Cooley, H. L., Mara, C. A., Carle, A. C., & Gurses, A. P. (2018). The NASA Task Load Index as a measure of overall workload among neonatal, paediatric and adult intensive care nurses. Intensive and Critical Care Nursing.

Verwey, W.B., Zaidel, D.M., 1999. Preventing drowsiness accidents by an alertness maintenance device. Accident Analysis and Prevention 31, 199–211.

Voyer, D., Voyer, S., & Bryden, M. P. (1995). Magnitude of sex differences in spatial abilities: a meta-analysis and consideration of critical variables. Psychological Bulletin, 117, 250–270. doi:10.1037/0033- 2909.117.2.250

Wilks, D. S. (1995). Statistical methods in the atmospheric sciences, Academic, New York.

Wilson, G. F., & Fisher, F. R. A. N. K. (1991). The use of cardiac and eye blink measures to determine flight segment in F4 crews. *Aviation, space, and environmental medicine, 62*(10), 959-962.

Whelan, R. R. (2007). Neuroimaging of cognitive load in instructional multimedia. Educational Research Review, 2, 1–12

Wraga, M., Creem, S. H., & Profitt, D. R. (2000). Updating displays after imagined object and viewer rotations. Journal of Experimental Psychology: Learning, Memory, & Cognition, 26, 151-168.

Zander, T., & Kothe, C. (2011). Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general. Journal of Neural Engeneering, 8, 025005.

Zhang, S., Sulankivi, K., Kiviniemi, M., Romo, I., & Eastman, C. (2015). BIM-based fall hazard identification and prevention in construction safety planning. Safety Science, 72, 31-45.

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Chapter 5: Conclusions

This dissertation has accomplished three primary objectives. The 1st objective is to provide a detailed review of CHPtD literature and differentiate scientific evidence and subjective theory relating to CHPtD theory. This includes describing the relevant literature regarding hazard recognition methods during design, the tools used to supplement hazard recognition in design, and the technology applications for incorporating safety into construction design. With this information, key knowledge gaps were identified and testable hypotheses were developed. The 2nd contribution centers around understanding the effects that construction design information has on hazard recognition performance during simulated CHPtD safety review processes. Many knowledge gaps exist in literature with respect to using design information for hazard recognition. Three primary hypotheses are tested that evaluate these effects. Lastly, the 3rd objective of this dissertation was to examine the effects of humans' spatial cognition (i.e., the ability to mentally interpret the rotation of object) and mental workload of hazard recognition tasks. Specifically, the relationships between the mental workload of hazard recognition tasks and the format of design information used are examined. These three objectives were accomplished in three studies. An overview of each studies results is presented in the sections below.

5.2 Study #1 Conclusions

The purpose of the first study was to assess the current state of CHPtD research and to identify current trends and experimental hypotheses for future empirical research. This study departs from current literature by presenting a conceptual framework for the advancement of the CHPtD research agenda through empirical hypothesis testing. Overall, the Construction Hazard

Prevention through Design (CHPtD) theory has seen an abundance of research in recent years, most of which research has been conducted to validate the CHPtD concept using logical argument and subjective evidence. (Behm 2005; Seo and Choi 2008; Driscoll et al. 2008; Ghaderi and Kasirossafar 2011). Through this research, the CHPtD theory has been validated as a viable safety management strategy. Although this literature is rich with many valuable contributions, there is a dearth of empirical evidence validating it use for risk reduction in practical construction settings (Hardison et al. *In press*). The results of study #1 identify key knowledge gaps, create scientifically testable hypotheses, and justify those hypotheses with the current state of knowledge. The motivation for this work was to establish the need for the construction and testing of new empirical hypotheses relating to CHPtD theory. The hypotheses identified in study #1are:

Ho1: CHPtD design solutions do not reduce lifecycle safety risks.

Ho2: Risk-based approaches cannot be used to select design alternatives that optimize lifecycle safety.

Ho3: Not all construction safety hazards are recognizable during design phases.

Ho4: CHPtD tools do not affect hazard recognition or the selection of optimal design solutions.

Ho5: The modality of design information does not affect hazard recognition and removal during design.

Ho6: The risks reduced by the various levels of the hierarchy of controls are not equal.

These hypotheses relate to lifecycle safety risks (*Ho1, and Ho2*), hazard recognition in design (*Ho3*, *Ho4*, *and Ho5*), and the hierarchy of safety controls (*Ho6*). Additional information relating to each of these hypotheses can be found in chapter 2 of this dissertation. Overall, these hypotheses are presented to the research community in hopes to shift attention to evidence-based methods that test assumptions and address the gaps in CHPtD research. These hypotheses were also used as the foundation for studies #2 and #3.

5.3 Study #2 Conclusions

Within existing literature, there are two key assumptions that provided the inspiration for this research. First, researchers suggest that both two-dimensional computer aided design (CAD) drawings and BIM both provide a rich opportunity for hazard recognition in design (De Lapp et al. 2004 and Ganah and John 2015). Researchers have suggested that the use of design information will enhance the ability to recognize hazards stemming from downstream construction work, and therefore it is assumed that the use of design information increases the efficacy of hazard recognition in design (De Lapp et al. 2004; Chantawit et al. 2005; Ku and Mills 2010; Bansal 2011; Kasirossafar and Shahbodaghlou 2012; Ganah and John 2015; Martinez-Aires et al. 2018). Second, it is assumed that the format of design information affects hazard recognition performance during design. Researchers suggest CAD alone is insufficient as a platform for hazard recognition in design as it limits the ability to acquire project information (Collier 1994; Young 1996; Chantawit et al. 2005; Zhang et al. 2015). Conversely, researchers suggest that BIM offers enhanced opportunities to recognize safety hazards by digitally replicating the physical work environment and aiding in the mental interpretation of spatial constraints and construction sequences (Ku and Mills 2010; Bansal 2011; Ganah & John 2015; and Zhang et al. 2015). Although these propositions are consistently made in literature, they have not been empirically tested and provided the inspiration for this research.

This work tested 117 subjects hazard recognition skills using 3 formats of design information (i.e., 2D CAD, 3D visualizations, and a combination of the two) crossed with 3 treatment variables (i.e., construction activities) via a Latin square experimental design to determine the effects of design information formats on subjects' hazard recognition skill. This papers primary contribution to the body knowledge is the identification of how design information, and the different formats of design information, affect hazard recognition performance during project design phases. Subjects' performed a simulated Construction Hazard Prevention through Design (CHPtD) safety review of one construction design, presented in 3 different information formats, and were asked to identify potential safety hazards arising from 3 separate construction activities. The following hypotheses were tested:

Ho1: Provision of design information in general does not affect hazard recognition performance.
Ho2: The format of design information does not affect hazard recognition performance.
Ho3: Years of construction experience does not predict hazard recognition performance.

To test (Ho1), the hazard recognition performance between all populations treatment and control groups were examined using mean and dispersion t-test procedures. The treatment groups of the study were provided a mixture of three formats of design information for three independent construction activities. The control group was not provided any design information. Both treatment and control groups were provided descriptions of the construction work activities and asked to identify all safety hazards associated with the construction work activity. A t-test examined hazard recognition performance (i.e., the HR_{index}) across and within practitioner population groups and revealed that the intervention of design information as a treatment condition had no significant effect on HR_{index}. This was a very surprising finding, as the implication is that the design information provides no additional benefit in the HR_{index} and that a practitioner can perform equally as well by simply thinking about the work activity in abstraction. Therefore, the authors fail to reject research null hypothesis (Ho1).

To test Ho2, analysis of variance (ANOVA) was used to examine the variability of hazard recognition performance of the independent variables (i.e., design information format) crossed with the treatment factors/dependent variables (i.e., construction activity) within all populations treatment groups. The control groups were not included in the analysis as they did not receive any design information and are thereby not needed for testing Ho1. Surprisingly, the results suggest that there is no significant difference in the proportion of safety hazards identified across the three independent variables (i.e., design information formats). The ANOVA analysis suggests that no statistical significance exists to reject the null hypotheses for any population group. Therefore, the results suggest failure to reject null hypothesis (Ho2).

Lastly, the participants came from a wide range of construction experience. To determine if years of construction experience played a significant role in hazard recognition performance, both one-way analysis of variance (ANOVA) and Multiple Linear Regression (MLR) were applied within each treatment and control group to test hypothesis (Ho3). For ANOVA analysis, a median split of "high" and "low" experience levels were conducted for each of the populations treatment and control groups. The ANOVA analysis suggests that there was no significant effect of the years of construction experience within population groups. However, the results suggest that construction experience does have a significant effect on the HR_{index} for the aggregate of all participant data. These results were reconfirmed with MLR analysis. Although MLR analysis suggests that construction experience does not predict hazard recognition performance within groups, the results do reconfirm the ANOVA as experience does predict HR_{index}.

Overall, the results of this study are contrary to current assumptions in construction safety literature. First, as this study suggests, it may not be true that design information is useful for recognizing safety hazards in design. Future research is needed to discover which types of safety hazard are recognizable during design phases and which ones remain latent until construction. The overall premise of CHPtD is to recognize safety hazards in design so they may be eliminated or managed prior to construction (Hecker and Gambatese 2003; Gambatese et al 2008). Understanding which types of construction hazards are recognizable will be beneficial for the advancement of CHPtD theory into commercial practice.

Secondly, it was found that the format of design information had no effect on the HR_{index}. This is an interesting find since the prevailing literature assumes that 3D visualizations will yield higher hazard recognition performance (Kasirossafar and Shahbodaghlou 2012; Ganah and John 2015; and Martinez-Aires et al. 2018). The assumption that one format is superior to another is thereby rejected, and if cannot be proven false with additional research, stands to be tested. This is an important finding in the domain of construction safety as it suggests that various formats of design information will fail to yield variability in hazard recognition performance during design stages. Coupled with the last finding of this study, which suggests that construction experience predicts hazard recognition, it is here proposed that a multi-disciplinary team consisting of experienced professionals is more important for hazard recognition than the format of design information used for CHPtD review processes. If findings of this type continue to hold true in future research, there will be strong practical implications on CHPtD theory and implementation.

5.4 Study #3 Conclusions

Study #3 is focuses on the nexus of mental workload and spatial cognition of hazard recognition tasks. This is done in the context of CHPtD research using the same experimental deign and sample as study #2. However, different research hypotheses were tested using different metrics. This section provides a brief overview of the results from study #3.

Within existing literature, there are a few knowledge gaps that provided the inspiration for study #3. It has been suggested that CAD and BIM are useful for hazard recognition in design (De Lapp et al. 2004 and Ganah and John 2015), and it has further been suggested that BIM provides more efficacy of CHPtD processes as it is suggested to decrease the required mental workload to interpret the physical work environment (Ku and Mills 2010; Bansal 2011; Kasirossafar and Shahbodaghlou 2012; Ganah & John 2015; Zhang et al. 2015; Martinez-Aires et al 2018). Additionally, the concept of spatial cognition, which is considered as the ability to retain, manipulate, and generate precise visual images (Lohman 1979), has been tested in construction research and has been found to be related to construction craft productivity (Dadi et al. 2014b; Goodrum et al. 2016). Mental workload and spatial cognition, however, have not been examined in the context of construction safety research. Although spatial cognition is related to craft performance (Dadi et al. 2014b; Goodrum et al. 2016), it was unknown if it is related to hazard recognition performance of tasks using various formats of design information. Given this information in the prevailing literature, research questions remain untested and give rise the inspiration for study #3. Given the same human subjects, protocol, and experimental design as study #2, the following hypotheses were tested:

Ho1: The mental workload of hazard recognition tasks is not related to design information format.

Ho2: Spatial cognition is not related to design information format and hazard recognition performance.

Ho3: Design information reduces mental workload of hazard recognition tasks.

H04: Time of hazard recognition trial is not related to hazard recognition performance.

To test these hypotheses, Multiple Linear Regression (MLR) analysis was used to examine the relationships between several predictor variables and the response variable (i.e., hazard recognition performance). This study evaluated the influence of *mental workload*, *spatial cognition*, *total time of research trials*, and *years of construction experience* as predictor variables via MLR. MLR models were constructed for the aggregate of all research participants across all population treatment groups. The results across all populations treatment groups and formats of design information suggest that the *mental workload* of hazard recognition tasks nor participants *spatial cognition* or the interaction thereof predict HR_{index}. Therefore, the authors fail to reject null hypotheses (Ho1), (Ho2), and (Ho3).

Although, *mental workload* of hazard recognition tasks nor participants *spatial cognition* were found to be significant; participants' *years of construction experience* and the *total time of research trial* were found to be significant within the model and therefore predict the HR_{index}. These two predictor variables are the only predictor variables that are found to be statistically significant in the MLR model. The results of the overall model across all population treatment groups and formats of design information suggest that *years of construction experience* and *total time of research trial* are significant. Therefore, the authors reject null hypothesis (Ho4).

Overall, the results of study #3 also conflict with a prevailing assumption in literature. Researchers have postulated that BIM is superior for recognizing hazards from design information as it will require less mental effort than 2D CAD alone. This is proposed because it is assumed that 3D BIM environments allow users to interpret the physical work environment better than CAD designs (Ku and Mills 2010; Bansal 2011; Kasirossafar and Shahbodaghlou 2012; Ganah & John 2015; Zhang et al. 2015; Martinez-Aires et al 2018). The results of this study suggest this assumption is false.

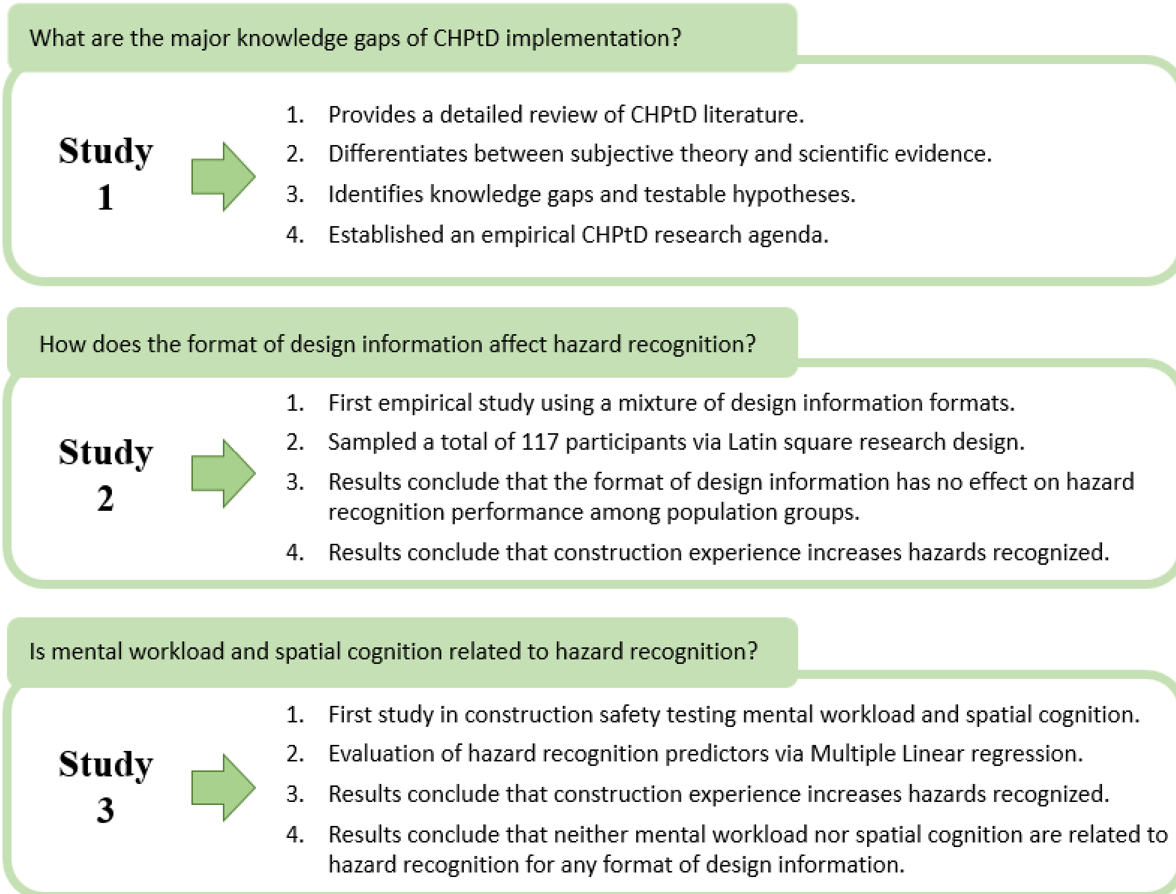

Figure 6: Research questions, scopes, and key findings

5.5 Suggestions for future hazard recognition research in construction

Hazard recognition has seen much research over the last 10 years as it is foundational to safety management programs. For this reason, hazard recognition has been the focus of construction and engineering research (Carter and Smith 2006; Bahn 2013; Lopez del Puerto et al. 2013; Albert et al. 2013 and 2014; Hallowell and Hansen 2016). Although past research has made advances in safety science, little research has attempted to investigate the mental workload and human cognitive processes of hazard recognition tasks. This knowledge gap is critical in reducing the estimated 1,000 fatalities and 230,000 injuries in the US construction industry each year and lies at the forefront of hazard recognition research.

