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The Relationship Between Emotion and Situational Interest In Context of Naturalistic Construction Injury Demonstrations

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By

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Abstract

Despite OSHA regulations and strong advancements in construction safety over the past few decades, construction is still one of the most dangerous industries worldwide. Researchers have shown that safety training is crucial to injury prevention. Therefore, improving the way they are delivered so that they meet andragogical principles of learning is logical. However, when delivering new safety training it is imperative to understand the implications of the change on learning, retention, interest, emotion, and behavior. Although some literature can be used to reliably evaluate the implications of the proposed change in safety training, the relationship among injury experience, emotion, and situational interest remains unknown. To address this implications, this study tests the hypothesis that emotional responses to Live safety demonstrations (LSD) increase workers' engagement and situational interest and elicits a strong emotional response. To test this hypothesis, a controlled experiment was designed and conducted that exposed 492 subjects tot eh live safety demonstrations (LSD) and measured emotional responses and situational interest before and after exposure. Once these data were collected, a principal component analysis (PCA) was performed to identify uncorrelated clusters of correlated emotions. Finally, a multivariate logistic regression was performed to test the hypothesis that some clusters of emotions can predict change (increase or decrease) in situational interest. The results show a strong relationship between negative emotional states and situational interest and no significant link to positive emotions. The implications of these findings are that workers in mid-negative and strong negative emotional states are more likely to maintain their interest in safety and be engaged in trainings than workers in positive emotional states. The relationships between the LSD and emotional response and situational interest response were explored in a separate paper.

Table of Contents

INTRODUCTION

Construction is one of the most dangerous industries worldwide (Sacks et al., 2009). The international Labor Organization (ILO, 2003) estimated that at least 60,000 workers are killed on construction sites annually worldwide. In the US 4,585 workers were killed on job sites in 2013 (OSHA, 2013). Before OSHA was created in 1971, an estimated 14,000 workers were killed on the job every year (38 fatal injuries per day). With OSHA regulations, these numbers dropped to 12 per day (see Figure 1). Moreover, all types of construction injuries result in many direct and indirect financial losses. It has been estimated that employers pay almost $1 billion per week for direct workers' compensation costs alone (OSHA, 2009). This increasing injury rate is not only related to workplace conditions but to human errors as well (Feyer and Williamson 2006). Abundant research that aims to reduce the alarming injury and fatality rates, improve performance on construction sites, and implement effective injury prevention practices has reached saturation (Esmaeili & Hallowell, 2012; Tixier, 2014). Fortunately, psychological approaches are emerging, bringing hope for safety practices through engaging safety meetings, interesting and emotionally stimulating learning strategies (Bhandari and Hallowell, 2015).

Accidents are not random events. Research has indicated that human factors play a significant part in accident causation. Also, according to Bureau of Statistics (2013), the injury and fatality rate is hgiher for Hispanic workers than their White counterparts. Thus, it seems crucial to understand the psychological and ethnic factors that might drive these rate differences to improve safety training. In fact, a study comparing workers' activities, attitudes, and accomplishments before and after health and safety education (Becker and Morawetz, 2004) showed statistically that training programs impact workplaces in important ways. Safety education increases trainees' self-confidence, willingness to make safety and health improvements and their effectiveness at making these improvements. Such important role makes safety trainings crucial in injury prevention. Therefore, improving the way they are delivered so that they meet andragogical principles of learning (Wilkins 2011) seems natural.

In the academic field, there has been an increased focus on the effects of situational factors on student interest and even more extensive research on the mutual influence of interest and learning (Buehl, & Mulhern, 2002; Durik & Harackiewicz, 2007). Relatively speaking, however, there is little research on how psychological factors such as induced emotions, can promote interest in a particular domain. In the construction field in particular, this void is even more noticeable. A reason for this lack of research may be that the field lacks a tool for measuring contextual (e.g., situational) interest in a variety of content domains and across a variety of educational levels. As such, our goal was to develop such framework (Situational interest framework) that would be appropriate for workers with different ethnicities, educational levels, and work experiences. In order to test the proposition that emotional states are correlated to situational interest, a tool had to be developed to induce emotions as well. The research team developed Live Safety Demos that included realistic simulations of injuries using biologically accurate replications of human hands, and showed statistical change in emotions (see Bhandari and Hallowell, 2015). This study is the first to statistically investigate the interplay between emotional states and situational interest (Figure a).

Figure1 Injury rate per 100,000 workers before and after OSHA (1971)

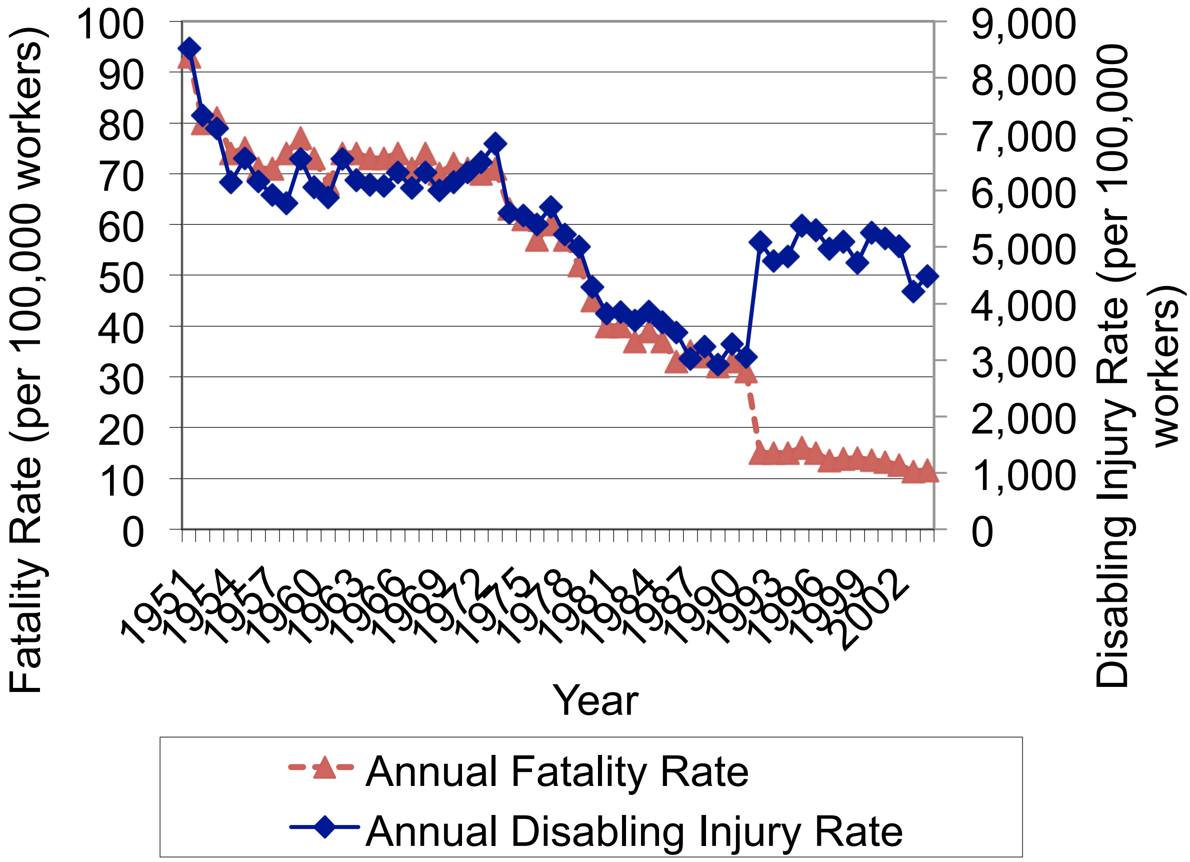
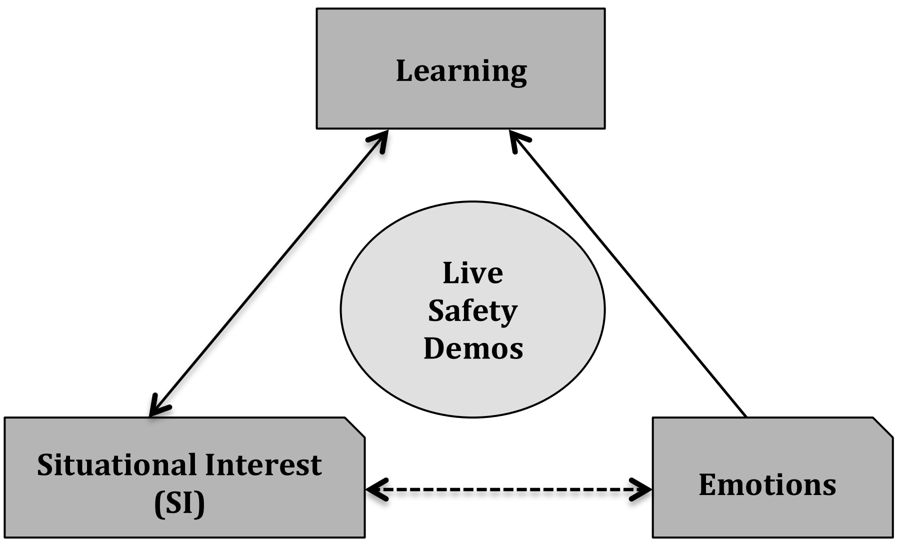


Figure a Current Knowledge about the topic. The gap this study aims to fill is the link between SI and emotions.



LITERATURE REVIEW

To understand how this study departs from current knowledge, and the interplay between the previously discussed areas, relevant literature has been reviewed. The main areas investigated in this literature review are: Risk-Perception, Emotions, Learning, and Situational Interest. Because the construction field is devoid of rigorous empirical investigations of the psychology of Situational Interest, this study will include findings from other industries.

Definition of Emotions

Emotion is defined as a five-step process, where the organism reacts to an external or internal stimulus (Scherer, 1987, 2001). Three of the steps have long-standing status: arousal, subjective experience or feelings, and body and face expressions. Emotion is frequently confused with feeling, mood, or attitude. These subjective experiences are only a component of the total emotional process and integrate the subjective experience of emotion (commonly denoted "feeling component"). In fact, according to Scherer (2004b), ''feelings integrate the central representation of appraisal-driven response organization in emotion''. Therefore, confusing feelings and emotions can hamper our understanding of emotions as a multi-model process.

Emotions are easily distinguishable from other psychological states as they: (1) rarely steady states, they tend to change rapidly to adapt to changing circumstances and evaluations (Scherer, K. R, 2005). (2) Emotional responses are thought to be relatively intense which can be an important feature to distinguish emotion from mood (Linnenbrink-Garcia & Pekrun, 2011). (3) As emotions demand tremendous mobilization of resources and energy to synchronize the interrelated changes, they have to be short in time. In fact, according to Scherer (2005), emotions are short in duration to allow behavioral adaptability.

In the current literature, there is a consensus on a distinction between positive emotions and negative emotions. Many researchers make even more specific distinctions: positive activating emotions such as enjoyment, hope, and pride; Negative deactivating emotions such as hopelessness and boredom; Positive deactivating and negative activating such as relief, anger, anxiety, and shame. Positive activating emotions are thought to promote motivation, encourage use of adaptable learning strategies, and promote self-regulation, therefore positively affecting performance (Lane, Whyte, Terry, & Nevill, 2005). Conversely, negative deactivating emotions, are known to simultaneously decrease motivation and willing to make effort to process information, implying negative effects on academic performance (Turner & Schallert, 2001). Positive deactivating and negative activating show more complex and less predictable behavior (Boekaerts, 1993; Hembree, 1988; Pekrun, 2006).

If we accept Scherer's (2005) definition of emotions, there is no objective method to measure emotions. In fact, according to Scherer (2005) given the multi-model nature of emotions, only a method that would measure all component changes involved can provide a comprehensive measure of an emotion. In other words, we need to measure every component of the emotional process: the response patterns generated in nervous systems, the motivational changes produced by the appraisal results, the patterns of facial and vocal expression, and the nature of the subjectively experienced feeling state that reflects all of these component changes. Obviously, such comprehensive measurement of emotion has never been performed before and is unlikely to become standard procedure due to its complexity.

There have been major advances in recent years with respect to measuring individual components such as appraisal (Scherer et al., 2001), brain mechanisms (Davidson et al., 2003a), physiological response patterns (Stemmler, 2003), and expressive behavior (Harrigan et al., 2005). Nonverbal behavior (e.g. facial and vocal expression) and physiological indicators can be used to infer the emotional state of a person, there are no objective methods of measuring the subjective experience of a person during an emotion episode (Scherer, 2005).

Given the definition of feeling as a subjective cognitive representation, reflecting a unique experience of mental and bodily changes in the context of being confronted with a particular event, there is no access other than to ask the individual to report on the nature of the experience (Stemmler, 2003; Schraw and Lehman, 2001). Based on this knowledge, we implemented a before and after (AB) experimental design where Rottenberg et al.'s (2007) emotional polarity questionnaire was used to survey workers before and after the Live Demos. On this questionnaire, the participants were asked to rate their emotions on 8-point scale.

