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Identifying and Quantifying Construction Safety Risks at the Attribute Level

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IDENTIFYING AND QUANTIFYING CONSTRUCTION SAFETY RISKS AT THE
ATTRIBUTE LEVEL

by

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B.S., Amirkabir University of Technology, 2006

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A thesis submitted to the
Faculty of the Graduate School of the
University of Colorado in partial fulfillment
of the requirement for the degree of
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2012

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This thesis entitled:
Identifying and Quantifying Construction Safety Risks at the Attribute Level
written by Behzad Esmaeili
has been approved for the Department of Civil, Environmental, and Architectural Engineering

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The final copy of this thesis has been examined by the signatories, and we
Find that both the content and the form meet acceptable presentation standards
Of scholarly work in the above mentioned discipline.

Esmaeili, Behzad (Ph.D., Civil Engineering)

Identifying and Quantifying Construction Safety Risks at the Attribute Level

Thesis directed by Assistant Professor Matthew R. Hallowell

The number of injuries and fatalities is disproportionately high when compared with other industries. In addition to physical pain and emotional suffering experienced by the victims and their families, these incidents have staggering societal costs. Therefore, investing in construction safety and developing innovations that improve safety is critical. The dissertation includes five manuscripts. The first explores the diffusion patterns of traditional injury prevention practices using common innovation diffusion models. The implications of the findings are that the construction industry has now reached saturation with respect to traditional injury prevention strategies and new safety innovations are needed. One of the most recent advancement in the preconstruction safety management strategies, that is proved to be highly effective, is to integrate safety risk data in to the schedule of project. Therefore, the second and third papers identify safety risks of common highway construction work tasks and their temporal and spatial interactions using the Delphi method and integrate them into a decision support system to produce predictive plots of safety risk over time based on the temporal and spatial interactions among concurrent activities. While, the results indicate that integrating safety risk data with schedule of project is highly effective, using the current methods to quantify safety risks for every individual task that can be experienced is infeasible with current risk modeling and data collection approaches. To address this limitation, the forth paper presents an attribute-based risk identification and analysis method that helps safety managers to identify and model the safety risk independently of specific activities or trades. The fundamental attributes that cause accidents are identified and their associated risks quantified by conducting reliable content analysis on 1771 accident reports from the National databases. The last paper uses the attribute-based risk management concept and proposes several safety predictive models to determine the outcome of

possible injuries in early phases of a project. This research yield robust data and mathematical forecasting models that can be to objectively, accurately, and reliably predict hazardous conditions based on the identifiable attributes that characterize the workplace. It is expected that the findings of this research will transform the current risk analysis techniques and the created database have the potential to be applied to information models and emerging construction technologies.

For my mom,
for teaching me about unconditional love.
For my dad,
for teaching me about the importance of education.
For my sister,
for teaching me to believe in myself.

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CHAPTER 1
INTRODUCTION

OBSERVED PROBLEM

The construction industry is dangerous. Although injury rates have declined dramatically since the inception of the Occupational Safety and Health Act of 1970, in each of the past 15 years the construction industry has accounted for over 1,200 death and 460,000 disabling injuries in the United States (NSC 2009). In fact, the construction industry had the highest number of fatal injuries (774) in 2010 among all industry sectors in US and its rate of fatality was 2.7 times higher than the all worker fatal injury rate (BLS 2012). In addition to staggering financial burden of injuries, moral or humanitarian concerns regarding the consequences of these incidents are extremely high (Everett and Frank, 1996).

To respond to this relatively high incident rate, attempts have been made to improve safety throughout the lifecycle of a project. Typically, safety management activities take place during the construction phase (e.g., job hazard analyses and site audits). In recent years, new safety management strategies have been introduced that help the project team to identify and control hazards during design and preconstruction. In fact, several studies indicate that preconstruction safety activities are the most effective in reducing injuries (Szymberski 1997) and, consequently, there is a great interest among safety researchers to introduce new practices that can be implemented in early stages of a project. For example, safety can be considered during the design of the permanent facility (Gambatese et al. 2005) and it can be integrated in to the constructability reviews (Hinze and Wiegand 1992) or project schedules (Yi and Langford 2006). Key concepts in preconstruction safety activities is identifying and mitigating hazardous situations during the early stages of the project. One of the effective techniques for identifying and controlling safety hazards before the project begins is risk management.

Risk management techniques have shown to be effective in improving safety performance in many ways. For example, they can be used to identify safety hazards when scheduling (Navon and Kolton 2006), chose alternative means and methods of construction during planning (Hallowell and Gambatese 2009), or strategically select injury prevention practices (Hallowell 2011). However, many of these state-of-the-art and innovative strategies have not diffused through the construction industry due to the lack of robust risk database. Current risk quantification methods are problematic because they require every new infrastructure feature and construction method to be individually evaluated using laborious research processes and data from previous failures. Consequently, existing risk databases are limited and rarely employed by practicing professionals because they only include a small fraction of work scenarios and are not robust to departures from existing means and methods. This lack of knowledge has led to mismanagement of new work environments and an increase in injury rates for projects with advanced technologies.

To address this gap in knowledge, the objectives of this dissertation is to create a robust risk databases and develop new risk management techniques. To achieve these objectives, an attribute-based risk identification and analysis method is presented that helps designers to identify and model the safety risk independently of specific activities or trades. The key concept of the new model is that the safety risks can be mapped for any tasks at any time by identifying and modeling fundamental hazardous attributes. In this method, accidents are considered the outcome of interaction among physical conditions of the jobsite, environmental factors, administrative issues, and human error. The main advantage of attribute-based hazard identification is that risk can be quantified for most of the tasks using limited number of attributes in preconstruction phase of the project. It is expected the results of the study provide a strong foundation for safety risk

quantification and management. In order to limit the scope of the research, the authors focused on struck-by accidents.

DISSERTATION FORMAT AND CONCEPTUAL OVERVIEW

This dissertation follows a five journal paper format. Each of the subsequent chapters (chapters 2 to 6) are independent papers and have their own abstract, introduction, literature review, research methods, results, conclusions, and references. While the papers are independent, each builds directly on the findings of previous chapter. The research limitations of each chapter are the observed problems of the next chapter. This adds to the integrity and cohesiveness of the dissertation and provides a logical flow of information. A summary of theoretical and practical contributions of the dissertation and suggestions for future studies are provided in the concluding chapter. Finally, references used in each the five papers are combined in the integrated references chapter.

The research questions and different methods that were used to answer them are summarized in Table 1. The first paper (chapter 2) investigates the relationship between the construction safety improvements since 1998 and implementing safety program elements by exploring the diffusion patterns of traditional injury prevention practices. One of the main implications of this chapter is that the construction industry reached saturation with respect of adopting traditional safety program elements and there is a need for new injury prevention practices. This paper has been published by the *Journal of Construction Engineering and Management*.

Considering the emergence of introducing new injury prevention practices, in the second and third papers (chapters 3 and 4) quantify safety risks of common highway construction work tasks

and their temporal and spatial interactions using Delphi method and integrate these data in to the project schedule. The second paper is published in *Construction Management and Economics* and the third paper is under review.

Table 1. Research questions and methods of dissertation

Ch.#	Research questions	Data Collection and analytical methods
2	✓ Is there any relationship between adoption of traditional safety program elements and deceleration of construction safety improvement since 1998?	<ul style="list-style-type: none"> • Surveys • Investigating innovation diffusion models
3	✓ What is the percentage increase or decrease in safety risk resulting from the concurrent performance of the tasks in the same physical workspace?	<ul style="list-style-type: none"> • Delphi
4	<ul style="list-style-type: none"> ✓ What are the relative safety risk values for common highway construction activities? ✓ Is it possible to integrate safety risk data in to the schedule of project? ✓ If yes, how valid is such integration and how much value does it add to the current safety practices? 	<ul style="list-style-type: none"> • Delphi • Prototyping (developing decision support systems) • Multi attribute utility assessment • Case study
5	✓ Is it possible to identify and model the safety risk independently of specific activities or trades in preconstruction phase of project?	<ul style="list-style-type: none"> • Content analysis
6	✓ Is it possible to predict safety related outcomes such as accident severity in preconstruction phase of project using fundamental safety risk attributes?	<ul style="list-style-type: none"> • Principal component analysis (PCA) • Generalized linear models (GLMs)

While integrating safety risk data with schedule of project is a highly effective practice, using the current methods to quantify safety risks for every individual task can be a laborious research process. To address this limitation, the forth paper (chapter 5) presents an attribute-based risk identification and analysis method that helps safety managers to identify and model the safety risk independently of specific activities or trades. The last paper (chapter 6) represents one of the practical implications of the attribute-based risk management concept by developing several

probabilistic safety predictive models and forecast the severity of possible injuries in early phases of a project.

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CHAPTER 2

DIFFUSION OF SAFETY INNOVATIONS IN THE CONSTRUCTION INDUSTRY

ABSTRACT

Safety performance in the construction industry has improved significantly in the past four decades. This improvement has been attributed to the increased implementation of injury prevention strategies. Though the relative effectiveness of these strategies has been studied in previous research, there has been no attempt to evaluate their diffusion. In order to address this gap in knowledge, twelve highly effective administrative safety innovations were identified in literature and fifty eight firms were interviewed to investigate their adoption rate. The diffusion patterns of the identified safety innovations were explored using four common innovation diffusion models: the internal, external, Bass, and Gompertz. The findings indicate that the internal and Bass models have the highest explanatory power and that internal factors are the most influential factors in adoption of safety innovations by construction firms. It was also found that project-specific safety training (91%), frequent worksite inspections (91%), and safety and health orientation and training (90%) are the three most commonly-adopted safety innovations and employment of a site safety manager (62%), subcontractor selection and management (64%), and substance abuse programs (69%) were the three innovations most infrequently implemented. The implication of the findings is that the construction industry has now reached saturation with respect to traditional injury prevention strategies and new safety innovations are needed.

KEYWORDS: Innovation diffusion models, injury prevention practices.

INTRODUCTION

Safety performance in the construction industry has improved significantly during the past four decades. In fact, between 1973 and 2004 the fatality rate decreased from 71 to 11.6 per 100,000 workers and the disabling injury rate decreased from 8,520 to 4,478 per 100,000 workers (NSC

2006). These findings have been confirmed by other sources such as the Bureau of Labor Statistics (BLS 2009). Some researchers believe that these improvements are the result of an increased adoption of highly effective injury prevention strategies (e.g., Jaselskis et al. 1996; Findley et al. 2004; Hallowell and Gambatese 2010). These strategies, which were novel for their time, can be considered safety innovations according to Sarah Slaughter's widely accepted definition of innovation. In her definition innovation is any "use of a non-trivial change and improvement in a process, product, or system that is novel to the institution developing the change" (Slaughter 1998, p 226).

In the large body of innovation literature two main groups of innovation are discussed: technological and administrative (Daft 1978). While technological innovations commonly encompass engineering and scientific products, administrative innovations usually include managerial and business practice improvements (Manley and McFallen 2003). Injury prevention strategies, such as job hazard analyses or substance abuse programs, that have improved safety performance, are good examples of administrative innovations as they are primarily tied to management practices. Though many research studies have quantified the relative effectiveness of these practices (e.g., Jaselkis et al. 1996; Sawacha et al. 1999; Findley et al. 2004; Hallowell and Gambatese 2009), no studies have attempted to evaluate their diffusion throughout the industry. Exploring the diffusion pattern of safety innovations may help to explain deceleration of construction safety improvement since 1998 (see Figure 1) and to predict the diffusion patterns of future safety innovations.

The objectives of the present study are to: (1) evaluate the extent to which administrative safety innovations have diffused through the construction industry and (2) describe the patterns of safety

innovation diffusion using reliable innovation diffusion models. To achieve these objectives highly effective safety strategies (i.e., administrative safety innovations) were identified from literature and extensive interviews were conducted with a representative sample of US construction companies. Interview questions aimed to determine if and when safety innovations had been initially adopted by each organization. Finally, the time series of adoption data were fit to four mathematical functions to identify the model that best describes the data. In order to limit the scope the study, the authors have decided to focus on the injury prevention strategies that can be classified as administrative innovations.

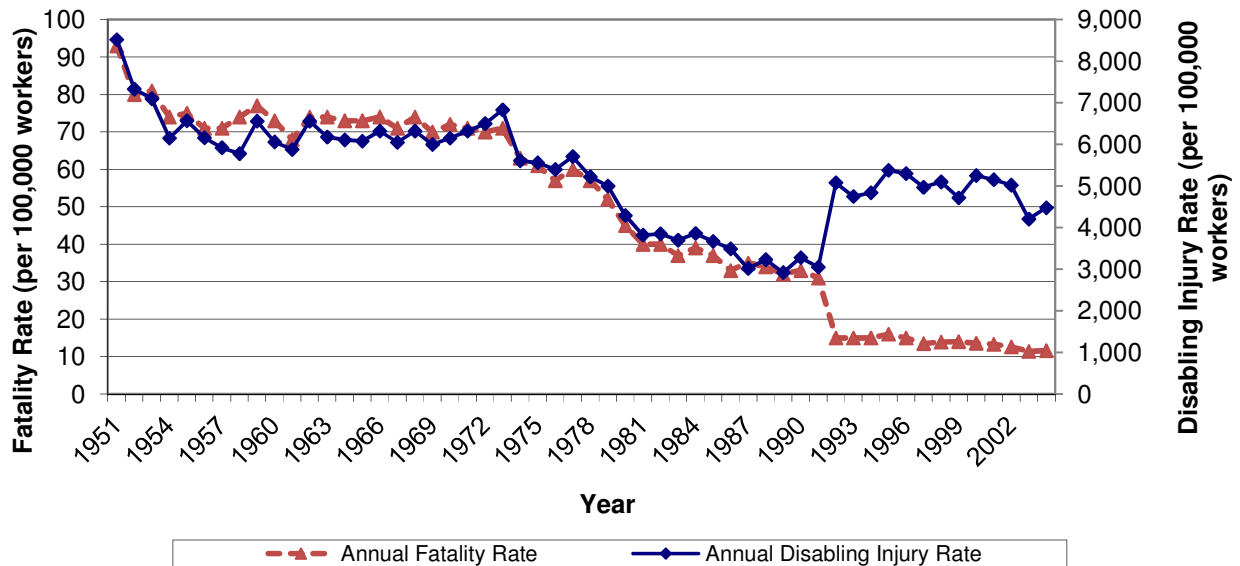


Figure 1 - Annual fatality and disabling rate for construction industry 1952-2004

Please note that the sudden changes in injury and fatality rates in 1992 represent new methods of data collection and benchmarking adopted by the National Safety Council (NSC 2006, as cited in Hinze 2006)

LITERATURE REVIEW

In an effort to identify the salient safety innovations and appropriate diffusion models, a thorough literature review was conducted on the topics of injury prevention in construction, innovation

diffusion models, and diffusion patterns of construction innovations. The literature that provides context for the present study and served as the basis for data collection and analysis are reviewed.

Injury prevention strategies

As previously discussed, injuries have reduced dramatically since the legislation of the Occupational Safety and Health Act of 1970. To comply with regulations and prevent citation, contractors began to invest in safety programs (Findley et al. 2004; Aksorn and Hadikusumo 2008). Though Rajendran (2006) found that there are now literally hundreds of different injury prevention strategies, a few studies have attempted to identify the essential components of an effective safety program. In an initial effort to evaluate the relative effectiveness of safety program elements Jaselkis et al. (1996) quantified the extent to which individual elements reduced organizations' Experience Modification Rate (EMR). Building on this research, Sawacha et al. (1999) evaluated 120 questionnaire responses and conducted a factor analysis on the data to determine the strategies that had the greatest impact on an organization's recordable injury rate. Similarly, Findley et al. (2004) evaluated 48 safety program practices in order to identify key practices that can reduce frequency of fatalities and injuries in the jobsite and Aksorn and Hadikusumo (2008) reviewed literature to identify 16 "critical success factors" of safety programs in Thailand. Recently, McDonald et al. (2009) used interviews, focused groups, and field observations to study the factors that contributed to better safety records, Rajendran and Gambatese (2009) identified and prioritized 329 safety practices, and Hallowell and Gambatese (2009) used the Delphi method to quantify the risk mitigated by individual safety practices. The consensus of these numerous studies is that there are twelve highly effective injury prevention strategies. These are listed in Table 1. These twelve administrative safety innovations were the foci of the present study.

Table 1. Injury prevention strategies identified in previous literature

Injury prevention strategies	Jaselkis et al. (1996)	Sawacha et al. (1999)	Findley et al. (2004)	Abudayyeh et al. (2006)	McDonald et al. (2009)	Rajendran and Gambatese (2009)	Hallowell and Gambatese (2009)
Upper management support	✓	✓	-	✓	✓	✓	✓
Project-specific training	-	-	-	-	✓	✓	✓
Employee involvement	-	-	-	✓	✓	✓	✓
Subcontractor selection and mgt	-	-	-	-	-	✓	✓
Job hazard analyses (JHAs)	-	-	-	-	✓	✓	✓
Record keeping and accident analysis	-	-	✓	-	✓	✓	✓
Emergency response planning	-	-	✓	-	✓	✓	✓
Frequent worksite inspections	✓	-	✓	-	✓	✓	✓
Safety committees	✓	✓	-	-	-	✓	✓
Safety orientation and training	✓	✓	✓	✓	✓	✓	✓
Substance abuse programs	✓	-	✓	-	-	✓	✓
Safety manager on site	✓	✓	✓	✓	✓	✓	✓

Innovation diffusion models

Knowledge of diffusion modeling has increased greatly in the past few decades. Innovation diffusion models aim to investigate rates and patterns of innovation adoption in a social system in an effort to describe the relationship between the rate of diffusion and the number of potential adopters over a predefined time period (Mahajan et al. 1990). By assuming that this relationship is proportional, the most popular groups of fundamental diffusion models emerged (Mahajan and Peterson 1985). The general equation for this group of diffusion models is as below:

$$\frac{dN(t)}{dt} = g(t)[m - N(t)] \quad \text{Equation 1}$$

Where, $N(t)$ cumulative number of adopters of innovation at time period, t ; m = total number of potential adopters in the social system; and $g(t)$ is the coefficient of diffusion.

By substituting different coefficients of diffusion $[g(t)]$ within Equation 1, various diffusion patterns can be modeled. The three types of fundamental diffusion models, characterized by the $g(t)$ function, are summarized in Table 2.

Table 2. Fundamental diffusion models with their coefficient of diffusion functions

Model name	The coefficient of diffusion	Model equation	Equation number
Internal	$a \times N(t)$	$\frac{dN(t)}{dt} = aN(t)[m - N(t)]$	2
External	b	$\frac{dN(t)}{dt} = b[m - N(t)]$	3
Bass	$b + a \times N(t)$	$\frac{dN(t)}{dt} = [b + aN(t)][m - N(t)]$	4

In each of these models a represents the coefficient of internal influence (otherwise known as “imitation”) and b represents the coefficient of external influence. The internal model of innovation diffusion is more applicable to those innovations that are diffused by imitative behavior (Mansfield 1961). Imitation behavior exists when innovations diffuse primarily through contact between members of a social network. The interaction between these members helps later adopters to learn from the experiences of the earlier adopters and, consequently, increases the overall rate of adoption for successful innovations (Mansfield 1961). In fact, the internal model considers that the diffusion occurs as a, “pure imitation process” (Easingwood et al. 1983, p. 279). The highest rate of adoption in the internal model occurs at the inflection point, the time when the innovation has been adopted by 50% of potential firms. This inflection point is important because rate of adoption decreases after this time (Sultan et al. 1990). The shape of this model is an S-curve with symmetry about the point of inflection.

In contrast to the internal model, the external model assumes that innovations are diffused only due to external influences (Coleman et al. 1966). External influences are those that exist outside of the adopting organization such as governmental regulations, mass media, advertisement, consumer demand, and consulting services (Teng et al, 2002; Kale and Arditì 2005). The external model also implies that there is little communication between the members of social system. As a result, the number of previous adopters has no effect on adoption of the innovation by new adopters in the model. Thus, the number of adopters increases continually, the diffusion pattern has a concave shape (exponential), and there is no point of inflection. This model has been used to successfully study the diffusion patterns when there is minimal communication among potential adopters such as the diffusion of new medications (Coleman et al. 1966).

In 1969, Frank Bass introduced a mixed model, which models that the diffusion of an innovation is influenced with both internal and external factors (Bass 1969). In this model, the probability that an innovation will be adopted is linearly related to number of previous adopters. The shape of the model is S-curve and inflection point is between 0% and 50%. This model has been used to successfully investigate the diffusion of variety of products and innovations including information technology (Teng et al. 2002); computer aided design (Kale and Arditì 2005); and ISO 9000 (Kale and Arditì 2006).