Future research is needed to investigate the mental workload and physiological responses of construction workers during hazard recognition experiments. Research employing eye-tracking technology can be used to investigate information acquisition, decision making processes, and attentional processes of hazard recognition activities and may unlock new discoveries in safety science. Eye-tracking technology is used to determine what objects participants view within a stimulus, how long they view them, and the order in which the objects are viewed (Bass et al. 2016). This technology has been used in construction safety research (Dzeng et al. 2016; Hasanzadeh et al. 2016; Pinherio et al. 2016; and Hardison et al. 2017). However, knowledge gaps still exist with respect to understanding human cognition during decision-making processes (Hardison et al. 2017).

Additionally, the use of functional near-infrared spectroscopy (fNIRS) may be used to evaluate participants cognitive responses during hazard recognition experiments. Worn as a cap, fNIRS systems allow researchers to investigate the variability of time to peak cognitive responses of related safety hazards via visual stimuli (Chen et al. 2016). fNIRS neuroimaging technology could one day be used to learn how the brain processes and responds to safety hazards in simulated work environments. Together, eye-tracking and fNIRS can be paired to understand cognitive demand and localization of brain activation and can provide a more detailed understanding of hazard recognition patterns and neural processes.

This type of research will expand on the current hazard recognition research methods with more objective measures of human physiology. Although subjective metrics of mental workload were used in this dissertation, future research must strive to understand how to better quantify the cognitive responses and mental workload of hazard recognition tasks using more objective physiological measurements. Expanding mental workload assessment with physiological metrics provides an objective metric in which true cognitive responses can be measured and therefore increase the internal validity and scientific rigor of hazards recognition research.

Another aspect of hazard recognition research would be examining the pattern or sequence of hazards which are recognized during experimental trials. This type of analysis would be useful in describing the types of safety hazard that are most frequently identified at the beginning of experiments and which ones are infrequently identified. Pre- and post-test experimental trails with hazard recognition training as an intervention could be conducted to determine if different training approaches change the order in which hazards are recognized and therefore increase hazard recognition performance and overall situational awareness in dynamic construction environments.

Similarly, examining the types of hazardous energy sources recognizable by the construction workforce could possibly open the door to increasing the efficacy of hazard recognition training. Pre- and post-test training assessments could also be conducted to determine what types of safety training methodologies allow workers to best recognize different sources of hazardous energy in construction. Additionally, objective eye-tracking and fNIRS measurements could be applied to these types of research scopes to increase the scientific rigor of experiments. Overall, the application of more rigorous empirical hypothesis testing may ensure that safety research continues to mature by developing studies with strong ecological validity and rigorous scientific approaches. Additionally, empirical hypothesis testing will become the catalyst in which overall safety management theories will begin to transition into scientifically supported safety management strategies with known industrial benefits.

5.6 Suggestions for advancing CHPtD through empirical research

The construction safety research community has made beneficial advances in terms of CHPtD research. However, more objective and rigorous hypothesis testing is needed if the community aims to advance unbiased, valid, and reliable knowledge. The consensus within the body literature is that CHPtD is effective in preventing injuries, can enable hazard recognition and communication in design, and new design technologies like BIM offer opportunities for integration of reliable safety data into design (Hallowell et al. 2016). However, the current body of CHPtD literature lacks empirical hypothesis testing needed to ensure the method achieves the theories primary objective of reducing risks over the projects entire lifecycle, including construction, maintenance, repair, and demolition. Therefore, future research is needed to help mature CHPtD theory.

Themes of future empirical research include understanding the effects of CHPtD solutions on lifecycle safety risks, further examining the efficacy of recognizing construction safety hazards during design, and evaluating the level of holistic safety risk reduction by applying the various steps of the hierarchy of safety controls to industrial safety management processes. To date, there is no scientific evidence to suggest that a specific CHPtD solution reduces lifecycle safety risks. Because of this future research is needed to examine the effects that CHPtD solutions have on holistic project risks. Additionally, research building on this dissertation is needed to understand how varying levels of design complexity and completeness of designs affect hazard recognition capability. Examining the types of safety hazards recognizable by energy type and magnitude may be beneficial in uncovering necessary CHPtD training needs. These research opportunities are further explained in chapter 2 of this dissertation.

Additionally, future research is needed which addresses the hypotheses tested in this dissertation using the same experimental constructs in a group setting. This dissertation has preserved internal validity by sampling participant data on a “1 on 1” basis. However, testing these hypotheses in a group setting would increase the ecological validity of the results at the expense of internal validity. The CHPtD process has been developed as being a multidisciplinary process (Gambatese 1997; Ganah and John 2015; Sacks et al. 2015) which aims to solicit the opinions of many key project stakeholders. The results of this study may be affected by having a multidisciplinary team of construction and design professionals review the construction design for safety hazards in simulated CHPtD review processes. This provides additional opportunities for the advancement of CHPtD research.

5.7 Limitations of current data set

Despite the rigorous methodology presented in this dissertation, a few key limitations prevail. First, further samples of construction industry practitioners are needed to further generalize these research findings to a broader audience. This research strived to maintain external validity and generalizability to those involved in commercial high-rise construction. Although a diverse population of construction workers and designers were solicited for participation; the results may not hold consistency for those outside of the scope of commercial high-rise construction. Also, performing similar studies in which certain construction trades are solicited to perform hazard recognition experimentation of construction designs related to employment scope may also yield variability in results. Lastly, all research participants were within the United States. Therefore, the results may not be externally generalizable on a global scale.

Secondly, future researchers should attempt to ensure that all safety hazards present during actual constructions are accounted for to ensure that the proportion of hazards recognized by research participants accurately captures true subject hazard recognition performance. Ensuring all safety hazards are accounted for will ensure a correct benchmark in which participants hazard recognition performance can be compared. This will help to increase internal validity and strengthen the quality of overall results.

Third, as described in this dissertation, 3D visualizations of BIM environments were used to increase internal validity at the expense of some ecological validity. This was done to ensure that BIM user experience and model navigation issues did not create a confound in the result. Additionally, 3D visualizations were used as a method to remove researcher bias by providing easy to navigate 3D PDF's to participants. More sophisticated BIM environments may lead to variability in the results different to what is presented in this dissertation. Additionally, those with more experience in BIM may be able to better navigate the BIM environment and therefore yield different levels of hazard recognition performance. However, these methods provide a novel approach in which additional research can be built.

5.8 Personal reflections

This was one of the most exciting and challenging times of my life. I met some extremely interesting people, had a lot of fun, and enjoyed focusing on the topic of construction safety. This experience has taught me how to (1) critically evaluate subject matter, (2) plan and execute studies and communicate results; and (3) bridge research into teaching. I am happy I have pursued this degree. My advice to those who follow my path is to find something you are passionate about, keep writing, and enjoy the experience. Overall, I am proud of what I have achieved. I hope this work will help save one workers life. If so, it's worth it. Either way, my work has just begun.

5.9 References

Albert, A., Hallowell, M. R., & Kleiner, B. M. (2013). Enhancing construction hazard recognition and communication with energy-based cognitive mnemonics and safety meeting maturity model: Multiple baseline study. Journal of Construction Engineering and Management, 140(2), 04013042.

Bass, S. B., Gordon, T. F., Gordon, R., & Parvanta, C. (2016). Using eye tracking and gaze pattern analysis to test a “dirty bomb” decision aid in a pilot RCT in urban adults with limited literacy. BMC medical informatics and decision making, 16 (1), 1-13.

Bahn, S. (2013). Workplace hazard identification and management: The case of an underground mining operation. *Safety science*, *57*, 129-137.

Bansal, V. K. (2011). Application of geographic information systems in construction safety planning. *International Journal of Project Management*, *29*(1), 66-77.

Behm, M. (2005). Linking construction fatalities to the design for construction safety concept. *Safety science*, *43*(8), 589-611.

Carter, G., & Smith, S. D. (2006). Safety hazard identification on construction projects. *Journal of construction engineering and management*, *132* (2): 197-205.

Chen, J., Song, X., and Lin, Z. (2016). “Revealing the ‘Invisible Gorilla’ in construction: Estimating construction safety through mental workload assessment.” Automation in Construction, 63, 173–183.

Dadi, G. B., Goodrum, P. M., Taylor, T. R., & Maloney, W. F. (2014b). Effectiveness of communication of spatial engineering information through 3D CAD and 3D printed models. *Visualization in Engineering*, *2*(1), 9.

Driscoll, T. R., Harrison, J. E., Bradley, C., & Newson, R. S. (2008). The role of design issues in work-related fatal injury in Australia. *Journal of Safety Research*, *39*(2), 209-214.

Dzeng, R. J., Lin, C. T., & Fang, Y. C. (2016). Using eye-tracker to compare search patterns between experienced and novice workers for site hazard identification. Safety science, (82): 56-67.

Esmaeili, B., and Hallowell, M. R. (2012). “Diffusion of safety innovations in the construction industry.” J. Constr. Eng. Manage., 10.1061/(ASCE)CO.1943-7862.0000499, 955–963.

Gambatese, J. A., Behm, M., & Rajendran, S. (2008). Design’s role in construction accident causality and prevention: Perspectives from an expert panel. *Safety science*, *46*(4), 675-691.

Ganah, A., & John, G. A. (2015). Integrating building information modeling and health and safety for onsite construction. *Safety and health at work*, *6*(1), 39-45.

Ghaderi, R., & Kasirossafar, M. (2011). Construction safety in design process. In *AEI 2011: Building Integration Solutions* (pp. 464-471).

Goodrum, P. M., Miller, J., Sweany, J., & Alruwaythi, O. (2016). Influence of the format of engineering information and spatial cognition on craft-worker performance. *Journal of Construction Engineering and Management*, *142*(9), 04016043.

Hallowell, M. R. and D. Hansen (2016). "Measuring and improving designer hazard recognition skill: Critical competency to enable prevention through design." *Safety Science* 82: 254-263.

Hallowell, M. R., Hardison, D., & Desvignes, M. (2016). Information technology and safety: Integrating empirical safety risk data with building information modeling, sensing, and visualization technologies. *Construction Innovation*, *16*(3), 323-347.

Hardison, D., Sears, M., Hallowell, M., & Goodrum, P. (2017). USING EYE TRACKING TECHNOLOGY TO EVALUATE FOCAL ATTENTION LOCATION AND ITS RELATIONSHIP TO HAZARD RECOGNITION. In *Canadian Society of Civil Engineers* (2017).

Hasanzadeh, S., Esmaeili, B., & Dodd, M. D. (2016). Measuring Construction Workers' Real-Time Situation Awareness Using Mobile Eye-Tracking. In Construction Research Congress (2016): (2894-2904).

Hecker, S. and J. Gambatese (2003). "Safety in Design: A Proactive Approach to Construction Worker Safety and Health." Applied Occupational and Environmental Hygiene 18(5): 339-342.

Kasirossafar, M., & Shahbodaghlou, F. (2013). Building Information Modeling or construction Safety Planning. In *ICSDEC 2012: Developing the Frontier of Sustainable Design, Engineering, and Construction* (pp. 1017-1024).

Ku, K., & Mills, T. (2010). Research needs for building information modeling for construction safety. In *International Proceedings of Associated Schools of Construction 45nd Annual Conference, Boston, MA.*

Lingard, H. C., Cooke, T., & Blismas, N. (2012). Designing for construction workers' occupational health and safety: a case study of socio-material complexity. *Construction Management and Economics*, *30*(5), 367-382.

Lohman, D. F. (1979). "Spatial ability: A review and reanalysis of the correlational literature". Rep. No.
ADA075972, U.S. Office of Naval Research, Arlington, VA.

Lopez del Puerto, C., Clevenger, C. M., Boremann, K., & Gilkey, D. P. (2013). Exploratory study to identify perceptions of safety and risk among residential Latino construction workers as distinct from commercial and heavy civil construction workers. *Journal of Construction Engineering and Management, 140* (2): 04013048 - 1 – 04013048 - 7.

Manu, P. A., Ankrah, N. A., Proverbs, D. G., & Suresh, S. (2012). Investigating the multi-causal and complex nature of the accident causal influence of construction project features. *Accident Analysis & Prevention*, *48*, 126-133.

Martínez-Aires, M. D., López-Alonso, M., & Martínez-Rojas, M. (2018). Building information modeling and safety management: A systematic review. *Safety Science*, *101*, 11-18.

Pinheiro, R. B. O., Pradhananga, N., Jianu, R., & Orabi, W. (2016, January). Eye-Tracking Technology for Construction Safety: A Feasibility Study. InISARC. Proceedings of the International Symposium on Automation and Robotics in Construction, (33).

Seo, J. W., & Choi, H. H. (2008). Risk-based safety impact assessment methodology for underground construction projects in Korea. *Journal of construction engineering and management*, *134*(1), 72-81.

Szymberski, R. (1997). "Construction project safety planning." TAPPI Journal 80(11): 69-74.

Toole, T. M. (2005). Increasing engineers’ role in construction safety: Opportunities and barriers. Journal of Professional Issues in Engineering Education and Practice, 131(3), 199-207.

Zhang, M., and Fang, D. (2013). “A continuous behavior-based safety strategy for persistent safety improvement in construction industry.” J. Autom. Constr., 34(1), 101–107.

Zhang, S., Sulankivi, K., Kiviniemi, M., Romo, I., & Eastman, C. (2015). BIM-based fall hazard identification and prevention in construction safety planning. Safety Science, 72, 31-45.

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Bibliography

Akinci, B., Fischer, M., & Kunz, J. (2002). Automated generation of work spaces required by construction activities. Journal of construction engineering and management, 128(4), 306-315.