Definition of Situational Interest

Interest has always held a central position for educator when it comes to learning. Professional educators often refer to interest when they talk about motivational prerequisites for teaching and learning. The literature distinguishes between two different types of interest: Situational Interest (SI) and Individual Interest (Figure3). While Individual Interest, as noted in (Rathunde, 1993; Renninger, 2000; Renninger, Hidi, & Krapp, 1992; Schiefele, 1991), has a dispositional quality, residing in the person across situations, SI is more a respond to the external environment, which can be either an attentional or an affective reaction to the situation (Hidi & Anderson, 1992; Hidi & Baird, 1986; Hidi & Renninger, 2006; Krapp, 2002).

One can distinguish between two forms of Situational Interest (Dewey, 1913; Hidi & Baird, 1986; Hidi & Harackiewicz, 2000; Hidi & Renninger, 2006; Krapp, 2002; Mitchell, 1993):

- Triggered-SI involves intensifying the affective experiences individuals associate with their environment. While the concept of Triggered-SI refers more specifically to initiating interest, it is still very similar to Mitchell's (1993) conceptualization of "catch". In fact, both concepts involve arousing or grabbing an individual's interest (Hidi, 2001; Hidi & Harackiewicz, 2000; Hidi & Renninger, 2006).
- Maintained-SI, which is also referred to as "hold," is a more involved, deeper form of situational interest in which individuals begin to forge a meaningful connection with the content of the material and realize its deeper significance (Dewey, 1913; Hidi, 2001; Mitchell, 1993).

The more individuals acquire knowledge in a specific domain and come to value it, the more interest increases, which in turn inspire curiosity and further exploration of this domain.

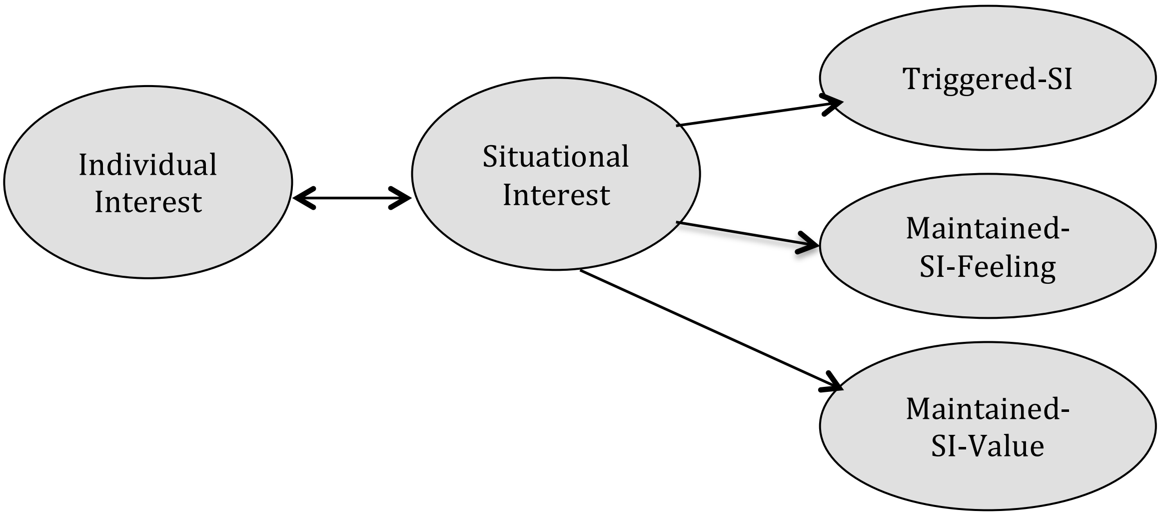
Schiefele (1991, 2001) added an additional layer of decomposition of stored value introducing two components: feeling-related components, which define the affective experiences of individuals while engaging with domain content (e.g., enjoyment, excitement), and value-related components, which emerge as individuals come to believe a domain is important and meaningful.

Some models show that situational interest can grow into individual interest, regardless of their conceptual distinction (Hidi & Renninger, 2006; Krapp, 2002). In fact, Maintained-SI represents the link between triggered-SI and individual interest. For example, in the case of students receiving course materials and honing in (triggered-SI), those who are more likely to value it beyond the context of that particular course and may be more in contact with the domain and expand their knowledge, are those who view it as enjoyable and meaningful (maintained-SI). It is through this transformation of maintained-SI that individual interest is thought to develop.

A three-factor model for SI has been supported by (Linnenbrink-Garcia et al., 2010, Hidi & Renninger, 2006; Krapp, 2002; Schiefele, 2001), introducing three different factors: triggered-interest, maintained-interest-feeling and maintained-interest-value. Separating triggered-SI and maintained-SI distinguishes between, for example, the student's reactions to the presentation of course material and his reactions to the material itself. Linnenbrink-Garcia (2010), showed that: these three factors were empirically distinct, triggered-SI arises from students' positive emotions reactions to lecture presentations and that this particular factor is a purely affective experience. This is also consistent with theoretical descriptions of triggered-SI (Schraw & Lehman, 2001). Triggered-SI is more about individuals' responses to the presentation of material rather than the material itself (Schraw & Lehman, 2001). In contrast, Maintained-SI-feeling refers to affective reactions to the domain's content.

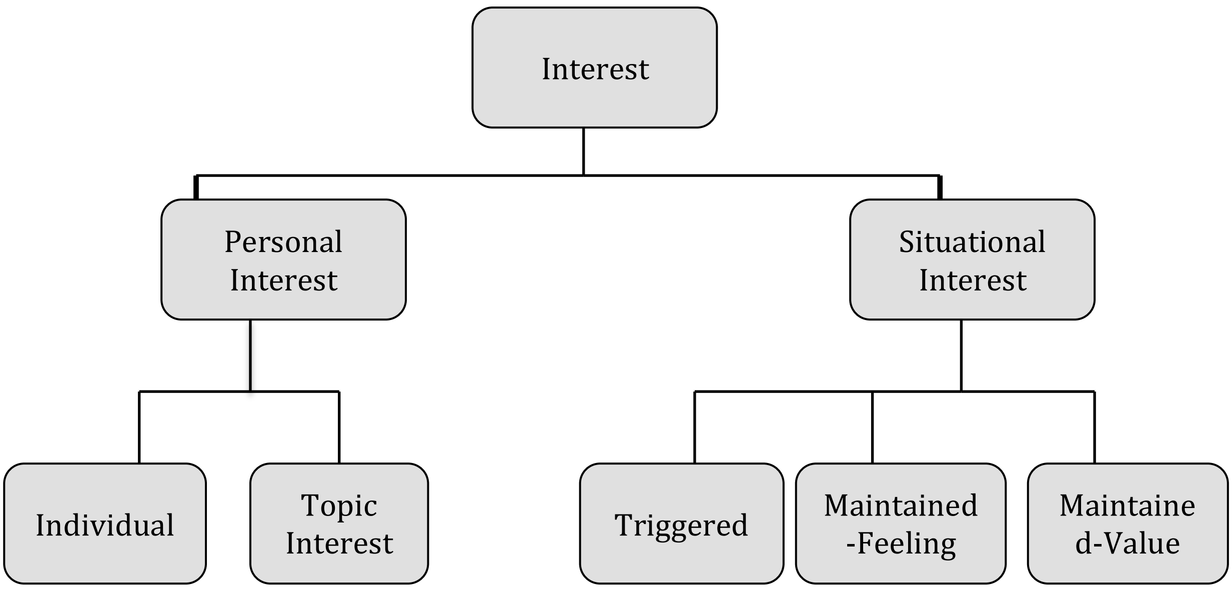
On the other hand, research showed that we can divide SI to three different types: text, task and knowledge-based interest, all related to learning (Schraw and Lehman, 2001). The most noticeable text-based factors are vividness, coherence and ease of comprehension. Coherence, along with the other factors, generally increases interest and learning. However, highly interesting segments (for ex. Seductive details), may interfere with learning. Task-based factors can be divided in two categories: encoding task and change-of-text manipulations. Both influence situational interest, indicating that it may change due external or internal manipulation (cf. Dewey, 1913). Knowledge-based factors appear to be linearly related to interest and learning. However, there is currently no empirical study designed to address this question. Topic knowledge frequently is unrelated to interest (Alexander and Jetton, 1996).

Figure 2 Three-Dimensional Model for Situational Interest (Linnenbrink-Garcia et al., 2010)



Emotion is a mechanism that allows flexible adaptation to the environment. It is considered as a theoretical construct that consists of five components corresponding to five distinctive functions (David Sander*, Didier Grandjean, Klaus R. Scherer, 2005 see Figure 2 for a list of the functions, the systems that sub-serve them and the respective emotion components). In the framework of the component process model, emotion is defined as an episode of interrelated, synchronized changes in the states of all or most of the five organismic subsystems in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organism (Scherer, 1987, 2001). Concretely, the term "emotion" is defined by the times when several organismic subsystems are coupled or synchronized to produce, for an important event for the individual's well being, an adaptive reaction.

Figure 2 Situational Interest Framework (Linnenbrink-Garcia et al., 2010; Rathunde, 1993; Schiefele (1991, 2001))



Interplay between Emotions and Learning

Many emotions are considered as critical for the individual's motivation, learning, performance and health (Schutz & Pekun, 2007). A non-exhaustive list of these emotions contains learning, hope, pride, anger, anxiety, shame, hopelessness, or boredom. For example, emotions related to achievement are those who are directly linked to achievement activities or outcomes (Pekrun et al., 2011). Pekrun (2006, 2007) developed a control-value theory, providing an integrative approach that helps analyzing different emotions experienced in various contexts of achievement, either personal or professional (e.g. sports, studies, professional activities). The control-value theory, which agrees with contemporary component process models of emotions (Scherer, 2009), defines emotions as sets of interrelated psychological processes, by which multiple components (either motivational, cognitive, physiological or affective) are of primary importance. For example, anxiety can trigger affective components (uneasy and tense feelings), cognitive ones (worries), motivational (impulses to escape from the situation) and physiological (peripheral activation). These models extend the state of the art conceptions of test anxiety (Pekrun et al., 2011) in an important way. In accordance with this theory, achievement emotions can affect the individual's learning and performance. There are many intermediate mechanisms that can cause these effects, such as the individual's motivation, strategy use, and regulation of learning (Pekrun, 1992b, 2006).

Emotions influence the individual's motivation on two levels: their intrinsic motivation to learn (interest / curiosity in learning) and their extrinsic motivation (achievements /aim for positive outcomes / prevention of negative outcomes) (Pekrun et al., 2011). Research showed that a variety of emotions could be involved in the learning process. For example, when activities are viewed as controllable and valuable, one can experience enjoyment of achievement (Pekrun, 2006). When their outcome seems uncertain, hope and anxiety are triggered. In the other hand, boredom arises when they lack of incentive value. A manager in a company will experience anxiety before important meeting if thinks it's important for his career and he is not sure about succeeding. He could even experience hopelessness if he perceives the situation as uncontrollable. Finally, when success (or failure) are perceived to be induced by internal factors, pride (resp. shame) is triggered (Pekrun, 2006).

Psychological literature provides important results regarding the correlation between emotions, variables of learning and performance. In fact, positive activating emotions influence learning positively, while negative deactivating emotions are negatively correlated to learning (Pekrun, 2011). Examples of positive activating emotions include enjoyment, hope, and pride, and they influence positively the individual's motivation and efforts put in learning, whereas hopelessness and boredom have the opposite effect.

In the academic environment, emotions serve multiple functions, such as self-regulation of learning activities, achievement, and promoting or undermining behavioral and cognitive engagement (Linnenbrink-Garcia & Pekrun, 2011). Also, research has showed that, in most cases, emotions have pool of distal antecedents, as have showed investigation the source of students' achievement emotions (Ainley et al., 2005; Assor et al., 2005; Pekrun, 2002; Ruthing et al., 2008). These studies were crucial to reproduce learning environments that increase students' performances, by promoting positive emotional experiences.

Marchand & Gutierrez (2012) showed emotions can predict (student-reported) use of learning strategies. In fact, their studies demonstrated that emotion such as hope, frustration and anxiety were influenced by self-efficacy for research methods, task-value beliefs, and perceived relevance of instruction. Marchand & Gutierrez (2010) studied mid-semester students emotions for both traditional and distance education settings. They found that self-efficacy for learning research methods represented the most important predictor of emotions for different settings. Perceived self-efficacy was a moderate strength negative predictor for frustration and anxiety. They also noticed that, despite the fact that self-efficacy was a positive antecedent for hope in both conditions, the relation was stronger in the traditional setting. This result may be interpreted as optimism's sources (in relation with research methods) are more nuanced in distance environment than face-to-face ones.