The final model, which is very similar to internal model, is Gompertz-function (Hendry 1972; Dixon 1980). The Gompertz function is unique because it assumes that rate of adoption is a function of the logarithm of the number of potential adaptors. Consequently, the inflection point is at 37% adoption and there is no symmetry. This function is included as Equation 5.

$$\frac{dN(t)}{dt} = aN(t)[Ln(m) - Ln(N(t))] \quad \text{Equation 5}$$

According to Tornatzky and Klein (1982), studying a single innovation does not provide enough insight for generalization of similar diffusions in an industry or society. Thus, this paper investigates the diffusion of twelve administrative safety innovations. Since Mead and Islam (2006) found that the internal, external, Bass, and Gompertz are the most popular mathematical diffusion models, all four were tested.

Diffusion of construction innovations

Although the construction industry does not have a strong reputation for adopting innovative products (Egan 1998), the number of publications in this domain is amazing. Attwell (1992) stated that innovation studies have been conducted at two levels: the ‘adopter’ or the ‘macro’ level. While research at the adopter level focuses on the behavior of individual firms, research at macro level focuses on the ability of a network of companies to adopt an innovation. Taylor and Levitt (2004) recognized three distinct themes in previous macro level literature: (1) impact of regulations on diffusion (e.g., Gann et al. 1998; Seaden and Manseau 2001), (2) impact of decentralized industry structure on diffusion (e.g., DuBios and Gadde 2002), and (3) exploring diffusion of innovations in the industry (e.g., Arditi and Tangkar 1997). Kale and Arditi (2010) argue that innovation diffusion models at the macro level have not received sufficient attention in academic research.

In recent years, Kale and Arditi (2005; 2006; 2010) have studied the diffusion of specific innovations in the construction industry. In an initial effort, Kale and Arditi (2005) used the

internal, external, and Bass models to investigate diffusion of computer aided design (CAD) technology in Turkish architectural industry. They found that the Bass model has the highest explanatory power to explain diffusion pattern of CAD technologies and internal factors influence diffusion more than external factors. In a similar study, Kale and Arditì (2006) evaluated the diffusion of ISO 9000, an administrative innovation, in the Turkish precast concrete industry. Their findings were similar to their previous work indicating that internal factors were most influential. In a follow-up study, Kale and Arditì (2010) applied the non-uniform influence (NUI) model to obtain a deeper insight into the diffusion patterns of CAD and ISO 9000. They found that the influence of internal factors changed for these innovations throughout the diffusion period and that the influence may increase or decrease over time depending on the innovation under investigation.

POINT OF DEPARTURE

This study deviates from the current body of literature by evaluating the diffusion patterns of twelve administrative safety innovations. This study provides insight to the diffusion patterns of safety innovations and helps to explain the lack of significant safety improvement over the past decade.

RESEARCH METHODS

As mentioned before, the current study aims to measure the extent to which administrative safety innovations have diffused through the construction industry and describe the patterns of safety innovation diffusion using reliable innovation diffusion models. These objectives have been achieved in two distinct phases. In the first phase, the data regarding the adoption of administrative safety innovations have been obtained using structured interviews. In the second

phase, four common innovation diffusion models have been utilized to the temporal trends in the implementation of safety innovations.

Phase I

In order to evaluate the extent of diffusion of administrative safety innovations, one must collect time series data on the diffusion of injury prevention practices in the construction industry. A structured interview approach was selected as the data gathering method for several reasons. First, the research team was concerned about potential inconsistencies in the definitions of the twelve safety innovations and interviews provided the opportunity to discuss the teams' definitions with each interviewee. Second, interviews allow the researcher to describe the methods used by the interviewees to estimate the initial implementation date for each innovation. Finally, multiple representatives from each firm were able to participate via conference call. For these reasons, interviews were preferred over surveys despite the fact that interviews required a greater time investment from the participants and researchers.

All interviews were conducted in three steps. First, the objectives of the research were introduced and demographic data were gathered. The second step involved determining: (1) which of the injury prevention strategies listed in Table 1 had already been introduced in the interviewee's organization; (2) the year that these strategies were first implemented (up to 2008); and (3) if and when the organization planned to introduce new injury prevention strategies (from 2008 to 2020). If the company adopted a safety innovation in 2008 or before, the innovation was considered to be fully adopted. The year 2008 was selected as the cut-off because data collection was performed in 2009 and a one-year period ensured that a company had sufficient time to adopt and adapt to the new practice. In order to increase the accuracy of the predictions, 2020 was

considered to be the upper limit for all planned activities. In the third and final step interviewees were asked to quantify the percentage of projects on which each safety innovation is implemented and to describe their approach for selecting specific injury prevention strategies for individual projects. Because some interviewees needed extra time to gather information once the objectives of the research were introduced, steps two and three were sometimes conducted in a follow-up interview.

To obtain a representative sample of American construction companies, firms that were members of the Associated General Contractors (AGC) chapters in the Western United States were contacted. Specifically, AGC chapters in Washington, Oregon, California, Colorado, Montana, Arizona, Idaho, and Wyoming were contacted because these organizations were willing to provide their contact lists to the research team. To limit the scope of this study, the focus was on “vertical” contractors that specialized in constructing commercial and office buildings, residential buildings, industrial facilities, and manufacturing plants. Of the 211 contractors that were contacted, a total 58 firms agreed to participate. These firms were categorized as small, medium and large based on their revenues. Twenty-six (44%) were categorized as small contractors (annual revenue < \$10 million); 15 (25%) firms as medium-sized firms (\$10 million < annual revenue < US\$100 million); and 25 (31%) as large firms (\$100 million < annual revenue).

Finding an appropriate person who had intimate historical knowledge of their organization was a major challenge. Only individuals who had enough experience in the organization to describe the history of their safety program were able to answer the interview questions posed. This challenge may explain why many organizations declined to participate. Nevertheless, the response rate of 28 percent is considered acceptable in similar research (Gibson and Whittington 2010).

Interviewees primarily included executives (48%), senior project managers (28%), and safety managers (24%). Executives were primarily the owners or presidents of the organizations. The interviewees averaged 18.5 years of professional experience within their organization.

Phase II

Once the data were collected, the following four mathematical models were selected to explore the diffusion of the administrative safety innovations: External, Internal, Bass, and Gompertz. In previous studies, different methods have been used to estimate the value of the diffusion parameters including Ordinary Least Square (OLS), the maximum likelihood procedure, and nonlinear methods (Sultan et al. 1990). The diffusion parameters of the twelve safety innovations have been estimated in this analysis using the Levenberg-Marquardt method of non-linear least squares. This method was selected over the aforementioned alternatives because it has been successfully implemented in related research (e.g., Teng et al. 2002; Kale Arditi 2006; 2010), nonlinear methods have been found to provide more reliable (Sultan et al. 1990), and the results are more conservative (Teng et al. 2002). By conducting an Analysis of Variance (ANOVA) test, the coefficient of determination (R^2) and F-value were calculated to compare and the accuracy of each diffusion model.

One should note that describing the patterns of safety innovation diffusion requires evaluating the temporal trends in the implementation of safety innovations. The authors assumed that a comprehensive safety program, regardless of financial constraints, should eventually include all elements listed in Table 1, which is supported by many prominent references such as Hinze (1997). Therefore, the average percentage of the twelve innovations implemented by the 58 firms was calculated for each year in the diffusion period under investigation (1971 to 2008).

RESULTS AND ANALYSIS

The results of the 58 interviews indicate that, on average, each company had adopted 9. The 13 innovations in Table 1 by 2008. Thirty nine firms (67%) have implemented ten or more of the innovations and nine firms (16%) implemented less than five of the innovations. Although 24 (41%) firms now include all safety innovations in their program, no innovation was implemented by all companies. In other words, no innovation has been diffused completely (100% rate of adoption) in the sample. . As of 2008, the three most commonly-adopted safety innovations were project-specific safety training (91%), frequent worksite inspections (91%), and safety and health orientation and training (90%). The three innovations most infrequently implemented are employment of a site safety manager (62%), subcontractor selection and management (64%), and substance abuse programs (69%). is the completed adoption data are shown in Table 3. It should be noted that once a safety innovation was adopted, no firm has discontinued use.

The interviewees were also asked to identify if and when they planned to introduce new injury prevention innovations between 2008 and 2020. This question applied only to the elements not yet implemented by each organization. The results indicated that the vast majority (77%) of companies that had not yet introduced a particular innovation had no plans to introduce the innovations in the next decade (i.e., before 2020). For the organizations with plans to implement new innovations between 2008 and 2020, the most commonly targeted strategies were employee involvement and evaluation (7.5%), substance abuse programs (7.2%), and safety manager on site (6.7%). Subcontractor selection and management (0%); specific project training & safety management (1.2%); and record keeping/analyses (1.4%) have the lowest planned growth from 2008 to 2020. The percent of the firms that plan to adopt new innovation from 2008 to 2020 is

shown in Table 4. Another interesting trend is the decrease in the introduction of new strategies after 2005 and apparent saturation by 2020 (see Tables 3 and 4).

Table 3. Trends in safety innovation adoption (percent of firms implementing)

Injury prevention strategies	Before 1971	1971-1980	1981-1990	1991-1995	1996-2000	2001	2002	2003	2004	2005	2006	2007	2008	Total
Upper management support	9	5	22	9	17	2	9	2	9	2	2	2	0	88*
Job hazard analyses (JHA)	3	7	16	10	12	10	7	3	5	3	3	2	2	84*
S&H orientation/training	3	5	24	16	10	9	2	7	7	2	3	2	0	90
Worksite inspections	7	3	17	12	22	2	3	7	7	3	3	2	2	91*
Emergency response plan	3	2	19	17	16	5	5	5	5	0	5	2	0	84
Record keeping/analyses	5	2	26	9	22	3	3	7	5	2	0	2	0	86
Specific project training and safety management	7	0	21	14	16	12	2	9	5	0	5	2	0	91*
Safety and health committees	2	2	14	16	17	7	3	7	3	2	0	2	0	74*
Substance abuse programs	2	0	26	12	17	5	0	2	3	0	2	0	0	69
Safety manager on site	2	0	14	7	10	7	5	7	2	2	2	3	2	62*
Subcontractor selection & management	3	3	19	5	12	3	5	5	5	0	0	2	0	64*
Employee involvement & evaluation	3	0	21	5	21	5	5	7	3	2	2	2	2	78
Median	3	2	20	11	16	5	4	7	5	2	2	2	0	85
Mean	4	2	20	11	16	6	4	6	5	1	2	2	1	80
Total	50	29	238	131	193	71	50	67	60	17	28	21	7	962

* Due to rounding, the sum of some of the rows may not add up to the last column.

According to findings from the third step of the interviews, more than 60% of firms implemented at least 10 elements on 90-100% of their projects. Record keeping and accident analysis (79%), upper management support (68%), and frequent work site inspection (68%) have the highest rate of consistent implementation throughout the industry. Another interesting trend is that once a firm creates a safety program comprised of individual elements, 92% implement this program on all projects. That is, most firms do not modify their safety program for individual projects.

Table 4. Percent of companies that will implement each safety program elements in the future

Injury prevention strategies	2009	2010	2011-2015	2016-2010	After 2020	Total
Upper management support	0.0	0.0	0.0	2.0	0.0	2.0
Job hazard analyses (JHA)	1.6	0.0	0.0	1.6	0.0	3.1*
S&H orientation/training	1.5	0.0	0.0	1.5	0.0	3.0
Frequent worksite inspections	1.1	0.0	1.1	0.0	0.0	2.2
Emergency response plan	1.4	0.0	0.0	0.0	1.4	2.8
Record keeping/analyses	0.0	1.4	0.0	0.0	0.0	1.4
Specific project training & safety mgt	0.0	0.0	0.0	0.0	1.2	1.2
Safety and health committees	3.0	0.0	0.0	0.0	0.0	3.0
Substance abuse programmes	2.4	2.4	0.0	0.0	2.4	7.2
Safety manager on site	2.2	2.2	2.2	0.0	0.0	6.7*
Subcontractor selection & management	0.0	0.0	0.0	0.0	0.0	0.0
Employee involvement & evaluation	5.0	0.0	2.5	0.0	0.0	7.5
Median	1.4	0.0	0.0	0.0	0.0	2.9
Mean	1.5	0.5	0.5	0.4	0.4	3.3
Total	18.2	6.0	5.8	5.0	5.0	40.0

* Due to rounding, the sum of some of the rows may not add up to the last column.

As indicated, four mathematical models were used to estimate the diffusion parameters. The coefficients of determination (R^2 and F-value) were included to compare models. It was found that internal and Bass (mixed) models provide more accurate estimates of the diffusion parameters. Alternatively, the external model estimated the external influence coefficient, b , to be zero and the standard error for estimated number of adopters, m , is extremely high ($1.5E+8$). Similarly, the Gompertz model estimated m to be unreasonably high ($6E+10$). Therefore, the external and Gompertz models were excluded from the research. The results of the parameter estimation for the Bass and Internal models are presented in Table 5.

In order to better understand the 'goodness of fit' of the models, it is helpful to compare the coefficients of determination with the research results from comparable studies of different

innovations. A wide range of the coefficients of determination has been reported in previous research. For example, Sultan (1990) reported a range of [0.07, 0.97] for R^2 and Kale and Arditi (2006 and 2010) found a range of [0.25, 0.66] for R^2 . A comparison of the results in Table 5 to these previous studies reveals that the Internal and Bass models fit the data reasonably well.

Table 5. Diffusion of safety program strategies in United State construction industry.

Title	Model	Parameters			R^2 *	F	Number of adopters	Cost-effectiveness ratio **
		m	a	b				
Cumulative	Bass	65.0	0.124	0.002	0.996	63	-	-
	Internal	45.0	0.005	-	0.972	1385	-	-
Upper management support	Bass	83.4	0.093	0.003	0.994	5104	51	6.10
	Internal	44.2	0.006	-	0.944	767	-	-
Job Hazard Analyses (JHAs)	Bass	197.2	0.076	0.001	0.993	3936	49	4.12
	Internal	48.0	0.005	-	0.942	715	-	-
SH Orientation and Planning	Bass	77.7	0.101	0.004	0.995	5487	52	3.83
	Internal	50.0	0.004	-	0.972	1557	-	-
Worksite Inspections	Bass	76.2	0.126	0.002	0.998	12343	53	2.22
	Internal	53.6	0.004	-	0.987	3019	-	-
Emergency Response Planning	Bass	60.3	0.149	0.002	0.998	10665	49	3.33
	Internal	47.4	0.005	-	0.984	2340	-	-
Recordkeeping and Accident Analyses	Bass	63.1	0.133	0.003	0.993	3678	50	3.09
	Internal	47.0	0.005	-	0.968	579	-	-
Project-specific Training and Safety Meetings	Bass	108.4	0.08	0.008	0.991	2917	53	2.72
	Internal	54.9	0.004	-	0.977	1770	-	-
Safety and Health Committees	Bass	52.7	0.172	0.001	0.997	7901	43	2.92
	Internal	45.9	0.005	-	0.992	4772	-	-
Substance Abuse Programs	Bass	51.3	0.081	0.023	0.995	6821	40	4.03
	Internal	39.4	0.006	-	0.977	2334	-	-
Safety Manager on site	Bass	315.2	0.062	0.002	0.987	1803	36	2.44
	Internal	41.7	0.005	-	0.973	1408	-	-
Subcontractor Selection and Mgt	Bass	63.6	0.092	0.004	0.989	2660	37	8.62
	Internal	36.2	0.006	-	0.96	1073	-	-
Employee Involvement	Bass	150.8	0.061	0.005	0.985	1704	45	4.10
	Internal	49.4	0.004	-	0.972	1476	-	-

*Note: All models are significant at $p < 0.01$.

**Values are unit less and obtained from Hallowell (2010).

One measure of concern is the saturation level, which is estimated as the number of potential adopters, m. To see the efficacy of the predictive models tested, one may compare m from Table

5 with the actual number of adopters for each strategy in the 8th column of Table 5. This comparison reveals that the internal model best estimates the number of potential adopters. The mixed model overestimated this parameter for all strategies and, consequently, provided a more inaccurate estimate of m . To facilitate comparison between models, average statistical indicators of the coefficients of determination, F-value, and diffusion parameters are summarized in Table 6. In order to provide unbiased statistical indicators in Table 6, cumulative values have been omitted from calculations. On average, the Bass model ($R^2 = 0.993$ and $F = 5419$) fit the data better than the internal model ($R^2 = 0.971$ and $F=1818$). Similar observations have been reported by previous researchers (e.g., Sultan 1990; Kale and Arditi 2005; 2006).

Table 6. Statistical indicators of diffusion parameters

Title	Model	Parameters			R^2 *	F
		m	a	b		
Internal	Min	36.22	0.004	-	0.942	580
	Median	47.20	0.005	-	0.973	1517
	Mean	46.48	0.005	-	0.971	1818
	Max	54.90	0.006	-	0.992	4773
Mixed (Bass)	Min	51.33	0.061	0.001	0.985	1704
	Median	76.93	0.093	0.003	0.994	4520
	Mean	108.33	0.102	0.005	0.993	5419
	Max	315.20	0.172	0.023	0.998	12343

*Note: All models are significant at $p < 0.01$.

As shown in Table 6, the average coefficient of internal influence, a , and external influence, b , for the Bass model are 0.102 and 0.005, respectively. This indicates that internal influence factors dominated external influence factors in the diffusion of safety strategies. This is an interesting finding because the authors initially hypothesized that the dissemination of injury prevention strategies would be driven primarily by external factors such as legislation of Occupational Safety and Health (OSH) Act of 1970. A potential explanation for this phenomenon is that the OSH Act

was legislated prior to the diffusion period and it has a consistent effect on all safety innovations which cannot be separated from diffusion patterns. As a result, imitation behavior (i.e., the ‘bandwagon effect’) may have played a more important role in adopting new safety innovations. Despite this unexpected finding, similar observations have been reported in previous studies that have investigated diffusion of administrative innovations (e.g., Sultan 1990; Kale and Arditi 2005; 2006). Furthermore, Kimberley (1981) stated that in diffusion of managerial (administrative) innovations, imitation plays a more significant role. This happens because successful strategies often are “portable”, not “patentable” (O’Neil et al. 1998, p101).

Two hypotheses have been used extensively to explain the internal influence in the society: rational efficiency and bandwagon pressure (Abrahamson and Rosenkopf 1993):. The rational efficiency implies that an innovation will be adopted by social members when s/he receives convincing information regarding the expected efficiency or returns of the innovation (Farrell and Saloner 1985; Katz and Shapiro 1985). In other words, number of adopters increases as the non adopters receive more information regarding profitability of the innovation from adopters (Farrell and Saloner 1985; Katz and Shapiro 1985). On the other hand, the bandwagon hypothesis suggests that social members adopt an innovation due to social pressure created from an increased number of adopters. For example, Scharfstein and Stein (1990) observed that some organizations will adopt an innovation even though they have knowledge that it may fail in order to be evaluated more favorably by peers. Additionally, Abrahamson (1996) found that in some social networks a specific strategy becomes “norm” for dealing with uncertainties, which creates pressure within the network to adopt the strategy. Bandwagon pressures may also exist in committee meetings, social gatherings, and coordination meetings. In a society with high level of bandwagon pressure, members may be afraid that if they do not adopt the innovation they will

lose their legitimacy, competitive advantage, and stakeholders' support (Tolbert and Zucker, 1983; Abrahamson and Rosenkopf 1993).

By comparing the total rate of adoption (see Tables 3 and 4) and number of adopters (see Table 5) with cost effectiveness ratios (see last column of Table 5) of safety innovations, the writers observed that the most cost-effective strategies (e.g., upper management support and subcontractor selection and management) have a relatively low adoption rate by the firms interviewed. This provides additional evidence that the bandwagon effect is a viable explanation for the dominance of internal influence in diffusion of safety innovations.

Some researchers have tried to quantitatively model the bandwagon effect to objectively evaluate the patterns of adoption resulting from social pressures (Abrahamson and Rosenkopf 1993, 1997; Rosenkopf and Abrahamson 1999). Although there is strong evidence of existence that mathematical models can be created, such modeling of administrative safety innovations is outside of the scope of this study.

The cumulative number of adopters of administrative safety innovations from 1971 to 2008 and the predicted values from the Bass and Internal Models are shown in Figure 2. As one can see, there was a brief lag in implementation following the OSH Act of 1970, as would be expected for any new legislation. From 1980 to 2005, there was a constant and rapid acceleration in adoption from 5% to 70%.