Akintoye, A., and Skitmore, M. (1994). "Models of UK private sector quarterly construction demand." J. Constr. Manage. Econ., 12(1), 3–13

Albert, A., Hallowell, M. R., & Kleiner, B. M. (2013). Enhancing construction hazard recognition and communication with energy-based cognitive mnemonics and safety meeting maturity model: Multiple baseline study. Journal of Construction Engineering and Management, 140(2), 04013042.

Albert, A., M. Hallowell, B. Kleiner, A. Chen, and M. Golparvar-Fard. (2014). "Enhancing Construction Hazard Recognition with High-Fidelity Augmented Virtuality." Journal of Construction Engineering and Management 140 (7): 04014024.

Alexander, D., Hallowell, M., & Gambatese, J. (2017). Precursors of Construction Fatalities. II: Predictive Modeling and Empirical Validation. Journal of Construction Engineering and Management, 143(7), 04017024.

Aminbakhsh, S., Gunduz, M., & Sonmez, R. (2013). Safety risk assessment using analytic hierarchy process (AHP) during planning and budgeting of construction projects. Journal of safety research, 46, 99-105.

Argyris, C. (1976). Theories of action that inhibit individual learning. American Psychologist, 31(9), 638.

Azhar, S. (2011). Building information modeling (BIM): Trends, benefits, risks, and challenges for the AEC industry. Leadership and management in engineering, 11(3), 241-252.

Babyak, M. A. (2004). What you see may not be what you get: a brief, nontechnical introduction to overfitting in regression-type models. Psychosomatic medicine, 66(3), 411-421.

Bahn, S. (2013). Workplace hazard identification and management: The case of an underground mining operation. Safety science, 57, 129-137.

Ball, S., & Bogatz, G. A. (1970). The first years of sesame street: An evaluation. Princeton, N.J.: Educational Testing Service.

Bansal, V. K. (2011). Application of geographic information systems in construction safety planning. International Journal of Project Management, 29(1), 66-77.

Baracz, S. J., Everett, N. A., McGregor, I. S., & Cornish, J. L. (2016). Oxytocin in the nucleus accumbens core reduces reinstatement of methamphetamine-seeking behaviour in rats. Addiction biology, 21(2), 316-325.

Barnett, R. L., & Brickman, D. B. (1986). Safety hierarchy. Journal of Safety Research, 17(2), 49-55.

Battista, M. T., Wheatley, G. H., & Talsma, G. (1982). The Importance of Spatial Visualization and Cognitive Development for Geometry Learning in Pre-service Elementary Teachers. Journal for Research in Mathematics Education, 13(5), 332-340.

Battiste, V., & Bortolussi, M. (1988, October). Transport pilot workload: A comparison of two subjective techniques. In Proceedings of the Human Factors Society Annual Meeting (Vol. 32, No. 2, pp. 150-154). Sage CA: Los Angeles, CA: SAGE Publications.

Baxendale, T., & Jones, O. (2000). Construction design and management safety regulations in practice—progress on implementation. International Journal of Project Management, 18(1), 33-40.

Behm, M. (2005). Linking construction fatalities to the design for construction safety concept. Safety science, 43(8), 589-611.

Bhandari, S., & Hallowell, M. R. (2017). Emotional Engagement in Safety Training: Impact of Naturalistic Injury Simulations on the Emotional State of Construction Workers. Journal of Construction Engineering and Management, 143(12), 04017090.

BIMForum. (2017). Level of Development Specification. Retrieved February 18, 2018, from http://bimforum.org/wp-content/uploads/2017/11/LOD-Spec-2017-Part-I-2017-11-07-1.pdf

Birney, D. P., Halford, G. S., & Andrews, G. (2006). Measuring the influence of complexity on relational reasoning: The development of the Latin Square Task. Educational and Psychological Measurement, 66(1), 146-171.

Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., & Babiloni, F. (2014). Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. Neuroscience & Biobehavioral Reviews, 44, 58-75.

Bowden, S., Dorr, A., Thorpe, A., Anumba, C. (2006). "Mobile ICT Support for Construction Process Improvement". Automation in Construction Vol. 15 (5). 664–676.

Cao, A., Chintamani, K. K., Pandya, A. K., & Ellis, R. D. (2009). NASA-TLX: Software for assessing subjective mental workload. Behavior research methods, 41(1), 113-117.

Carswell, C. M., Clarke, D., & Seales, W. B. (2005). Assessing mental workload during laparoscopic surgery. Surgical innovation, 12(1), 80-90.

Carter, G., & Smith, S. D. (2006). Safety hazard identification on construction projects. Journal of construction engineering and management, 132 (2): 197-205.

Casanovas, M. D. M., Armengou, J., & Ramos, G. (2013). Occupational risk index for assessment of risk in construction work by activity. Journal of Construction Engineering and Management, 140(1), 04013035.

Chae, Soungho, and Tomohiro Yoshida. 2008. "A Study of Safety Management Using Working Area Information on Construction Site." Proceedings of the 25th International Symposium on Automation and Robotics in Construction, June, 292–99.

Chantawit, D., Hadikusumo, B. H., Charoenngam, C., & Rowlinson, S. (2005). 4DCAD-Safety: visualizing project scheduling and safety planning. Construction Innovation, 5(2), 99-114.

Cheng, T., & Teizer, J. (2012). Modeling tower crane operator visibility to minimize the risk of limited situational awareness. Journal of Computing in Civil Engineering, 28(3), 04014004.

Coble, R. J., & Blatter, R. L. (1999). Concerns with safety in design/build process. Journal of Architectural Engineering, 5(2), 44-48.

Collier, E. B. 1994. ''Four-dimensional modelling in design and construction.'' thesis, Stanford Univ., Stanford, Calif.

Cooke, T., Lingard, H., Blismas, N., & Stranieri, A. (2008). ToolSHeDTM: the development and evaluation of a decision support tool for health and safety in construction design. Engineering, Construction and Architectural Management, 15(4), 336-351.

Cooper, M. D., & Phillips, R. A. (2004). Exploratory analysis of the safety climate and safety behavior relationship. Journal of safety research, 35(5), 497-512.

Costin, Aaron, Nipesh Pradhananga, and Jochen Teizer. 2014. "Passive RFID and BIM for Real-Time Visualization and Location Tracking." In Construction Research Congress 2014, 169–78. American Society of Civil Engineers.

Coyle, S., Ward, T., Markham, C., & McDarby, G. (2004). On the suitability of near-infrared (NIR) systems for next-generation brain–computer interfaces. Physiological measurement, 25(4), 815.

Dadi, G. B., Goodrum, P. M., Taylor, T. R., & Carswell, C. M. (2014a). Cognitive workload demands using 2D and 3D spatial engineering information formats. Journal of Construction Engineering and Management, 140(5), 04014001.

Dadi, G. B., Goodrum, P. M., Taylor, T. R., & Maloney, W. F. (2014b). Effectiveness of communication of spatial engineering information through 3D CAD and 3D printed models. Visualization in Engineering, 2(1), 9.

Daily, J. T., & Neyman, C. A. (1967). Development of a curriculum and materials for teaching basic vocational talents. Final report for Office of Education, contract No. OE-5085-023. Washington, D.C.: George Washington University, Education Research Project.

Daniel, E. (2016). Motivational and cognitive correlates of avoidance of ambiguity: The role of values and relational complexity. Personality and Individual Differences, 102, 149-152.

De Lapp, J. A., Ford, D. N., Bryant, J. A., & Horlen, J. (2004). Impacts of CAD on design realization. Engineering, Construction and Architectural Management, 11(4), 284-291.

Dewlaney, K. S., & Hallowell, M. (2012). Prevention through design and construction safety management strategies for high performance sustainable building construction. Construction Management and Economics, 30(2), 165-177.

Dewlaney, K. S., Hallowell, M. R., & Fortunato III, B. R. (2011). Safety risk quantification for high performance sustainable building construction. Journal of Construction Engineering and Management, 138(8), 964-971.

De Waard, D., 1996. The measurement of drivers' mental workload. Ph.D. Thesis. Traffic Research Centre, University of Groningen, Haren, The Netherlands.

Dharmapalan, V., Gambatese, J. A., Fradella, J., & Moghaddam Vahed, A. (2014). Quantification and assessment of safety risk in the design of multistory buildings. Journal of Construction Engineering and Management, 141(4), 04014090.

Dielman, TE. (2005). Applied Regression Analysis: a Second Course in Business and Economic Statistics 4th ed. Mason, OH: South-Western Cengage Learning.

Ding, L. Y., & Zhou, C. (2013). Development of web-based system for safety risk early warning in urban metro construction. Automation in Construction, 34, 45-55.

DoD. (2012). MIL-STD-882E. Retrieved December 3, 2017, from http://www.system-safety.org/Documents/MIL-STD-882E.pdf

Driscoll, T. R., Harrison, J. E., Bradley, C., & Newson, R. S. (2008). The role of design issues in work-related fatal injury in Australia. Journal of Safety Research, 39(2), 209-214.

Eberly L.E. (2007) Multiple Linear Regression. In: Ambrosius W.T. (eds) Topics in Biostatistics. Methods in Molecular Biology™, vol 404. Humana Press

Edwards, A. L. (1951). Balanced Latin-square designs in psychological research. The American journal of psychology, 64(4), 598-603.

Ekstrom, R. B., French, J. W., Harman, H. H., and Dermen, D. (1976). "Manual for kit of factor-referenced cognitive tests." Educational Testing Service, Princeton, NJ.

Emerson. (1962). Surveys of the Problems Before the Construction lndustry: a report prepared for the MinisQ of Works. HMSO, London, 1962

Emmitt, S., and Gorse, C. (2003). Construction communication, Blackwell, Oxford, U.K.

Esmaeili, B., and Hallowell, M. R. (2012). “Diffusion of safety innovations in the construction industry.” J. Constr. Eng. Manage., 10.1061/(ASCE)CO.1943-7862.0000499, 955–963.

Esmaeili, B., Hallowell, M. R., & Rajagopalan, B. (2015). Attribute-based safety risk assessment. II: Predicting safety outcomes using generalized linear models. Journal of construction engineering and management, 141(8), 04015022.

Fang, D. P., Huang, X. Y., & Hinze, J. (2004). Benchmarking studies on construction safety management in China. Journal of Construction Engineering and Management, 130(3), 424-432.

Fang, Q., Zhang, D., & Wong, L. N. Y. (2011). Environmental risk management for a cross interchange subway station construction in China. Tunnelling and Underground Space Technology, 26(6), 750-763.

Fellows, R, & Liu, A. (2008). Research Methods for Construction (3rd ed.). Malden, MA: Wiley-Blackwell Publishing.

Fine, W. T. (1975). A Management Approach in Accident Prevention (No. NSWC/WOL/TR-75-104). NAVAL SURFACE WEAPONS CENTER WHITE OAK LAB SILVER SPRING MD.

Fonseca, E. D., Lima, F. P., & Duarte, F. (2014). From construction site to design: The different accident prevention levels in the building industry. Safety science, 70, 406-418.

Fennema, E. & Tartre, L. (1985). "The Use of Spatial Visualization in Mathematics by Boys and Girls." Journal for Research in Mathematics Education, 16(3), 184-206.

Francis, V. E., Chen, S. E., Mehrtens, V. M., Sidwell, A. C., & McGeorge, W. D. (1999). Constructability strategy for improved project performance. Architectural Science Review, 42(2), 133-138.

Fullerton, C. E., Allread, B. S., & Teizer, J. (2009). Pro-active-real-time personnel warning system. In Construction Research Congress 2009: Building a Sustainable Future (pp. 31-40).

G Gerjets, P., Walter, C., Rosenstiel, W., Bogdan, M., & Zander, T. O. (2014). Cognitive state monitoring and the design of adaptive instruction in digital environments: lessons learned from cognitive workload assessment using a passive brain-computer interface approach. Frontiers in Neuroscience, 8, 385

Gagnon, D. (1985). Videogames and spatial skills: An exploratory study. *ECTJ*, *33*(4), 263-275.

Gambatese, J. A., Behm, M., & Rajendran, S. (2008). Design’s role in construction accident causality and prevention: Perspectives from an expert panel. Safety science, 46(4), 675-691.

Gambatese, J. A., Hinze, J. W., & Haas, C. T. (1997). Tool to design for construction worker safety. Journal of Architectural Engineering, 3(1), 32-41.

Gambatese, J. and J. Hinze (1999). "Addressing construction worker safety in the design phase: Designing for construction worker safety." Automation in Construction, 8(6), 643-649.

Ganah, A., & John, G. A. (2015). Integrating building information modeling and health and safety for onsite construction. Safety and health at work, 6(1), 39-45.

Gerjets, P., Walter, C., Rosenstiel, W., Bogdan, M., & Zander, T. O. (2014). Cognitive state monitoring and the design of adaptive instruction in digital environments: lessons learned from cognitive workload assessment using a passive brain-computer interface approach. Frontiers in Neuroscience, 8, 385

Ghaderi, R., & Kasirossafar, M. (2011). Construction safety in design process. In AEI 2011: Building Integration Solutions (pp. 464-471).

Gibb, A., Lingard, H., Behm, M., & Cooke, T. (2014). Construction accident causality: learning from different countries and differing consequences. Construction Management and Economics, 32(5), 446-459.

Goedert, J., and P. Meadati. 2008. “Integrating Construction Process Documentation into Building Information Modeling.” Journal of Construction Engineering and Management 134 (7): 509–16.

Goh, B. H. (1999). “An evaluation of the accuracy of the multiple regression approach in forecasting sectoral construction demand in Singapore.” J. Constr. Manage. Econ., 17(2), 231–241.

Goodrum, P. M., and Miller, J. M. (2015). “Innovative delivery methods of information to the crafts. Construction Industry Institute”, Univ. of Texas at Austin, Austin, TX. RT 327.

Goodrum, P. M., Miller, J., Sweany, J., & Alruwaythi, O. (2016). Influence of the format of engineering information and spatial cognition on craft-worker performance. Journal of Construction Engineering and Management, 142(9), 04016043.

Gould, F, & Joyce, N. (2013). Construction Project Management (4th ed.). New Jersey: Prentice Hall.

Grassmann, M., Vlemincx, E., von Leupoldt, A., & Van den Bergh, O. (2017). Individual differences in cardiorespiratory measures of mental workload: An investigation of negative affectivity and cognitive avoidant coping in pilot candidates. Applied ergonomics, 59, 274-282.

Griffith, A., & Phillips, N. (2001). The influence of the Construction (Design and Management) Regulations 1994 upon the procurement and management of small building works. Construction Management and Economics, 19(5), 533-540.

Güven, B., & Temel, K. O. S. A. (2008). The effect of dynamic geometry software on student mathematics teachers' spatial visualization skills. *TOJET: The Turkish Online Journal of Educational Technology*, *7*(4).

Hadikusumo, B. and S. Rowlinson (2004). "Capturing Safety Knowledge Using Design-for-Safety-Process Tool." Journal of Construction Engineering and Management 130(2): 281-289.

Hadikusumo, B. H. W., & Rowlinson, S. (2002). Integration of virtually real construction model and design-for-safety-process database. Automation in Construction, 11(5), 501-509.

Hallowell, M. R. and D. Hansen (2016). "Measuring and improving designer hazard recognition skill: Critical competency to enable prevention through design." Safety Science 82: 254-263.