Interplay between Situational Interest and Learning

Interest has a great influence in the learning process, since it determines, on one hand, what information on wants to learn, and in the other hand, how well this information is learned (Garner, 1992; Alexander, 1996). Interest appears in multiple forms, such as active engagement, focusing of the individual's attentional resources, and overlearning (learning more than the individual would learn otherwise). Even though theory around interest has been developed in the early 20s, pioneered by Dewey's (1913) work (Interest and effort in education), empirical studies began roughly in early nineties. One of the most interesting results was that interest can be viewed as a "multifaceted phenomenon" (Hidi, 1990, 1995; Krapp, Hidi, and Renninger, 1992). A distinction between the emotional interest and the cognitive one has been made by Kintsch (1980). Kintsch suggested that the former can be more easily triggered by important life subjects, such as death, sex, or interpersonal struggle. It's often appears when a strong affective response, such as great happiness happiness, anger or disgust, is evoked by a text information for the reader. On the other hand, cognitive interest is triggered when the reader is engaged in otherwise ordinary text events, through an increase in the novelty, or unexpectedness in the text events (Wade, 1992). Another way is through relating supposedly dull information to important text themes (Schraw and Dennison, 1994). Kintsch suggested that cognitive interest could be correlated to text comprehension most strongly when interest was moderately high. Extremely low levels of cognitive interest presumably led to reader boredom; extremely high levels made it difficult to construct a single, coherent text base. Schank's work (1979) represented also an important contribution toward a theory of interest. His most important theory was that interest is essential to the strategic allocation of limited cognitive resources. He referred to this as "interest-based parsing", in which readers selectively focus their attention on information that is judged to be interesting and important. Therefore, one potential issue of interest-based parsing is that readers may focus more on engaging information, but that is uncorrelated to the text's main themes.

Many empirical studies of interest appeared between 1975 and 1985, focusing on three different themes: "how interest affected children's reading", "the relationship between text structure and interest", and "how interest was related to prior knowledge". Early studies (Asher, 1980; Asher & Markell, 1974; Asher, Hymel, and Wigfield, 1978) showed that grade-school children learned more when information was perceived as highly interesting. Summarized in Anderson, Shirey, Wilson and Fielding (1987), this researched was in line with Asher's theory that interest is positively related to learning, but disapproved the one saying that interest Improves learning because it helps individuals to selectively allocate their attention. Anderson et al. noticed that while interest was related to attention in grade-school readers, attention was not directly related to learning. Therefore, interest increased attention and learning separately (Shirey, 1992).

They also noticed that self-selected tradebooks, magazines, and narrative literature were more interesting to younger readers than basal readers and textbooks.

Exploring a different aspect of interest, Hidi and colleagues (Hidi and Baird, 1988; Hidi, Baird, and Hildyard, 1982) noticed that interest ratings were affected by changes in text structures, but so was not necessarily learning from text. For example, Hidi and Baird (1988) conducted an experiment with students, and asked them to choose what to read: an interesting base text, a text that included important descriptive elaborations of great text information, or a resolution one in which the main text creates a greater need for thematic resolution. The three versions provided an expository account of famous inventors. The results were that the second and third texts were judged as more interesting.

Many results showed that interest, especially the personal dimension, was strongly related to prior knowledge (Tobias 1994). Renninger and Wozniak (1985) reported that preschoolers shifted their attention on the basis of personal and gender-related interests. Interest also affected pictorial recognition and recall of play objects. Baldwin, Peleg-Bruckner, and McClintock (1985) found that interest and prior knowledge both affected learning in middle-school students, but that interest and prior knowledge were unrelated.
Overall, we can infer the following points about situational interest: (a) it was related to attention and learning, (b) it varied from person to person, and (c) it was elicited by a variety of factors such as prior knowledge, unexpected text content, text structure, and reader goals.

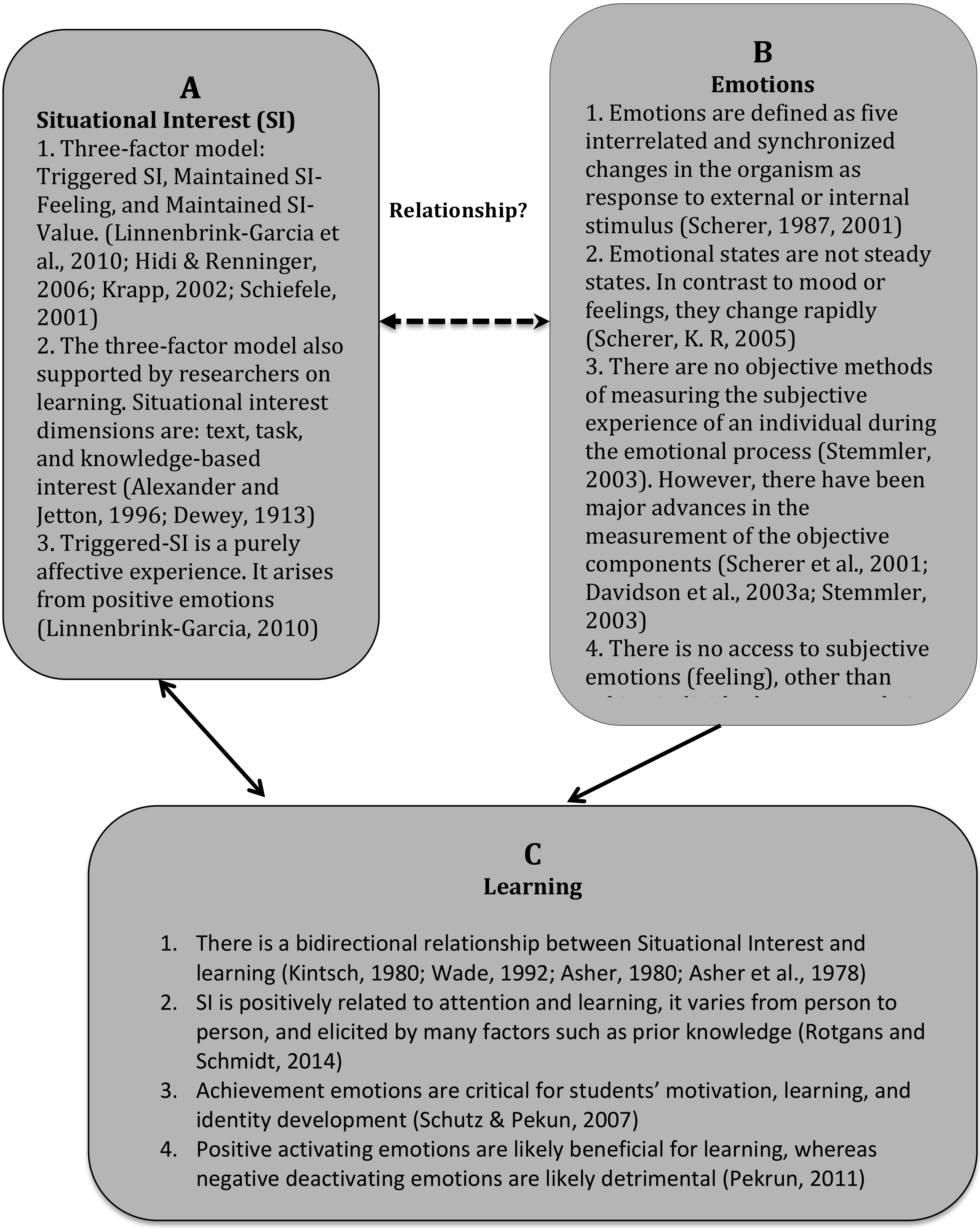
The literature reviewed suggests that both personal and situational interest are related to comprehension (Hidi, 1990; Schiefele, 1999). Situational interest has been shown to have stronger, positive relationship to comprehension. This pattern can be explained by the fact that personal interest is more related to prior knowledge (Alexander and Jetton, 1996; Tobias, 1994).
Even though many studies showed that higher interest is related to more learning (Alexander and Jetton, 1996; Hidi and Baird, 1988; Hidi, 1990; Schraw, 1997; Schraw et al., 1995; Wade and Adams, 1990; Wade et al., 1995), the relationship is not straightforward. Many studies reported that "seductive details" might induce more learning (Garner et al., 1989, 1991; Harp and Mayer, 1998). Moreover, each of the dimensions of situational interest is related to learning (Gregory Schraw and Stephen Lehman, 2001). In addition, situational interest is related to other variables besides knowledge. These variables include: text coherence (Schraw et al., 1995;Wade, 1992), the inclusion of emotionally charged or provocative information (Kintsch, 1980, Schank, 1979), the degree to which text information engages the reader (Mitchell, 1993), and the relevance of information to the reader's goals (Schraw and Dennison, 1994; Shirey, 1992). Almost all studies reveal that higher levels of situational interest are correlated positively to better learning (Schraw et al., 1995;Wade et al., 1993), including the understanding of text's main themes (Schraw, 1997). However, several studies reported that seductive text segments interfered with seductive, but less important main ideas (Garner et al., 1991 and Harp and Mayer (1997, 1998)). Positive correlation was also reported with sophistication of holistic text interpretations.

POINT OF DEPARTURE

The previous literature review reveals a meticulous study of the mutual influence of situational interest and emotions on learning. Interest was found to influence positively knowledge and learning strategies in general. Similarly, a complex relationship has been proven between

emotions and learning. However, fewer studies have been found on the interactions between situational interest and emotions. The purpose of this pilot study is to investigate the concept of situational interest and its potential relationship to emotions. Figure 2 summarizes the major findings from the literature review and the void in the current knowledge this study aims to fill.
It is clear that emotions play a significant role in the learning process; similarly there is a clear relationship between emotions and learning. Therefore, one can argue that there might be a relationship between situational interest and emotions, according to the transitive principle. In mathematics, a binary relation R over a set X is "transitive if whenever an element 'a' is related to an element 'b', and b is in turn related to an element c, then a is also related to c" (Hazewinkel & Michiel, 2001). However, it is also obvious that these relationships are complex and not completely understood. Thus, no conclusions could be drawn from the aforementioned relationships. An Independent study is needed where the research procedure is not biased by the previous research. Moreover, because of the numerous challenges associated with observing, measuring, and inducing emotions, most of the aforementioned research was conducted through artificial contexts. In addition, there is a clear framework defining situational interest in the literature, but there is still disparity in opinions concerning its measurement. Consequently, to test the hypothesis that there is an association between emotional states and dimensions of situational interest in construction environments, a controlled experiment was designed and executed in a real construction site. The data collection objectives were to (1) induce various positive and negative emotions using validated live safety demonstrations (Bhandari and Hallowell, 2015). (2) Objectively measure emotional states using a survey as it is the only way to measure the subjective emotional process (Stemmler, 2003). (3) Measure change in interest before and after delivering Live safety Demonstrations. Finally statistically analyze the data to infer whether or not there is a linear relationship between these variables.

Figure 2 Our Thesis Hypothesis: if A is related to C and C related to B then is A related to B?


A
Situational Interest (SI)
1. Three-factor model: Triggered SI, Maintained SI-Feeling, and Maintained SI-Value. (Linnenbrink-Garcia et al., 2010; Hidi & Renninger, 2006; Krapp, 2002; Schiefele, 2001)
2. The three-factor model also supported by researchers on learning. Situational interest dimensions are: text, task, and knowledge-based interest (Alexander and Jetton, 1996; Dewey, 1913)
3. Triggered-SI is a purely affective experience. It arises from positive emotions (Linnenbrink-Garcia, 2010)
Relationship?
B
Emotions
1. Emotions are defined as five interrelated and synchronized changes in the organism as response to external or internal stimulus (Scherer, 1987, 2001)
2. Emotional states are not steady states. In contrast to mood or feelings, they change rapidly (Scherer, K. R, 2005)
3. There are no objective methods of measuring the subjective experience of an individual during the emotional process (Stemmler, 2003). However, there have been major advances in the measurement of the objective components (Scherer et al., 2001; Davidson et al., 2003a; Stemmler, 2003)
4. There is no access to subjective emotions (feeling), other than
C
Learning
1. There is a bidirectional relationship between Situational Interest and learning (Kintsch, 1980; Wade, 1992; Asher, 1980; Asher et al., 1978)
2. SI is positively related to attention and learning, it varies from person to person, and elicited by many factors such as prior knowledge (Rotgans and Schmidt, 2014)
3. Achievement emotions are critical for students' motivation, learning, and identity development (Schutz & Pekun, 2007)
4. Positive activating emotions are likely beneficial for learning, whereas negative deactivating emotions are likely detrimental (Pekrun, 2011)

Data Collection

This study is part of a broader research conducted by Dr. Hallowell and Bhandari. The main objectives are: (1) validate the findings of the pilot study, about the interplay between risk perception and emotions (Tixier, 2013). (2) Investigate the influence of demographic factors such as: ethnicity, age, education, and marital status…etc. (3) look into potential relationships between situational interest and emotional states which is the core purpose of this report. Even though learning plays an important role to interpret the results and constitutes an essential application, the purpose of this research was not to study the learning process or validate any findings directly linked to knowledge or learning.