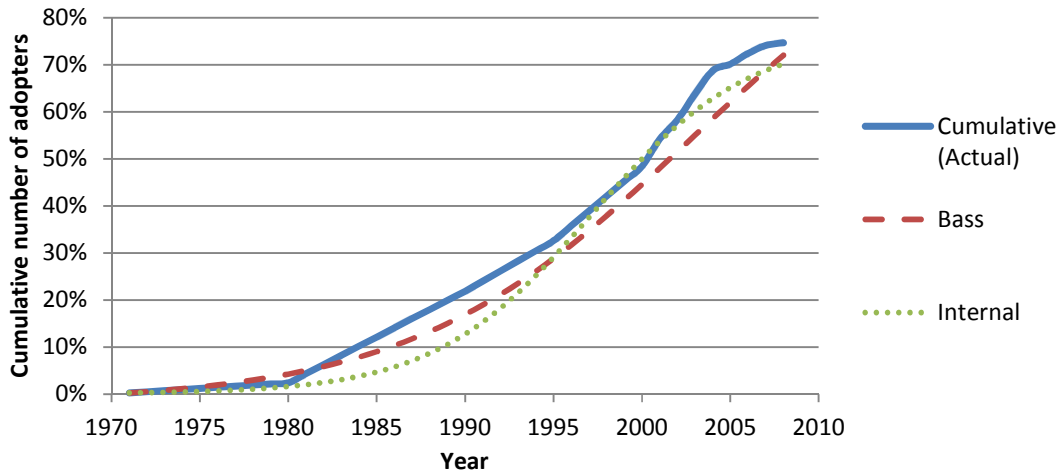


Figure 2. Cumulative values of average usage of safety program elements and its diffusion models

IMPLICATIONS

The current research has practical and academic implications. First, it has been revealed that the construction industry is saturated by the current safety innovations (see Tables 3 and 4), which may explain the deceleration of construction safety improvement in the past two decades (see Figure 1). This is an important finding because it shows the importance of introducing new injury prevention practices and can be used by safety managers to justify additional safety expenditures. Second, one of the major contributions of the study is an accurate model of the adoption patterns for safety innovations. This model can be used by researchers and practitioners to identify the drivers that lead to higher adoption rate for specific types of safety innovations. Third, the diffusion model can be used to predict the diffusion patterns of new injury prevention strategies through the construction industry. Specifically, these models can be used by decision makers to make more cost effective safety investments that will have more immediate impacts to their organization and by national research agencies (e.g., NIOSH) to measure the level of diffusion of new strategies. Forth, the study provides interesting data regarding the safety management

behavior since the inception of the OSH Act of 1970. This is a significant period because, in many ways, these are the formative years for safety management in the US. Fifth, the parameters of the diffusion models show the relative importance of social factors on the diffusion of safety innovation and the lesser importance of external factors such as regulatory pressure, which may be important to regulatory agencies like OSHA. Finally, from an academic perspective this study is important because it is the first significant integration of safety management and innovation diffusion theory.

LIMITATIONS

There are several limitations of the research methods that impact the internal and external validity (i.e., accuracy and generalizability) of the results. First, the contractors who participated in the interviews were members of the AGC chapters in the Western United States and primarily constructed “vertical” structures (i.e., buildings and industrial facilities). Thus, from a statistical perspective, the results may not be representative of other geographic regions or industrial sectors. Second, the models used in the analysis of the diffusion data require a simplification of the real-world data (Fornerino 2003). For example, the popular diffusion models do not account for specific social, political, or technological factors. Rather, the models classify influence factors as “internal” or “external” to the adopting organization (Kale and Arditi 2010). Consequently, it is possible that the models tested do not account for the fact that, due to some unique organizational structure, some firms are not able to adopt a specific administrative safety innovation. Finally, the accuracy of the models may also be influenced by the fact that the models assume that internal and external influences are relatively constant over time (Easingwood et al. 1983). The writers suggest that future researchers investigate dynamic influence factors in an effort to refine the model.

CONCLUSIONS

This study investigated the adoption trends of highly effective safety innovations in the construction industry in an effort to create a predictive model for the diffusion of administrative safety innovations. Diffusion was explored using four popular mathematical models: internal, external, Bass, and Gompertz. The results show that administrative safety innovations are influenced most by internal factors and that the Bass model most accurately predicted the diffusion pattern. Understanding the trend of adoption of historical innovations provides insights for exploring the diffusion pattern of future innovations. In fact, the research presented here provides a strong basis for predicting diffusion patterns of future safety innovations (e.g. integrating safety and schedule of a project). Another major finding was that the rate of adoption of the twelve common safety innovations has dropped significantly after 2005 and a significant portion of construction firms interviewed do not have plans to implement new safety innovations in the next decade. The implication is that the industry has reached saturation with respect to administrative safety innovations. Though causal inferences cannot be drawn, a coincidental trend, which can be seen in data (see Tables 3 and 4), is the deceleration of safety improvement in the past decade. Considering that construction is one of the most dangerous industries, these findings are alarming.

By integrating the concept of construction safety and innovation theory, this study reveals several new research areas that may enhance safety performance. First, the results of this research indicate that additional research into new safety strategies is needed. Potential strategies for investigation include knowledge management (Cooke et al. 2008), integration of safety risk management into design and planning (Hinze et al. 2005; Yi and Langford 2006; Navon and

Kolton 2006; Sacks et al. 2009; Hallowell et al. 2011), including safety data into building information models (Ku and Mills 2010), and utilizing leading indicators of safety performance (Grabowski et al. 2007).

In addition to research in emerging safety strategies, the writers recommend additional research into the diffusion of safety innovations to identify novel methods to facilitate adoption of new injury prevention practices, an area that has seen little attention in literature. Research that identifies enablers and barriers to the diffusion of safety innovations could provide valuable information that would help organizations to apply the best practices that increase the potential success of a safety innovation. Also, since this study found that safety strategies are more driven by internal influences, more research is needed to investigate the influence of dynamic intraorganizational forces. Finally, according to the rational efficiency hypothesis, communication channels can play a prominent role in spreading information regarding new innovations (Farrell and Saloner 1985; Katz and Shapiro 1985). Therefore, research is suggested in the intersection between safety knowledge management and social network analysis to explore relationship between communication channels and diffusion of safety strategies.

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CHAPTER 3
SAFETY RISK INTERACTIONS AMONG HIGHWAY CONSTRUCTION WORK
TASKS

ABSTRACT

Recent research has produced frameworks for integrating safety risk data into project schedules, visual models, and other construction planning tools. Unfortunately, only a few studies have attempted to quantify base-level safety risk for construction tasks and no study has attempted to quantify the degree to which spatial and temporal interactions among tasks contribute to the potential for injury. A research study was performed to quantify the impact that pair-wise spatial and temporal interactions have on the base-level risk of 25 common highway construction work tasks in the United States. Six-hundred risk interactions were quantified by obtaining and aggregating over 23,500 individual ratings from certified experts using the Delphi method. The results indicate that incompatible tasks may increase the base-level risk up to 60%. The most incompatible highway construction tasks are: (1) installing curbs and gutters and installing rigid pavement and (2) construction zone traffic control and installing rigid pavement. Additionally, watering and dust palliatives and pavement marking is the one compatible task pair and there are forty-five neutral task pairs. The resulting database and analysis have the potential to increase the efficacy of existing frameworks for integrating of safety risk data with project planning tools.

KEYWORDS: Occupational health and safety; scheduling; risk management, risk interactions.

INTRODUCTION

Over the last forty years the construction industry has accounted for an injury and fatality rate that is nearly five-times greater than the all-industry average (BLS 2010). Although injury rates have declined dramatically in this time, in each of the past 15 years the construction industry has accounted for over 1,200 death and 460,000 disabling injuries in the United States (NSC 2009).

In addition to physical pain and emotional suffering experienced by the victims and their families,

these incidents have substantial societal costs totaling an estimated \$15.64 billion annually (NSC 2009). Furthermore, it has also been shown that injuries alone account for 7.9 to 15% of the costs of new construction (Everett and Frank 1996). These costs cripple entrant firms and have a strong, negative impact on the Gross Domestic Product (GDP).

Following the Occupational Safety and Health Act of 1970, numerous attempts have been made to improve understanding of construction safety. For example, Bernold and Guler (1993) identified common activities and physical motions that contribute to back injuries; Hinze et al. (1998) suggested a new classification method for identifying root causes of injuries; Chi et al. (2005) identified key contributing factors to fall incidents; Hinze et al. (2005a) studied the root causes of struck-by accidents; Sobeih et al. (2009) identified causes of musculoskeletal disorders; Lombardi et al. (2009) evaluated factors affecting workers' perception of risk; and Mitropoulos and Guillama (2010) suggested a protocol to evaluate the potential for injury when constructing residential framing. Though the contributions of these previous studies are considerable, they are limited in application because they evaluate injuries, activities, and preventive measures as individual issues and isolated subjects (Sacks et al. 2009).

Construction projects are characterized by complexity and uncertainty which stems from an ever-changing environment. The dynamic nature of construction projects requires safety measures to be adapted to new situations. Consequently, many experts believe that injury prevention activities should be conducted early in the project lifecycle (Hinze 2006). One emerging proactive safety management strategy is to integrate safety information into project schedules (Kartam 1997; Hinze et al. 2005a; Chantawi et al. 2005). Recently, Yi and Langford (2006) and Sacks et al. (2009) developed techniques for "safety loading" safety risk data into Critical Path Method

(CPM) schedules. According to Yi and Langford (2006), the quantity of safety risk varies during the project schedule and limited resources should be allocated to projects in proportion to their safety risk at any given time. To analyze temporal safety risk, both studies concluded that safety risk data should be numerically integrated into the project schedule. Prior to these efforts, resource allocation for safety management was inefficient because resources (e.g., safety personnel) were assigned to projects for longer periods than they were actually required (Sacks et al. 2009).

In order to effectively integrate safety risk data with project schedules, managers must identify and quantify safety risk for all scheduled tasks. Though the framework for schedule integration established by Yi and Langford (2006) only requires base-level risk data for the performance of individual tasks, in isolation, under typical circumstances, several authors have postulated that the actual risk of construction operations also depends on the interactions that occur among tasks throughout space and time (Lee and Halpin 2003; Sacks et al. 2009; Rozenfeld et al. 2010). These studies argue that interactions among incompatible tasks may contribute to a greater risk than the sum of the base-level task risks alone. Unfortunately, no study has quantified these potential interactions.

The objective of the present study was to quantify the impact that the interactions of common highway construction tasks have on base-level safety risk levels. Risk interactions are defined as the pair-wise impacts that tasks have on each other due to task compatibility or incompatibility. Interactions were measured as the *percent increase or decrease in safety risk resulting from the concurrent performance of the tasks in the same physical workspace*. The research focused on the highway construction sector because this is one of the most dangerous in the construction

industry (Bai 2002; Bai and Cao 2003; BLS 2008) and highway construction tasks are limited in number and well-defined (Pandey 2009).

LITERATURE REVIEW

Spatial and temporal interactions

Traditionally, safety has not received the attention that it deserves in comparison with other objectives in jobsite planning (Anumba and Bishop 1997). Recently, however, researchers have begun to study the impact of site layout schemes on safety performance. For example, Shapira and Lyachin (2009) showed that crowded jobsites, resources constraints, and overlap of activities may increase safety risks. In an effort to integrate safety into site layout planning, Elbeltagi et al. (2004) presented a method of modeling safety zones around temporary facilities. They used genetic algorithm to optimize the distances between facilities in order to minimize their negative interactions. Similarly, El-Rayes and Khalafallah (2005) suggested a model to consider the influence of crane operations, hazardous materials, and travel routes on safety. Navon and Kolton (2006) took a different approach and showed how interactions among site layouts and planned tasks can produce fall hazards. This body of literature confirms the importance of studying risk interactions but has two main limitations: (1) the models are conceptual and are not based upon an underlying database and (2) the interactions among tasks were ignored in the quantitative analyses.

While spatial safety management typically occurs during site layout planning, temporal safety management typically involves safety-schedule integration. Kartam (1997) made the first attempt to integrate safety data into schedules; however, as Hinze et al. (2005b) recognized, there was not an actual relation between schedule and safety resources in Kartam's model. Consequently, Hinze

et al. (2005b) developed software called SalusLink which allows safety personal to load safety components in to the schedule of a project. Taking schedule integration a step further, Yi and Langford (2006) suggested a framework to integrate safety risk in to schedules using a similar method as resource loading (i.e., assigning a safety risk quantity to each scheduled activity). This framework can be used to identify periods with a relatively high level of safety risk and allows managers to use resource leveling techniques to level the safety risk in a schedule. Similar to the spatial modeling of safety, these schedule-based techniques are not based on robust underlying data nor do they consider the interactions among tasks.

Sacks et al. (2009) recently proposed CHASTE, a model that simultaneously considers spatial and temporal interactions of work tasks. By using information available in 4D geographic models and user-provided data for “loss-of-control events,” the method can be used to produce a 4D view of the regions of the worksite with high level of safety risk (Sacks et al. 2009). The most significant limitation of this framework is that, in order to quantify the risk for “loss-of-control events,” the hazards related to each task must be identified and quantified by the user, which can be time intensive and laborious. As discussed by Jannadi and Almishari (2003), quantifying these risk values is not practical for most firms. To address the limitations in the current body of literature and to enhance the efficacy of the aforementioned safety integration models and frameworks, a database of task interactions was created.

Safety risk quantification

The prevailing methods of injury risk assessment typically involve qualitative risk ratings on either linguistic or numerical scales (e.g., Hallowell and Gambatese 2009). Typically, injury risks are evaluated using a combination of frequency ratings, severity ratings, and exposure durations.

When sufficient historical data are available, safety risk can be calculated by finding the product of likelihood of occurrence and magnitude of impact (Navon and Kolton 2006; Barandan and Usmen 2006). To date, no research has evaluated the impact of risk interactions in risk assessment. Rather, base-level task risks are evaluated individually and are rarely aggregated.

The methods used to obtain risk data and the units of analysis are diverse in existing literature. For example, Jannadi and Almishari (2003) considered risks posed by construction activities, equipment, hazardous substances, and external stimuli to estimate total safety risk on worksites; Barandan and Usmen (2006) used American Bureau of Labor Statistics (BLS) data to analyze safety risk in sixteen different construction trades; Hallowell and Gambatese (2009) quantified risk at the activity level using the Delphi method; Gurcanli and Mungen (2009) proposed a fuzzy rule based system to analyze safety risk with linguistic variables; and Rozenfeld et al. (2010) used a technique similar to job hazard analysis to identify loss of control events for 14 construction activities. As previously indicated, one of the major limitations of this previous work is that risk analyses consider activities, tasks, and processes to be independent. That is, safety risks are quantified for individual tasks in isolation without considering the impacts of other concurrent tasks.

RESEARCH METHOD

In order to develop an appropriate scope for data collection, clear definitions of common highway construction work tasks were needed. Recently, Pandey (2009) used data from literature, project schedules, and interviews to identify and describe 25 common highway construction tasks (see Table 1). As will be described in detail, the interactions among these 25 highway construction tasks were quantified using the Delphi method.

Table 1. Highway reconstruction work tasks and descriptions (after Pandey 2009)

Work tasks in highway reconstruction	Description
Clear and grub	Clearing vegetation, debris, and existing structures (e.g., abandoned utility services)
Excavation	Excavating and constructing embankments and the construction of erosion control devices
Demolition of existing pavement	Removing existing pavement
Landscape	Preparing soil, mulching, and constructing irrigation systems
Watering and dust palliatives	Applying water for density and moisture control of soil, applying palliatives for dust control, and soil stabilization
Reset structures	Installing guardrails, fencing, cattle guards, delineators, and lighting
Lay aggregate base course	Furnishing and placing one or more courses of additives on a prepared sub grade
Recondition bases (compaction)	Blading, shaping, wetting, and compacting the existing sub grade
Installing flexible pavement/patching	Laying hot mix asphalt and installing geosynthetics beneath pavements
Install rigid pavement (concrete)	Forming, pouring, floating, and finishing rigid pavement
Heat and scarifying	Recycling the top portion of existing bituminous pavement by cleaning, heating, scarifying, re-leveling, compacting, and rejuvenating existing pavement
Recycle cold bituminous pavement	Pulverizing the existing bituminous pavement, surfacing to the required depth, and mixing a recycling agent with water
Prime, coat, rejuvenate pavement	Preparing and treating an existing pavement surface with bituminous and blotter materials
Seal joints and cracks	Furnishing and placing hot-poured joint and crack sealant in properly prepared cracks in asphalt pavements
Install cribbing	Installing concrete cribbing, rip rap, and paving slopes/ditches
Install culverts, subsurface drains, and maintain sewers	Constructing culverts, sewers, storm drains, under drains, edge drains, geocomposite drains, and French drains.
Install curb and gutters	Installing curb and gutters, constructing sidewalks and bikeways, and installing median cover material
Install traffic control devices	Constructing signs, signals, street markings and other restriction systems that regulate and guide traffic
Install water control devices	Constructing water and erosion control devices
Install culvert pipe and water lines	Constructing culvert pipe and installing of water lines
Install field facilities	Installing field offices, laboratories, and sanitary facilities on the worksite
Survey	Surveying the worksite during planning, construction, and operation
Mobilization/demobilization	Mobilizing and demobilizing personnel and equipment
Pavement marking	Furnishing and applying pavement markings and removing existing markings
Construction zone traffic control	Preparing or removing lane closures, flagging, traffic diversions, cones, delineators, barricades, sign stands, flashing beacons, flashing arrow trailers, and changeable message signs

The Delphi method is a systematic and interactive research strategy for achieving consensus among a panel of experts. With this technique, panelists are selected according to specific guidelines and are invited to participate in two or more rounds of structured surveys. After each round, an anonymous summary of the experts' input from the previous survey is provided as feedback to the panel. In each subsequent round, participants are encouraged to review the feedback provided by the other panelists and consider revising their previous response. The process is concluded after a pre-defined criterion (e.g., number of rounds or the achievement of consensus) is achieved.

The Delphi method was selected over alternative research methods because archival data are incomplete (Shapira and Lyachin 2009; BLS 2008; Rozenfeld et al. 2010), empirical data could not be obtained during a realistic timeframe, and because the Delphi method is preferred when attempting to obtain complex data that cannot be separated from project context due to confounding factors (Linstone and Turoff 1975). Furthermore, the Delphi method has seen increased use over the past decade for construction engineering and management research (Hallowell and Gambatese 2010). In fact, this method has been successfully employed to enhance bridge condition assessments and predict remaining service life (Saito and Sinha 1991), select procurement systems for construction projects (Chan et al. 2001), identify and evaluate factors affecting international construction (Gunhan and Arditi 2005), identify components and characteristics of supply change flexibility (Lummus et al. 2005), quantify indicators for measuring partnering performance (Yeung et al. 2008), and to select contractors using qualitative measures (Manoliadis et al. 2009).

Expertise requirements

The careful selection of expert panelists is one of the most important aspects of the Delphi method. A well-qualified, well-rounded, and diverse panel of experts is essential to ensure minimal bias and maximum internal and external validity. A review of literature reveals various methods to qualify an individual as an “expert” using objective criteria. Though Rogers and Lopez (2002) and Linstone and Turoff (1975) are the two most commonly cited references when selecting expertise requirements, these publications offer very different sets of requirements. To address these inconsistencies, Hallowell and Gambatese (2010) created a new set of objective and flexible requirements that can be used when certifying potential panelists as “experts” in the field of construction engineering and management. According to this study every panelist must score at least 12 total points in the related field of research using the point system shown in Table 2 to qualify.

Table 2. Flexible point system for the qualification of expert panelists (After Hallowell and Gambatese 2010)

Achievement or Experience	Points (each)
Professional Registration	3
Year of professional experience	1
Conference presentation	0.5
Member of a committee	1
Chair of a committee	3
Peer-reviewed journal article	2
Faculty member at an accredited university	3
Author/Editor of a book	4
Author of a book chapter	2
Advanced degrees:	
BS	4
MS	2
PhD	4

To ensure that the panel is well-rounded and professionally-oriented every panelist was required to have at least eight years of professional experience in the architecture, engineering, and

construction (AEC) industry. It was expected that safety managers, project managers, safety officers, Occupational Safety and Health Administration (OSHA) representatives, construction safety and health researchers, and representatives from workers compensation insurance providers would be the most highly-qualified panelists.

More than 500 potential experts in the field of highway safety risk management were identified. Contact information for potential experts was gathered mainly from The National Work Zone Safety Information Clearinghouse website (www.workzonesafety.org), OSHA, Departments of Transportation (DOTs), the Federal Highway Administration (FHWA), Associated General Contractors (AGC), and university websites. Invitation emails that included basic information for the project and estimated time commitments were sent to all potential experts. Of the initial pool of 500 potential experts, 57 individuals agreed to participate. All 57 potential experts were asked to fill out an introductory survey that solicited information that was later used to assess each individual's level of expertise. Of the 51 introductory surveys that were received, 37 individuals were certified as experts using the aforementioned criteria and were randomly assigned to one of three panels.