Hallowell, M. R., Alexander, D., & Gambatese, J. A. (2017). Energy-based safety risk assessment: does magnitude and intensity of energy predict injury severity? Construction Management and Economics, 35(1-2), 64-77.

Hallowell, M. R., Hardison, D., & Desvignes, M. (2016). Information technology and safety: Integrating empirical safety risk data with building information modeling, sensing, and visualization technologies. Construction Innovation, 16(3), 323-347.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. Advances in psychology, 52, 139-183.

Hecker, S. and J. Gambatese (2003). "Safety in Design: A Proactive Approach to Construction Worker Safety and Health." Applied Occupational and Environmental Hygiene 18(5): 339-342.

Hertz, D. B., & Thomas, H. (1983). Risk analysis and its applications (pp. 11-15).

Hicks, T. G., & Wierwille, W. W. (1979). Comparison of five mental workload assessment procedures in a moving-base driving simulator. Human Factors, 21(2), 129-143.

Hill, S. G., Iavecchia, H. P., Byers, J. C., Bittner Jr, A. C., Zaklade, A. L., & Christ, R. E. (1992). Comparison of four subjective workload rating scales. Human factors, 34(4), 429-439.

Hinze, J., & Wiegand, F. (1992). Role of designers in construction worker safety. Journal of construction engineering and management, 118(4), 677-684.

Howard, R. A. (1984). Readings on the Principles and Applications of Decision Analysis: Professional Collection (Vol. 2). Strategic Decisions Group.

Howard, Rob, and Bo-Christer Björk. 2008. “Building Information Modelling – Experts’ Views on Standardisation and Industry Deployment.” Advanced Engineering Informatics, Network methods in engineering, 22 (2): 271–80.

Huang, X., & Hinze, J. (2006). Owner’s role in construction safety. Journal of construction engineering and management, 132(2), 164-173.

Huttenlocher, J., & Presson, C. C. (1979). The coding and transformation of spatial information. Cognitive Psychology, 11, 375-394.

Hwang, S. (2012). Ultra-wide band technology experiments for real-time prevention of tower crane collisions. Automation in Construction, 22, 545-553.

Jainta, S., & Baccino, T. (2010). Analyzing the pupil response due to increased cognitive demand: an independent component analysis study. International Journal of Psychophysiology, 77(1), 1-7.

Johnson, N., Creasy, T., & Fan, Y. (2016). Recent Trends in Theory Use and Application within the Project Management Discipline. Journal of Engineering, Project, and Production Management, 6(1), 25.

Jordani, David. 2008. “BIM: A Healthy Disruption to a Fragmented and Broken Process.” Journal of Building Information Modelling 2 (2): 24–26.
Judd, C. M., McClelland, G. H., & Ryan, C. S. (2011). Data analysis: A model comparison approach. Routledge.

Kasirossafar, M., & Shahbodaghlou, F. (2013). Building Information Modeling or construction Safety Planning. In ICSDEC 2012: Developing the Frontier of Sustainable Design, Engineering, and Construction (pp. 1017-1024).

Kim, H., H. Lee, M. Park, B. Chung, and S. Hwang. 2014. “Information Retrieval Framework for Hazard Identification in Construction.” Journal of Computing in Civil Engineering 0 (0): 04014052.

Kim, J. H., Parameshwara, N., Guo, W., & Pasupathy, K. S. (2018). The Impact of Interrupting Nurses on Mental Workload in Emergency Departments. International Journal of Human–Computer Interaction, 1-12.

Knab, L. I. (1978). Numerical aid to reduce construction injury losses. Journal of the Construction Division, 104(4), 437-445.

Kozhevnikov, M., & Hegarty, M. (2001). A dissociation between object manipulation spatial ability and spatial orientation ability. *Memory & Cognition*, *29*(5), 745-756.

Ku, K., & Mills, T. (2010). Research needs for building information modeling for construction safety. In International Proceedings of Associated Schools of Construction 45nd Annual Conference, Boston, MA.

Kuchinke, L., Võ, M. L., Hofmann, M., & Jacobs, A. M. (2007). Pupillary responses during lexical decisions vary with word frequency but not emotional valence. International Journal of Psychophysiology, 65, 132–140. doi:10.1016/j.ijpsycho.2007.04.004

Lam, P. T., Wong, F. W., & Chan, A. P. (2006). Contributions of designers to improving buildability and constructability. Design Studies, 27(4), 457-479.

Lenné, M., Triggs, T.J., Redman, J.R., 1997. Time of day variations in driving performance. Accident Analysis and Prevention 29, 431–437.

Leung, S., Starmer, G., 2005. Gap acceptance and risk-taking by young and mature drivers, both sober and alcohol-intoxicated, in a simulated driving task. Accident Analysis and Prevention 37, 1056–1065.

Li, H., Ma, Z., Shen, Q., & Kong, S. (2003). Virtual experiment of innovative construction operations. Automation in Construction, 12(5), 561-575.

Li, N., Becerik-Gerber, B., Krishnamachari, B., & Soibelman, L. (2014). A BIM centered indoor localization algorithm to support building fire emergency response operations. Automation in Construction, 42, 78-89.

Liberda, M., Ruwanpura, J., & Jergeas, G. (2003). "Construction Productivity Improvement: A Study of Human, Management and External Issues". ASCE. Construction Research Congress. 1–8. 10.1061/40671(2003)5

Lingard, H. (2013). Occupational health and safety in the construction industry. Construction management and economics, 31(6), 505-514.

Lingard, H. C., Cooke, T., & Blismas, N. (2012). Designing for construction workers' occupational health and safety: a case study of socio-material complexity. Construction Management and Economics, 30(5), 367-382.

Lingard, H., & Holmes, N. (2001). Understandings of occupational health and safety risk control in small business construction firms: barriers to implementing technological controls. Construction Management & Economics, 19(2), 217-226.

Lohman, D. F. (1979). "Spatial ability: A review and reanalysis of the correlational literature". Rep. No. ADA075972, U.S. Office of Naval Research, Arlington, VA.

Lopez del Puerto, C., Clevenger, C. M., Boremann, K., & Gilkey, D. P. (2013). Exploratory study to identify perceptions of safety and risk among residential Latino construction workers as distinct from commercial and heavy civil construction workers. Journal of Construction Engineering and Management, 140 (2): 04013048 - 1 – 04013048 - 7.

Maeda, Y., & Yoon, S. Y. (2013). A meta-analysis on gender differences in mental rotation ability measured by the Purdue spatial visualization tests: Visualization of rotations (PSVT: R). *Educational Psychology Review*, *25*(1), 69-94.

Manu, P. A., Ankrah, N. A., Proverbs, D. G., & Suresh, S. (2012). Investigating the multi-causal and complex nature of the accident causal influence of construction project features. Accident Analysis & Prevention, 48, 126-133.

Martin, S. (2014). Measuring cognitive load and cognition: metrics for technology-enhanced learning. Educational Research and Evaluation, 20(7-8), 592-621.

Martínez-Aires, M. D., Rubio Gámez, M. C., & Gibb, A. (2016). The impact of occupational health and safety regulations on prevention through design in construction projects: Perspectives from Spain and the United Kingdom. Work, 53(1), 181-191.

McGee, M. G. (1979). Human spatial abilities: Psychometric studies and environmental, genetic, hormonal, and neurological influences. *Psychological bulletin*, *86*(5), 889.

McNemar, Q. (1951). On the use of Latin squares in psychology. Psychological bulletin, 48(5), 398.

Mead, R., R.N. Curnow, and A.M. Hasted. 2003. Statistical methods in agriculture and experimental biology. Chapman and Hall/CRC, Boca Raton, FL.

Melzner, J., Zhang, S., Teizer, J., & Bargstädt, H. J. (2013). A case study on automated safety compliance checking to assist fall protection design and planning in building information models. Construction Management and Economics, 31(6), 661-674.

Moses, B. E. (1977). The nature of spatial ability and its relationship to mathematical problem-solving. Dissertation Abstracts International. 38(8), 4640A. (University Microfilms No. AAG7730309)

Mulder, L. J. M. (1988). Assessment of cardiovascular reactivity by means of spectral analysis.

Navon, R. and O. Kolton (2006). "Model for Automated Monitoring of Fall Hazards in Building Construction." Journal of Construction Engineering and Management 132(7): 733-740.

Ng Boyle, L., Tippin, J., Paul, A., Rizzo, M., 2008. Driver performance in the moments surrounding a microsleep. Transportation Research Part F 11, 126–136.

Nilsson, T., Nelson, T.M., Carlson, D., 1997. Development of fatigue symptoms during simulated driving. Accident Analysis and Prevention 29, 479–488.

NIOSH. (2012). PREVENTION THROUGH DESIGN. Retrieved December 3, 2017, from https://www.cdc.gov/niosh/programs/ptdesign/nora.html

NIOSH. (2013). Preventing Falls through the Design of Roof Parapets. Retrieved June 11, 2017, from https://www.cdc.gov/niosh/docs/2014-108/pdfs/2014-108.pdf

NIOSH. (2015). Hierarchy of Controls. Retrieved December 3, 2017, from https://www.cdc.gov/niosh/topics/hierarchy/default.html

NIOSH. (2017). Prevention Through Design. Retrieved August 05, 2017, from https://www.cdc.gov/niosh/topics/ptd/default.html

Oloufa, A. A., Ikeda, M., & Oda, H. (2003). Situational awareness of construction equipment using GPS, wireless and web technologies. Automation in Construction, 12(6), 737-748.

Ortiz, O., Castells, F., & Sonnemann, G. (2009). Sustainability in the construction industry: A review of recent developments based on LCA. Construction and Building Materials, 23(1), 28-39.

OSHA. (2008). Occupational Noise Exposure. Retrieved December 3, 2017, from https://www.osha.gov/pls/oshaweb/owadisp.show_document?p_table=standards&p_id=9735

OSHA. (2015). Design for Construction Safety: Instructors Guide. Retrieved June 11, 2017, from https://www.osha.gov/dte/library/DfCSInstructorGuide.pdf

OSHA. (2017a). Commonly Used Statistics. Retrieved June 11, 2017, from https://www.osha.gov/oshstats/commonstats.html

OSHA. (2017b). Small Entity Compliance Guide for the Respirable Crystalline Silica Standard for Construction. Retrieved December 3, 2017, from https://www.osha.gov/Publications/OSHA3902.pdf

Park, H. K., Han, S. H., and Russell, J. S. (2005). “Cash flow forecasting model for general contractors using moving weights of cost categories.” J. Manage. Eng., 4(164), 164–172.

Pedhazur, E. (1997). Multiple Regression in Behavioral Research: Explanation and Prediction. Holt, Rinehart and Winston.

Peng, Y. H., Lee, C. H., Popuri, S. R., & Kumar, K. S. (2016). Preparation of High-Purity Ultrafine Copper Powder in Mass-Production by Chemical Reduction Method: Taguchi Robust Design Optimization. Powder Metallurgy and Metal Ceramics, 55(7-8), 386-396.

Perlman, A., Sacks, R., & Barak, R. (2014). Hazard recognition and risk perception in construction. Safety science, 64, 22-31.

Pink, S., Morgan, J., & Dainty, A. (2014). Safety in movement: Mobile workers, mobile media. Mobile Media & Communication, 2(3), 335-351.

Presson, C. C. (1982). Strategies in spatial reasoning. Journal of Experimental Psychology: Learning,Memory, & Cognition, 8, 243-251.

Qi, J., Issa, R. R. A., Hinze, J., & Olbina, S. (2011). Integration of safety in design through the use of building information modeling. In Computing in Civil Engineering (2011) (pp. 698-705).

Rakauskas, M.E., Ward, N.J., Boer, E.R., Bernat, E.M., Cadwallader, M., Patrick, C.J., 2008. Combined effects of alcohol and distraction on driving performance. Accident Analysis and Prevention 40, 1742–1749.

Rajendran, S. and J. A. Gambatese (2013). "Risk and Financial Impacts of Prevention through Design Solutions." Practice Periodical on Structural Design and Construction, 18(1): 67-72.

Rajendran, S., Gambatese, J. A., & Behm, M. G. (2009). Impact of green building design and construction on worker safety and health. Journal of Construction engineering and Management, 135(10), 1058-1066.

Rubio, S., Díaz, E., Martín, J., & Puente, J. M. (2004). Evaluation of subjective mental workload: A comparison of SWAT, NASA-TLX, and workload profile methods. Applied Psychology, 53(1), 61-86.

Ruppel, U., and P. Abolghasemzadeh. 2009. “BIM-Based Immersive Evacuation Simulations.” In 18th International Conference on the Application of Computer Science and Mathematics in Architecture and Civil Engineering. Weimar, Germany.

Saaty, T. L. (1990). How to make a decision: the analytic hierarchy process. European journal of operational research, 48(1), 9-26.

Sacks, R., J. Whyte, et al. (2015). "Safety by design: dialogues between designers and builders using virtual reality." Construction Management and Economics 33(1): 55-72.

Sacks, R., Perlman, A., & Barak, R. (2013). Construction safety training using immersive virtual reality. Construction Management and Economics, 31(9), 1005-1017.

Sacks, R., Whyte, J., Swissa, D., Raviv, G., Zhou, W., & Shapira, A. (2015). Safety by design: dialogues between designers and builders using virtual reality. Construction Management and Economics, 33(1), 55-72.

Salas, R., & Hallowell, M. (2016). Predictive validity of safety leading indicators: Empirical assessment in the oil and gas sector. Journal of Construction Engineering and Management, 142(10), 04016052.

Salomon, G. (1979). Interaction of Media Cognition and Learning. San Francisco: Jossey-Bass.

Seashore, R. H., & McCollom, I. N. (1932). Studies in Motor and Mechanical Skills. *Science*, *75*(1944), 358-359.

Seo, J. W., & Choi, H. H. (2008). Risk-based safety impact assessment methodology for underground construction projects in Korea. Journal of construction engineering and management, 134(1), 72-81.

Small, D. & Small, S. (1982). The experts' guide to beating Asteroids, Battlezone, Galazian Ripoff and Space Invaders. Creative Computing, I8(1), 18-33.

Sorby, S. A., & Baartmans, B. J. (1996). A Course for the Development of 3-D Spatial Visualization Skills. *Engineering Design Graphics Journal*, *60*(1), 13-20.

Strangman, G., Culver, J. P., Thompson, J. H., & Boas, D. A. (2002). A quantitative comparison of simultaneous BOLD fMRI and NIRS recordings during functional brain activation. Neuroimage, 17(2), 719-731.

Suraji, A., Duff, A. R., & Peckitt, S. J. (2001). Development of causal model of construction accident causation. Journal of construction engineering and management, 127(4), 337-344.

Sweany, J., Goodrum, P., Miller, J. (2016). "Analysis of empirical data on the effects of the format of engineering deliverables on craft performance". Automation in Construction, Volume 69. (2016) 59-67

Svensson, E., Angelborg-Thanderz, M., & Sjöberg, L. (1993). Mission challenge, mental workload and performance in military aviation. Aviation, space, and environmental medicine.

Szymberski, R. (1997). "Construction project safety planning." TAPPI Journal 80(11): 69-74.

Tam, C. M., & Fung IV, I. W. (1998). Effectiveness of safety management strategies on safety performance in Hong Kong. Construction Management & Economics, 16(1), 49-55.