As previously indicated, our research goal for this study was to measure: emotional response and situational interest change to the active, experience-based demonstrations that incorporated theory of andragogy (Bhandari, 2015). In order to achieve this goal, Bhandari and Hallowell (2015) delivered the demos to 1,200 construction workers in Kenedy, Texas. The same procedure was followed through sixteen sessions (about 75 workers per session). The procedure followed insured a great internal and external validity. Workers were given choice to participate or not to the study. Out of 1,200 workers, 489 (40%) volunteered. In addition, no compensation or encouragement of any sort was provided to eliminate any external influences. For reliability and replicability purposes, instructors followed a set script. The surveys provided before and after the demos, were given in both English and Spanish, as some workers were Native Americans and others Hispanic.

In order to measure change in situational interest before and after delivering Live Safety Demos a questionnaire was developed. The survey included twelve questions (Figure 3), where workers were asked to rate their interest on 5-point scale. This questionnaire was built on a thorough review of the literature. Linnenbrink-Garcia et al. (2010), developed a similar framework that distinguish the three different dimensions of situational interest (Figure 3): Triggered interest, which is similar to the concept of "catch" as both arouse and grab attention (Mitchell's, 1993); Maintained Interest referred to as "hold," is a more involved, deeper form of situational interest. Individuals begin to build a meaningful and durable connection with the content of the material and realize its deeper significance (Dewey, 1913; Hidi, 2001; Mitchell, 1993). Our questionnaire respects the three-factor model for situational interest (Linnenbrink-Garcia et al., 2010), also supported by (Hidi & Harackiewicz, 2000; Hidi & Renninger, 2006 ; Schraw and Lehman, 2001). Surveys also included a questionnaire to measure workers' emotional response to the live demos. Bhandari and Hallowell (2015) validated the experimental design and the main results are summarized in Figure 4 below.

For a detailed description of how the dataset was gathered and how the experiment was conducted, please consult Bhandari and Hallowell (2015). This study focuses on the analyses of these data.

Figure 3 Situational Interest Questionnaire By Dimension

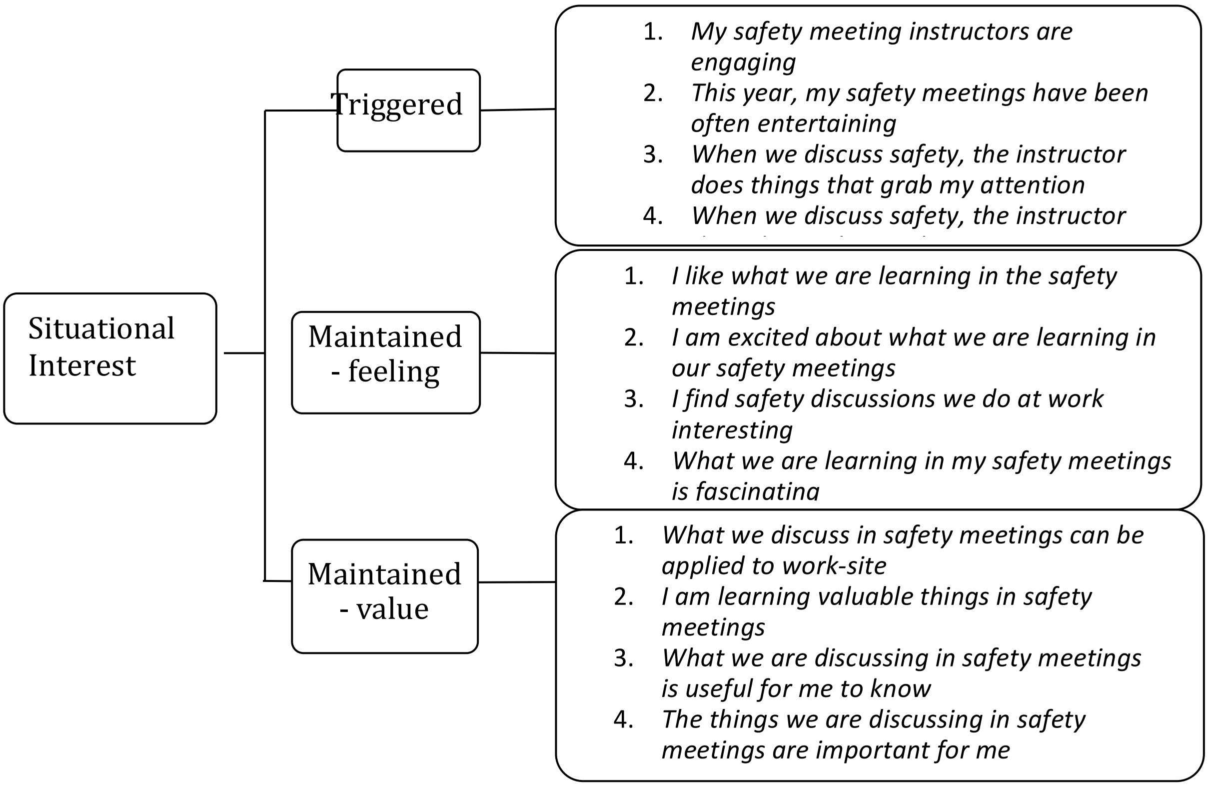
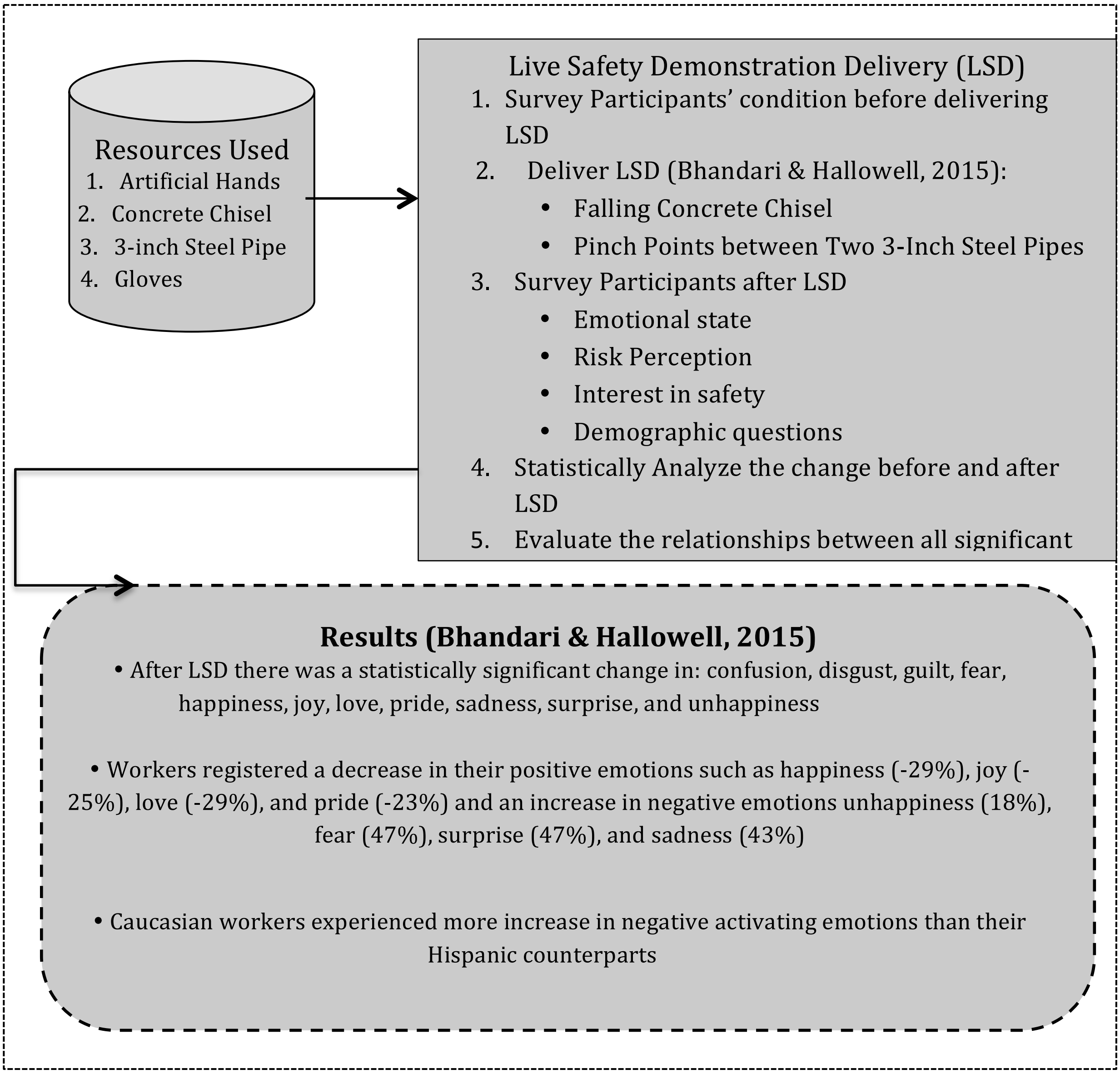


Figure 4 Summary of Bhandari and Hallowell (2015) Pilot study



Results

In this study we further analyzed the data previously collected by Bhandari and Hallowell (2015). We used a paired t-test to evaluate the change in Situational Interest's dimensions before and after delivering the Live Demos. After measuring the impact of the live demos on situational interest, we used multivariate statistical methods to reduce the dimension of the dataset and measure the relationship between emotions and situational interest. Our choice of paired t-test was driven by the fact that both measurement variables are related to the same nominal variable (McDonald, J.H. 2014). As in most psychology and construction research papers, we considered results statistically significant when p-value was less than 0.05 (95% significance).

As mentioned above, the sample size consisted of 492 volunteers out of 1,200 initial workers. All participants volunteered and were not offered any compensation. This particularity of our study makes our results very strong, because it reduces procedural bias drastically. Shuttleworth (2009) argues that employees asked to fill out a questionnaire during their break period are likely to rush, rather than reading the questions properly. In addition, 48% workers had more than 32 years (mean of the sample) professional experience in the construction industry. Workers' large experience in the industry makes increasing their interest in safety related subjects more challenging and, therefore, our results more significant.

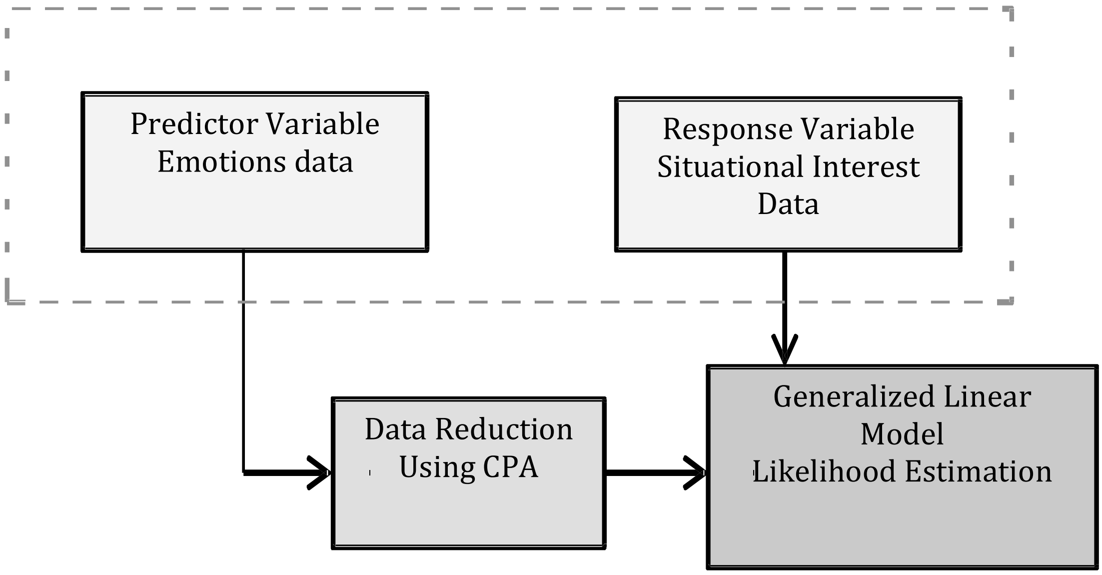
The sample size consisted of workers with a mean age of 38 years old and 67% of them were married, 2% were single and 31% declined to answer. Among participants 30% were Caucasian, and 69% were Hispanic or African American. Therefore no ethnic minorities were omitted. Participants also represented all levels of education. 34% had some college education, 58% stopped at high school and the remaining 8% did not answer. These statistics show a divers representation of many experience, educational levels, age, and ethnic groups, which reduces considerably any omission bias or inclusive bias. However, the absence of women representation in the sample hampers extrapolations to the entire gender population.

To test the effect of Live Safety Demos on situational interest (SI), we tested the difference in means of SI before and after delivering Live demos. Since the variance of the sample is unknown and the data is normally distributed (see figure 5), a paired t-test seemed the most appropriate and the most powerful (Rubin, Donald B, 1973). For the overall population, 10 out of 12 questions of situational interest showed a strong statistical increase. Although two questions of maintained interest were not statistically significant (p-value>0.05), they showed a positive trend (Table2). Therefore we can infer that Live Demos increased all dimensions of situational interest.