The 37 experts had an average of over 21 years of professional experience with highway work zone safety management. Approximately 80% of the respondents are Professional Engineers (PE), Certified Safety Professionals (CSP), or have at least a bachelor's degree in a related field. In addition to the professional experience of respondents, the panel has collectively authored 457 conference papers and 45 peer-reviewed journal articles on safety or risk-related topics. Moreover, the panel was geographically dispersed including all major regions of the United States except for Alaska and Hawaii (i.e., the contiguous United States).

Number of panelists

The number of panelists has varied in previous studies from 3 to 80 (Rowe and Wright 1999). In fact, the number of panelists is affected by the volume of data targeted, time frame of the research, number of accessible experts in the field, and the capability of the facilitator to handle the panelists (Linstone and Turoff 1975). The relationship between the number of panelists and accuracy of the results was investigated by Brockhoff (1975) and Boje and Murnighan (1982). These studies found that optimum number of panelists ranges from 8 to 15. A range between 10 and 13 was targeted for this study because this number ensures an adequate population if a member defaults during the process, is easily manageable, and ensures a high level of internal and external validity (Rajendran and Gambatese 2009).

Due to the great volume of data required for this study (i.e., aggregated ratings of 600 interactions), the authors elected to conduct the study using three independent panels with 12 or more panelists each. Two panels were responsible for quantifying the pair-wise interaction among eight tasks (i.e., 192 ratings) each while the third panel quantified the pair wise interactions among nine tasks (i.e., 216 ratings). The task interactions were randomly assigned to each panel using a pseudo random number generator in Microsoft Excel.

Number of iterations and feedback process

There are two prominent reasons to conduct multiple iterations of surveys during the Delphi process: reaching consensus by reducing variance and improving precision (Hallowell and Gambatese 2010). The number of rounds and methods used to measure consensus has been seen as an indicator for accuracy of Delphi method. The number of iterations in previous large-scale studies ranged from two to six (Dalkey et al. 1972; Gupta and Clarke 1996; Linstone and Turoff

1975). Over half of these studies found acceptable convergence after three or fewer iterations. Hallowell and Gambatese (2010) suggested that a study with three iterations is ideal because expert panelists may review reasons for outlying responses in the third and final round thereby minimizing several forms of cognitive bias. Thus, this Delphi study was designed to include three initial rounds of data collection and a fourth round to cross validate the results. A description of each round is provided in Table 3.

Table 3. Iterations of the Delphi process

	Duration (Days)	Description
Introductory survey	15	Individuals were asked to fill out introductory surveys that solicited information used to objectively qualify potential panelists as experts.
Round 1	30	Panelists were asked to rate the pair wise interactions among randomly assigned tasks (i.e., the increase or decrease in base-level safety risk resulting from compatibility or incompatibility of work tasks).
Round 2	30	Medians responses and personal ratings from Round 1 were provided as feedback for Round 2. Panelists were asked to provide written reasons for Round 2 ratings that they believe were $\geq 10\%$ greater or less than the median response from Round 1.
Round 3	30	In addition to medians and personal ratings from Round 2, reasons supplied by experts for outlying responses were included for consideration. Panelists were given the opportunity to review medians and reasons for outlying responses. The median ratings from this round represented the final aggregated rating.
Round 4 (Validation)	30	Panelists were asked to evaluate the median responses provided by one of the other panels. Panelists had the opportunity to accept the medians provided by other panelists or choose a new rating.

A feature of the Delphi method that distinguishes it from other similar methods is providing anonymous feedback to decrease the potential impacts of cognitive bias. Providing anonymous feedback facilitates indirect communication among panelists in an effort to reach a high level of consensus (Linstone and Turoff 1975; Chan et al. 2001). Research has been conducted to evaluate the effects of different forms of feedback on accuracy of final results (Best 1974, Rowe

and Wright 1999). These studies found that Delphi studies lead to more accurate results when reasons and simple statistical summaries are included in feedback. For the present study, medians and reasons for outlying responses have been chosen as feedback because median responses are impacted very little by biased responses and reviewing and providing reasons for outlying responses requires deeper thinking about more complex interactions. The specific feedback provided in each round is provided in Table 3.

Methods to minimize bias

The research team held the minimization of cognitive bias paramount because the validity and reliability of Delphi process depends on the unbiased judgment of its experts. Various sources of bias may exist despite the panelists' status as certified experts. Identifying potential cognitive biases that affect one's ability to accurately rate risk values is essential because it allows the research team to strategically design the Delphi process in such a way that potential biases are minimized. Any panelist is likely to be susceptible to one or more of the following eight forms of judgment-based bias during the Delphi process: collective unconscious, contrast effect, neglect of probability, Von Restorff effect, myside bias, recency effect, primacy effect, and dominance (Hallowell and Gambatese 2010). Literature suggests several different methods to avoid the cognitive biases listed above. Specific controls that apply to this study include: (1) maintaining the anonymity of the respondents; (2) providing reasons as a part of the controlled feedback; (3) reporting results as medians rather than means; (4) randomizing the question order of the surveys. It was expected that these controls would reduce the potential effects of cognitive bias thereby enhancing the reliability and validity of the results.

RESULTS

In each round of the Delphi process, experts were asked to provide 192 or 216 ratings, depending on their panel assignments. Of the 37 experts who agreed to participate in this research effort, 28 completed all survey rounds resulting in an ultimate Delphi response rate of 76 percent. In total, over 5,900 ratings were obtained per round resulting in a total of 17,776 ratings after the three rounds of initial data collection. The validation effort conducted in the fourth round required an additional 5,900 ratings.

One of the goals of the Delphi process is to reach consensus; however, measure of consensus is not consistent in previous studies. Lummus et al. (2005) compared changes in standard deviations between rounds and conducted t-test to measure level of significance. Another test that has been used to assess level of agreement between panelists in Delphi research is Kendall's coefficient of concordance (W) (Chan 2001; Yeoung et al. 2007; Yeoung et al. 2008; Hon et al. 2010). Using Kendall's coefficient to measure consensus is not appropriate for this study because the test is designed to measure the level of concordance among rankings with few ties within the resulting database. The data targeted, however, are ratings of pair-wise influence. Ties among ratings were welcomed for interactions of the same magnitude. Thus, the absolute deviation (i.e., average deviation from the median) alone was used as a measure of consensus, which is consistent with Delphi studies with similar data profiles (e.g., Hallowell and Gambatese 2009).

Prior to initiating the Delphi process, the research team set the goal to reach an absolute variance of less than 5% for all three Delphi panels after the third round with a 95% agreement in the validation ratings. The absolute variance for each panel after each round is provided in Table 4.

As shown, the target consensus of <5% was achieved for all panels after the third round of Delphi surveys. Notably, medians did not change from round 2 to round 3.

Table 4. Absolute variance of responses for panels in different rounds (percent deviation)

	Round 1	Round 2	Round 3
Panel 1	14.67%	5.71%	4.95%
Panel 2	30.39	9.94	4.22
Panel 3	34.31	6.42	1.35

A portion of the resulting dataset (after round 3) is shown in Table 5. Each median rating in Table 5 represents the aggregate of at least 8 expert panelists' ratings. These ratings are the percent increase or decrease in effectiveness that result from the concurrent performance of two tasks in a proximate physical space. One should note that for each interaction, two different ratings exist in the database. Two ratings are provided for each interaction because the effect of activity A on activity B is not necessarily equal to the effect of activity B on A. For example, when laying aggregate base course and installing rigid pavement are performed simultaneously in overlapping physical work spaces, the base-level safety risk of laying aggregate base course increases by 40% while the base-level safety risk of installing rigid pavement increases by only 20%. The range of the interactions is from -5% up to 60%. The only compatible interaction is the effect of pavement marking on watering and dust palliatives (-5%). This shows that performing different activities at the same time will usually increase safety risk. For some activities, the interaction is zero, which means that there is no risk interaction when the task pairs are concurrently implemented.

Table 5. Median safety risk interaction after Round 3 (percent increase in base-level risk) *

Tasks	Effect on											
	Clear and grub	Excavation	Demolition of existing pavement	Landscape	Watering and dust palliatives	Reset structures	Lay aggregate base course	Recondition bases (compaction)	Installing pavement/patching	Install rigid pavement (concrete)	...	Construction zone traffic control
Clear and grub		20	20	10	0	10	20	20	10	0	...	0
Excavation	40		40	40	40	30	20	20	20	20	...	20
Demolition of existing pavement	20	20		20	20	40	20	20	20	40	...	40
Landscape	40	40	10		20	0	20	0	20	0	...	0
Watering and dust palliatives	0	20	20	0		20	20	20	0	0	...	0
Reset structures	20	20	40	20	20		20	20	20	60	...	40
Lay aggregate base course	0	20	30	10	0	20		30	20	40	...	40
Recondition bases (compaction)	20	20	30	20	20	20	20		20	40	...	20
Installing pavement/patching	0	20	20	20	20	40	20	50		50	...	40
Install rigid pavement (concrete)	0	20	20	10	20	20	20	40	20		...	60
Heat and scarifying	0	20	20	10	20	20	10	30	20	20	...	20
Recycle cold bituminous	0	20	30	20	10	10	20	40	20	20	...	35
Prime, coat, rejuvenate	0	0	20	10	0	20	20	40	20	30	...	40
Seal joints and cracks	0	0	30	0	0	30	20	20	20	40	...	40
Install cribbing	20	20	20	20	20	20	10	0	20	20	...	20
Install culverts, drains, and	20	40	40	20	20	30	20	40	20	30	...	20
Install curb and gutters	0	20	40	20	20	30	20	40	20	60	...	20
Install traffic control devices	0	20	20	20	20	0	20	40	30	30	...	40
Install water control devices	20	40	20	20	20	10	10	10	0	20	...	20
Install culvert pipe and water	40	40	40	20	20	20	20	30	20	30	...	20
Install field facilities	0	0	10	0	0	20	0	0	0	0	...	0
Survey	0	20	20	10	0	0	20	0	10	0	...	0
Mobilization/demobilization	0	0	10	10	0	0	20	10	10	0	...	0
Pavement marking	0	0	20	10	-5	20	10	30	20	20	...	20
Construction zone traffic control	0	20	40	0	30	20	40	40	50	50	...	

*Please note that table is summarized.

As indicated, experts were asked to provide reasons for outlying responses during the Delphi process. Though there was a high degree of consensus after the three rounds of surveys, several respondents provided compelling reasons for outlying responses. For example, a few experts believed that that safety risk interactions among specific tasks (e.g. mobilization and demolition

of existing pavement) should be rated higher because of the concurrence of equipment intensive tasks, using heavy and noisy machinery, and changing of traffic patterns. Overlap between such attributes was thought to increase the chance of spatial interference and, consequently, safety risk. Another example involved the interaction between tasks with heavy materials and noisy machinery. Such tasks were thought to impact other tasks more than the median rating because communications among workers becomes more difficult. Finally, construction zone traffic control was expected to increase the risk of other tasks because of changing of traffic patterns.

In addition to the increases in risk interactions, some experts provided reasons why some interactions should have lower ratings. For example, one of the experts stated that resetting structures takes place primarily beyond the shoulder of the road while prime, coating, and rejuvenating pavement would occur on the roadway. Consequently, it is unlikely that these tasks would have a spatial interaction. Similarly, watering and dust palliatives and pavement marking are very unlikely to be performed concurrently in the same location on a project. Other experts noted that it would be very unrealistic for some tasks to be performed concurrently due to typical construction sequencing. However, the research team purposefully did not remove any task interactions from the analysis to minimize the potential for bias from the research team and to preserve a comprehensive dataset.

ANALYSIS

By summing the rows and columns of this matrix (Table 5), one can evaluate the impacts that each task has on the others and the extent to which each task is affected by the presence of

others. The results of this analysis are provided in Table 6. It should be noted that the measures in this table are a unit-less relative measure of influence.

Table 6. The Cumulative effect of activities on each other (relative unit-less measure)

Tasks	Total effects of the activity on other activities	Total effects of other activities on the activity
Clear and grub	2.30	2.40
Excavation	6.10	4.60
Demolition of existing pavement	4.90	6.10
Landscape	2.60	3.40
Watering and dust palliatives	1.50	3.35
Reset structures	5.80	4.50
Lay aggregate base course	4.80	4.40
Recondition bases (compaction)	5.00	5.90
Installing flexible pavement/patching	6.20	4.30
Install rigid pavement (concrete)	5.05	6.20
Heat and scarifying	4.00	5.50
Recycle cold bituminous pavement	4.75	5.30
Prime, coat, rejuvenate pavement	4.30	4.65
Seal joints and cracks	4.20	3.25
Install cribbing	3.20	2.20
Install culverts, drains, and sewers	4.90	4.50
Install curb and gutters	5.50	5.30
Install traffic control devices	5.20	4.70
Install water control devices	3.10	3.80
Install culvert pipe and water lines	5.30	4.60
Install field facilities	0.50	0.10
Survey	1.50	3.30
Mobilization/demobilization	1.10	1.10
Pavement marking	4.10	4.00
Construction zone traffic control	7.10	5.55

Three activities: construction zone traffic control (7.10), installing flexible pavement/patching (6.20), and excavation (6.10) have the greatest impact on the other activities. Thus, when performing these tasks simultaneously with other tasks, there is a great increase in the base level risk of the other activities. Additionally, the base-level safety risk installing rigid pavement (concrete) (6.20), demolition of existing pavement (6.10), and recondition bases (compaction) (5.90) are affected most by the presence of other activities. Another interesting finding is that construction zone traffic control has the most significant impact on base-level risk of all tasks

and yields the most unstable work environment. Alternatively, installing field and facilities is the most stable task because it is affected the least by presence of other tasks and has the lowest effect on other tasks.

An analysis of the distribution of interaction ratings produced interesting results. The average, median and standard deviation of all ratings were 0.17, 0.2, and 0.14 respectively. Twenty nine percent of the ratings were between 0.0 and 0.1, forty percent were between 0.2 and 0.3, and eleven percent was between 0.4 and 0.5.

Another analysis was performed to identify the most significant two-way interactions. The magnitude of these two-way interactions was calculated by summing both interactions for each pair. For example, if demolition increases the base-level risk of excavation by 20% and excavation increases the base-level risk of demolition by 40%, the magnitude of the two-way interaction for this pair would be 60. This two-way interaction value is a relative, unit-less measure that quantifies the relative magnitude of a two-way interaction between two tasks. Of these two-way interactions, the most significant are installing rigid pavement and installing curb and gutters (120); installing rigid pavement and construction zone traffic control (110); construction zone traffic control and sealing joints and cracks (100); construction zone traffic control and installing traffic control devices (100); construction zone traffic control and installing pavement and patching (90); and installing traffic control devices and heating and scarifying (90). Interestingly, there were 45 two-way interactions with a magnitude of zero indicating that there are a significant number of neutral interactions. Finally, there was one two-way interaction, pavement marking and watering and dust palliatives (-5), that is compatible indicating that

overlapping these two tasks in the project schedule *decreases* the base-level safety risk. It should be noted that the actual impact that these two-way interactions have on site safety depends on the magnitude of the base-level risks.

VALIDATION

As previously stated, the members of three distinct panels of experts and each panel were asked to provide safety risk interaction ratings for 196 or 216 interactions. The first three rounds focused on obtaining initial interaction ratings while the fourth or final round was used to cross-validate the resulting matrix. To perform this validation, surveys similar in structure to the initial Delphi surveys were distributed. In the validation round, experts were asked to review the round 3 responses from a different panel that rated a completely different set of interactions. Panelists were given the option to agree with the other group's collective assessment or provide a new rating. In order to decrease bias, surveys were randomly assigned to the panelists. The only limitation was that no panelist was allowed to rate the same interactions that they were assigned during the initial Delphi process. Of the 28 surveys that were sent, 27 surveys were returned resulting in a 96 percent response rate for the validation. One month was allocated for this validation process and a total of 5,276 ratings were obtained. Absolute variance of responses for each panels have been calculated 0.6, 1.13, and 0.9 percent for panel 1, 2, and 3, respectively. Additionally, medians from validation were the same as medians of each panel, which is evidence of strong validation.

APPLICATION OF RESULTS

There are several potential applications of this database to safety management and planning, which served as the impetus for this research effort. One of the most important aspects of the interaction database is its application to project schedule integration. Previously, researchers have developed a model for integrating safety risk data into project schedules (Yi and Langford 2006; Sacks et al. 2009). This technique involves safety-loading the risk data with the project schedule using the same strategy as resource loading a schedule. This framework is mathematically summarized in Equation 1.

$$[SF]_{1 \times n} = [R_{Individual}]_{1 \times 25} \times [X_{Schedule \& Time}]_{25 \times n} \quad \text{Equation 1}$$

Where:

$[SF]$: is ultimate safety risk matrix and its members are total safety risk for each time unit (day, week, and month); $[R_{Individual}]$: is a matrix which includes safety risk values related to performing each task individually; $[X_{Schedule \& Time}]$: is a matrix which includes just 0 and 1. If in time t , activity i is performing, then $X_{it} = 1$, otherwise $X_{it} = 0$.

Unfortunately, this model, and available safety risk data only allow one to model the independent, base-level risks associated with various work tasks and does not account for the influence that multiple concurrent work tasks can have on one another. With the new dataset in Table 5, each task risk can be adjusted by multiplying the base-level risk by all interaction values for all concurrent tasks. The new data from Table 5 can be incorporated into a schedule analysis using a modification of Yi and Langford's (2006) framework shown in Equation 2.

$$[SF_{Task}]_{1 \times n} = [R_{Individual}]_{1 \times 25} \times ([R_{Interaction}]_{25 \times 25} \times [X_{Schedule}]_{25 \times n}) \quad \text{Equation 2}$$

Where:

$[SF_{Task}]$: is safety risk matrix resulted from performing tasks by considering interaction among them and its members are total safety risk for each time unit (day, week, and month); $[R_{Individual}]$: is a matrix which includes safety risk values related to performing each task individually; $[R_{Interaction}]$: is a matrix (Table 5) which includes impact of performing each task simultaneously with other tasks on safety risk values of other tasks; $[X_{Schedule}]$: is a matrix which includes just 0 and 1. If in time t, activity i is performing, then $X_{it} = 1$, otherwise $X_{it} = 0$.

In this new framework, the safety risk data, which includes spatial and temporal interactions of work tasks, can be simply integrated with the schedule and the safety risk can be plotted over time. This method can be used to identify high risk periods that may not be identified intuitively. In response, contractors can attempt to consume float to level risk, take extra precautionary measures during these high risk periods (e.g., lane closure), inform workers of high risk periods, and strategically design injury prevention strategies to focus on high risk tasks. When the risk profiles for multiple concurrent projects are overlaid in the same plot a manager can identify when and where safety resources should be deployed and could evaluate the risk profile for the company's portfolio simply by computing the cumulative risks for all projects in the company's program and plotting the risk over time.

In addition to integrating these safety data into schedules, risk interaction values can be applied to information models. For example, safety risk data for specific construction tasks and the task

interaction data can be assigned to temporal and spatial elements of the model in the same way as cost, duration, quality, material, and other data. These data are essential to identify high-risk locations and time periods based on the planned sequence and location of tasks. The collection and dissemination of the risk data presented takes a major step towards the creation of a safety information model. Though the dataset presented does not include tasks associated with building construction tasks as would be necessary to integrate with building information models, the research methods and framework could be applied to a future study on the topic.

Several limitations to the application of the results should be noted. First, the interaction data may only be applied to the highway work tasks as they are described in Table 1. Though these task descriptions are representative of typical work scenarios, as described by Pandey (2009), the data presented are not representative of any deviations from these standard procedures. For example, if a crane were used to install field facilities or if excavations were unusually deep, the magnitude of any task interactions associated with these deviations may no longer be accurate. This limitation was essential because adding new criteria to the Delphi survey would have resulted in an overwhelming burden to the panelists, each of whom had already been asked to provide 1,800 ratings over the course of three rounds of surveys. Because of this limitation, the writers suggest future research on the impacts of relevant subtasks, alternative means and methods, and specialty equipment. The second major limitation is that these data should only be applied to daytime construction on projects in the contiguous United States. The limitation must be imposed because the Delphi panelists only had significant experience in the contiguous United States and the construction deviates significantly from standard means and methods when work is performed at night. Finally, the data must be applied with the understanding that the task

descriptions are general in nature and do not reference specific design features, environmental conditions, crew capabilities and competencies, or any other project-specific characteristics.

CONCLUSIONS AND STUDY LIMITATIONS

The research objective was to quantify the pair-wise safety interactions among 25 highway construction work tasks that result from task compatibility or incompatibility using the Delphi method. After three iterations of Delphi surveys with three separate panels, consensus was achieved. In a fourth and final round, the results were successfully cross-validated.