Tang, J. C. S., Karasudhi, P., and Tachopiyagoon, P. (1990). "Thai construction industry: Demand and projection." J. Constr. Manage. Econ., 8(3), 249–257

Teizer, J., Kim, C., Haas, C., Liapi, K., & Caldas, C. (2005). Framework for real-time three-dimensional modeling of infrastructure. Transportation Research Record: Journal of the Transportation Research Board, (1913), 177-186.

Thiffault, P., Bergeron, J., 2003. Monotony of road environment and driver fatigue: a simulator study. Accident Analysis and Prevention 35, 381–391.

Tixier, A. J. P., Hallowell, M. R., & Rajagopalan, B. (2017). Construction safety risk modeling and simulation. Risk analysis, 37, 1917-1935.

Tixier, A. J. P., Hallowell, M. R., Albert, A., van Boven, L., & Kleiner, B. M. (2014). Psychological antecedents of risk-taking behavior in construction. Journal of Construction Engineering and Management, 140(11), 04014052. Chicago

Tixier, A. J. P., Hallowell, M. R., Rajagopalan, B., & Bowman, D. (2016). Application of machine learning to construction injury prediction. Automation in construction, 69, 102-114.

Tixier, A., Albert, A., & Hallowell, M. R. (2013). Teaching construction hazard recognition through high fidelity augmented reality. In Proc., 2013 American Society of Engineering Education Annual Conf (pp. 1-23).

Tixier, J., Dusserre, G., Salvi, O., & Gaston, D. (2002). Review of 62 risk analysis methodologies of industrial plants. Journal of Loss Prevention in the process industries, 15(4), 291-303.

Toole, T. M. (2005). Increasing engineers' role in construction safety: Opportunities and barriers. Journal of Professional Issues in Engineering Education and Practice, 131(3), 199-207.

Toole, T. M. (2011). Internal impediments to ASCE's vision 2025. Leadership and Management in Engineering, 11(2), 197-207.

Toole, T. M., Gambatese, J. A., & Abowitz, D. A. (2016). Owners' role in facilitating prevention through design. Journal of Professional Issues in Engineering Education and Practice, 143(1), 04016012.

Travis, B., Lennon, E., (1997). Spatial skills and computer-enhanced instruction in calculus. Journal of Computers in Mathematics and Science Teaching. 16(4), 467-475

Tubbs-Cooley, H. L., Mara, C. A., Carle, A. C., & Gurses, A. P. (2018). The NASA Task Load Index as a measure of overall workload among neonatal, paediatric and adult intensive care nurses. Intensive and Critical Care Nursing.

Verwey, W.B., Zaidel, D.M., 1999. Preventing drowsiness accidents by an alertness maintenance device. Accident Analysis and Prevention 31, 199–211.

Votano, S., & Sunindijo, R. Y. (2014). Client safety roles in small and medium construction projects in Australia. Journal of Construction Engineering and Management, 140(9), 04014045.

Voyer, D., Voyer, S., & Bryden, M. P. (1995). Magnitude of sex differences in spatial abilities: a meta-analysis and consideration of critical variables. Psychological Bulletin, 117, 250–270. doi:10.1037/0033- 2909.117.2.250

Walter, L., & Styhre, A. (2013). The role of organizational objects in construction projects: the case of the collapse and restoration of the Tjörn Bridge. Construction management and economics, 31(12), 1172-1185.

Wang, X., & Dunston, P. S. (2008). User perspectives on mixed reality tabletop visualization for face-to-face collaborative design review. Automation in construction, 17(4), 399-412.

Whelan, R. R. (2007). Neuroimaging of cognitive load in instructional multimedia. Educational Research Review, 2, 1–12

Wilson, G. F. (2002). An analysis of mental workload in pilots during flight using multiple psychophysiological measures. The International Journal of Aviation Psychology, 12(1), 3-18.

Wilks, D. S. (1995). Statistical methods in the atmospheric sciences, Academic, New York.

Wilson, G. F., & Fisher, F. R. A. N. K. (1991). The use of cardiac and eye blink measures to determine flight segment in F4 crews. Aviation, space, and environmental medicine, 62(10), 959-962.

Workcover, A. (2001). Construction Hazard Assessment Implication Review–CHAIR.

Wraga, M., Creem, S. H., & Profitt, D. R. (2000). Updating displays after imagined object and viewer rotations. Journal of Experimental Psychology: Learning, Memory, & Cognition, 26, 151-168.

Young, S. (1996). ‘‘Construction safety: A vision for the future.’’ J. Manage. Eng., 12(4), 33–36.

Yu, Q. Z., Ding, L. Y., Zhou, C., & Luo, H. B. (2014). Analysis of factors influencing safety management for metro construction in China. Accident Analysis & Prevention, 68, 131-138.

Zander, T., & Kothe, C. (2011). Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general. Journal of Neural Engeneering, 8, 025005.

Zhang, C., Hammad, A., & Rodriguez, S. (2011). Crane pose estimation using UWB real-time location system. Journal of Computing in Civil Engineering, 26(5), 625-637.

Zhang, L., Wu, X., Ding, L., Skibniewski, M. J., & Lu, Y. (2014). Bim-based risk identification system in tunnel construction. Journal of Civil Engineering and Management, 22(4), 529-539.

Zhang, M., and Fang, D. (2013). “A continuous behavior-based safety strategy for persistent safety improvement in construction industry.” J. Autom. Constr., 34(1), 101–107.

Zhang, S., Sulankivi, K., Kiviniemi, M., Romo, I., & Eastman, C. (2015). BIM-based fall hazard identification and prevention in construction safety planning. Safety Science, 72, 31-45.

Zhang, S., Teizer, J., Lee, J. K., Eastman, C. M., & Venugopal, M. (2013). Building information modeling (BIM) and safety: Automatic safety checking of construction models and schedules. Automation in Construction, 29, 183-195.

Zhao, D., McCoy, A. P., Kleiner, B. M., Mills, T. H., & Lingard, H. (2016). Stakeholder perceptions of risk in construction. Safety science, 82, 111-119.

Zhou, W., Whyte, J., & Sacks, R. (2012). Construction safety and digital design: A review. Automation in Construction, 22, 102-111.

Zhou, Z., Irizarry, J., & Li, Q. (2013). Applying advanced technology to improve safety management in the construction industry: a literature review. Construction Management and Economics, 31(6), 606-622.

Zou, P. X., & Li, J. (2010). Risk identification and assessment in subway projects: case study of Nanjing Subway Line 2. Construction Management and Economics, 28(12), 1219-1238.

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Appendix 1: Construction Research Congress Paper, New Orleans, Louisiana, 2018

Identifying Safety Hazards in Design: Evaluating the difference between BIM and 2D CAD drawings

Dylan HARDISON[1] and Matthew HALLOWELL[2]

[1] University of Colorado at Boulder, Department of Civil Engineering, 111 Engineering Dr., Boulder, CO 80302; email: dylan.hardison@colorado.edu

[2] University of Colorado at Boulder, Department of Civil Engineering, 111 Engineering Dr., Boulder, CO 80302; email: matthew.hallowell@colorado.edu

ABSTRACT

The design for safety concept has gained traction in the construction industry as being a viable method for removing safety hazards. Much research has used subjective data to support arguments for the concept; however, the concept has limited support from empirical research. In an effort to better understand how hazards are identified in design, this research explores the extent to which different forms of design information (e.g., three-dimensional building information models and two-dimensional computer aided designs) affect hazard identification capability. To do this, 7 construction designers and 11 construction supervisors from Colorado and North Carolina were asked to analyze real design information and identify all associated downstream construction safety hazards. The associated hazards for each work activity were known based upon previously validated research. The forms of design information included three-dimensional building information models, two-dimensional computer aided design drawings, and a combination of the two. The preliminary results suggest that empirical research can be performed to validate the design for safety concept and early results suggest that three-dimensional

information is superior to two-dimensional with respect to safety hazard recognition. Further empirical and experimental research is needed to explore this topic.

INTRODUCTION

There is no denying that construction work is dangerous. Construction workers are continually faced with the risk of on-the-job accidents that can lead to life-threatening injuries and death. For this reason, safety management programs are implemented to ensure methods are put in place to reduce worker's exposures to safety hazards. One of the first steps in safety management process is hazard recognition (Albert and Hallowell 2012), which can occur at any stage of a project lifecycle (Hecker and Gambatese 2003). Hazard recognition is important because hazards must first be recognized if they are to be removed or managed. However, the ability to effectively recognize hazards depends on the ability to distinguish safety hazards from other sources of irrelevant information that may exist in in design documents (Lu et al. 2011).

Research has shown that construction workers hazard recognition skills are low. Several researchers have examined hazard recognition in construction and have consistently found that workers recognize approximately half of all hazards to which they are exposed (Carter and Smith, 2006; Bahn, 2013; Lopez del Puerto et al., 2013; and Albert et al., 2014a). Additionally, Hallowell and Hansen (2016) found that construction designers also lack abilities to recognize roughly 50% of safety hazards in the design phase that can arise during downstream construction work. These alarming statistics demonstrate the need for industry improvement with respect to construction hazard recognition.

The purpose of this study is to investigate the extent to which different modes of design information impact the proportion of safety hazards recognized during the design phase of a construction project. Hazard recognition performance levels were compared for 27 subjects who were provided with one of three modes of design information: 3D building information model (3D BIM), 2D set of paper based computer aided drawings (CAD drawings), or a combination of the two. The hypothesis of interest is: "*Does the mode of design information impact hazard recognition performance during design?"* By knowing how the mode of design information impacts the proportion of hazards identifiable during design, researchers and practitioners can begin to understand what design stimuli are best suited for hazard recognition during the design phases of construction projects. This information will help to streamline the construction hazard prevention through design (CHPtD) process by facilitating more efficient hazard recognition in design through employing design stimuli that have been found to yield higher levels of hazard recognition performance.

LITERATURE REVIEW

Construction Hazard Prevention through Design (CHPtD)

There are many opportunities to recognize safety hazards in construction. The design phase is the earliest opportunity to foresee the necessary construction operations required to transform design intent into finished projects. The central premise of CHPtD is the recognition of safety hazards during design so that solutions may be implemented to reduce overall project safety risks. CHPtD is a complex task that involves recognizing, projecting, and removing design elements that pose danger to construction workers (Ganah and John 2015). Effective CHPtD implementation requires stakeholders to gather relevant safety details from design information, which takes many different forms (Brexendale and Jones, 2000 and De Lapp et al. 2004). Primarily, the use of two-dimensional computer-aided-design (2D CAD) drawings and 3D Building Information Modelling (BIM) software are used to convey design intent (De Lapp et al. 2004 and Ganah and John 2015).

In the past 20 years, there has been abundant research into CHPtD, which has resulted in a large and dispersed body of literature. Although this body is rich with many valuable contributions, existing publications have focused heavily on subjective research methods rather than empirical ones. Investigating CHPtD with empirical and experimental methods will help to distinguish training needs to improve hazard recognition skills in design, identify the attributes of hazards recognizable during, and will provide more robust data in which actual risk-based decisions can be made.

Hazard Identification in Construction

Predictive hazard recognition methods rely on worker's ability to foresee construction conditions that can lead to accidents (Albert et al. 2014a). Predicting hazards in the design phase typically involves listing hazards associated with design attributes and planned work (Albert et al. 2013). Predictive methods require that workers use relevant information to abstract safety details relating to the upcoming work. These activities can be done any time before the work is performed, from design to pre-job planning. The difference is typically the information available. As the project progresses, more information becomes available such as the details of the facility and even the weather on the workday.

In design, one must rely on design documents and models that often take the form of 2D CAD drawings or 3D BIM (Ganah and John 2015). One of the major obstacles of using 2D CAD drawings for the hazard recognition process is that these drawings may not convey building components and spatial information in a way that may be easy for workers to understand (Collier 1994; Young 1996; and Zhang et al. 2015). Researchers have suggested that the use of 3D visualizations of construction environments may lead to better hazard recognition than 2D alone, as 3D visualizations can digitally replicate the physical work environment and aid in the mental interpretation of spatial configurations (Ku and Mills 2010; Bansal 2011; Ganah & John 2015; and Zhang et al. 2015). This assumption is a rich opportunity for empirical hazard recognition research and the maturity of CHPtD.

Although much research has discussed the validity of the CHPtD concept over the last 20 years, no study has focused on the effects that design information has on workers' hazard recognition performance. Addressing this knowledge gap is essential as identifying hazards during design is the foundation of the CHPtD concept. Objectively measuring which hazards are and are not recognizable during design will aid in the development of designer CHPtD tools and possibly increase the efficiency of virtual construction techniques which can influence safe construction. Additionally, examining the effects that 2D and 3D design information have on hazard recognition performance is a rich opportunity to provide the research community with empirical evidence to test the assumption that CHPtD is a superior safety management strategy.

RESEARCH OBJECTIVES AND POINT OF DEPARTURE

This study aims to evaluate the impact of different modes of design information on hazard recognition performance through quasi-experimental trials. To perform this experiment, the following objectives were targeted: (1) identify a series of work modules; (2) obtain the design information associated with each module in 2D CAD and BIM; (3) randomly assign participants to a treatment group; and (4) conduct quasi-experimental trials to identify hazard recognition performance levels for each work module and each mode of design information. The corresponding null hypothesis for the experiment is:

H_0: ***The mode of design information does not affect the proportion of hazards identified during design***.

After the experiment, the variability of hazard identifications across the three modes of design information can be evaluated.

RESEARCH METHODS

The research objectives of this study were achieved in two distinct phases. The first involved creating 3D building information models in Autodesk Revit software using 2D design information for three independent work activities. The work activities were selected from Hallowell and Hansen (2016) because the actual hazard associated with each design module were known from field observations. The second stage of the study involved conducting a series of quasi-experimental trials. The specific research protocol for each phase is provided in the sections below.

Phase 1: Construction of Research Modules

Selection of Work Activities

The first phase of the research consisted of developing a set of research modules to use in the experiment. The research modules were adopted from previous research conducted by Hallowell and Hansen (2016). In this study, they collected data and obtained 2D construction plans for 12 construction tasks from 5 projects in the Denver Metropolitan region. They identified hazards for the work modules by observing the actual construction work, attending pre-job safety meetings, and conducting post work interviews. The output of their work was a comprehensive list of the safety hazards associated with each of the 12 work modules (e.g., skylight installation).

They defined a construction process module as "*a discrete building element and the associated activities required for its installation*." Each process module was limited to commercial high-rise construction and component installation duration was limited to 1-5 hours each. Additionally, each component was discrete as components were self-contained in 2D plans and were independent of adjacent tasks (Hallowell and Hansen 2016). Of the 12 construction process modules previously created, 3 work scenarios were selected to ensure that the results are externally generalizable to vertical commercial construction. In addition to this, each work activity was selected on the basis that the safety hazards are diverse in that they include a variety of construction methods, tools, materials, and equipment that contain minimal overlap between independent activities. The three work activities and their descriptions can be seen in Table 1 below.

Table 1. Work Activities and Descriptions

Work Activity	Activity Description
Skylight Installation	This work involves the construction of a skylight. The framing for the skylight and original roof has previously been demolished and opened up. A temporary cover was installed. Includes: removal of temporary cover and installation of new skylight. Does not include removal of debris or materials.
Soffit Drywall Installation	This work involves the construction of a drywall soffit. Includes: all preparatory work and setup, and installation of soffit and wall drywall.
Interior Wall Stud Framing	This work involves the construction of an interior wall. Includes: vertical members of metal stud framing.