We further analyzed the influence of live demos on interest of Hispanic and Caucasian workers separately. Hispanic workers showed much higher change in situational interest than Caucasian workers. In fact, table 3 shows that Hispanic workers experienced a significant increase in all SI questions. Whereas Caucasian workers registered significant increase in 6 questions and decrease in 5 questions. Table 4 also shows that maintained interest-value based is the dimension of situational interest that decreased. In addition, participants above 38 years old experienced a statistical significant increase in all situational interest dimensions. For workers below 38 years, the trend was less uniform. Triggered situational interest questions were the only significant ones (Table 5)

The paired test also revealed different trends for workers who have been injured and those who have not. Workers who have never experienced an injury registered a significant increase in all situational interest dimensions. Whereas workers who experienced a degree of injury showed less significant increase and some situational interest dimensions registered a negative trend. However, we cannot conclude that experiencing an injury decreases situational interest, as not all dimensions were significant (Table 7). We also tested the influence of other demographics such as marriage and years of professional experience in the industry. Married workers showed twice the increase that single workers experienced. Ten out of twelve questions were significant for married workers, whereas only 5 prompts were significant for single workers (Table 6). Workers with less than 9 years in the industry were much more interested in live demonstrations than more experienced workers. In fact, 11 questions out of 12 registered a statistically significant increase. In contrast, workers with more experience had only 3 statistically significant increases, with 4 prompts showing a decreased situational interest. Therefore, we can infer that prior experience strongly increases interest in safety, but after a threshold (9 years in this study) workers were less interested (Table 7b). This result is similar to other studies showing that interest is strongly related to prior knowledge (Tobias 1994).

Figure 5 Processes of Data Handling and Multivariate Testing



Multivariate Data Analysis

The multivariate data analysis section includes analysis of data using all variables at the same time. In contrast to the first approach of this study, we tested linear relationships between each emotion and each dimension of situational interest. This approach has the advantage of reducing the dataset to principal emotions using PCA. We will thoroughly discuss this statistical technic in the following section. Using these principal emotional groups, we fitted a logistic regression to the situational interest data. This method allowed us to predict the likelihood that there will be an increase in SI given certain values of emotional states. This process is illustrated in Figure 5.

Clustering Emotions using Principal Component Analysis

To model the relationship between subjects' emotions and their situational interest, the dimension of the data set was reduced using principal component analysis (PCA). Principal component analysis (PCA) is a multivariate procedure aimed at reducing the dimensionality of multivariate data while accounting for as much of the variation in the original data set as possible. This technique is especially useful when the variables within the data set are highly correlated and when there is a higher than normal ratio of explanatory variables to the number of observation. Principal components seeks to transform the original variable to a new set of variables that are (1) linear combinations of the variables in the data set, (2) uncorrelated with each other, and (3) ordered according to the amount of variation of the original variables that they explain (Gregory B. Anderson, 2011). Figure 6a represents a scatterplot of emotions' data. The figures show that variables are highly correlated. Looking at the correlation matrix also supports this claims, because many coefficient are significantly different from 0.

In R there are two general methods to perform PCA without any missing values: (1) spectral decomposition (R- mode also known as eigen decomposition) and (2) singular value decomposition (Q-mode; R Development Core Team 2011). Both of these methods can be performed longhand using the functions eigen (R-mode) and svd (Q- mode), respectively, or can be performed using the many PCA functions found in the stats package and other additional available packages. We used the function princomp to perform principal component analysis using the spectral decomposition of a matrix (i.e., R-mode PCA). The calculation is actually done using eigen on either the correlation or covariance matrix (Kim and Mueller, 1978); however, the function is called using either a data matrix or a formula with no response variable. For this study we used a data matrix. The arguments for the function are as follows: formula (e.g., ~X1+X2), data (optional data frame containing the variables), subset (an optional vector used to select particular rows of the data matrix), na.action (a function to indicate how missing values should be treated), x (a matrix or dataframe to be used), cor (a logical statement; if TRUE then the PCA is performed on the correlation matrix, if FALSE the PCA is performed on the covariance matrix), scores (a logical statement indicating if the scores should be calculated), covmat (a covariance matrix to be used instead of the covariance matrix of x), and newdata (Kim and Mueller, 1978).

This method allows identifying small subsets of data set that contains most of the variability of the observed system (Joliffe 1986). This transformation is specifically used to spot highly correlated emotions and group them as new uncorrelated and independent emotional groups.

We used R functions to perform the PCA. The model is such a way that the first principal component has the largest possible variance (accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is uncorrelated (orthogonal) to the preceding components. For deeper specifications, the principal components are uncorrelated because they are the eigenvectors of the covariance matrix, which symmetric. In the scope of our study we will not expand further in the theory of PCA; however, we will explain the results and other tests related to PCA. PCA has many advantages: (1) It provides uncorrelated set of emotional groups, which in turn will be much more efficient to test relationships between situational interest and emotions; (2) While it dramatically reduces the dimensionality of the original data set, it retains most of the information initially present (Massey 1965). Although PCA is primarily intended for continuous variables Muthén and Kaplan (1985) showed that PCA performs quite well with ordered categorical variables such as answers to Likert scales, especially for data reduction and clustering. More precisely, Muthén (2004) found that it is possible to find true parameter values in PCA with Likert scale data. In this study, PCA was only used as a way to identify clusters among the independent related variables. This approach is very similar to the study conducted by Tixier and Hallowell (2014). The large data set we used for this study (492 observations) allowed us to keep all 16 emotions. In fact, a minimum of 10 observations per independent variable is an absolute minimum to use PCA (Comrey and Lee (1992) and Tabachnick and Fidell (2001)). In addition, in order for the PCA groupings to be significant and strong, the number of subjects should be greater than five times the number of variables being analyzed (Hatcher, 1994). With 16 variables and a number of participants of 492, this requirement was obviously validated. We used as mentioned above R to perform PCA.

Three-Component Model

First Iteration

Two iterations of the PCA were needed before obtaining significant results. The first iteration led to the selection of the best variables, following the recommendations of Norman and Streiner (2007). In fact, according to Norman and Streiner, the best variables for PCA are those with individual sampling adequacy scores above 0.5. For this purpose, we conducted a Kaiser-Meyer-Oklin (KMO) test to identify individual sampling adequacy scores for all our emotional variables. KMO is a test developed by Henry Kaiser (1970) and modified later by Kaiser and Rice (1974) that measures sampling adequacy for factor analytic data matrices. The Kaiser-Meyer-Olkin criterion indicates whether a data set is suitable for a factor analysis. Interpretive adjectives for the Kaiser-Meyer-Olkin Measure of Sampling Adequacy are: in the 0.90 as marvelous, in the 0.80's as meritorious, in the 0.70's as middling, in the 0.60's as mediocre, in the 0.50's as miserable, and below 0.50 as unacceptable. The value of the KMO Measure of Sampling Adequacy for the overall set of variables is 0.8749083, which would be labeled as 'meritorious'. Since the KMO Measure of Sampling Adequacy meets the minimum criteria, we do not have a problem that requires us to examine the Anti-Image Correlation Matrix. Bartlett's test of sphericity tests the hypothesis that the correlation matrix is an identify matrix; i.e. all diagonal elements are 1 and all off-diagonal elements are 0, implying that all of the variables are uncorrelated. If the Sig value for this test is less than our alpha level, we reject the null hypothesis that the population matrix is an identity matrix. The Sig. value for this analysis leads us to reject the null hypothesis and conclude that there are correlations in the data set that are appropriate for factor analysis (p-value <0.01). This analysis meets this requirement. Overall, the KMO and Bartlett's test of sphericity showed that the variables under study were related. In addition, the KMO measure is strong and suggests that PCA is an appropriate method to reduce the dimension of variables. According to Norman and Streiner (2007), variables with sampling adequacy scores below 0.7 had to be removed from the data set. Table 7a shows the individual sampling adequacy per variable. Amusement and anger were therefore removed, because they had individual sampling adequacy scores of 0.67<0.7 each. The final three-component model has been chosen following the recommendations of Gregory B. Anderson (2011).

Second Iteration

After removing amusement and anger emotions, all individual sampling adequacy scores improved to more than 0.7. The second iteration showed significant loadings. In addition, since we were interested in clustering emotions we only used the pattern matrix from R outputs. Table 8a shows the variability that every component accounts for. From the literature (Bro, R., & Smilde, A. K., 2014; Abdi, H., & Williams, L. J., 2010, Antoine, 2014) we could infer that the most important principal components are those with variance greater than 1. For this particular reason a three-component model seems the most appropriate. In addition, this model account for approximately 65% of the variance present in the initial data set (Table 8a and Figure8a) shows the importance of components. In other words, the cumulative proportion is the amount of information represented by the component model. Among the outputs of R function used, the loadings matrix or the pattern matrix, which will help cluster emotions into groups (Table 10a).

Loadings are considered significant when equal to 0.3 or higher (Kline 2002). Furthermore, each component should include few loadings close to zero (Kline, 2002;Bryant and Yarnold, 1995). From the pattern matrix (Table 10a), an almost perfect simple structure is reached. Only two emotions could be qualified as somewhat complex (anxiety and fear). The loading coefficients for these two variables were almost significant (0.29 and 0.28). In addition, the model seems logical from a theoretical standpoint. As all significant loadings on component 1 measure mid negative emotions (confusion, embarrassment, guilt, and disgust). Similar conclusions for component 2 (Happiness, Joy, Love, Pride) and component 3 (sadness and unhappiness). Component 2 measure positive emotions and component 3 measure strong negative emotions.

Table7a First Iteration- Individual Sampling Adequacy Scores

	Sampling adequacy scores
Amusement	0.6690321
Anger	0.6690321
Anxiety	0.9459322
Confusion	0.9127532
Disgust	0.9550345
Embarrasment	0.9384236
Fear	0.9353199
Guilt	0.9488285
Happiness	0.7654725
Joy	0.8390439

Love	0.8732927
Pride	0.8825258
Sadness	0.8173285
Shame	0.9457734
Surprise	0.8933004
Unhapiness	0.939639

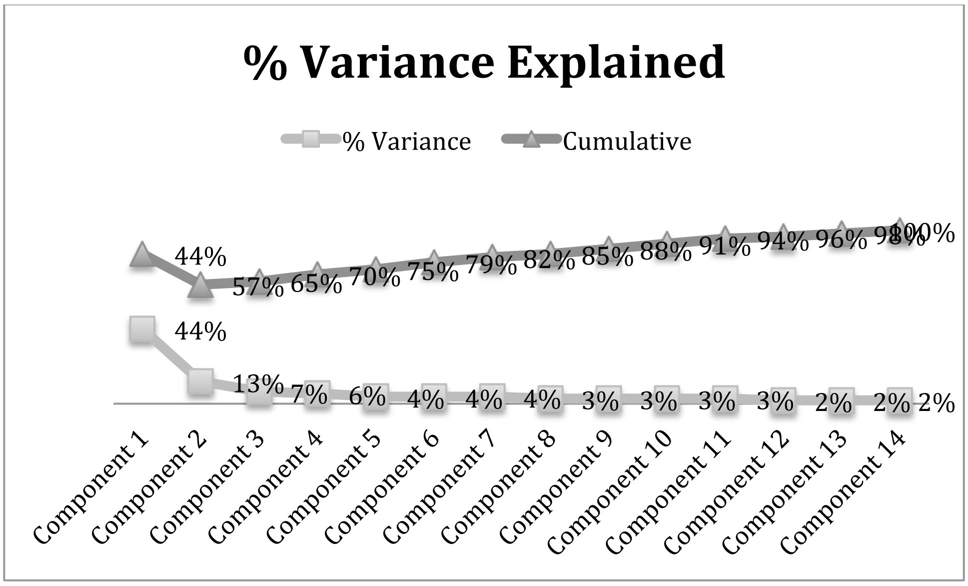
Table 8a Second Iteration-Total Variance Explained By Principal Components

	Total	% Variance	Cumulative
Component 1	2.4859834	44%	44%
Component 2	1.3573179	13%	57%
Component 3	1.01526332	7%	65%
Component 4	0.8853073	6%	70%
Component 5	0.78907636	4%	75%
Component 6	0.7520788	4%	79%
Component 7	0.70072873	4%	82%
Component 8	0.65987722	3%	85%
Component 9	0.64268909	3%	88%
Component 10	0.60618702	3%	91%
Component 11	0.59971756	3%	94%
Component 12	0.57611279	2%	96%
Component 13	0.5650053	2%	98%
Component 14	0.5069651	2%	100%

Table 10a Second Iteration- Clustering Emotions

	Component 1	Component 2	Component 3
Anxiety	-0.2986328	-0.11512462	-0.180534335
Confusion	-0.3075111	-0.15832071	-0.080311027
Disgust	-0.3020295	-0.12031972	0.10427066
Embarrasment	-0.3255268	-0.09553933	-0.017616835
Fear	-0.2828245	-0.20614431	-0.196813961
Guilt	-0.3144987	-0.06777676	-0.042886978
Happiness	-0.1590116	0.48147378	-0.430874954
Joy	-0.1939659	0.48333066	0.192447488
Love	-0.2264308	0.407476	0.314098175
Pride	-0.2092936	0.39959924	0.210249652
Sadness	-0.2260147	-0.26009332	0.573665632
Shame	-0.3059906	-0.03278963	0.012999341
Surprise	-0.2102292	0.02816768	-0.46298312
Unhappiness	-0.3054103	-0.17415002	0.005769698

Figure 8a Variance Explained by Principal Components



Comparing Clusters to Past Literature

In fact, the examination of the pattern matrix reveals that happiness, joy, love, pride were clearly defined by the second component. Moreover, embarrassment, guilt, and disgust were also defined by component 1. However, anxiety and fear failed to load significantly on any of the factors. Component 1 involved a combination of guilt, confusion, disgust, and embarrassment subscales, which in the context of this study can be qualified as mid negative emotions. Guilt and disgust registered a modest increase, while embarrassment and confusion decreased. Therefore, participants experimented moderate introvert negative emotional states (Boyle, 1984). Component 2 involved a cluster of positive mood states. Interestingly, all positive emotional states loaded significantly on component2. However, in the context of this study and due to the fact that all these positive emotions decreased after delivering Live Safety Demos, this component may not represent strong positive mood. Finally, component 3 is a combination of sadness and surprise. In past literature, surprise could be assigned to positive mood as well as negative mood (Izard, 1972; Boyle, 1984; Cisler et al. 2009) Overall, clustering emotions using PCA revealed statistically significant components but also emotional groups supported by past literature (Cisler et al. 2009; Boyle 1984, Tixier and Hallowell, 2014).