The results of this research indicate that construction zone traffic control, installing flexible pavement/patching, and excavation have the greatest impact on the base level risk of other construction activities. In contrast, installing rigid pavement (concrete), demolition of existing pavement, and reconditioning bases (compaction) are affected most by other concurrent activities. Though the pair-wise data are interesting and valuable on their own, the most significant contribution is that these data can be effectively integrated with cost, schedule, and quality planning. As discussed, the database produced can be attached, along with base-level safety risk data to common highway construction work tasks in a project schedule thereby allowing a manager to “safety-risk-load” a project schedule in the same way one would resource load a schedule. The risk interaction data can be used to more accurately quantify temporal safety risk on projects with many concurrent tasks. The resulting temporal plot includes the base-level safety risk and the influence that multiple concurrent work activities have on each other’s risk level. Though it may be unrealistic to separate concurrent construction tasks, such an analysis may yield more accurate and reliable temporal risk analyses. Being able to proactively

identify high risk periods and communicate risks with construction crews is very important for successful safety management.

There are several limitations of this research. First, though several controls were implemented to enhance the rigor of the study and to promote the validity and reliability of the results, there are inherent limitations associated with quantifying risk-related information using expert ratings. Second, the pair-wise interaction database is limited to only 25 tasks (600 interactions). The creation of a sufficiently representative and robust database would require the quantification of many more task interactions, including building construction tasks. Thus, additional research in this area is suggested. Third, these task interactions apply to the construction environment at the time that the study was conducted. Therefore, if common construction tasks were to change due to the implementation of technological innovations or new means and methods the pair-wise interactions and base-level risk must be re-evaluated. Fourth, the assumption made in this research is that the tasks are performed as described in Table 1 and that this performance is consistent throughout the industry. Satisfying this assumption requires competent and capable crews with sufficient leadership and management control. The authors recognize, however, that construction sites are composed of spectrum of crews with different level of safety experience, competencies, and capabilities. Therefore, the safety interaction risks presented here are average for the industry and can be varied for different projects and crews. Finally, this research does not consider the impacts of environmental risk factors such as weather or light conditions, the safety program of the contractor, or productivity pressure from top managers. Despite these limitations, the resulting database makes a significant contribution to the body of knowledge which can be

used to enhance project management capabilities through the integration of safety with other project management functions.

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CHAPTER 4
INTEGRATION OF SAFETY RISK DATA WITH HIGHWAY CONSTRUCTION
SCHEDULES

ABSTRACT

The construction industry is characterized by a relatively high injury and illness rate compared to other industries. Within the construction industry, the highway construction and maintenance sector is one of the most dangerous. To improve safety in this sector, proactive methods of safety improvement and reliable risk data are needed. Recent research has revealed the importance of quantifying safety risks so that safety data can be objectively integrated into design and planning. This paper describes the results of a study that aimed to quantify safety risks of highway construction and maintenance tasks and test a decision support system that integrates safety risk data into the project schedules. Relative safety risks were quantified for twenty five common highway construction tasks using the Delphi method. To ensure valid and reliable results, experts were selected according to rigorous requirements and multiple controls were employed to decrease cognitive biases. The data were incorporated into a decision support system called Scheduled-based Safety Risk Assessment and Management (SSRAM) that facilitates integration of safety risk data with project schedules. The resulting data-driven system produces predictive plots of safety risk over time based on the temporal and spatial interactions among concurrent activities. To test the utility of the decision support system and the validity of the underlying risk data, the system was tested on 11 active case study projects in the US. The results indicate that the database and associated decision support tool produce accurate and reliable risk forecasts that increase the viability of existing safety preconstruction activities.

KEYWORDS: Occupational health and safety; scheduling; decision support.

INTRODUCTION

Since the Occupational Safety and Health (OSH) Act of 1970 construction workplace injuries and fatalities have decreased significantly; however, construction still accounts for over 1,200 deaths and 460,000 disabling injuries per year (Center for Construction Research and Training 2008). To respond to this relatively high incident rate, attempts have been made to improve safety throughout the lifecycle of a project. Typically, safety management activities take place during the construction phase (e.g., job hazard analyses and site audits). In recent years, new safety management strategies have been introduced that help the project team to identify and control hazards during design and preconstruction.

According to Szymberski (1997), the potential to influence site safety and health conditions decreases exponentially as the project commences. Recent research has confirmed these findings and indicates that the most effective safety program elements occur during the programming and preconstruction phases (Rajendran and Gambatese 2009). Unfortunately, the current methods for considering safety and health in these early phases are inconsistent, informal, and based primarily on intuition and judgment (Hallowell and Gambatese 2007). Thus, there is clearly a need to enhance preconstruction safety management strategies, to create user-friendly tools, and to increase their use in all sectors of the industry.

One of the preconstruction methods that have shown to be highly effective is the integration of the safety into project schedules using risk data (Yi and Langford 2006). Unfortunately, integration is limited because of a lack of data for specific construction work tasks and the lack of reliable tools that interface with existing scheduling software. The current study aimed to test

the theory that loading safety risk data in to the schedule of project is practical and will improve predictions of high risk work periods. The objective of this paper is to describe a recent study that aimed to (1) quantify relative safety risk values for common highway construction activities; (2) integrate these risk data into project schedules using a novel decision support system; and (3) validate the analytical procedure on case study projects.

This study focuses on risk quantification and risk modeling for highway construction because the highway construction sector is one of the most dangerous in the industry (BLS 2012). In 2005, this sector accounted for approximately 469 vehicle- and mobile heavy equipment-related deaths, 279 of which (59%) occurred in traffic work zones (Center for Construction Research and Training 2008). Furthermore, the Federal Highway Administration (2004) estimates that a work zone fatality occurs once every ten hours and a work zone injury occur every thirteen minutes. The presence of high-speed traffic near work zones, prevalence of nighttime work, use of heavy equipment, exposure to weather, and highly repetitive work tasks contribute to this relatively high number of injuries (Bryden and Andrew 1999; Arditi et al. 2005). The value of this research is that it aims to help practitioners to identify, analyze, and respond to high risk periods on highway construction projects.

LITERATURE REVIEW

This study was guided by a large body of literature. In particular, literature that focused on the safety-schedule integration and construction engineering and management (CEM) decision support systems (DSSs) proved to be most helpful. This body of literature was used to guide the

risk quantification process and the development of a framework for integrating safety risk into project schedules. A review of the salient findings from relevant literature is provided below.

Safety schedule integration

Integrating safety planning and management in early phases of construction projects is essential to effective injury prevention and the development of a culture of safety (Tarrant 1980; Sawacha et al. 1999). Coble and Elliott (2000) argued that integration of safety into planning starts with considering safety during the scheduling of a construction project. There have been a multitude of studies that attempt to integrate various forms of safety information with project schedules. These studies can be divided into two general categories: those that attempted to attach safety planning, injury prevention, and regulatory information and those that integrated risk data. The majority of studies focused on the former because these safety data, such as regulatory information, are readily available and not difficult to obtain.

Safety-schedule integration began with the work of Kartam (1997) who designed a framework for integrating extensive safety knowledge (e.g., OSHA regulations) into Critical Path Method (CPM) schedules using Microsoft Project, Primavera P6, Primavera Suretrack, and Timeline. According to Hinze et al. (2005) the major weakness of this initial effort was that there was never any success in making a link between the safety elements and the electronic schedule. In response to this shortcoming, Hinze et al. (2005) built upon this research effort by developing SalusLink, a tool that allows project managers to access textual safety data contained in databases managed by Primavera P6 and Suretrack. Though this research produced a working prototype, the software is not commercially available. Saurin et al. (2004) and Cagno and Trucco

(2001) took a different approach by developing safety planning and control models that attached injury prevention strategies and methods of safety planning to scheduled activities.

In the past five years, researchers have attempted to integrate risk data into project schedules as a means to identify high risk work periods and leverage scheduling controls to prevent periods of excessive risk. For example, Wang et al. (2006) developed a simulation-based model (SimSAFE) that integrates expected injury cost data for each activity in a network schedule. This stand-alone software system allows safety managers to identify work zones that are associated with relatively high risk as measured by cumulative potential accident costs. Yi and Langford (2006) took risk integration a step further by developing a robust framework for “safety resource scheduling” using patterns which are similar to resource leveling. Although Yi and Langford (2006) offered a strong framework for the integration of safety risk data with project schedules, there were no robust risk data as the database only included fatalities that occurred as a result of falls from height. Furthermore, Navon and Kolton (2006; 2007) created an automated monitoring and control model that is capable of identifying fall hazards and their location. The major limitations of this body of literature are that there is not a robust safety risk database and the interactions (i.e., compatibility and incompatibility) among tasks were ignored.

Researchers have begun to model the interactions among risk factors and create frameworks that integrate detailed user-provided data into preconstruction planning tools. For example, a series of studies modeled the spatial and temporal interactions of concurrent work tasks by using information available in 4D geographic models and user-provided data for “loss-of-control events” (Sacks et al. 2009; Rozenfeld et al. 2009; and 2010). The major limitation of these

models is that hazards related to each task must be identified and quantified by the user, which can be time intensive, laborious, and unrealistic in practice (Rozenfeld et al. 2009). In another study, Hallowell et al. (2011) adapted Yi and Langford's (2006) model and suggested a new framework to integrate safety risk data into project schedules. In addition to integrating base-level risks for individual tasks, this framework also considered robust task interactions obtained through the Delphi process. The limitation of this work was that they did not test the applicability of the framework on actual projects and base-level task risks were not quantified. Thus, the current research aims to address the limitations of the previous studies by quantifying highway construction safety risks for common work tasks and testing the efficacy of the framework presented by Hallowell et al. (2011) on active projects.

CEM Decision Support Systems

As computing technologies have improved, increased attention has been paid to the development of computer applications that increase the speed and quality of decision making. One category of these tools is decision support systems (DSSs), which are defined as, "an interactive IT-based system that helps decision makers utilize data and models in making their decisions" (Carter, et al. 1992, p3). Typically, the two main objectives for using DSSs are: performing a given task in the decision making process more quickly and with fewer resources (efficiency); and improving the quality of the outcome of decision making process (effectiveness). In addition, DSSs help a manager to make more informed decisions, consider a multitude of criteria and alternatives, reduce the time needed to make an effective decision, and focus attention on the most important elements of a scenario. They also reduce complexity of the problem to a manageable level and reduce uncertainty (Carter et al. 1992). In CEM, DSSs have been utilized in many areas such as:

resource sharing (Perera 1983); prequalifying subcontractors (Russell et al. 1990); optimizing heavy lift planning (Lin and Hass 1996); resource leveling (Leu et al. 2000); making go/no-go decisions for international projects (Han and Diekman 2001); selecting appropriate project delivery methods (Molenaar and Songer 2001); scheduling steel fabrication (Karumanasseri and AbouRizk 2002); and providing guidance during dispute resolution (Palaneeswaran and Kumaraswamy 2008).

In addition to the applications mentioned above, some DSSs have been developed to enhance decision making in the area of safety. For example, Kak et al. (1995) developed a knowledge-based program to facilitate access to the explicit safety knowledge on the construction sites. Their program searches applicable safety regulations (e.g. OSHA) for a particular task and provides suggestions to improve compliance. Gambatese et al. (1997) presented a tool for incorporating safety related issues in the design phase of a project called “Design for Construction Safety ToolBox,” which has the ability to identify project specific hazards and provide design suggestions to mitigate those hazards. Recently, Hadikusumo and Rowlinson (2004) applied visual reality concept to develop a design for safety tool to capture tacit knowledge of safety professionals. This study aims to contribute to the current arsenal of CEM and safety tools by providing an applied DSS that integrates safety risk data into project schedules.

POINT OF DEPARTURE

This paper departs from the current body of knowledge by assessing the relative safety risk of common highway reconstruction tasks and testing the efficacy of a DSS that integrates safety

risk data into project schedules. A thorough review of relevant literature revealed no study that has directly quantified highway reconstruction safety risks or attempted to assess temporal models for safety risk integration using actual data. It is expected that the findings presented will aid project managers in their preconstruction safety management activities and will be especially effective for safety managers who are responsible for multiple concurrent projects.

RESEARCH METHODS

The research objectives were achieved in three distinct phases. In the first phase, the Delphi method was employed to quantify relative safety risks. In the second phase, a graphical user interface was developed in MATLAB, called Scheduled-based Safety Risk Assessment and Management (SSRAM), that is capable of creating temporal safety risk profiles for highway construction projects. Finally, the output of the system was validated by employing a Multi-Attribute Utility Assessment (MAUA) technique and conducting 11 case studies. The following sections discuss the details of the research methods employed in these three phases.

Phase I method: Risk quantification

In order to develop an appropriate scope for data collection, clear definitions of common highway construction work tasks were needed. Therefore, the 25 highway tasks identified and described by Pandey (2009) and refined by Hallowell et al. (2011) were used as a foundation. To quantify the relative risk values for these tasks, the Delphi method was selected. This study follows the traditional paradigm in risk quantification adopted by Brauer (1994) and Hallowell and Gambatese (2009) where frequency and severity ratings for each task are solicited from an expert panel through multiple rounds of surveys and controlled feedback.

The Delphi method was chosen for obtaining safety risk values for six main reasons. First, there were no objective highway repair and maintenance safety risk data available from government databases. The common national databases such as Occupational Safety and Health Administration Integrated Management Information System (OSHA IMIS) and National Institute of Occupational Safety and Health Fatality Assessment and Control Reports (NIOSH FACE) include only high severity injuries and do not provide enough information regarding the task performed when the injury occurred. Second, according to Gyi et al. (1999), the validity of statistical data obtained from accident reports is significantly compromised by underreporting, especially for minor injuries. Third, Snashall (1990) stated that accident report processes are not consistent between and within companies (e.g. definition of construction activities) such that empirical data cannot be easily interpreted and compared. Fourth, accidents happen in a complex system created by interrelated worksite characteristics that cannot be separated from the project context (Mitropoulos et al. 2005). Fifth, according to Dijksterhuise et al. (2006), intuitive decision processes like Delphi that use heuristic principals lead to accurate risk estimates in complex scenarios. Finally, Delphi is a rigorous process that allows researchers to obtain unbiased data using the judgment of qualified experts, which has been used successfully for risk quantification in similar studies (e.g. Hallowell and Gambatese 2009; and Hallowell et al. 2011).

The Delphi method was developed by Rand Corporation for the US Air Force in late 1940s to elicit reliable and unbiased judgments from a group of experts by conducting an iterative process and providing controlled feedback (Helmer 1967; Linstone and Turoff 1975). The Delphi method involves assembling qualified experts, developing appropriate questionnaires, and

conducting multiple rounds of surveys with controlled feedback between rounds to achieve consensus (Cabaniss, 2001; Hallowell and Gambatese 2010). This method is applied under the assumption that the collective expertise of the panel is superior to the judgment of individuals (Hogarth 1978; Boje and Murnighan 1982; Hill 1982).

The Delphi process was conducted in two rounds where expert panelists were asked to provide independent frequency and severity ratings for each of the 25 highway construction tasks. In order to maintain consistency, the authors have adopted an objective risk scale created by Hallowell and Gambatese (2009) that incorporate a complete spectrum of frequency and severity scales (see Table 1). The severity scale ranges from negligible injury to fatality and the frequency scale ranges from one incident occurrence every 6 min (0.1 w-h) to one incident occurrence every 100 million or more worker-hours (>100 million w-h). After the first round of surveys, the data were aggregated and the level of consensus was measured and evaluated. In the second round, panelists were asked to review the median responses from the first round and provide final ratings. As will be discussed, a third round of data collection was not needed because the target consensus was achieved in the second round.

Table 1. Frequency and severity scales (adopted from Hallowell and Gambatese 2009)

Frequency Worker hours per incident	Severity	
	Subjective level	Score
>100 million	Temporary discomfort	2
10-100 million	Persistent discomfort	4
1-10 million	Temporary pain	8
100,000-1 million	Persistent pain	16
10,000-100,000	Minor first aid	32
1,000-10,000	Major first aid	64
100-1,000	Medical case	128
10-100	Lost work time	256
1-10	Permanent disablement	1,024
0.1-1	Fatality	26,214

Selection of expert panelists

As the number of panelists in a Delphi study increases, the accuracy of the results also tends to increase (Murphy et al. 1998). In a review of past Delphi studies, Rowe and Wright (1999) found that the number of panelists has ranged from of 3 to 80. As noted by Linstone and Turoff (1975) factors such as the expected volume of the data, time constrained, and the number of experts available can affect the appropriate number of panelists. Because this study attempted to quantify risks for tasks that can be performed in a variety of work environments, a relatively large panel was desired.

Careful attention was paid to ensure that all panelists were highly qualified. The expert panel was assembled using the 165 contacts provided on <www.workzonesafety.org>. Because this website provides no information regarding the qualification of any of the contacts as 'experts', the research team independently validated expert status with an introductory survey using guidance provided by Hallowell and Gambatese (2010). Of the 165 individuals contacted, 75 (45%) responded, and 27 (36%) were qualified as experts. According to Moser and Kalton (1971), this response rate is acceptable for Delphi studies.

The resulting pool of individuals averaged over 25 years of highway construction safety experience. Over 80% of respondents had a Professional Engineering (PE) license, were a Certified Safety Professional (CSP), or had at least a bachelor's degree in a related field and all respondents were upper-level managers or executives (e.g., corporate safety manager, director of research, and senior project manager). It should be noted that, despite the relative large

publication lists of some participants, the panel was largely professional in nature. This was preferred as accurately quantifying relative risks relies upon a wealth of professional experience.

Number of iterations and feedback

One of the objectives of the Delphi process is to reach consensus, which can be achieved by conducting multiple iterations of questionnaires and providing anonymous feedback between rounds. Two to seven rounds have been used in the previous large-scale Delphi studies (Dalkey et al. 1972). According to Jolson and Rossow (1971), iterations can be terminated when the changes in variance are no longer significant. The research team administered two rounds of surveys because the size of the expert panel (27) exceeded the minimum size recommended (8) for traditional Delphi studies (Brockhoff 1975; Boje and Murnighan 1982) and there was a high degree of consensus among the experts after the second round.

Cognitive biases

In order to decrease the complexity of probability assessment, many individuals use a limited number of heuristic controls (Tversky and Kahneman 1974). However, relying on these heuristics may produce systematic errors in judgment known as cognitive biases. Despite their importance, cognitive biases have not received adequate attention in previous Delphi studies (Hallowell and Gambatese 2010). In this study the following eight biases were identified and controlled: collective unconscious, contrast effect, neglect of probability, Von Restorff effect, myside bias, recency effect, primacy effect, and dominance (Hallowell and Gambatese 2010).

To minimize the potential influence of cognitive biases, several controls were implemented. First, respondents were kept anonymous. Maintaining the anonymity of respondents reduces the impact of group dynamics, dominant personalities, and the bandwagon effect (Manoliadis, et al. 2006). Second, randomizing the question order of the surveys minimizes the potential influence of primacy and contrast effects (Hallowell and Gambatese 2010). Third, the median ratings from the previous rounds were provided as feedback, which significantly reduces variability among panelists (Martino 1970). Forth, experts were asked to rate frequency and severity levels separately to avoid the neglect of probability bias. Finally, to ensure internal validity and to enhance the reliability of the results, all experts were provided with consistent task names and descriptions.

Phase II method: Decision support system development

One of the structured design methods to develop a decision support system (DSS) is prototyping (Andriole 1989). This research follows prototyping principals established by Boar (1984) where the development of a DSS involves input from perspective users and is refined with professional feedback in an iterative process. Following the guidance provided by Andriole (1989), the first step in designing the DSS involved identifying the tasks that system must perform and the requirements of the user. According to Boar (1984), 20 to 40% of DSS's problems can be attributed to the design process. Well defined requirements will make a link between users, tasks, and organizational needs (Andriole 1989). Here, a quick prototype was made and its features were modified by receiving feedback from the users in an iterative process. In the second step of the DSS development, the safety risk data were mathematically integrated with activity sequences. The data from Hallowell et al. (2011) and those established through the Delphi

process in this study were used to populate the theoretical model shown in Equation 1. In the subsequent phase of this study the research team tested this model with active construction projects in the US.

$$[SF_{Task}]_{1 \times n} = [R_{Individual}]_{1 \times 25} \times ([R_{Interaction}]_{25 \times 25} \times [X_{Schedule}]_{25 \times n}) \quad \text{Equation 1}$$

Where:

$[R_{Individual}]$: is a matrix that includes safety risk values for individual tasks; $[R_{Interaction}]$: is a matrix that includes the safety risk interactions among tasks from Hallowell et al. (2011); $[X_{Schedule}]$: is a matrix that includes 0's and 1's depending on whether or not particular activities are scheduled for a given time period. If in time t, activity i is performing, then $X_{it}=1$, otherwise $X_{it}=0$. $[SF_{Task}]$: is the resulting safety risk matrix that includes the resulting risk for each time period.