Developing 3D and 2D Design Information

The two-dimensional design information collected by Hallowell and Hansen (2016) was transformed into 3D BIM in Autodesk Revit software. Multiple screenshots of 3D views of the BIM environment were assembled into a single portable document file (PDF). Screenshot angles were carefully selected to ensure that all attributes of the 3D BIM environment were included in the PDF. Screenshots were used to reduce the possible confound of user BIM navigation and strengthen the internal validity of the study. Additionally, all attributes of the design were included in the 2D plans to ensure that research participants had a realistic experience while obtaining information from the 2D design documents. 2D CAD, 3D BIM, and a combination of 2D and 3D were the three modes of design stimuli developed for hypothesis testing.

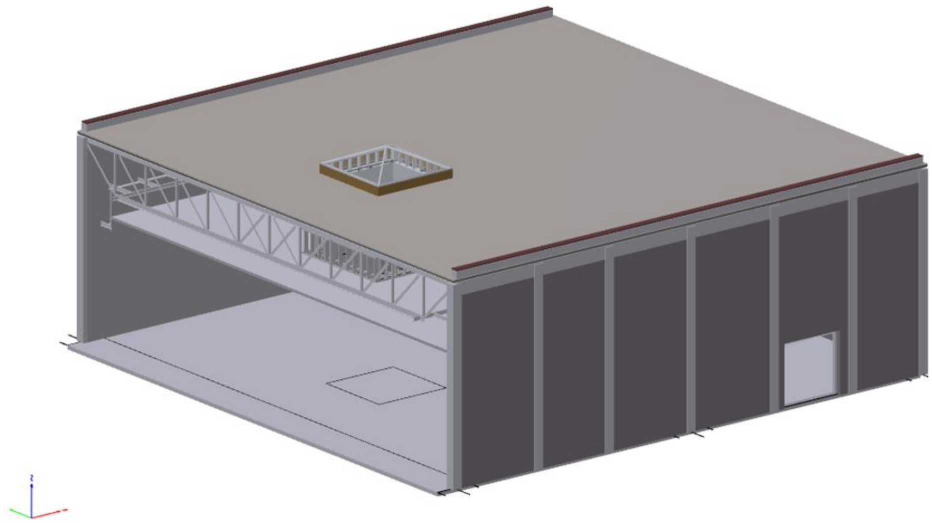


Figure 1. 3D BIM Environment Screenshot

Phase 2: Quasi-experimental Testing

The focus of this research was to test the efficacy of the experimental method with a smaller sample size. Eighteen participants from Colorado and North Carolina were selected to participate, which included seven designers and eleven construction supervisors. A mixture of these professions was included because they have been found to be critical for effective CHPtD implementation (Hecker and Gambatese 2003 and Ganah and John 2015). A breakdown of the sample population demographics is provided in table 2 below.

Table 2: Participant demographics

Occupation	N	Age (µ years)	Experience (µ years)
Designer	7	41.0	18.1
Supervisor	11	35.7	14.9

A 3x3 Latin square design (see Table 3) was employed to cross the treatment factor (i.e. work activities) with the independent variable (i.e. information modality). Additionally, a sample size of 18 participants allowed for research module counterbalancing to ensure that any learning curve attained during the research trials is normalized across participants. As can be seen in Table 3, the 3x3 Latin square design is robust to sample sizes divisible by 3.

Six participants were randomly placed into each of the three module categories. The three module categories (A, B, and C) and the ordering sequence (1, 2, and 3) are shown below to demonstrate the counterbalancing of research modules across participants. For example, a supervisor given module A would first receive the 3D BIM skylight installation activity, then the 2D CAD soffit drywall installation activity, and finally, a combination of 3D BIM and 2D CAD interior wall stud framing activity.

Table 3: 3X3 Latin square design

3X3 Latin Square Research Design		**Stimulus Category**		
		3D (BIM)	2D (CAD)	Combination
Work Activity	Skylight Installation	**A-1**	**C-3**	**B-2**
	Soffit Drywall Installation	**B-3**	**A-2**	**C-1**
	Interior Wall Stud Framing	**C-2**	**B-1**	**A-3**

Each participant was provided a copy of work activity descriptions (Table 1) to ensure they understood the scope of the work activity under investigation. After reviewing the work activity descriptions, participants were provided with the correct design stimuli and work activity combination determined by module category and ordering sequence. Participants were provided the 3D stimulus via PDF presentation shown on 17" laptop computer monitor. Participants used a mouse with a scroll wheel to navigate through the pdf. presentation. Additionally, participants were provided with a set of 24"X18" 2D paper drawings and a combination of 3D and 2D stimuli when appropriate. Participants were allowed an unlimited amount of time to view all design information and recognize hazards. Participants were asked to verbally narrate safety hazards as they were recognized. All hazards were transcribed during the experiment by the lead researcher.

For the purposes of this study, safety hazards were identified as "*a source of energy that, if released, and results in exposure, could cause injury or death*." Participants were asked to identify "*ways that workers could become injured, ill, or be killed in the work situation*" and were asked to "*disregard citing infractions of safety and health regulations*." This was done to ensure that the participants intent of the hazard narration was accurately captured rather than capturing nonessential safety violation data.

RESULTS

Participants hazard recognition performance scores were only used to examine the variability of hazard recognition performance across the 3 stimulus categories. Variability in hazard recognition performance was not examined for the three work activities. By examining hazard recognition performance for stimulus category, the research hypothesis can be tested and conclusions made regarding the stimulus category that yields the highest proportion of recognized safety hazards during design. As noted previously, this pilot test demonstrates the efficacy of the first CHPtD experiment but the sample size is not yet adequate to make broad and strong inferences.

Calculating the Hazard Recognition Index

Hazard recognition performance was examined for each of the stimulus categories for each of the 18 participants. The Hazard Recognition index (HR_{index}) previously used by Albert et al. (2014a) is a viable method to evaluate hazard recognition performance. The HR_{index} results in proportion data. The numerator in the equation is the total number of hazards that participants correctly recognized from the stimulus. The denominator of the index is the total number of safety hazards for each work activity (HR_{index}) [Eq. (1)]:

$$[1]\ \mathrm{HR}_{index} = \frac{\text{H recognized}}{\text{H total}}$$

Surprisingly, the preliminary results suggest that there is no discernable difference in the proportions of hazards identified across the three treatment groups. The 2D CAD stimulus yielded a HR_{index} of 41% and the Combination of 2D CAD and 3D BIM yielded 42%. However, the 3D BIM alone only yielded a HR_{index} of 39% (see Table 3). ANOVA analysis suggests that no statistical significance exists to reject the null hypotheses ($F_{2,49}$ = 0.159, p = 0.85).

Table 3. Work Activities and Descriptions

Stimulus Category	**Activity Description**
2D CAD	41%.
3D BIM	39%
Combination (2D & 3D)	42%
Average	**40.66%**

CONCLUSIONS

Improving construction worker safety is of the upmost importance for the construction industry. Protecting the safety and health of the workforce is imperative and a useful focus of industry and research efforts (Rajendran and Gambatese 2009 and Toole and Carpenter 2012a). Although much subjective research has strived to investigate the viability of CHPtD as a method for improving worker safety, little objective research has strived to validate these theories with sound empirical evidence. This is the first attempt in research to objectively examine how different modes of design information influence hazard recognition performance and consequently, Design for Safety efforts.

The results of this study suggest that the mode of design information does not affect hazard recognition performance. The preliminary results indicate that there are no statistically significant differences among the design modes. For this reason, more research is needed to understand how the attributes of design types, levels, complexity, and project end use affect hazard recognition at various stages of project designs.

One reason for the lack of any visible tendency in hazard recognition performance across the different modes of design information in this study could lie in the complexity and inclusions of the construction design employed. The design used is of a single-story commercial, open ballroom style structure, with few technical systems. Other designs and associated work activities that include complex structural designs, underground utilities, advanced mechanical systems, and more unique construction operations may present an opportunity to observe greater variability in the proportions of safety hazards identified across the different modes of design information. However, the strength of the approach used lies in the verified list of safety hazards identified in previous research. More empirical research with designs of varying complexity and work activities are needed to determine if design complexity affects hazard recognition performance during design.

Another reason for the lack of change in the proportions of safety hazards recognized across design modality may be the inclusion/exclusion of building elements in the construction design.

For this study, only the architectural and structural aspects of the design were included in 2D CAD and 3D BIM. Elements such as mechanical, electrical, plumbing, etc. were omitted from the design to reduce the time and effort required to visually obtain design information. Research that investigates how the level of design completion affects hazard identification in the Design for Safety review process will help to identify the optimum timeframe in the design process for effective hazard recognition execution.

Further research is also needed to empirically investigate the efficiency of the Design for Safety review process. Data that includes the time required for hazard recognition of individual work activities crossed with design modality could be used to quantify the time required to recognize safety hazards and obtain productivity data for Design for Safety review processes. Additionally, quantifying the cognitive workload of hazard recognition tasks during the Design for Safety review process can provide real-time information that can be used to help develop Design for Safety training programs that could potentially reduce the mental workload of hazard recognition tasks and increase the efficiency of the Design for Safety review process. Furthermore, research is also needed to understand how both experience with construction design and independent work activities influence hazard recognition performance. More research that investigates the effects of safety training, hazard recognition experience, and work activity familiarity could help to identify the true level of individual's reliance upon design information for hazard recognition during project design. These opportunities for research present a unique opportunity for the advancement of objective research in the arena of construction safety.

Although there are no statistically significant findings to suggest that the mode of design information influences hazard recognition performance, this study builds on current knowledge by developing a new and effective method for objectively testing the viability of the theory known as CHPtD. This approach is valuable to research and practice by providing a methodological framework for testing CHPtD and provides a pathway for the maturity of CHPtD research and safety science. With empirical evidence, construction researchers and practitioners can continue to build methods to ensure that CHPtD may be more effectively implemented in construction and accomplish the common goal of protecting workers from the many dangers of construction.

REFERENCES

Albert, A., and Hallowell, M. R. (2012). Hazard recognition methods in the construction industry. In *Construction Research Congress* (pp. 407-416).

Albert, A., Hallowell, M. R., and Kleiner, B. M. (2013). Enhancing construction hazard recognition and communication with energy-based cognitive mnemonics and safety meeting maturity model: Multiple baseline study. *Journal of Construction Engineering and Management*, *140*(2), 04013042.

Albert, A., Hallowell, M. R., Kleiner, B., Chen, A., and Golparvar-Fard, M. (2014a). Enhancing construction hazard recognition with high-fidelity augmented virtuality. *Journal of Construction Engineering and Management*, *140*(7), 04014024.

Bahn, S. (2013). Workplace hazard identification and management: The case of an underground mining operation. *Safety science*, *57*, 129-137.

Bansal, V. K. (2011). Application of geographic information systems in construction safety planning. *International Journal of Project Management*,*29*(1), 66-77.

Baxendale, T. and O. Jones (2000). "Construction design and management safety regulations in practice—progress on implementation." *International Journal of Project Management* 18(1): 33-40.

Carter, G., & Smith, S. D. (2006). Safety hazard identification on construction projects. *Journal of construction engineering and management*, *132* (2): 197-205.

Collier, E. B. 1994. ‘‘Four-dimensional modelling in design and construction.’’ thesis, Stanford Univ., Stanford, Calif.

De Lapp, J. A., Ford, D. N., Bryant, J. A., & Horlen, J. (2004). Impacts of CAD on design realization. *Engineering, Construction and Architectural Management*, *11*(4), 284-291.

Ganah, A., & John, G. (2015). Integrating Building Information Modelling and Health and Safety for Onsite Construction. Safety and Health at Work, 39-45.

Hallowell, M. R., & Hansen, D. (2016). Measuring and improving designer hazard recognition skill: Critical competency to enable prevention through design. *Safety science, 82*, 254-263.

Hecker, S., & Gambatese, J. A. (2003). Safety in design: a proactive approach to construction worker safety and health. *Applied Occupational and Environmental Hygiene*, *18*(5), 339-342.

Ku, K., & Mills, T. (2010). Research needs for building information modeling for construction safety. In *International Proceedings of Associated Schools of Construction 45nd Annual Conference, Boston, MA.*

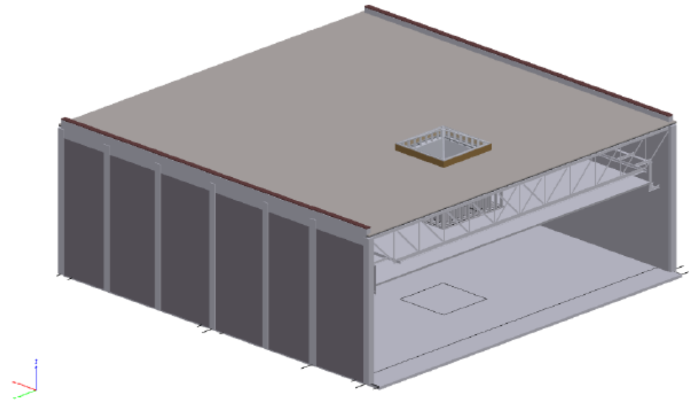
Lopez del Puerto, C., Clevenger, C. M., Boremann, K., & Gilkey, D. P. (2013). Exploratory study to identify perceptions of safety and risk among residential Latino construction workers as distinct from commercial and heavy civil construction workers. *Journal of Construction Engineering and Management, 140* (2): 04013048 - 1 – 04013048 - 7.

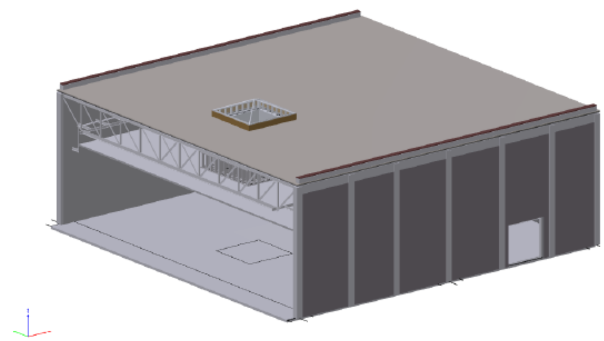
Lu, Y., Hinze, J., and Li, Q. (2011). “Developing fuzzy signal detection theory for workers’ hazard perception measures on subway operations.” Safety Science, 49 (3): 491–497.

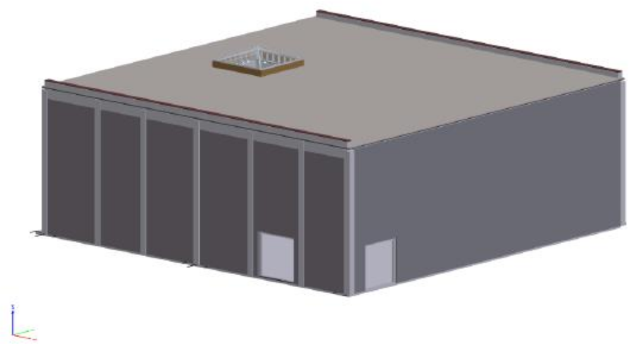
Young, S. (1996). ‘‘Construction safety: A vision for the future.’’ *J. Manage. Eng.,* 12(4), 33–36.