Testing for classification in situational interest using multivariate generalized linear model

In supervised learning problems, the goal is to predict outputs (or label), based on inputs (or features) (Alex Smola and S.V.N. Vishwanathan, 2008). In the real world, outputs can be either quantitative, if we want, for example, to predict an action's price, or qualitative (or categorical) if we predict the belonging to two or many classes (such as hand written digits for example). While the problems that predict the further class of problems are called regression problems, they are called classification problems if the labels are categorical (Alex Smola and S.V.N. Vishwanathan, 2008).

Binary Classification

For this study, we used binary classification technique to analyze the relationship between emotional clusters and variance of situational interest. Binary classification is a prediction problem where the outputs can belong to two different classes. We will model these outputs as a variable $y \in \{0, 1\}$. These variables are drawn from a pattern $x \in \mathbb{R}^p$, where p is the number of features (Alex Smola and S.V.N. Vishwanathan, 2008). In contrast, a traditional linear model will try to predict the output Y, given the input x via the model

$$\hat{Y} = \beta_0 + \sum_{j=1}^{p} x_j \beta_j = X^T \beta$$

The term β_0 is the intercept (or bias), the β_j is the coefficient correspond to each feature $j \in \{1 .. p\}$. For better readability, we have included the intercept in the weights vector β, and added a feature $x_0 = 1$ to the feature vector x. However, linear regression is best suited for regression problems. For classification tasks, logistic regression is preferred (Alex Smola and S.V.N. Vishwanathan, 2008).

Logistic regression

Logistic regression is one of most widely algorithms used for classification problems, for its simplicity and its ability to handle very large amount of data (Alex Smola and S.V.N. Vishwanathan, 2008). The logic behind the model is to model the posterior probabilities of the output classes as a linear function of x, while ensuring at the same time that the probabilities sum to one and are included in [0,1]. The model has the form:

$$\log \frac{\Pr(Y = 0 | X = x)}{\Pr(Y = 1 | X = x)} = \beta_0 + \sum_{j=1}^{p} x_j \beta_j = X^T \beta$$

Using $\Pr(Y = 0 | X = x) + \Pr(Y = 1 | X = x) = 1$, we end with the following equations:

$$\Pr(Y = 0 | X = x) = \frac{1}{1 + e^{-X^T \beta}}$$

$$\Pr(Y = 1 | X = x) = \frac{1}{1 + e^{X^T \beta}}$$

Those two equations can be summarized in the following one:

$$\Pr(Y = y | X = x) = \frac{1}{1 + e^{-y.X^T \beta}}$$

To perform a logistic regression, we had first to convert our dataset of situational interest from a response scale (continuous data) to a binary data set. When change in situational interest was greater or equal to zero then the response variable was 1, in contrast when SI increased we affected 0 to the response variable. To measure the relationship between the categorical dependent variable (SI) and the dependent variables (components from the PCA analysis), we estimated the probabilities mentioned above.

Results and Analysis

The generalized linear model from R commands provided: (1). Estimated log odds, which are estimated scores of the linear model. (2). P values for every independent variable (PC) showing the significance of the predictive variable. (3). Confidence intervals for the coefficient estimates.
Table 11 shows the estimated scores for every independent variable. The logistic regression coefficients give the change in the log odds of the outcome for a one-unit increase in the predictor variable. To test the overall effect of the components (predictor variables) we used the wald.test function of the aod library. The order in which the coefficients are given in the table of coefficients is the same as the order of the terms in the model (Table 11). To use the wald.test function: b supplies the coefficients, while Sigma supplies the variance covariance matrix of the error terms, finally Terms tells R which terms in the model are to be tested. The chi-squared test statistic, with three degrees of freedom is associated with a p-value indicating that whether the overall effect of our components is statistically significant or not. We also wished to measure the goodness of fit (how well the model fits). The output produced by the summary command included indices of fit (shown below the coefficients), including the null and deviance residuals and the AIC. One measure of model fit is the significance of the overall model. This test asks whether the model with predictors fits significantly better than a model with just an intercept (i.e., a null model). The test statistic is the difference between the residual deviance for the model with predictors and the null model. The test statistic is distributed chi-squared with degrees of freedom equal to the differences in degrees of freedom between the current and the null model (i.e., the number of predictor variables in the model).

(1). "What we discuss in safety meetings can be applied to work-site" registered a significant predictor (PC3, p-value=0.005). For every one unit change in strong-negative emotions, the log odds of first question (Maintained SI value based) deceases by 0.60. The confidence interval for this coefficient is -1.02 and -0.18. We note that for logistic regression models, confidence intervals are based on the profiled log-likelihood function. Moreover, the wald.test has a p-value of 0.023 indicating that the overall effect of the components is statistically significant. We performed a deviance test with a p-value of 0.03. The model as a whole fits significantly better than an empty model (constant model). Therefore, these results may mean that workers in strong negative emotional states are more likely to maintain their interest in safety and particularly the practical application of safety meetings to work-site.

(2). "When we discuss safety, the instructor does things that grab my attention" showed a significant predictor (PC3, p-value=0.04). For every one unit change in strong negative emotions, the log odds of second question (Triggered SI) deceases by 0.40. The confidence interval for this coefficient is -0.78 and -0.01. Moreover, the wald.test has a p-value of 0.21 indicating that the overall effect of the components is not statistically significant. We performed a deviance test with a p-value of 0.19. The model as a whole does not fit significantly.

(3). "It's easy to pay attention to my safety meetings" showed a significant predictor (PC3, p-value=0.03). For every one unit change in strong negative emotions, the log odds of question

(Triggered SI) deceases by 0.42. The confidence interval for this coefficient is -0.81 and -0.02. Moreover, the wald.test has a p-value of 0.17 indicating that the overall effect of the components is not statistically significant. We performed a deviance test with a p-value of 0.15. The model as a whole does not fit significantly.

(4). “My safety meeting instructors are engaging” did not show any significant predictor. Moreover, the wald.test has a p-value of 0.16 indicating that the overall effect of the components is not statistically significant. We performed a deviance test with a p-value of 0.13. The model as a whole does not fit significantly. Therefore, we could infer that for this question emotional states are not predictive.

(5). “This year, my safety meetings have been often entertaining” did not show any significant predictor. Moreover, the wald.test has a p-value of 0.84 indicating that the overall effect of the components is not statistically significant. We performed a deviance test with a p-value of 0.83. The model as a whole does not fit significantly. Therefore, we could infer that for this question emotional states are not predictive.

(6). “I am excited about what we are learning in our safety meetings” did not show any significant predictor. Moreover, the wald.test has a p-value of 0.12 indicating that the overall effect of the components is not statistically significant. We performed a deviance test with a p-value of 0.10. The model as a whole does not fit significantly. Therefore, we could infer that for this question emotional states are not predictive.

(7). “What we are learning in my safety meetings is fascinating” registered a significant predictor (PC1, p-value=0.01). For every one unit change in mid-negative emotions, the log odds of question (Maintained SI feeling based) deceases by 0.15. The confidence interval for this coefficient is -0.27 and -0.03. Moreover, the wald.test has a p-value of 0.031 indicating that the overall effect of the components is statistically significant. We performed a deviance test with a p-value of 0.03. The model as a whole fits significantly better than an empty model (constant model).

(8). “The things we are discussing in safety meetings are important for me” registered a significant predictor (PC1, p-value=0.009). For every one unit change in mid-negative emotions, the log odds of question (Maintained SI value based) deceases by 0.16. The confidence interval for this coefficient is -0.28 and -0.04. Moreover, the wald.test has a p-value of 0.015 indicating that the overall effect of the components is statistically significant. We performed a deviance test with a p-value of 0.01. The model as a whole fits significantly better than an empty model (constant model).

(9). “I find safety discussions we do at work interesting” registered a significant predictor (PC3 p-value=0.005). For every one unit change in strong negative emotions, the log odds of question (Maintained SI feeling based) deceases by 0.50. The confidence interval for this coefficient is -0.86 and -0.14. Moreover, the wald.test has a p-value of 0.056 indicating that the overall effect of the components is statistically significant. We performed a deviance test with a p-value of 0.04. The model as a whole fits significantly better than an empty model (constant model).

10). “I like what we are learning in the safety meetings” registered two significant predictors (PC1 and PCA3 with respectively p-value=0.04 and p-value=0.02). For every one unit change in mid and strong negative emotions, the log odds of question (Maintained SI feeling based) deceases respectively by 0.30 and 0.38. The confidence interval for these coefficients are: -0.60, -0.004 and -0.70, -0.05. Moreover, the wald.test has a p-value of 0.038 indicating that the overall effect of the components is statistically significant. We performed a deviance test with a p-value of 0.02. The model as a whole fits significantly better than an empty model (constant model)

11). "What we are discussing in safety meetings is useful for me to know" registered two significant predictors (PC1 and PCA3 with respectively p-value=0.02 and p-value=0.06). For every one unit change in mid and strong negative emotions, the log odds of question (Maintained SI value based) deceases respectively by 0.14 and 0.36. The confidence interval for these coefficients are: -0.27, -0.02 and -0.75, -0.02. Moreover, the wald.test has a p-value of 0.02 indicating that the overall effect of the components is statistically significant. We performed a deviance test with a p-value of 0.01. The model as a whole fits significantly better than an empty model (constant model).

(12). "I am learning valuable things in safety meetings" registered a significant predictor (PC3 p-value=0.03). For every one unit change in strong negative emotions, the log odds of question (Maintained SI value based) deceases by 0.39. The confidence interval for this coefficient is -0.75 and -0.02. Moreover, the wald.test has a p-value of 0.25 indicating that the overall effect of the components is not statistically significant. The likelihood test shows a p-value of 0.24. The model as a whole is not significantly better than an empty model (constant model). Therefore, this question could be qualified as complex, because despite the significant predictor (PC3) the overall goodness of fit is not significant.

Emotional states may not be predictive of this particular question. The findings reveal an interesting trend. Three questions of situational interest did not show any significant emotional predictors. Surprisingly these three questions belonged to triggered and maintained situational interest feeling based. In past literature, maintained-SI feeling based is defined as the affective experiences individuals associate with their environment while engaging in domain content (e.g., enjoyment, excitement) (Schiefele, 1991; 2001). Triggered-SI is also related to affective experiences; however, it refers more specifically to initiating or grabbing an individual's interest (Mitchell's, 1993; Hidi, 2001; Hidi & Harackiewicz, 2000; Hidi & Renninger, 2006). We would expect that emotional states predict most of triggered situational interest questions. Although the overall significance of fitted regression was not reliable for two questions of triggered interest, data showed that strong negative emotional states could predict significantly these two questions. Moreover, three out of four questions of maintained-SI feeling based were predicted by mid and strong negative emotional states. Similarly, maintained-SI value based was predicted significantly by strong negative emotional states. Therefore, we could infer that for both cognitive and affective related dimensions of situational interest, negative emotional states were significantly related to negative emotions. Surprisingly, positive emotional states did not show any significant relationship to situational interest dimensions. These findings are supported by theories in past literature. Researchers such as Kintsch (1980) distinguished between emotional and cognitive interest. Emotional interest is negative affective response to text information such as elation, disgust, or anger. Cognitive interest is also strongly related to emotions according to (Kintsch, 1980; Schraw & Denninson, 1994). In fact, Kintsch hypothesized that extremely low levels of cognitive interest would lead to reader boredom, also negative emotional states.