Phase III method: Risk data and DSS validation

One of the methods that have been used extensively to decompose the general measure of effectiveness of a DSS is Multi Attribute Utility Assessment (MAUA) (Riedel and Pitz 1986; Adelman and Donnell 1986; Sage 1991). MAUA is a formal structure that maps different measures of effectiveness against one another and is defined as, “scoring and weighting procedures to evaluate the overall utility of a knowledge-based system to users and sponsors” (Adelman and Riedel 1997, p37). This method has been used to evaluate similar DSS in several studies in the past (e.g. Adelman and Ulvila 1991). The total measure of effectiveness is the weighted sum of all the utility scores, shown as Equation 2 (Adelman 1992):

$$U(i) = w_1 \cdot u(x_{i1}) + w_2 \cdot u(x_{i2}) + \dots + w_j \cdot u(x_{ij}) \quad \text{Equation 2}$$

Where: $U(i)$ is the overall utility for alternative i ; w_j is the cumulative relative weight on attribute j ; $u(x_{ij})$ is the utility scale value for alternative i on attribute j .

Figure 1 presents the hierarchy of effectiveness criteria that was created from existing literature and discussions with potential users. The three main evaluation criteria were: usability, applicability, and reliability. Usability was defined as the system's ease of use, response time, ease of training, and graphic displays; applicability was defined as the extent that the program and its output can be used by a construction firm to enhance decision making and resource allocation; and reliability was defined as the predictive accuracy of the system. It is notable that predictive accuracy of the framework and developed DSS relies heavily on the reliability of the safety risk database. In other words, the reliability scores obtained from MAUA process is an indicator of the validity of quantified safety risks.

In order to determine the total utility of the system, the research team used a case study approach where relative weights of the criteria and scores for the system were obtained through interviews with prospective users. Case studies were chosen because the sample size and randomization requirements of a true experiment were not feasible (Adelman 1992) and case studies are appropriate for studying new strategies in context (Yin 2003). In this research, the main units of analysis were active or recently completed projects.

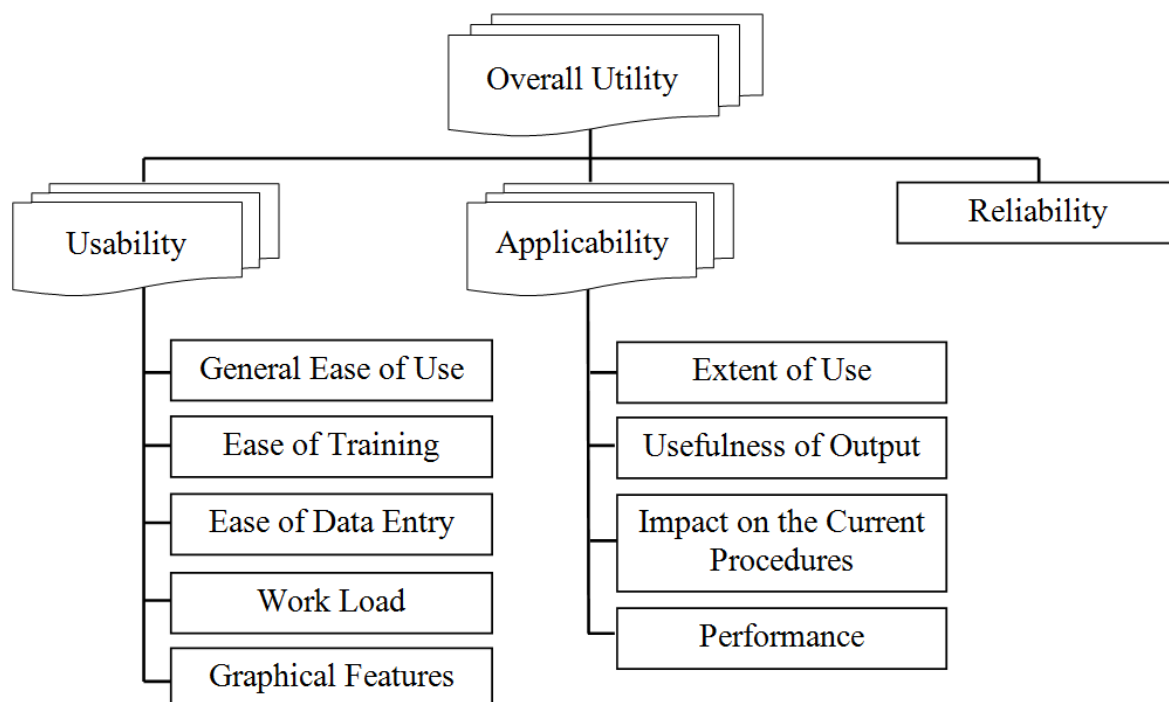


Figure 1. Hierarchy of measures of effectiveness

To obtain a representative sample of US highway construction projects, highway construction firms that were members of the Associated General Contractors (AGC) or the Colorado Asphalt Pavement Association were asked to participate. Of the 39 contractors that were contacted, a total of five firms agreed to provide project data and participate in a series of interviews. The revenue of the companies ranged from \$50 million to \$2.5 billion with the average of \$583 million. The companies, on average, had more than 700 workers and had been in the highway construction business for over 50 years.

According to Yin (2003), the number of cases completed and the quality of pattern matching has a significant impact on the validity and reliability of the results (Yin 2003). Literature suggests that four to ten cases will provide valid and reliable data as long as pattern matching is strong

and data are collected consistently among cases (Eisenhardt 1989, Yin 2003). To ensure adequate data, a total of 11 case studies were conducted. The demographics of these cases are summarized in Table 2. As shown in Table 2, a diverse set of projects is included ranging from large scope and long duration to small scope and short duration. Also, a higher number of projects were located in Colorado, which limits the external validity of the results.

Table 2. Projects demographic information

Project #	Scope (Million\$)	Duration (Month)	Percent of completion	Delivery method	Method of payment	Recordable injuries	Location
1	150	50	88%	Bid/Build	Unit Price	2	California
2	110	30	65%	Design/Build	Lump Sum	0	Utah
3	48	36	94%	Bid/Build	Monthly Progress	2	California
4	5.5	4	100%	-	Pay Estimates	0	Colorado
5	4.5	6	100%	Bid/Build	Unit Price	0	Washington
6	0.32	1.5	99%	Bid/Build	Unit Price	0	Colorado
7	0.38	3	90%	Bid/Build	-	0	Colorado
8	0.66	5	100%	-	-	0	Colorado
9	0.37	10	100%	Bid/Build	Unit Price	0	Colorado
10	0.49	1.5	100%	Bid/Build	-	0	Colorado
11	1.5	3	100%	-	Pay Estimates	0	Colorado

In order to increase the reliability and internal validity of the study, a specific case study protocol was implemented. The following four steps were conducted for *every* case study:

1. Interviews were conducted with the construction project manager or safety managers to quantify the relative weights of the attributes by conducting pairwise comparisons between criteria. The interviewees were asked to use a provided comparison scale that was based on previously successful studies described by Saaty (1980). A consistency ratio was then used to ensure that each respondent's ratings were internally consistent. As suggested by Shapira and Goldenberg (2005), participants were asked to repeat the rating process if their internal consistency ratio exceeded 0.1. In other words, if an individual's pairwise comparisons among criteria resulted in 10% or greater internal inconsistency, they were asked to repeat the process until their ratings were in agreement. This ratio

does *not* measure the consistency among respondents. An acceptable internal consistency ratio indicates that there is no intolerable conflict in the comparisons of a participant's response (Shapira and Goldenberg 2005).

2. After finding the weights, interviews were conducted to determine the DSS's scores for different criteria. In order to gather opinions about the usability and applicability of the DSS, the operation of the system was demonstrated to the participants. Immediately following the demonstration, the users were asked to complete an 18-question survey (two questions for each attribute) that addressed all criteria shown in Figure 1. The participants were asked to rate the system's performance on a scale from 0% (very poor performance) to 100% (very strongly performance), with 50% being neutral.
3. The project schedule was then obtained and the project manager was interviewed to ensure that the research team had an accurate understanding of the actual activities that were performed on the project. With the project manager, the tasks and durations were matched with the tasks described in Hallowell et al. (2011). This mapping process was required because the DSS was built around the data from previous research and consistency of task names was required for the system to operate effectively. Once the tasks were mapped, the schedule integration function of the DSS was used to produce a safety risk profile. The construction project manager or safety manager was then asked to compare the risk profile created by the DSS with the actual level of risk and provide an approximate percent agreement with the system. The interviewees aimed to compare the pattern of the risk profile with near misses and the actual hazards that existed during the work. In fact, the current study did not aim to predict injuries in the jobsite. Rather, the focus was on predicting high risk work periods where the potential for injury is relatively

high. It is important to distinguish the difference between hazards and accidents. For example, if a worker was exposed to adjacent traffic, there were significant hazards even though no injury was realized.

4. The final step of the case study involved a follow-up questionnaire that included open-ended questions that gave the participants an opportunity to share their thoughts on the perceived strengths and weaknesses of the system.

RESULTS AND ANALYSIS

Phase I results: Risk quantification

All 27 expert panelists provided complete responses to the Delphi surveys in the first round and the absolute variance of responses for frequency and severity were 0.733 and 0.838, respectively. Once the data were aggregated and summarized for the panel, second rounds of surveys were administered. In the second round, the median responses from the previous round were provided to the panelists and they were given the option to agree with other group's collective assessment or provide a new rating. Of the 27 surveys that were sent in the second round, 24 surveys were returned resulting in 89% percent response rate. Absolute variances of responses in the second round were 0.198 and 0.191 for frequency and severity, respectively. Because the established consensus was achieved in the second round, there was no need for a third round. Additionally, the median ratings did not change between rounds, which is evidence of strong internal validity.

To facilitate calculations, the frequency ratings were converted from a range of values with units of worker-hours per incident to a single point value with units of incidents per worker-hour. The

mean value was selected as a point value and inverted to obtain a number with appropriate units. For example, if the Delphi panel rated the average frequency as 10–100 w-h/incident, the mean value, 55 w-h/ incident, was inverted (0.018 incidents/ w-h) to determine the frequency value for that particular risk and activity. Severity values were not changed from the severity scale in Table 1.

The frequency ratings ranged from 1.8E-8 to 0.018 incidents per worker-hour and the severity ratings ranged from 4 to 256 units on the severity scale. Unit risk scores were calculated by multiplying the average frequency scores by the average severity scores. The resulting data for the twenty-five work tasks are provided in descending order of relative risk in Table 3. In this table, risk is described in terms of units of severity per worker-hour (S/w-h). The task “construction zone traffic control” has the highest unit risk (0.047 S/w-h) while “watering and dust palliatives” (1.8×10^{-8} S/w-h) and “install field facilities” (1.8×10^{-8} S/w-h) have the lowest unit risk.

Phase II results: DSS development

In order to provide a user friendly environment to integrate safety risk data and project schedules, a graphical user interface (GUI) was developed in MATLAB called Scheduled-based Safety Risk Assessment and Management (SSRAM). MATLAB was chosen for two main reasons: it is a strong programming language to develop graphical user interfaces and it allows the research team to make an active connection between a standard project management software and safety risk databases. An applied DSS for integrating safety risk data in to the schedule of project should include two main capabilities: (1) receiving the schedule from the user and (2)

creating the safety risk profile. These capabilities were considered during the development. Although the DSS can be used to manually add tasks, start dates, and end dates to build the schedule, the researchers built a bridge between Primavera 6, MS Project and the DSS using MS Excel as medium to increase efficiency. After entering projects to the program, the user can save the schedules as M-file (*.m or *.matt). The resulting DSS (SSRAM) is a knowledge-based system with a schedule integration engine.

Table 3. Safety risk data for common highway reconstruction work tasks

Task Name	Frequency score (incident/w-h)	Severity score	Unit Risk Scores (S/w-h)
Construction zone traffic control	1.8*E-2	256	4.7*E-2
Install traffic control devices	1.8*E-4	64	1.2*E-2
Installing flexible pavement/patching	1.8*E-4	64	1.2*E-4
Pavement marking	1.8*E-4	64	1.2*E-4
Seal joints and cracks	1.8*E-4	64	1.2*E-4
Excavation	1.8*E-4	64	1.2*E-4
Install culverts, drains, sewers	1.8*E-4	64	1.2*E-4
Install culvert pipe and water lines	1.8*E-4	64	1.2*E-4
Reset structures	1.8*E-4	64	1.2*E-4
Heat and scarifying	1.8*E-4	64	1.2*E-4
Survey	1.8*E-5	32	5.8*E-5
Clear and grub	1.8*E-6	16	2.9*E-5
Recycle cold bituminous pavement	1.8*E-6	16	2.9*E-5
Install curb and gutters	1.8*E-6	16	2.9*E-5
Install rigid pavement (concrete)	1.8*E-6	16	2.9*E-5
Install cribbing	1.8*E-6	16	2.9*E-5
Recondition bases (compaction)	1.8*E-6	16	2.9*E-5
Install water control devices	1.8*E-6	16	2.9*E-5
Lay aggregate base course	1.8*E-6	16	2.9*E-5
Mobilization/demobilization	1.8*E-6	16	2.9*E-5
Prime, coat, rejuvenate pavement	1.8*E-6	16	2.9*E-5
Demolition of existing pavement	1.8*E-6	16	2.9*E-5
Landscape	1.8*E-6	16	2.9*E-7
Install field facilities	1.8*E-8	4	7.3*E-8
Watering and dust palliatives	1.8*E-8	4	7.3*E-8

The conceptual formulation and computational process of the SSRAM is shown in Figure 2. The safety risk database includes the base level safety risk (obtained from Delphi panel in the first phase of this study) and the safety risk interactions (a 25×25 matrix from Hallowell et al. 2011).

The user can insert the schedule manually or import it from scheduling software (e.g. Primavera

6). Once the schedule is entered, the SSRAM loads safety risk data from database to the imported schedule using Equation 1 and subsequently plots the risk profile. A sample report is shown in Figure 3. There are several practical applications of the safety risk profiles. For example, the risk profiles can be used to identify high risk periods during the project, the safety risk can be leveled utilizing float of activities, or the project manager can allocate safety resources according to the risk profile. In addition, the program is able to create safety risk profiles for multiple projects or portfolio of a company. This is important because safety managers for highway construction companies must often manage multiple concurrent projects. Using the SSRAM helps them to strategically allocate their time and safety resources.

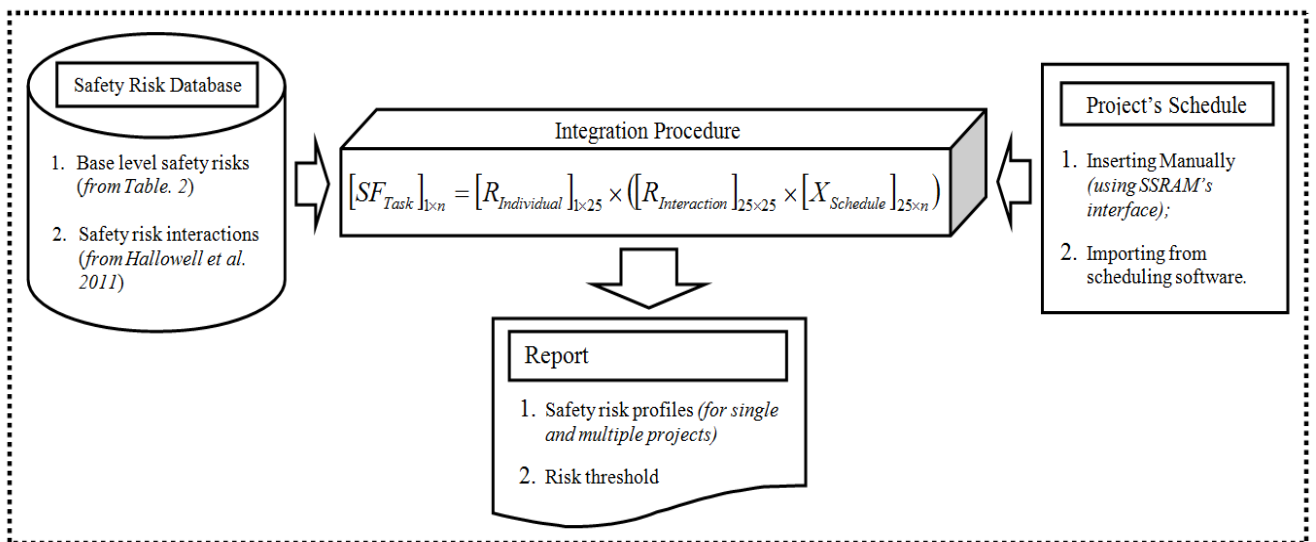


Figure 2. SSRAM's framework

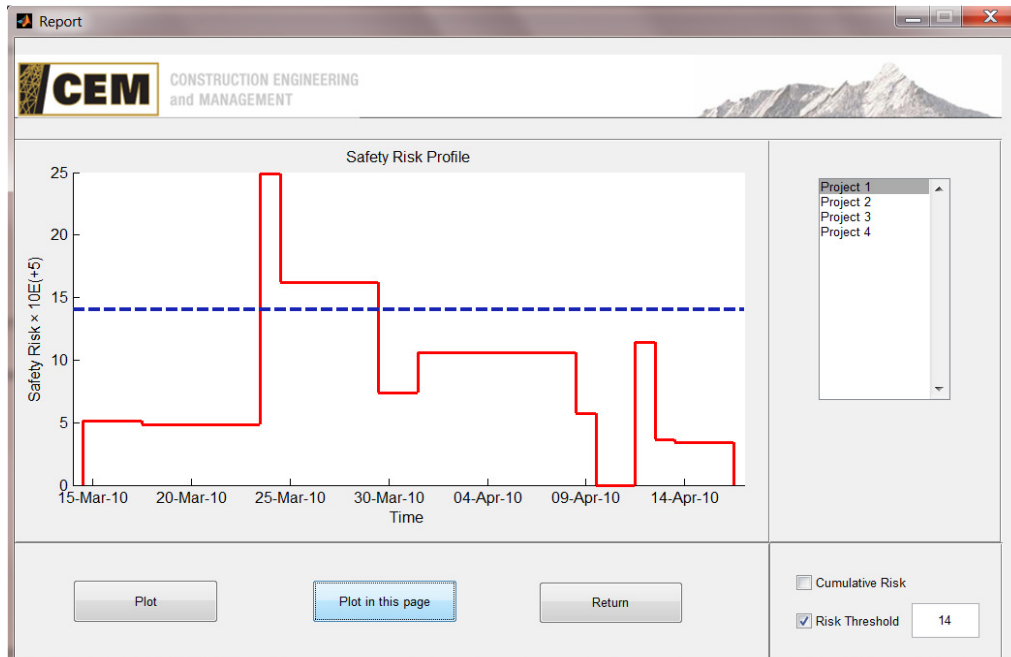


Figure 3. Safety risk profile for a single project with threshold

Phase III results: Risk data and DSS validation

The results of pairwise comparisons made by the user group are shown in Table 4. The users believed that the reliability, the general ease of use of the program, and the usefulness of the output are the most important attributes. Because the usability and applicability have a subset of attributes, the relative weights for the higher tier attributes were computed by finding the products of the subsets (see Table 4). For example, the relative weight of work load (0.17) was multiplied by the relative weight assigned to usability (0.15) to reach the total ‘work load’ weight of (0.03). Once the weights of the criteria were found, they were multiplied against the scores and the resulting products were summed to compute the global utility factor (0.67). This number can be interpreted as the value that the SSRAM adds to the current safety management practice, which ranges from a score of 1 that corresponds to a revolutionary product that completely changes current industry practice and is perfectly executed to a score of 0 where no value is added. One should note that the interviewees, who rated the output of the program, were not

informed of the analytical procedure that resulted in the output. Therefore, any inconsistencies among the interviewees' opinion and the Delphi experts' judgment decrease the actual utility of the system as a whole. In fact, the proposed validation methodology tested the ability of the SSRAM to *forecast* hazardous conditions. Considering the complex and dynamic nature of the construction projects, reaching 100% accuracy was not realistic.