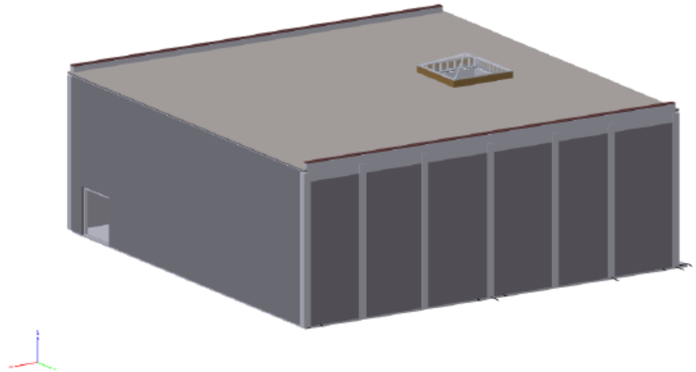
Zhang, S., Sulankivi, K., Kiviniemi, M., Romo, I., & Eastman, C. (2015). BIM-based fall hazard identification and prevention in construction safety planning. Safety Science, 72, 31-45.

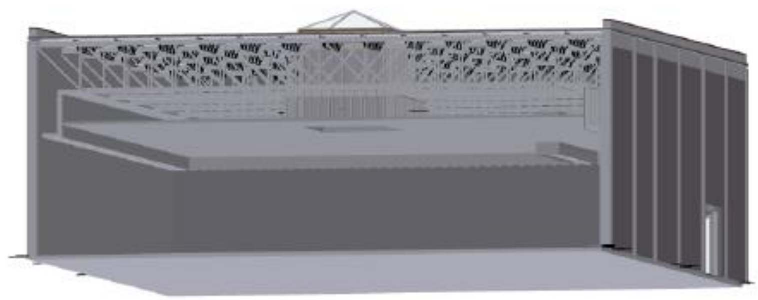
Appendix 2: 3D Visualizations

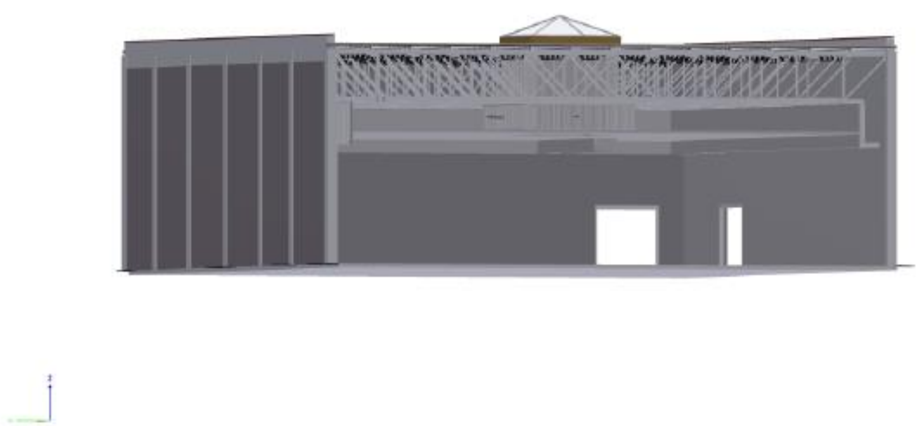


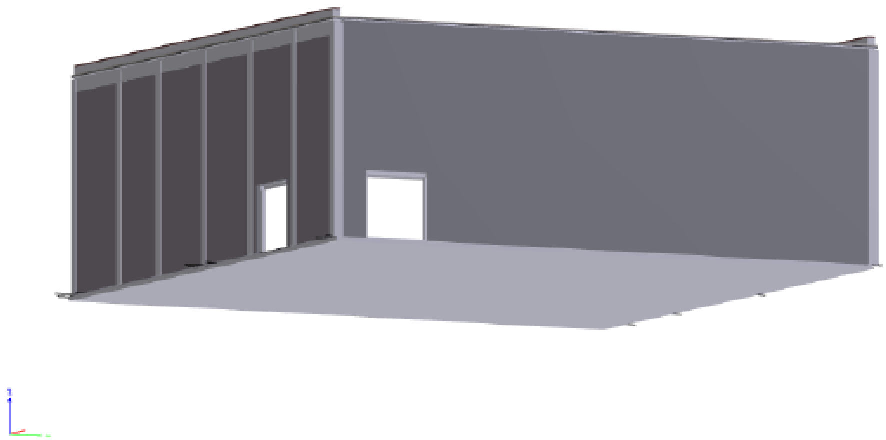


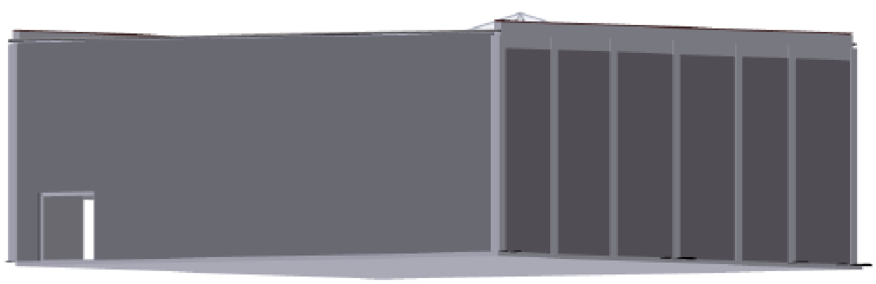


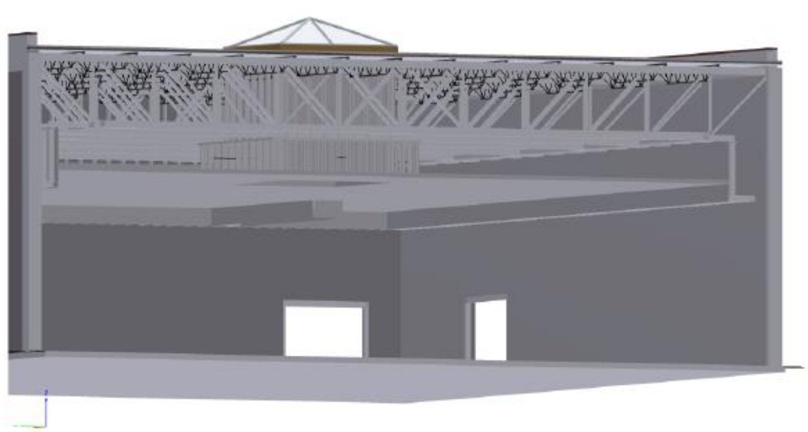


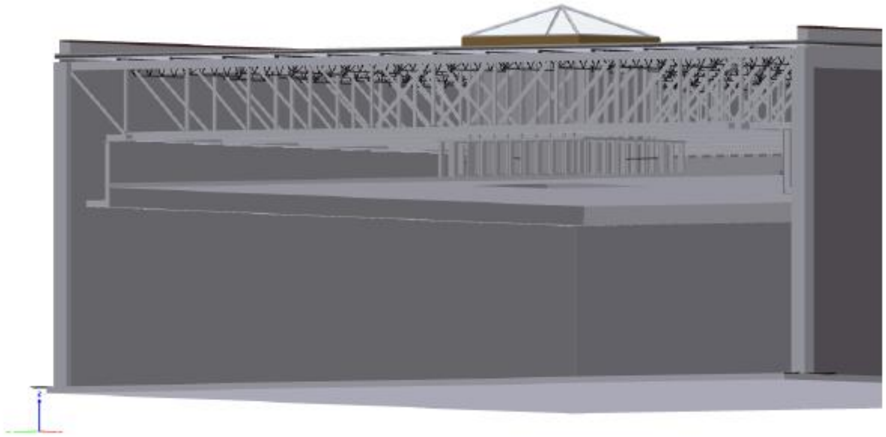


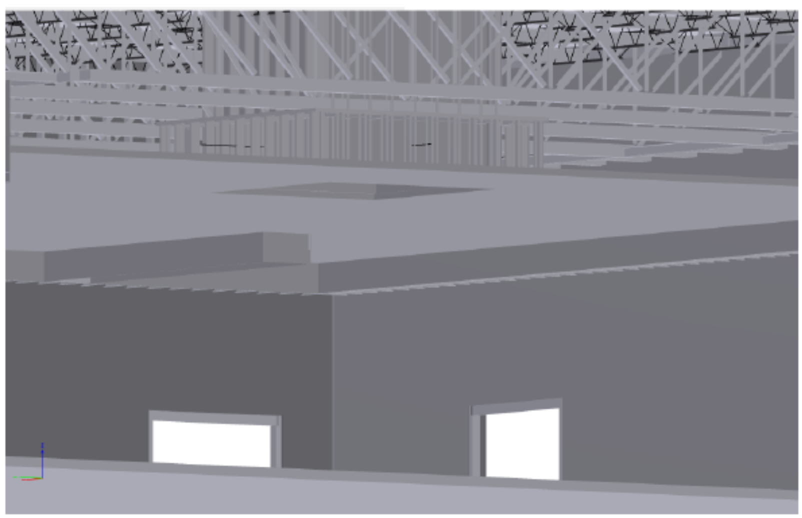


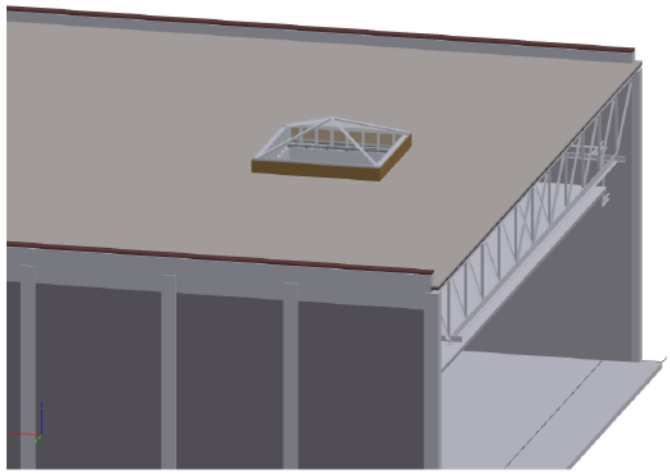


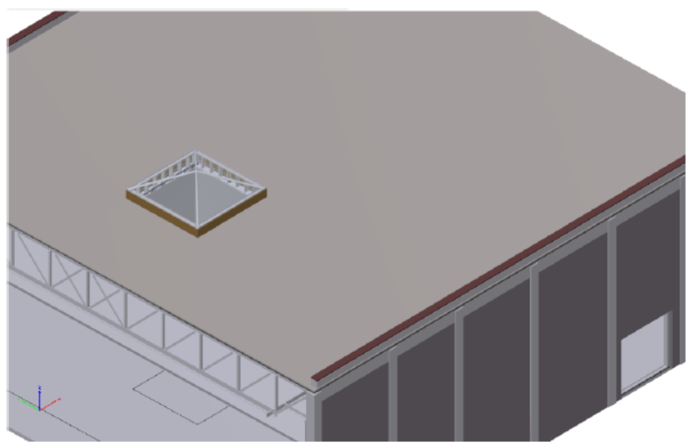


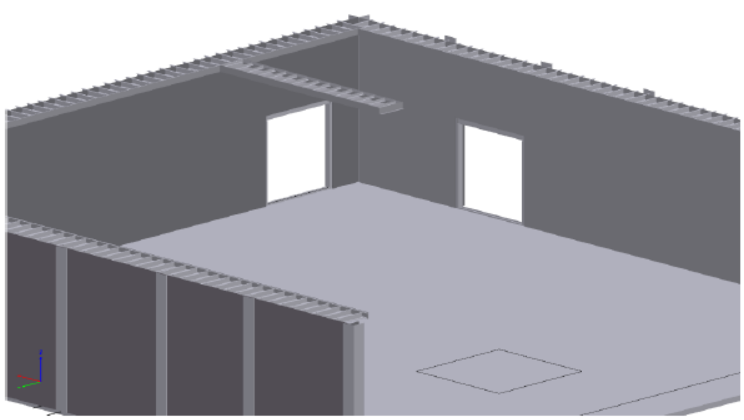


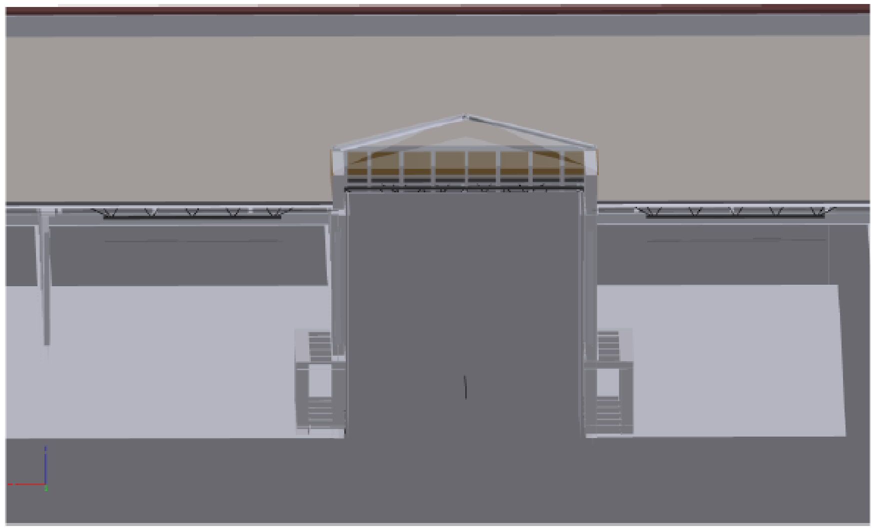


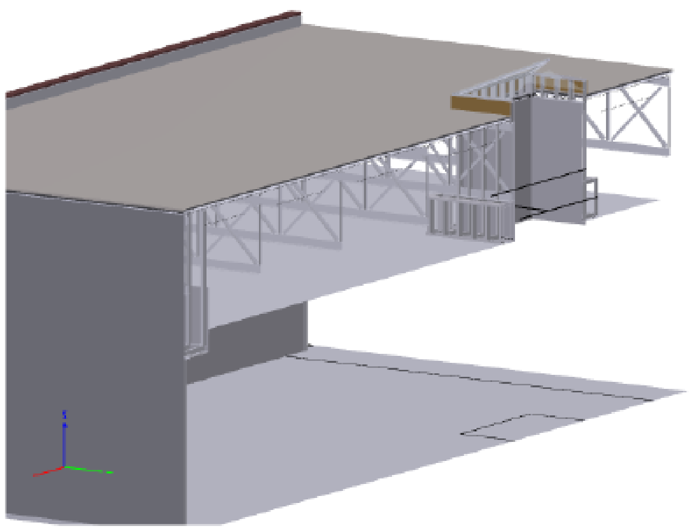


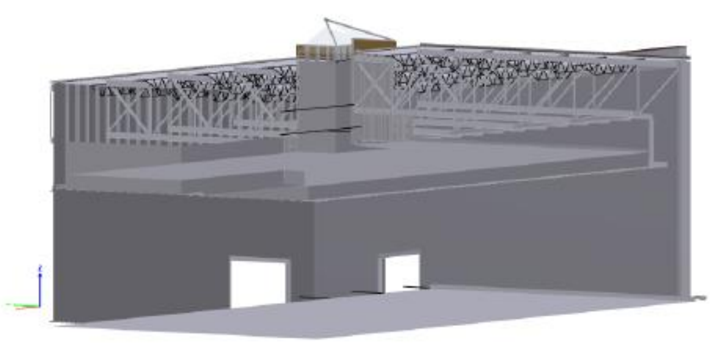










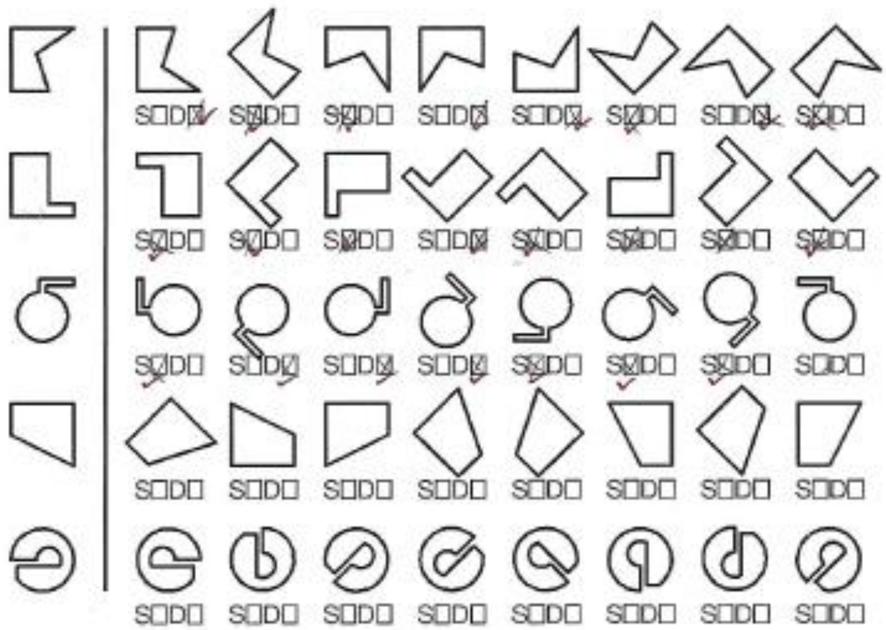


Appendix 3: Card Rotation Test

Pin? 1

Card Rotation Test (1.5 minutes)