Evaluation of Model Skill

The predictive power of this model was measured against the observed data through a rank probability score (RPS). To calculate the RPS, two vectors were constructed, as follows: (1) for forecasted probabilities (Pj), based on the GLM model predictions; and (2) for observed events (zj), from the observed data. Then the cumulative density function (CDF) of Pj and zj were constructed based on the GLM model predictions, resulting in the vectors PCDFj and zCDFj.
The RPS was computed using

$$\mathbf{RPS} = 1/N \times \sum_{i=1}^{j} (\mathbf{P}_{\mathrm{CDF},j} - \mathbf{z}_{\mathrm{CDF},j})$$

In order to test whether the observed data was reproduced by pure chance, it is necessary to compare the RPS obtained to the RPS of the random process. This test can be done through the ranked probability skill score (RPSS), which has been used in various climatological contexts to compare the model's skill in predicting categorical rainfall and streamflow quantities. The RPSS is computed by forming a ratio between the average RPS values of the model and chance. The RPSS compares the accuracy of a model's predictions against chance. The range for RPSS is from minus infinity to 1, where negative values indicate that the model results are worse than chance, 0 means that the model results reproduce chance events, and positive values show that the model results are closer to the original observations than chance (Esmaeili, 2015).

To measure the predictive power of the models, we implemented the widely used measure for categorical data, i.e rank probability skill score. As stated previously RPSS can range from minus infinity to 1. All positive values indicate that the model performance is strong and better than the base model compared to. Table 12 shows the RPS scores for our model compared to climatology scores and finally exhibits the RPSS scores for all situational interest dimensions. The positive values obtained for all SI questions shows that our predictive models are strong and reliable.

Table 12 Ranked Probability Skill Scores

	RPS Model	RPS Climatology	RPSS
SITUATIONAL INTEREST QUESTIONS			
My safety meeting instructors are engaging	9.77	10.13	0.03
I like what we are learning in the safety meetings	6.75	7.53	0.10
This year, my safety meetings have been often entertaining	9.25	10.65	0.14
When we dsicuss safety, the instructor does things that grab my attention	17.68	17.85	0.01
What we discuss in safety meetings can be applied to work-site	20.50	22.55	0.10
I am excited about what we are learning in our safety meetings	6.68	7.04	0.05
I am learning valuable things in safety meetings	5.8	5.96	0.02
I find safety discussions we do at work interesting	6.87	6.90	<0.01
What we are discussing in safety meetings is useful for me to know	5.13	5.28	0.03
The things we are discussing in safety meetings are important for me	4.69	5.41	0.13
What we are learning in my safety meetings is fascinating	7.33	7.73	0.05
It's easy to pay attention to my safety meetings	7.32	8.08	0.09

Limitations and Justifications

First and foremost, we used self-reports to measure emotional states. Previous research showed that people vary greatly in how they distinguish emotions when reporting their experience of them in a natural environment (Feldman, 1995a; Feldman Barrett, 1998; Feldman Barrett, Gross, Christensen, & Benvenuto, 2001). In these studies, some individuals had strong correlations between feeling states of the same valence, so that when they reported feeling sadness, for example, they also reported feeling anxious and angry. These individuals are low in emotional granularity: They reported their experience in global terms, using discrete emotion labels to communicate only the most general of information. However, other individuals had weaker correlations between emotional states of the same valence, indicating that they made finer distinctions in their experiences. These individuals are higher in emotional granularity and reported their emotional experience in more precise, differentiated terms, using discrete emotion labels such as happy, sad, angry, and so forth, in a way that captured the distinctiveness in these words (R. Goodman, H. Meltzer, V. Bailey, 1998). In this study we used self-reports to measure change in emotional states after Live Safety Demonstrations. Therefore, differences between emotional groups remain the same. This study is not impacted by the precision of participants' responses.

Second, when self-reporting some people use the same emotion words in very different ways to communicate their feelings. For example, the word tired, which is generally understood to refer to a state that is unpleasant and low in arousal, can be used to communicate a feeling of sleepiness (emphasizing the low arousal property), annoyance and misery (as in "I am tired of this," emphasizing the unpleasantness), or fatigued (emphasizing both low arousal and displeasure properties).

Third, the results do not statistically allow the conclusion that there is a causal relationship between emotional states and situational interest. Although suggestive of an existing relationship, the statistical methods used did not provide enough significant results to conclude that there is a linear relationship.

Fourth, results showed that Hispanic workers registered much higher change in situational interest than Caucasian workers. However, we cannot generalize these results to other ethnicities. We could infer though that ethnicity and situational interest are not independent.

Finally, Preacher and MacCallum (2002) argue that communalities should be greater than 0.6 to ensure the significance of principal component analysis. However, Suhr, D. D. (2005) also argues Kaiser's (1960) recommendations are followed, researchers should not be concerned about the validity of the components. Although the communalities we found in the PCA are not greater than 0.6 the recommendations of Kaiser were followed: Eigenvalues were all greater than 1, we performed a scree test to determine number of components, the proportion of variance for each component was 5 to 10 % as recommended, and the cumulative proportion of variance 70% which in the range suggested.

Conclusions, Contributions, and Recommendations

This pilot study is the first to investigate the relationship between situational interest and emotions. The results support the hypothesis that negative emotional states predict increase in situational interest. Specifically, the results support previous hypotheses that emotional states are linked to individual's interest. In an academic context, positive activating emotions influence learning positively, while negative deactivating emotions are negatively correlated to learning (Pekrun, 2011). Pekrun also hypothesized that positive emotions are more likely to trigger students' interest in a particular subject than negative emotions. Situational interest is an affective or attentional reaction to the situation (external environment) (Hidi & Anderson, 1992; Hidi & Baird, 1986; Hidi & Renninger, 2006; Krapp, 2002). In an academic context, researchers use academic texts to measure learning performances. Thus, one would expect that in this particular context, situational interest would be stimulated by positive activating emotional states. In the context of live safety demonstrations, our findings confirm the fact that situational interest is strongly liked to the external environment. Negative emotional states predicted most of SI dimensions, and positive emotional states did not show any relationship to SI. The chief theoretical contribution is that the impact of emotions on situational interest in an occupational-like context was measured for the first time. Additionally, this is the first study to implement a process for measuring emotional states, measuring relative situational interest in a realistic environment, and statistically relating these scores through a dimension reduction process and a

multivariate generalized linear model. The results allow the comprehension of how emotions may antecede situational interest, knowledge that is critical to eventually understanding, within the construction field, how to increase interest in safety and ultimately reduce injury rates. The practical implication of this study is that workers in mid negative and strong negative emotional states are more likely to be interested in safety related subjects than workers in positive emotional states. Thus, these findings may mean that pre-job safety meetings should include activities that reflect construction site hazards. Live Safety Demonstrations (LSD) are replicates of frequent construction hazards and may be used for this purpose.
The above-mentioned findings support the conclusions of Bandhari and Hallowell (2015). Live Safety Demos is an effective multi-media safety-training program, which combines andragogical principles of learning and induce the necessary negative emotional states to increase interest in safety. From a practical standpoint, these conclusions are crucial to improve the way pre-job safety meetings are delivered. In fact, we proved that Live safety Demos increase workers' engagement during safety trainings. From a research standpoint, the chief implication of this study is that emotional states are related to (predict) situational interest. The nature of this relationship is yet to be studied and confirmed.

In light of the encouraging findings of this exploratory pilot-study, future research that validates these findings with a larger and more diverse group of participants is suggested. Specifically, it is recommended to repeat the experiment using a different questionnaire, as well as collecting more data, in order for strong predictive models to be built. Additionally, extending testing to the relationships between situational interest and other aspects such as learning strategies and risk perception is recommended. Although this study shows strong evidence of a relationship between one's emotions and situational interest, fully understanding the nature of this relationship requires this additional research.

Appendix

Table 2 Change in Situational Interest (SI) After Live Demos- Significance of Paired t-test

SITUATIONAL INTEREST QUESTIONS	TRIGGERED/ MAINTAINED SI	Mean Before	Mean After	Covariance	P-value (%change)
My safety meeting instructors are engaging	Triggered Situtional Interest	4.42	4.6	0.07	0.004 (3.5%)
I like what we are learning in the safety meetings	Maintained Situtional Interest (feeling based)	4.53	4.66	0.11	0.0028 (3.1%)
This year, my safety meetings have been often entertaining	Triggered Situtional Interest	4.19	4.59	0.29	5.47e-13 (9.1%)
When we dsicuss safety, the instructor does things that grab my attention	Triggered Situtional Interest	4.28	4.68	0.16	4.92e-14 (9.4%)
What we discuss in safety meetings can be applied to work-site	Maintained Situtional Interest (value based)	4.64	4.79	0.13	0.0003 (3.1%)
I am excited about what we are learning in our safety meetings	Maintained Situtional Interest (feeling based)	4.46	4.66	0.26	1.6E-05 (4.2%)
I am learning valuable things in safety meetings	Maintained Situtional Interest (value based)	4.56	4.7	0.19	0.002 (2.9%)
I find safety discussions we do at work interesting	Maintained Situtional Interest (feeling based)	4.46	4.65	0.19	0.001 (3.6%)
What we are discussing in safety meetings is useful for me to know	Maintained Situtional Interest (value based)	4.64	4.71	0.2	0.114 (1.4%)
The things we are discussing in safety meetings are important for me	Maintained Situtional Interest (value based)	4.69	4.76	0.12	0.170 (1.1%)
What we are learning in my safety meetings is fascinating	Maintained Situtional Interest (feeling based)	4.09	4.49	0.39	1.55E-13 (9.7%)
It's easy to pay attention to my safety meetings	Triggered Situtional Interest	4.41	4.7	0.23	2.89E-08 (6.0%)

Table3 Change in Situational Interest for Hispanic Workers

Mean Before Hisp	Mean After Hisp	Covarian	P-value

		ce Hisp	(%change) Hispanic
4.34	4.63	0.04	0.00007 (6.39%)
4.52	4.7	0.08	0.0011 (4.21%)
4.27	4.68	0.25	1.90e-10 (9.5%)
4.34	4.73	0.11	5.30e-09 (9.02%)
4.61	4.81	0.15	4.186e-05 (4.57%)
4.55	4.71	0.2	0.00106 (3.67%)
4.58	4.77	0.12	0.000417 (4.04%)
4.53	4.71	0.1	0.0101 (3.43%)
4.61	4.74	0.19	0.0269 (2.59%)
4.66	4.8	0.07	0.011 (2.68%)
4,22	4.57	0.3	2.59E-08 (8.5%)
4.5	4.79	0.21	8.25E-07 (5.83%)

Table 4 Change in Situational Interest for Caucasian Workers

Mean Before Cau	Mean After Cau	Covariance Cau	(%change) Caucasians
4.55	4.51	0.12	0.36 (-1.75%)
4.54	4.57	0.18	0.768 (0.53%)
4	4.37	0.34	0.001 (8.17%)
4.17	4.56	0.27	0.0000131(9.36%)
4.73	4.73	0.12	0.8 (-0.33%)
4.26	4.51	0.4	0.018 (4.65%)
4.52	4.52	0.33	0.91 (-0.17%)
4.3	4.51	0.38	0.0477 (3.86%)
4.67	4.65	0.25	0.416 (-1%)
4.73	4.66	0.26	0.0851 (-2.14%)
3.77	4.27	0.49	3.137E-06 (12.42%)
4.17	4.51	0.24	0.00188 (7.41%)

Table5 Change in Situational Interest According by Workers' Age

SITUATIONAL INTEREST QUESTIONS	TRIGGERED/ MAINTAINED SI	P-value (%change) Age below or equal to 38	P-value (%change) Age above 38
My safety meeting instructors are engaging	Triggered Situtional Interest	0.1 (2.91%)	0.03 (3.94%)
I like what we are learning in the safety meetings	Maintained Situtional Interest (feeling based)	0.2 (2%)	0.0019 (4.47%)
This year, my safety meetings have been often entertaining	Triggered Situtional Interest	4.76e-06 (8.44%)	4.633E-07 (9.25%)
When we dsicuss safety, the instructor does things that grab my attention	Triggered Situtional Interest	5.58e-08 (10.13%)	1.125e-06 (8.63%)
What we discuss in safety meetings can be applied to work-site	Maintained Situtional Interest (value based)	0.367 (1.22%)	8.894E-05 (4.55%)
I am excited about what we are learning in our safety meetings	Maintained Situtional Interest (feeling based)	0.011 (3.65%)	0.00056 (4.95%)

I am learning valuable things in safety meetings	Maintained Situtional Interest (value based)	0.09 (2.34%)	0.002 (3.93%)
I find safety discussions we do at work interesting	Maintained Situtional Interest (feeling based)	0.062 (3.12%)	0.0037 (4.47%)
What we are discussing in safety meetings is useful for me to know	Maintained Situtional Interest (value based)	0.5 (-0.89%)	0.0046 (3.322%)
The things we are discussing in safety meetings are important for me	Maintained Situtional Interest (value based)	0.8191 (-0.29%)	0.018 (2.62%)
What we are learning in my safety meetings is fascinating	Maintained Situtional Interest (feeling based)	4.15e-06 (8.98%)	1.98e-07 (9.59%)
It's easy to pay attention to my safety meetings	Triggered Situtional Interest	0.0019 (5.17%)	1.139E-06 (6.74%)