Table 4. Weights of measures of effectiveness and their consistency ratio

Measures of effectiveness	Relative weights	Total weights	Scores	Utility	
Usability	0.15	-	-	-	
Applicability	0.25	-	-	-	
Reliability	0.60	0.60	0.66	0.40	
Usability	General ease of use	0.31	0.05	0.69	0.03
	Ease of training	0.26	0.04	0.75	0.03
	Ease of data entry	0.17	0.03	0.66	0.02
	Work load	0.17	0.03	0.60	0.02
	Graphical features	0.07	0.01	0.68	0.01
Applicability	Extent of use	0.23	0.06	0.58	0.03
	Usefulness of output	0.36	0.09	0.73	0.06
	Impact on the current procedures	0.29	0.07	0.61	0.04
	Performance	0.13	0.03	0.70	0.02
			Total	0.67	

Although the research team was satisfied with the results, there are no similar DSS validation studies to compare against. Fortunately, the follow-up interview questions validated the SSRAM global utility score because respondents indicated that the program is easy to use and greatly improves preconstruction safety management at the project and program levels.

LIMITATIONS

Though the results of this study have the potential to positively impact preconstruction safety management, there are several limitations of the research.

1. The risk quantification portion of the study required that the Delphi panel assume typical conditions in their ratings. Consequently, the data are limited by the fact that actual conditions such as weather, crew safety culture, and fatigue affect the true risk values (Manu et al. 2010). Because of the high number and probable range in values of external risk factors, estimating these distributions was unrealistic for this study. The influence of external factors may explain some of the variation between the predicted values and actual values during the case studies.
2. The risk values were estimated as a single point estimate for each task. The average risk values may not capture all characteristics of risk or, as Kaplan and Garrick (1981) stated, a single number cannot communicate risk effectively due to the great loss of information.
3. Although several measures were employed to decrease cognitive biases in the Delphi process, there are still several limitations to the frequency and severity values provided by experts. One of the common limitations is related to accidents with small probability of occurrence and large impacts. Taleb (2007), one of the prominent researchers in this area, called these extreme events, “Black Swans”. He stated that it is almost impossible to predict extreme events because they do not have predecessor events (Taleb 2007). In fact, predicting these low-probability, high-impact events is extremely difficult and more attention should be paid to reduce the vulnerability of the system towards their consequences than anticipating them (Taleb 2004).
4. The safety risks were quantified for only 25 tasks. In order to add a new task to the schedule, its base-level safety risk and the interactions with other tasks must be quantified separately.

5. The external validity of this study is limited because the data and DSS were validated on projects in Colorado, Oregon, California, Utah, and Washington, with a higher number in Colorado. Although it is expected that projects are representative of the US, the scope of inference is theoretically limited only to these states.

Despite these limitations, the resulting data and SSRAM significantly furthered knowledge and were accurate and useful enough to gain favorable responses from industry users.

CONCLUSIONS AND RECOMMENDATIONS

According to Esmaili and Hallowell (in press), the construction industry is saturated with respect to traditional injury prevention strategies and new safety innovations are needed. Previous research has established that the potential to prevent construction injuries is at its highest during the preconstruction phase and decreases exponentially as a project progresses (Gambatese et al. 1997; Szymberski 1997). Traditionally, preconstruction safety improvement techniques such as designing for safety have faced significant barriers that stem from the fact that they are largely designer-controlled (Hinze and Wiegand 1992; Gambatese et al. 2003; Hecker et al. 2004; Toole 2004). One of the contractor-controlled practices that can be used to overcome this shortcoming is safety-schedule integration.

Although there have been attempts to integrate safety risk data into project schedules (e.g. Yi and Langford 2006; Sacks et al. 2009), these attempts were not successful because of the absence of a valid and reliable safety risk database. This study addressed this limitation by quantifying the relative risk of 25 common highway construction tasks and using these data, along with risk interaction data obtained by Hallowell et al. (2011), to populate a new risk integration

framework. To facilitate implementation, validate the risk data, and test the utility of the underlying framework, the research team created a safety DSS (SSRAM) using MATLAB. The resulting tool interfaced with Primavera P6 to produce plots of safety risk over time for single or multiple concurrent projects. The tool was then tested on 11 case study projects. This validation effort revealed that the data are valid and reliable despite recognized limitations and the SSRAM has the potential to improve safety resource optimization and preconstruction safety management. To summarize, this study tested the validity of the risk database as an input and reliability of the risk profiles generated by integrating base-level risk data and risk interaction data with highway project schedules.

The traditional safety management approach involves investing safety resources such as time and money at a uniform rate throughout the lifespan of a project (Griffel et al. 2007, cited in Rozenfeld et al. 2009). However, because physical conditions change rapidly, safety risk levels may also fluctuate. Consequently, uniform resource allocation to safety within a project and among projects may not be the optimum strategy. One of the viable solutions for this problem is to apply lean thinking to the construction process (Womack and Jones, 2003) so that injury prevention practices can be treated as production control activities (Rozenfeld et al. 2010). According to Rozenfeld et al. (2010), the ability to predict fluctuating safety risk levels are essential to a practical lean-based safety management. The findings of this study can be used to predict safety risk levels and use schedule float to distribute or concentrate risk. In addition, risk profiles enable thoughtful safety planning and effective allocation of safety resources in a single or multiple projects.

In addition, the data and framework presented can be used by project managers to enhance preconstruction safety management by identifying high risk periods. In response, safety managers can plan for extra precautionary measures during these high risk periods (e.g., lane closure), develop customized injury prevention strategies, or at a minimum, inform workers of the tasks and interactions known to cause high risk periods. In addition to using the schedule-based technique described, the writers also recommend that practitioners focus attention on high risk work tasks (e.g., construction zone traffic control, installing traffic control devices, and excavation).

To address the aforementioned study limitations the writers suggest three complementary research efforts. First, new safety risk quantification methods should be explored to produce robust and reliable risk data independently from specific tasks, trades, and construction objects. For example, Esmacili and Hallowell (2011, 2012) utilized genome concept to quantify safety risks at attribute level independently from tasks and objects. Population of this method can be a major step towards a universal safety risk assessment in the construction industry. Second, researchers should consider modeling probability distributions of accident occurrence for individual tasks. Using probability distributions instead of the average estimated points allows an individual to consider uncertainty in the data and investigate its propagation through the model (Fischhoff et al. 1984). Finally, the relative impacts of environmental risk factors on the base safety risk values must be better understood to create robust models. The external risk factors may include the intensification of risk due to nighttime work, exposure to weather, and adjacent traffic.

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CHAPTER 5
ATTRIBUTE-BASED RISK MODELING

ABSTRACT

Struck-by injuries are a leading proximal cause of fatal injuries and are usually caused by a falling or suspended objects and contact between workers and heavy equipment. As with other injuries, struck-by risks are most effectively mitigated early in the planning phases of a project. Among different methods of preconstruction safety management, safety risk modeling and integration has been shown to be highly effective. Unfortunately, the current risk assessment strategies are problematic because they require every new infrastructure feature and construction method to be individually evaluated using laborious research processes. To enhance the current preconstruction safety management methods, the authors present an attribute-based risk identification and analysis method that helps designers and preconstruction planners to identify and model safety risk independently of specific activities or building components. To identify the attributes that contribute to struck-by incidents and quantify their relative risks, a robust manual and automated content analysis conducted on 1771 injury reports from the National databases. In total, 22 safety risk attributes were identified that leads to struck-by accidents. It was found that working with heavy equipment, transporting heavy materials horizontally, and falling objects have the highest frequency and risks among all attributes. The results can be used by practitioners to integrate robust safety risk data into project designs, schedules, building information models, and pre-task plans.

Keywords: Safety risk management, safety attributes, content analysis.

INTRODUCTION

The rate of adoption of the traditional safety strategies dropped significantly after 2005 and there is evidence that the industry has reached saturation with respect to these injury prevention strategies (Esmaeili and Hallowell, in press). To address the demand for new injury prevention practices, several innovative techniques such as construction hazard prevention through design (CHPtD), risk-based schedule control, proximity sensing, and construction hazard modeling in virtual environments have been introduced to the construction industry. The key concepts of these methods include identifying and mitigating hazardous situations before construction phase of the permanent facility. Although these techniques have shown to be viable to enhance safety performance, they have not seen widespread use due to the lack of underlying hazard data (Hallowell et al. 2011). Therefore, careful attention should be paid to identifying hazardous situations and mapping the risk factors on the site (Salelson and Levitt 1982; Young 1996; Abdelhamid and Everitt 2000).

Practical methods of hazard assessment, typically, involve applying risk analysis techniques that provide a quantitative foundation to compare hazardous situations. Current risk quantification methods are problematic because they require every new infrastructure feature and construction method to be individually evaluated using laborious research processes and data from previous failures. Consequently, existing risk databases are limited and rarely employed by practicing professionals because they only include a small fraction of work scenarios and are not robust to departures from existing means and methods. This lack of knowledge has led to mismanagement of new work environments and an increase in injury rates for projects with advanced technologies.

To address this gap in knowledge, the authors present an attribute-based risk identification and analysis method that helps designers to identify and model the safety risk independently of specific activities or trades. The key concept of the new model is that the safety risks can be mapped for any tasks at any time by identifying and modeling fundamental hazardous attributes. In this method, accidents are considered the outcome of interaction among physical conditions of the jobsite, environmental factors, administrative issues, and human error. The authors aimed to identify the fundamental attributes of a construction workplace that characterize safety risk and quantify their relative magnitude. The objective was fulfilled by conducting content analysis of large, representative, and reliable databases of injury reports. In order to limit the scope of the research, the authors focused on struck-by accidents. It is expected the results of the study provide a strong foundation for safety risk quantification and management.

LITERATURE REVIEW

The following is a brief discussion of the previous research results and analyses that relate to the proposed research activities. The information presented has been used to justify the importance of the research, to carefully identify weaknesses in the current body of knowledge, and to provide context for the reader. Specifically, accident causation, safety risk quantification, and content analysis in the construction research are reviewed as they are the impetus for the proposed research activities.

Accident Causation Models

Following the Occupational Safety and Health Act of 1970, numerous attempts have been made to improve understanding of the causes of injuries and the methods of prevention. Two types of studies have emerged to explain the causes of injuries. The first focuses on theory that explains the general causes of injuries and has been developed by integrating concepts from psychology, sociology, engineering, and systems analysis. The second attempts to explain the causal factors for specific injury types based on a situational analysis of the tasks performed or environments experienced by the workforce. The intersection of these two areas is reviewed below.

Accident causation theory

Most accident causation theories have been established by researchers in the occupational safety and health or psychology domains, which is independent from any one industry. The strength of these theories is that they are applicable to many work scenarios and help researchers and practitioners to understand the fundamental physiological, managerial, logistical, and systematic reasons why injuries occur. Nearly all conceptual models are based on the underlying theory that injuries are caused by the simultaneous presence of two primary factors: unsafe conditions and unsafe actions (Heinrich 1959; Reason 1990; Hinze 1997; Gibb et al. 2004). This concept was extended by the Naval Surface Weapons Center to include secondary factors such as design and management errors in the Chain of Events Theory (Fine 1975). In this theory, the cause of an injury is said to be the result of a failure or series of failures in the design, coordination, management, or execution of work. The model does not, however, name these deficiencies in the system; rather, it provides a conceptual framework for explaining the cause of an injury once it has occurred.

Recently, two advanced conceptual models have been established. First, Reason (1990) used psychological theory of human error to form the ‘Swiss cheese model,’ which is a conceptual model where each preventative method is modeled as an impermeable layer and each deficiency in the safety system as a hole in the respective layer. According to his theory, injuries occur as the result of a trajectory when the deficiencies (i.e., holes in the Swiss cheese) align. Second, Mitropoulis et al. (2005) described injuries using a systems model where they assumed that injuries are caused by many interrelated factors. This model included a small number of common risk factors and mitigation techniques and the direction (positive or negative) of their relationships. Unfortunately, the existing causation models are only predictive if the attributes of the work environment have been identified, the relationships among them are understood, and the model provides a measure or description of potential outcomes.

Causal factors for specific conditions

Research on the causal factors for injuries for specific construction tasks and scenarios abound. For example, Bernold and Guler (1993) identified common activities and physical motions that contribute to back injuries; Hinze et al. (1998) suggested a new classification method for identifying root causes of injuries; Chi et al. (2005) identified key contributing factors to fall incidents; Hinze et al. (2005) studied the root causes of struck-by accidents; Sobeih et al. (2009) identified causes of musculoskeletal disorders; Lombardi et al. (2009) evaluated factors affecting workers’ perception of risk; and Mitropoulos and Guillama (2010) suggested a protocol to evaluate the potential for injury for framing operations.

Though the contributions of these previous studies are considerable, the knowledge created is limited to a small proportion of tasks and potential scenarios encountered in the work environment (Sacks et al. 2009). Consequently, the research and professional communities are often unable to aggregate findings from these studies to predict unsafe work conditions. This research address this gap in knowledge by exploring causal risk factors from the perspective of the finite number of shared attributes among the nearly infinite number of work tasks and environments that may be encountered in contemporary and future work environments.

Safety Risk Quantification

Quantifying safety risks and performing comparative analyses is an emerging research field. Risk is defined in Webster dictionary as the “possibility of loss or injury”, however its notion is interpreted in a variety of ways in different domains such as engineering, economy, and military (Skorupka, 2008). For example, Wood and Ernest (1977) defined risk as the probability of a decision’s unfavorable outcome while Perry and Hayed (1985) considered risk as an exposure to economic loss or gain as a result of a construction process. Safety risk in this study is defined as a potential event that results in a negative safety incident that is different from what is planned.

In previous studies, risk at the trade level (Fredericks et al. 2005; Beavers et al. 2009) and activity level (Hallowell and Gambatese 2009) have been quantified. However, some unique temporal and spatial characteristics of construction jobsites such as continuous change in work environment, the dynamic composition of work crews, multiplicity of operations, and proximity of crews expose workers to unrecognized hazards and make it difficult to accurately predict hazardous environments (Helander 1991). This study advances safety risk analysis by using a

new, publically available source of empirical data and mathematical models that efficiently and scientifically prioritize, quantify, and relate risk factors.

Content Analysis in the Construction Research

Krippendorff (2004) defined content analysis as, “a research technique for making replicable and valid inferences from texts.” Content analysis is empirically grounded and is scientific method that helps researchers to gain insights to specific issue and quantify the frequency and distribution of content in textual data (Krippendorff 2004). Content analysis has been widely used in the social science and is getting a growing attention in the construction industry as a method of analyzing context in a systematic, objective, and quantitative manner. One of the potential areas for this method is analyzing contracts and request for proposals (RFPs). For example, Gransberg and Molenaar (2004) used content analysis to investigate owner’s approaches to address quality in design-build proposals. Considering that the quality of final product will be affected by contractual language, they reviewed 78 requests for proposals and found 6 different approaches to evaluating request for proposals by owners. Gransberg and Barton (2007), also, employed content analysis to investigate RFPs in order to identify federal owners’ interest in design build project. In order to conduct content analysis, five categories for evaluation factors were defined and frequencies of statements related to each category were calculated. The result of the study indicates that the RFPs emphasis on low cost and high quality of design build team and the schedule is not the first priority.

Content analysis has also been used in other construction domains. For example, Yu et al. (2006) used content analysis to identify and prioritize critical success factors (CSFs) in project briefing.

They conducted content analysis on open-ended questions provided by experts to identify, categorize, and prioritize the CSFs. In another study, Fisher (2008) used content analysis to investigate the content of information that currently available on state emergency management websites. He analyzed 50 websites to evaluate how critical variables to e-government communication are addressed. The findings of the study, illustrated a picture of level of interaction with people, disasters that has received more attention, targeted group and amount of information (Fisher 2008).

CONCEPTUAL FRAMEWORK

The concept of identifying and analyzing the underlying constituents of a more complex phenomenon in an effort to better understand its behavior has been implemented in other scientific inquiries (e.g., US DOE 2010; Castelluccio 2006; Starr 2006). Each of these “Genome” studies benefitted from breaking complex phenomena into fundamental attributes because they have resulted in more reliable and robust analyses with a greater range of practical application. For example, the largely publicized Human Genome Project had the primary aim of identifying and classifying the genes that constitute human DNA, storing the information in databases, improving tools for genetic data analysis, and transferring the knowledge to the private sector. We propose that hazard assessment for construction work environments will also benefit from an attribute-based assessment strategy. Figure 1 shows that the associated risk quantification framework is based on the idea that base-level risks are ultimately defined by the aggregation of the fundamental attributes.

As shown in the figure, in this model, an infinite number of tasks and objects linked to a finite number of attributes. Single tasks/objects may be linked to multiple attributes. Task/object risk is characterized by the attributes and the interactions among the attributes. Attributes are the real cause factors that lead to an accident. The practical application of this approach is that by identifying limited number of attributes, one can find the real causes of the potential accidents independently from any environmental conditions. This will help safety managers to select the most practical safety strategies according to the attributes that they have in their jobsite and provide training for the potential hazards.

RESEARCH METHODS

In order to identify safety attributes and quantify their risk, the research team conducted a content analysis on the accident reports. A rigorous content analysis protocol established by Neuendorf (2002) and Krippendorff (2004) was followed. Content analysis was appropriate for this research because hazardous attributes were latent in the accident report and identifying them requires recognizing patterns in written injury reports, which allows for the identification factors that are not reported in statistical data. This, in turn, helps to better understand the complete context of the environment in which injuries have occurred. To provide a robust database, over 2,000 documents from the following sources have been identified and obtained for analysis to ensure validity of the resulting data:

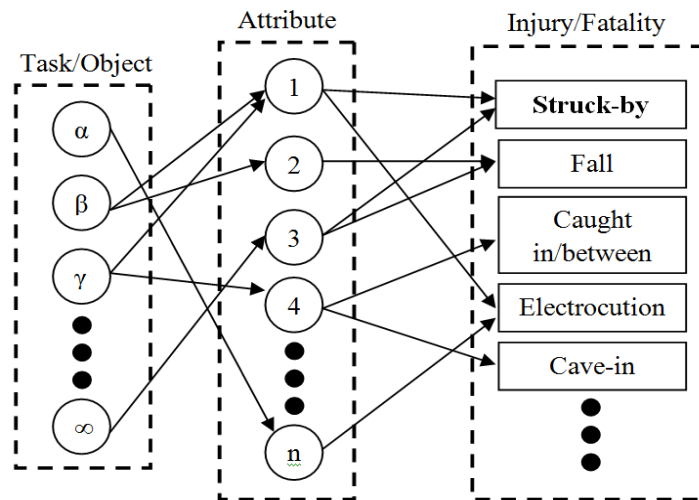


Figure 1 – Attribute-based risk modeling framework.

- *National Institute of Occupational Safety and Health Fatality Assessment and Control Reports (NIOSH FACE)* (www.cdc.gov/niosh/face/) - The NIOSH FACE program has produced 271 detailed investigations into fatalities and catastrophes that occur in construction environments. Each FACE report includes 2-10 pages of empirical data in the form of direct observations made by a NIOSH representative immediately following an incident.
- *Occupational Safety and Health Administration Integrated Management Information System (OSHA IMIS)* (<http://www.osha.gov/pls/imis/>) - OSHA implements a fatality reporting program separate from NIOSH to conduct investigations and provide pithy descriptions of representative fatal occupational incidents that has resulted in over 15,000 reports in the past decade. A sample accident report from OSHA IMIS is provided. In this example, a manual content analysis reveals the nail gun; working with power as the hazardous attributes.

Example OSHA IMIS report from SIC 1521 (202540373): On December 18, 2008, Employee #1, a carpenter, suffered a puncture wound in his foot after a coworker accidentally shot him in the foot with a nail gun. Employee #1 was working for a general contractor that specializes in small single family residence remodeling at the time of the event. The Employer reported that the injury Employee #1 sustained was not serious and that Employee #1 was not hospitalized. Employee #1 was treated for a puncture wound at the Santa Monica Hospital emergency room and released the same day. The Employer provided copies of his written IIPP, Heat Illness Prevention Program and records of safety training. No violations were found during the investigation.