S = same (only rotated)
D = different (flipped and/or rotated)



23 - 0 = 23 / 40

Correct Answers – Incorrect Answers = Total Score

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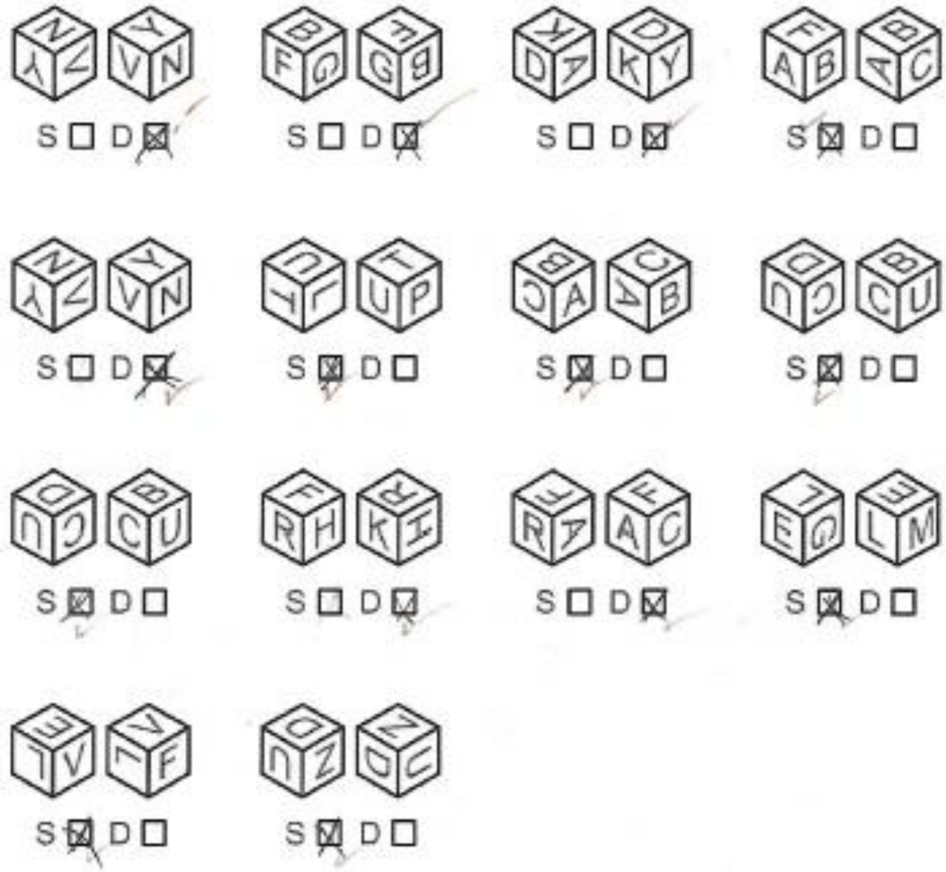
Appendix 4: Cube Rotation Test

Cube Comparison Test (2 minutes)

S = same (same cube)
D = different (different cubes)



14 – 0 = 14 / 14

Correct Answers – Incorrect Answers = Total Score

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Appendix 5: Model Comparisons Across and Within all Design Information Formats

Across All Design Information Formats

The original MLR model used for hypothesis testing in chapter 4 of this dissertation was built using the predictor variables associated with the primary research hypotheses. These variables included: mental workload average, spatial cognition average, years of industry experience, total time of research trial in minutes, and the interaction of experience and time and mental workload and spatial cognition. The model representing the aggregate of all the data is represented in table 29 below as seen in chapter 4 (table 23) of this dissertation.

Table 29: Linear Regression Model for HR_{index} Across All Design Information Formats and Population Treatment Groups

Across All Design Information Formats Model Equation [Eq. (5)]:		$Y (HR_{index}) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6$					
Variables		Coefficients β_n	Estimate X_n	Std. Error	*t*	F	*P*
Intercept		β_0	0.3461	0.1196	2.893	8.3694	0.0042
Predictor Variables	Mental Workload Average (X1)	β_1	-0.0017	0.0155	-1.107	-1.2254	0.2693
	Spatial Cognition Average (X2)	β_2	-0.1114	0.1566	-0.711	-0.5055	0.4776
	Years of Industry Experience (X3)	β_3	0.0055	0.0014	3.765	14.1752	0.0002*
	Total Time of Trial (Minutes) (X4)	β_4	0.0287	0.0076	3.779	14.2808	0.0001*
	Total Time of Trial (Minutes): Experience (X6)	β_5	-0.000	0.000	-1.640	-2.6896	0.1023
	Mental Workload Average: Spatial Cognition Average (X5)	β_6	0.0228	0.0211	1.085	1.1772	0.2789

Note: *t*, *F* = variance of the group mean; p = significance.

Asterisk (*) = Statistically significant difference beyond 95% confidence.

Additionally, an automated forward stepwise model generation procedure was conducted in R statistical package. The forward stepwise procedure resulted in three variables as being the best fit for the overall MLR model. These variables are: Years of Industry Experience, Total Time of Trial (Minutes), and the interaction of the two. The "best fit" model and model comparison can be seen in Tables 30 and 31 below:

Table 30: BEST FIT Linear Regression Model for HR_{index} Across All Design Information Formats and Population Treatment Groups

Across All Design Information Formats Model Equation [Eq. (5)]:		$Y(HR_{index}) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6$					
Variables		**Coefficients** β_n	**Estimate** X_n	**Std. Error**	***t***	**F**	***P***
Intercept		β_0	0.2596	0.0200	12.958	167.9100	0.0000
Predictor Variables	Years of Industry Experience (X3)	β_3	0.0056	0.0014	3.873	15.0001	0.0001*
	Total Time of Trial (Minutes) (X4)	β_4	0.0281	0.0073	3.851	14.8302	0.0001*
	Total Time of Trial (Minutes): Experience (X6)	β_5	-0.0007	0.0004	-1.592	-2.5344	0.1128

Note: *t*, *F* = variance of the group mean; p = significance.

Asterisk (*) = Statistically significant difference beyond 95% confidence.

Overall Model Significance	**RSE**	***F***	**DF**	**R^2**	**Adj. R^2**	***P***
All Formats	0.1479	16.5	3 & 239	0.1716	0.1612	0.000

Table 31: Model Comparison – All Design Information Formats Original Model and Best Model

Model Comparison	DF	*F*	*P*
All Formats	3	0.7407	0.5288

As can be seen in the ANOVA model comparison shown in Table 31, there is no statistically significant difference between the original model displayed in Table 23 of chapter 4 and the best fit model as displayed in table 30. However, the MLR model shown in table 30 does explain 0.0027 more variability without the additional predictor variables as shown in tables 23 and 29.

Within Each Design Information Format

In addition to the original MLR model which tested the effects of several predictor variables across all design information formats, MLR analysis was used to test the effects of the same predictor variables within each of the design information formats independently. The predictor variables for analysis included: mental workload average, spatial cognition average, years of industry experience, total time of research trial in minutes, and the interaction of experience and time and mental workload and spatial cognition. The MLR results as shown in Table 25 of chapter 4 are show again in table 32 below:

Table 32: Linear Regression Model for HR$_{index}$ for Each Information Format

Within Independent Design Information Format Model Equation [Eq. (6)]:		**Y (HR$_{index}$) = $\beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6$**					
Predictor Variables		**Coefficients** β_n	**Estimate** X_n	**Std. Error**	***t***	**F**	***P***
Intercept (**2D CAD Format**)		β_0	0.3846	0.2545	1.512	2.2861	0.1349
2D CAD Format Predictor Variables	Mental Workload Average (X1)	β_1	-0.0031	0.0064	-0.495	-0.2450	0.6218
	Spatial Cognition Average (X2)	β_2	-0.1420	0.3303	-0.430	-0.1849	0.6685
	Years of Industry Experience (X3)	β_3	0.0073	0.0033	2.202	4.8488	0.0308*
	Total Time of Trial (Minutes) (X4)	β_4	0.0196	0.0167	1.172	1.3735	0.2451
	Total Time of Trial (Minutes): Experience (X5)	β_5	-0.0014	0.0009	-1.551	-1.3342	0.1252
	Mental Workload Average: Spatial Cognition Average (X6)	β_6	0.0049	0.0088	0.561	0.3147	0.5762
Intercept (**3D Visualization Format**)		β_0	0.1925	0.1866	1.032	1.065	0.3056
3D Visualization Format Predictor Variables	Mental Workload Average (X1)	β_1	0.0006	0.0046	0.150	0.022	0.8811
	Spatial Cognition Average (X2)	β_2	0.0700	0.2389	0.293	0.085	0.7701
	Years of Industry Experience (X3)	β_3	0.0054	0.0032	1.669	2.785	0.0993
	Total Time of Trial (Minutes) (X4)	β_4	0.0006	0.0002	2.149	4.618	0.0349*
	Total Time of Trial (Minutes): Experience (X5)	β_5	-0.0000	0.0000	-0.252	-0.063	0.8014
	Mental Workload Average: Spatial Cognition Average (X6)	β_6	-0.0014	0.0062	-0.225	-0.050	0.8227
Intercept (**Combination Format**)		β_0	0.3860	0.2023	1.908	3.640	0.0602
Combination Format Predictor Variables	Mental Workload Average (X1)	β_1	-0.0058	0.0056	-1.040	-1.081	0.3018
	Spatial Cognition Average (X2)	β_2	-0.1764	0.2658	-0.664	-0.440	0.5083
	Years of Industry Experience (X3)	β_3	0.0036	0.0020	1.746	3.048	0.0849
	Total Time of Trial (Minutes) (X4)	β_4	0.0004	0.0001	3.002	9.012	0.0036*
	Total Time of Trial (Minutes): Experience (X5)	β_5	0.0078	0.0074	1.050	1.102	0.2973
	Mental Workload Average: Spatial Cognition Average (X6)	β_6	-0.0000	0.0000	-0.230	-0.052	0.8184

Note: *t*, *F* = variance of the group mean; p = significance.

Asterisk (*) = Statistically significant difference beyond 95% confidence.

Table 32: Overall Linear Regression Model Output for the 2D CAD Design Information Format

Information format of MLR Model	RSE	*F*	DF	R^2	Adj. R^2	*P*
2D CAD	0.1733	1.1840	6 & 74	0.0876	0.0135	0.3245
3D Visualization	0.1354	4.915	6 & 74	0.2849	0.2270	0.000*
Combination	0.1358	5.406	6 & 74	0.3048	0.2484	0.000*

Additionally, an automated forward stepwise model generation procedure was conducted in R statistical package independently for each of the design information formats. The forward stepwise procedure resulted in the following variables to be included within each design information format specific model: (1) 2D CAD Format Model includes Years of Industry Experience, (2) 3D Visualization Format includes Years of Industry Experience and Total Time of Trial (Minutes), and (3) Combination Format Model includes Years of Industry Experience and Total Time of Trial (Minutes). See table 33 below for the “Best fit” MLR models within each design information format.

Table 33: BEST FIT Linear Regression Model for HR_{index} for Each Information Format

Within Independent Design Information Format Model Equation [Eq. (6)]:		$Y (HR_{index}) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6$					
Predictor Variables		**Coefficients** β_n	**Estimate** X_n	**Std. Error**	***t***	**F**	***P***
Intercept (**2D CAD Format**)		β_0	0.3433	0.0260	13.163	173.2650	0.0000
2D CAD Format Predictor Variables	Years of Industry Experience (X3)	β_3	0.0031	0.0016	1.985	3.9402	0.0507*
Intercept (**3D Visualization Format**)		β_0	0.2400	0.0280	8.546	73.0341	0.0000
3D Visualization Format Predictor Variables	Years of Industry Experience (X3)	β_3	0.0046	0.0012	3.632	13.1914	0.0005*
	Total Time of Trial (Minutes) (X4)	β_4	0.0335	0.0106	3.164	10.0109	0.0022*
Intercept (**Combination Format**)		β_0	0.2527	0.0243	10.363	107.392	0.0000
Combination Format Predictor Variables	Years of Industry Experience (X3)	β_3	0.0034	0.0013	2.624	6.8853	0.0104*
	Total Time of Trial (Minutes) (X4)	β_4	0.0274	0.0068	4.018	16.1443	0.0001*

Note: *t*, *F* = variance of the group mean; p = significance.

Asterisk (*) = Statistically significant difference beyond 95% confidence.

Overall Model Significance	**RSE**	***F***	**DF**	**R^2**	**Adj. R^2**	***P***
2D CAD	0.1713	3.939	1 & 79	0.0474	0.0354	0.0506
3D Visualization	0.1321	15.39	2 & 78	0.2830	0.2646	0.0000
Combination	0.1344	15.33	2 & 78	0.2822	0.2637	0.0000

Table 34: Model Comparison – All Design Information Formats Original Model and Best Model

Model Comparison	**Comparison**	**DF**	***F***	***P***
2D CAD	Original vs. Best	5	0.6500	0.6624
3D Visualization		4	0.0506	0.9951
Combination		4	0.6014	0.6628

As can be seen in the ANOVA model comparisons shown in Table 34, there is no statistically significant difference between the original models for each design information format displayed in Table 25 of chapter 4 and the best fit model as displayed in table 33. However, the BEST FIT MLR model shown in table 33 does explain more explained variability within each design information format without the additional predictor variables as shown in the original MLR models. The Adjusted R2 values and the change between models can be seen in table 35 below.

Table 35: Adjusted R^2 Values and Change for Each Design Information Format

Information format of MLR Model	Adj. R^2 Original	Adj. R^2 BEST FIT	Adj. R^2 Difference
2D CAD	0.0135	0.0354	0.0219
3D Visualization	0.2270	0.2646	0.0376
Combination	0.2484	0.2637	0.0153