Table 6 Change in Situational Interest for Married and Single Workers

SITUATIONAL INTEREST QUESTIONS	TRIGGERED/MAINTAINED SI	P-value (%change) Married	P-value (%change) Single
My safety meeting instructors are engaging	Triggered Situtional Interest	0.00039 (5.43%)	0.342 (2.23%)
I like what we are learning in the safety meetings	Maintained Situtional Interest (feeling based)	0.0014 (4%)	0.171 (2.87%)
This year, my safety meetings have been often entertaining	Triggered Situtional Interest	1.7E-08 (8.91%)	1.754E-06 (11.56%)
When we dsicuss safety, the instructor does things that grab my attention	Triggered Situtional Interest	6.655E-10 (9.56%)	7.711E-05 (9.75%)
What we discuss in safety meetings can be applied to work-site	Maintained Situtional Interest (value based)	0.002 (3.38%)	0.14 (2.44%)
I am excited about what we are learning in our safety meetings	Maintained Situtional Interest (feeling based)	0.0001 (4.41%)	0.0078 (5.02%)
I am learning valuable things in safety meetings	Maintained Situtional Interest (value based)	0.0018 (3.66%)	0.158 (2.45%)
I find safety discussions we do at work interesting	Maintained Situtional Interest (feeling based)	0.003 (4%)	0.070 (3.56%)
What we are discussing in	Maintained	0.180	0.740 (0.5%)

safety meetings is useful for me to know	Situtional Interest (value based)	(1.47%)	
The things we are discussing in safety meetings are important for me	Maintained Situtional Interest (value based)	0.248 (1.22%)	0.819 (0.34%)
What we are learning in my safety meetings is fascinating	Maintained Situtional Interest (feeling based)	4.67E-11 (10.77%)	0.0002 (9.36%)
It's easy to pay attention to my safety meetings	Triggered Situtional Interest	4.868E-07 (7%)	0.004 (5.19%)

Table 7 Change in Situational Interest for workers according to their injury experiences

P-value (%change) Never injured	P-value (%change) First Aid	P-value (%change) Lost Work Time
0.004 (4.3%)	0.53 (-1.68%)	0.78 (0.77%)
0.007 (3.4%)	0.66 (0.967%)	0.57 (1.53%)
9..82e-11 (9.63%)	0.023 (6.69%)	0.44 (3.41%)
1..91e-09 (8.62%)	0.001 (11.07%)	0.047 (7.37%)
0.002 (3.28%)	0.158 (2.54%)	1 (0%)
0.0005 (3.91%)	0.128 (4.1%)	0.23 (4.098%)
0.0014 (3.59%)	0.77 (0.64%)	0.53 (-1.55%)
0.001 (4.11%)	0.57 (1.655%)	0.54 (-2.42%)
0.097 (1.76%)	0.54 (-1.23%)	1 (0%)
0.137 (1.52%)	1 (0%)	0.264 (-2.24%)
2..087e-09 (9.08%)	0.007 (9.73%)	0.011 (10.71%)
8..21e-05 (4.72%)	0.002 (9.79%)	0.083 (4.72%)

Table 7a Change in situational Interest according to workers' experience

SITUATIONAL INTEREST QUESTIONS	P-value (%change) Experience	P-value (%change) Expereince above 9
My safety meeting instructors are engaging	0.00038 (7.03%)	0.654 (-0.75%)
I like what we are learning in the safety meetings	0.0064 (4.66%)	0.87 (0.23%)
This year, my safety meetings have been often entertaining	1.98E-07 (9.84%)	0.01451 (5.18%)
When we dsicuss safety, the instructor does things that grab my attention	7.54E-08 (11.54%)	4.97E-05 (7.34%)
What we discuss in safety meetings can be applied to work-site	0.0025 (5.43%)	0.52 (-0.69%)
I am excited about what we are learning in our safety meetings	0.0007 (5.8%)	0.13 (2.37%)
I am learning valuable things in safety meetings	0.024 (3.9%)	0.93 (0.12%)
I find safety discussions we do at work interesting	0.0064 (5.5%)	0.48 (1.23%)
What we are discussing in safety meetings is useful for me to know	0.037 (3.39%)	0.183 (-1.87%)

The things we are discussing in safety meetings are important for me	0.153 (2.32%)	0.28 (-1.158%)
What we are learning in my safety meetings is fascinating	4.56E-05 (8.53%)	0.0005 (7.99%)
It's easy to pay attention to my safety meetings	1.93E-05 (7.73%)	0.143 (2.43%)

Table11 Logistic Regression –Wald test-Model Diagnostic

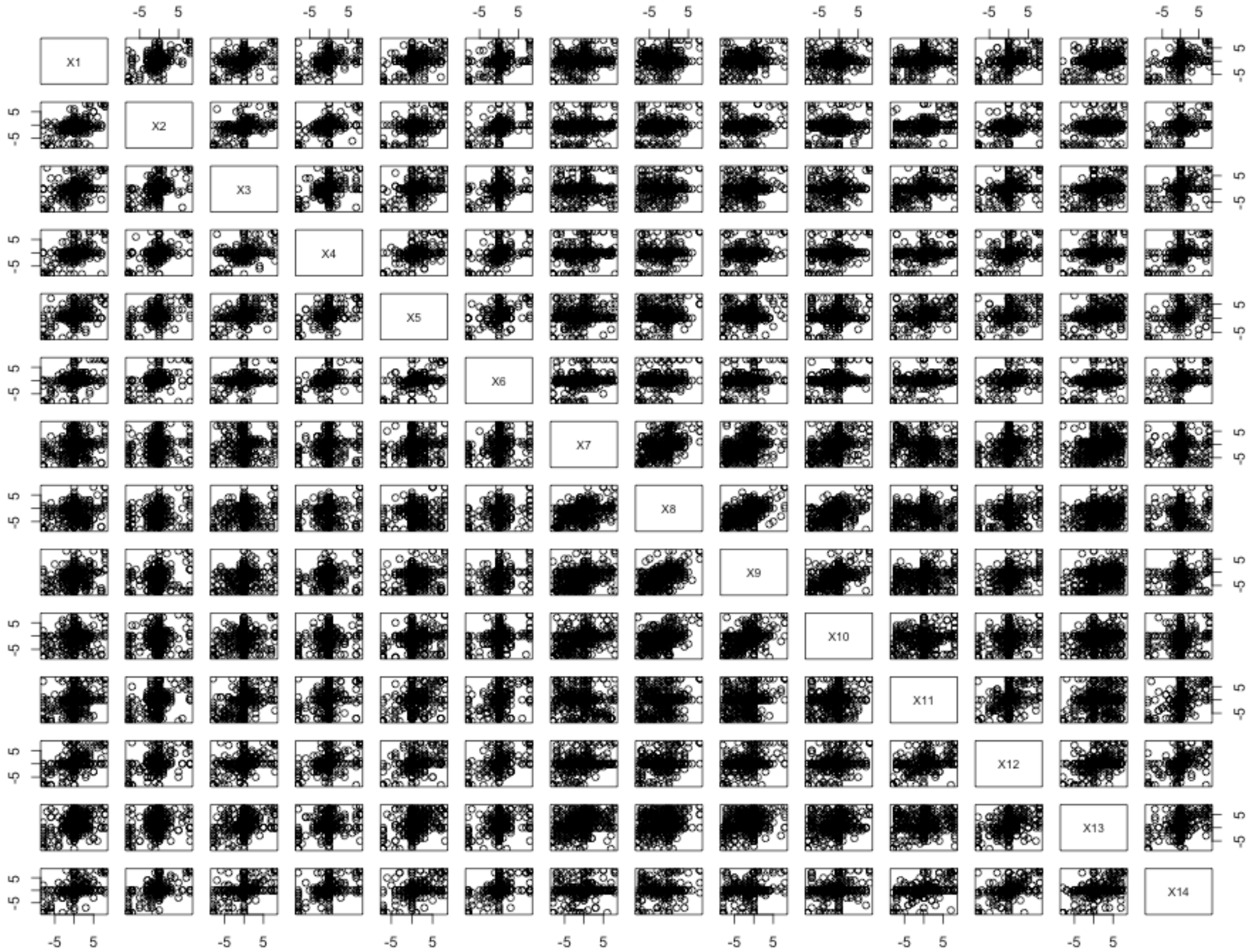
Logistic Regression		Odds Ratio	P-Value	CI 2.5%	CI 97.5%	Wald.test	Model diagnostic
Three-Factor Model	Situational interest question					Chi-squared test: pvalue	Likelihood Ratio Test: pvalue
Maintained SI-Value	What we discuss in safety meetings can be applied to work-site					0.023	0.03
Mid Negative group	PC1	-0.002676	0.77215	-0.1528873	0.1475353		
Positive group	PC2	-0.2506	0.70843	-0.6156173	0.1144169		
Negative group	PC3	-0.605487	0.00503	-1.0285373	-0.1824364		
Triggered SI	When we dsicuss safety, the instructor does things that grab my attention					0.21	0.19

Mid Negative group	PC1	-0.07894	0.2629	-0.2171322	0.05924893		
Positive group	PC2	0.05436	0.6564	-0.1850902	0.29380145		
Negative group	PC3	-0.39729	0.0427	-0.781461	-0.01311318		
Triggered SI	It's easy to pay attention to my safety meetings					0.17	0.15
Mid Negative group	PC1	-0.08457	0.2273	-0.2218735	0.05272789		
Positive group	PC2	0.01911	0.878	-0.2248431	0.2630555		
Negative group	PC3	-0.42229	0.0355	-0.8160325	-0.02855629		
Triggered SI	My safety meeting instructors are engaging					0.16	0.13
Mid Negative group	PC1	-0.06258	0.313	-0.1841505	0.05899553		
Positive group	PC2	-0.11584	0.279	-0.3253668	0.09369131		
Negative group	PC3	-0.26872	0.103	-0.5919033	0.05445925		
Triggered SI	This year, my safety meetings have been often entertainin g					0.84	0.83
Mid Negative group	PC1	0.03014	0.677	-0.1117627	0.1720453		
Positive group	PC2	0.0347	0.758	-0.1862612	0.2556588		
Negative group	PC3	0.01035	0.951	-0.3226159	0.3433179		
Maintained SI-feeling	I am excited about what we are learning in our safety meetings					pvalue= 0.12	pvalue=0.1 0
Mid Negative group	PC1	-0.0821	0.202	-0.2081587	0.04395088		
Positive group	PC2	-0.19201	0.121	-0.4347377	0.05072114		

Negative group	PC3	-0.26916	0.14	-0.6266212	0.0882932		
Maintained SI-feeling	What we are learning in my safety meetings is fascinating					pvalue=0.031	pvalue=0.03
Mid Negative group	PC1	-0.15383	0.0117	-0.2734787	-0.0341765		
Positive group	PC2	-0.0733	0.535	-0.3048346	0.15824109		
Negative group	PC3	-0.28011	0.125	-0.6379399	0.07771304		
Maintained SI-Value	The things we are discussing in safety meetings are important for me					pvalue=0.015	pvalue=0.01
Mid Negative group	PC1	-0.15991	0.00987	-0.2813691	-0.03844087		
Positive group	PC2	-0.16518	0.1893	-0.4118125	0.08145714		
Negative group	PC3	-0.30157	0.11774	-0.6794035	0.07627163		
Maintained SI-feeling	I find safety discussions we do at work interesting					pvalue=0.056	pvalue=0.04
Mid Negative group	PC1	0.0144	0.84456	-0.1295928	0.1584027		
Positive group	PC2	0.04391	0.71218	-0.1893792	0.2772041		
Negative group	PC3	-0.50254	0.00577	-0.8593659	-0.1457096		
Maintained SI-feeling	I like what we are learning in the safety meetings					pvalue=0.038	pvalue=0.02
Mid Negative group	PC1	-0.30349	0.0464	-0.6020929	-0.004891758		
Positive group	PC2	-0.11056	0.3104	-0.3242047	0.103074738		
Negative group	PC3	-0.37904	0.0215	-0.7022982	-0.055790776		

Maintained SI-Value	What we are discussing in safety meetings is useful for me to know					pvalue=0.02	pvalue=0.01
Mid Negative group	PC1	-0.14772	0.0205	-0.2726493	-0.0227967		
Positive group	PC2	-0.21397	0.0998	-0.4687846	0.04085442		
Negative group	PC3	-0.36307	0.0662	-0.7503633	0.024219		
Maintained SI-Value	I am learning valuable things in safety meetings					pvalue=0.25	pvalue=0.24
Mid Negative group	PC1	-0.02827	0.6917	-0.1679831	0.11145121		
Positive group	PC2	0.0951	0.4018	-0.1272369	0.31743742		
Negative group	PC3	-0.39163	0.0351	-0.7558648	-0.02740508		

Figure 6a Scatterplot Matrix-Correlations Between Emotions



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