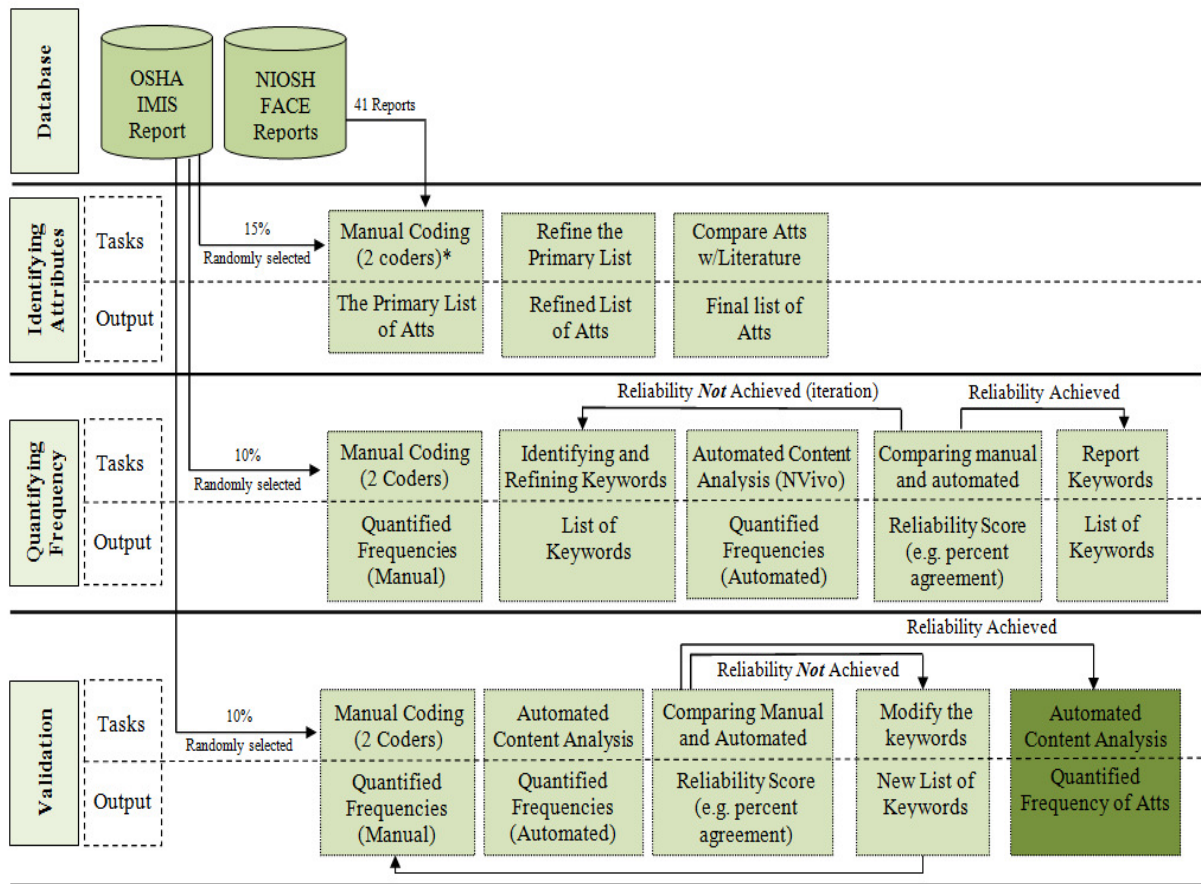
The accidents reports in the IMIS are classified based on the Standard Industrial Classification (SIC). The SIC is a four-digit code that is used by United States government to classify each industry. The first two digits of SIC code indicate the major group and the last two digit indicates the division in that major group. In order to limit the scope of study, the authors focused on two major groups with the highest rate of struck by accidents: (1) building construction general contractors and operative builders and (2) heavy construction other than building construction contractors. Table 1 shows the distribution of injury types within these classes. Several cases were omitted because they did not have specific accident severity or the description in the report was less than two lines.

Table 1. Accident reports analyzed

	SIC code	Description	Struck-by (%)	Without missing data
Major Group 15:	1521	General Contractors-Single-Family Houses	247 (28%)	149
Building Construction General Contractors And Operative Builders	1522	General Contractors-Residential Buildings, Other Than Single-Family	111 (29%)	71
	1531	Operative Builders	19 (34%)	14
	1541	General Contractors-Industrial Buildings and Warehouses	105 (27%)	86
	1542	General Contractors-Nonresidential Buildings, Other than Industrial Buildings and Warehouses	209 (27%)	178
Major Group 16:	1611	Highway and Street Construction, Except Elevated Highways	501 (65%)	463
Heavy Construction Other Than Building Construction Contractors	1622	Bridge, Tunnel, and Elevated Highway Construction	116 (41%)	104
	1623	Water, Sewer, Pipeline, and Communications and Power Line Construction	280 (34%)	226
	1629	Heavy Construction, Not Elsewhere Classified	183 (40%)	159
Total			1771	1450

Content analysis

The dataset were analyzed using a combined manual and automated content analysis to produce a highly valid and reliable results (see Figure 2). In the first step, the attributes were identified. In the second step, a list of keywords was developed to conduct automated content analysis. At the final step, validity of the developed keywords was checked towards a new randomly selected database. Before explaining the different steps in Figure 2, the reliability in content analysis should be discussed.



*Please note that every where that manual coding conducted, reliability score (e.g. percent agreement) was calculated.

Figure 2. Content analysis procedure (combined manual and automated content analysis produced a highly valid and reliable results)

Reliability in content analysis

Even if the principal investigator codes all of the materials, reliability should be tested by using a second coder (Evans 1996). When human coding is used in content analysis, inter-coder reliability should be assessed. Inter-coder reliability can be assessed by asking another person to code the same materials (Krippendorff 2004). Using multiple coders ensures that the results are not one individual's subjective judgment (Tinsley and Weiss 1975). Achieving an acceptable level of reliability of coding schemes indicates that more than one individual can use the coding scheme and achieve similar results. Although, a number of studies that confirm the importance of

reliability is increasing, evaluating and reporting the reliability of coded data has not received adequate attention in traditional research (Perreault and Leigh 1989; Kolbe and Burnett 1991).

The most common method of measuring inter-coder reliability is simple percent agreement (Neuendorf 2002) was used for this study. Percent agreement simply represents number of agreement over total number of measures from the below formula:

$$PA_0 = A/n \quad \text{Equation 1}$$

Where PA_0 represents percent agreement, A is the number of agreements between two coders, and n is the total number of units that the two coders have coded. This test ranges from 0 (no agreement) to 1 (perfect agreement). Simple percent agreement calculated for all of the manual coding and when there was a inconsistency among the coding, accident reports were reviewed in more details by authors and final decisions were made.

Identifying attributes

To identify attributes, content analysis conducted on all struck-by accidents of NIOSH FACE reports and randomly selected accident reports of OSHA IMIS (15%). Two trained coders reviewed each accident report and identified the attributes. The primary list of attributes was examined carefully to remove similar attributes. Moreover, the identified attributes were compared to the causes of struck-by accidents in other publications and the wording was changed to maintain consistency with existing literature. In order to organize the list of attributes, the

authors classified them in to the two main groups based on the phase of project delivery in which they initially appear.

Primary safety risk attributes are physical conditions that contribute to injuries and can be identified in design and planning phase (i.e. prior to breaking ground). Primary attributes are created by decisions in early stages of the project and usually do not change during the construction phase. For example, Workers on foot in proximity of moving equipments can create a hazard. If a designer does not eliminate primary attributes in design phase (e.g. by changing the jobsite layout or removing the exposure of workers on foot to moving equipments), they should provide some kind of mitigation strategies during construction.

Secondary attributes are those physical, environmental, and administrative conditions or workers' behavior that leads to falls in jobsite. Secondary attributes may change depending on construction strategies and controls. For example, competency of workers or sufficient training is not something that can be identified, managed, and controlled during design. The focus of this study is on primary attributes, because they can be identified in preconstruction phase of the project. From here on, attributes is referring to primary attributes.

Quantifying frequencies

The next step of the content analysis was to quantify the frequencies of identified attributes. In order to do that a combination of manual and automated content analysis were used. First, 10% of OSHA IMIS accident reports were randomly selected and manual content analysis with more than two trained coders were conducted to determine which attribute contributed to each

accident. Second, two trained coders reviewed the randomly selected accident reports from the previous step and identified keywords and phrases that recognize attributes in the text. Then, the automated content analysis conducted using the list of keywords and NVivo software to identify the frequency of occurrence of each attribute. The results were compared to the manual coding to find the reliability score (simple percent agreement). The authors aimed to achieve the percent agreement higher than 0.8 for all of the SIC categories. If the percent agreement was lower than 0.8, the coders would review the list of keywords and refine it by combining, removing, or adding new keywords. In an iterative process, the list of keywords was tuned in way that the preset objective for percent agreement was achieved.

Validation

In order to check the power of the refined list of keywords in identifying attributes for an unknown sample, again, 10% of OSHA IMIS accident reports were randomly selected. Manual coding with more than two trained coders conducted on the dataset and percent agreement calculated to check inter-reliability among coders. Then, the refined list of keywords was used to conduct an automated content analysis on the new dataset. The results of automated content analysis were compared with the results of manual coding. If the percent agreement was higher than 0.7 for all SIC categories, the list of keywords would be considered valid for conducting automated content analysis. Otherwise, the list of key words would be tuned and the reliability would be checked with another randomly selected sample.

RESULTS

The manual content analysis conducted on the randomly selected sample with two coders. Then a list of keywords has been created to conduct automated content analysis. The reliability scores (simple agreement) were calculated to compare the result of manual and automated content analyses. The list of keywords was tuned in an iterative process until the objective reliability was achieved. In order to obtain a better insight through the power of automated content analysis, the authors defined two types of error according to simple percent agreement. When the error type I occurs, it means that there was an attribute in manual coding which the automated coding did not identify and the error type II means that the automated coding identified an attribute that did not exist in the manual coding.

Unfortunately, there is no published 'acceptable' level of inter-coder reliability for content analysis (Krippendorff 2004; Perrault and Leigh 1989; Popping 1988; and Riffe, Lacy and Fico 1998). Krippendorff (2004) claimed that if meticulous attention has been paid to calculations, 67% agreement among coders can be considered reliable. However, other researchers reported that agreement should exceed 70% to be considered reliable (Ellis 1994; Frey et al. 2000; Popping 1988). The final results of reliability scores are shown in Table 2. The worst coding was for SIC 1623 with 19% total error and the best coding was for SIC 1631 with 0% error. On average, there was 9% error in identifying attributes using the developed automated content analysis. According to the previous literature, the results have acceptable level of inter-coder reliability.

Table 2 - Simple percent agreement among manual coding and automated coding

	SIC										
Error	1521	1522	1531	1541	1542	1611	1622	1623	1629	Total	Average
Type I	3%	6%	0%	3%	12%	6%	6%	12%	4%	7%	6%
Type II	6%	6%	0%	6%	0%	8%	0%	7%	0%	5%	4%
Total	9%	12%	0%	8%	12%	14%	6%	19%	4%	11%	9%

Tuning the keywords according to one sample can be a source of bias. In order to make sure that the list of keywords is valid to conduct content analysis on an unknown sample data, another sample (10%) randomly selected and coded manually and automatically. The reliability scores were calculated to compare manual and automated content analysis performance. The results are shown in Table 3. The range of percent agreement between the manual and automated content analysis was between 0% and 28% with an average of 21%. Expectedly, these values are higher because the keywords are not tuned for the new sample dataset. The simple percent agreement for all SIC groups are higher than 70% which indicates the list of keywords is reliable.

Table 3 - Simple percent agreement to measure inter-coder reliability among manual coding and automated coding for validation sample

	SIC Codes										
Error	1521	1522	1531	1541	1542	1611	1622	1623	1629	Total	Average
Type I	16%	0%	0%	13%	10%	13%	8%	20%	19%	14%	11%
Type II	9%	14%	0%	13%	10%	11%	15%	5%	9%	10%	10%
Total	25%	14%	0%	26%	21%	24%	23%	24%	28%	24%	21%

After achieving the objective reliability for the keywords in an iterative process, an automated content analysis conducted on all accident reports and frequencies of attributes were quantified. The results of automated content analysis are shown in Table 4. There are four attributes that have the highest frequency scores: working with heavy equipment, falling objects, transporting heavy materials horizontally, and lifting heavy materials.

Table 4 - Frequency of attributes for each SIC group

#	Struck-by Attributes	SIC Codes									Sum
		1521	1522	1531	1541	1542	1611	1622	1623	1629	
1	Working in swing area of a boomed vehicle	16	10	4	16	37	24	44	33	22	206
2	Workers on foot and moving equipments	6	3	3	0	6	55	3	14	17	107
3	Lack of vision or visibility	1	1	0	4	2	36	7	7	10	68
4	Flagger on the jobsite	0	1	0	1	3	55	1	9	3	73
5	Site topography	13	2	5	11	20	36	4	19	15	125
6	Working with heavy equipment	52	24	11	49	101	390	83	156	121	987
7	Falling out from heavy equipments	4	1	1	1	0	18	5	4	3	37
8	Nail gun	33	11	0	2	3	1	0	0	0	50
9	Working with power tools/large tools	37	12	0	3	3	0	1	0	0	56
10	Equipment back up	7	5	3	8	11	123	12	22	24	215
11	Working near active roadway	1	1	0	0	3	138	10	9	5	167
12	Vehicle Accident	2	0	0	0	1	24	2	2	1	32
13	Flying Debris/objects	0	2	0	5	4	7	1	20	18	57
14	Falling objects	53	26	6	38	83	42	30	65	47	390
15	Structure collapse	53	27	2	26	72	10	14	20	11	235
16	Material storage	19	15	6	34	50	25	20	42	15	226
17	Lifting heavy materials	52	11	3	37	69	75	31	52	33	363
18	Transporting heavy materials horizontally	42	14	9	38	71	75	29	52	36	366
19	Working at trench	2	1	1	2	10	10	1	57	10	94
20	Wind	5	2	0	5	10	2	0	1	0	25
21	Snow	0	0	0	0	3	0	0	0	0	3
22	Temperature	0	0	0	0	6	1	0	0	0	7
Total frequency		398	169	54	280	568	1147	298	584	391	3889
Total number of accident reports		149	71	14	86	178	463	104	226	159	1450

In addition to frequency, coders were asked to record the type of injury (e.g. hospitalized or fatality) to quantify the severity of each accident. Twenty six different types of injuries were identified in the reports and were categorized in five injury type as shown in Table 5. These injury types were interpreted according to the Hallowell and Gambatese's (2009) scale. This scale includes a complete spectrum of severity levels ranged from negligible injury (severity = 1) to fatality (severity = 26,214). The assigned severity scores and distribution of injury types for

each SIC group is summarized in Table 6. Notably, the fatalities and lost work time injuries dominated the injury type in most of the groups (except SIC 1521) which is reasonable, because OSHA IMIS database includes severe accidents that are required to be recorded by OSHA.

Table 5. Classifying injury types

Type of injury	Description	Type of injury	Description
First aid	Bruise/Contus/Abras, Non Hospitalized-Strain/Sprain, Non Hospitalized-Cut/Laceration, Non Hospitalized-Puncture, Non Hospitalized- Bruise/Contus/Abras	Lost work time	Hospitalized-Burn/Scald(Heat), Hospitalized-Fracture, Hospitalized-Foreign Body In eye, Hospitalized-Freezing/Frost Bite, Hospitalized-Rupture, Hospitalized-Dislocation, Hospitalized-Cut/Laceration
Medical case	Non Hospitalized-Amputation, Non Hospitalized-Concussion, Non Hospitalized-Dislocation, Non Hospitalized-Fracture, Non Hospitalized-Foreign Body In eye, Hospitalized-Strain/Sprain, Hospitalized-Bruise/Contus/Abras, Hospitalized-Impaled, Hospitalized-Puncture	Permanent disablement Fatality	Hospitalized-Amputation, Hospitalized-Concussion, Hospitalized-Severed spinal cord, Hospitalized-Paralyzed Fatality

Table 6 – Severity of accidents obtained from content analysis for each SIC group

Type of injury	Score	SIC Codes									
		1521	1522	1531	1541	1542	1611	1622	1623	1629	Total
First aid	48	10%	10%	7%	6%	9%	3%	6%	2%	7%	6%
Medical case	128	21%	21%	0%	13%	9%	4%	8%	8%	3%	9%
Lost work time	256	31%	29%	20%	35%	32%	13%	23%	23%	16%	22%
Permanent disablement	1024	8%	9%	7%	2%	6%	4%	6%	4%	4%	5%
Fatality	26214	30%	32%	67%	44%	44%	75%	57%	63%	70%	59%

The quantified frequency and severity were used to calculate safety risks. Among several methods to quantify risk of an event, this study utilized the quantification method presented by Brandan and Usmen (2006), illustrated by Equation 2.

$$\text{Unit risk} = \text{Frequency} \times \text{Severity} \quad \text{Equation 2}$$

The safety risks were calculated for each SIC group using Equation 2. The results are shown in Table 7. The attribute “working with heavy equipment” consistently has a high risk in all SIC groups. This attribute includes working with heavy construction equipments such as loader and bulldozer. In general, after working with heavy equipment, “falling object” and “transporting materials horizontally” had the higher risk values. In major group 15 (building construction general contractors and operative builders), five attributes have produced higher safety risks: falling objects, structure collapse, material storage, lifting heavy materials, and transporting heavy materials horizontally. This is reasonable because workers in this sector of the industry are less exposed to moving equipments. “Equipment back up” and “working near active roadway” are the most hazardous attributes in SIC 1611 (Highway and Street Construction, Except Elevated Highways). Attribute “working in swing area of a boomed vehicle” is only critical for SIC 1622 (Bridge, Tunnel, and Elevated Highway Construction) which means that more attention should be paid to using boomed vehicles in these type of projects.

CONCLUSIONS

Risk analysis methods have shown to be effective in improving safety performance in many ways. For example, they can be used to identify safety hazards during the schedule of project (Navon and Kolton 2006), chose alternative means and methods of construction (Hallowell and Gambatese 2009), or select injury prevention practices more strategically (Hallowell 2011). However, many of these state-of-the-art and innovative strategies have not diffused through the construction industry due to the lack of robust risk database. The main barrier of making a robust

safety risk database is that there are a large number of tasks in the construction industry and it is almost impractical to identify safety risk for each of them individually.

Table 7 – Risk of attributes (multiplied by 10^{-2}) for each SIC group

#	Struck-by Attributes	SIC Codes									Sum
		1521	1522	1531	1541	1542	1611	1622	1623	1629	
1	Working in swing area of a boomed vehicle	17.77	25.92	19.12	21.07	16.29	9.69	73.59	25.44	26.36	219.86
2	Workers on foot and moving equipments	3.61	7.53	56.17	0.00	4.39	23.87	7.56	11.58	26.23	136.74
3	Lack of vision or visibility	0.02	0.02	0.00	3.07	2.91	14.79	10.22	4.63	14.76	47.61
4	Flagger on the jobsite	0.00	3.69	0.00	2.98	2.93	22.78	2.52	9.20	4.92	46.22
5	Site topography	7.30	3.84	37.85	15.01	13.22	13.12	10.08	17.29	24.58	129.68
6	Working with heavy equipment	48.05	55.86	113.66	75.03	73.45	164.78	127.00	119.10	152.91	859.86
7	Falling out from heavy equipments	3.54	0.04	18.72	0.03	0.00	7.37	10.18	1.18	4.92	45.98
8	Nail gun	7.27	3.89	0.00	0.02	0.04	0.00	0.00	0.00	0.00	11.21
9	Working with power tools/large tools	7.44	3.93	0.00	0.05	0.04	0.00	2.52	0.00	0.00	13.97
10	Equipment back up	3.65	7.58	37.63	9.03	8.78	59.62	22.75	17.39	34.45	192.49
11	Working near active roadway	0.02	3.69	0.00	0.00	4.37	55.75	22.71	6.93	3.32	92.59
12	Vehicle Accident	0.02	0.00	0.00	0.00	0.00	7.44	5.04	1.19	0.02	13.71
13	Flying Debris/objects	0.00	0.07	0.00	0.06	2.94	1.71	0.02	16.14	5.01	23.16
14	Falling objects	32.30	37.60	38.58	59.98	50.21	16.51	50.67	39.62	55.97	333.87
15	Structure collapse	25.24	26.59	37.45	30.10	26.92	3.41	22.76	16.23	9.93	173.44
16	Material storage	12.67	29.86	56.57	45.24	28.16	9.11	27.86	31.20	13.20	227.27
17	Lifting heavy materials	26.95	7.84	38.18	51.28	44.26	33.46	40.92	38.16	41.18	280.24
18	Transporting heavy materials horizontally	30.29	15.29	94.75	51.04	38.47	28.50	43.08	42.76	44.43	352.24
19	Working at trench	0.03	3.69	0.18	3.01	8.83	3.96	0.01	38.16	8.27	57.76
20	Wind	5.31	0.04	0.00	8.94	4.49	1.13	0.00	1.15	0.00	16.87
21	Snow	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.04
22	Temperature	0.00	0.00	0.00	0.00	1.57	0.57	0.00	0.00	0.00	0.74

The current study resulted in developing a new injury causation theory that can be used not only to explain the causes of injuries but also to objectively, accurately, and reliably predict hazardous conditions based on the attributes that characterize the workplace. This research also has the potential to transform how safety risks are identified, evaluated, integrated, and controlled during infrastructure planning and execution. It is expected that the results will yield new knowledge

that practitioners and future researchers can integrate with existing and emerging visualization models, hazard proximity sensing systems, and augmented reality prototypes.

While the contribution of the study is great, there are some limitations that should be considered. First, the data sources used in this study were mainly focused on severe accidents that required to be reported by OSHA. However, the numbers of minor injuries or near misses are far greater than number of fatalities and medical cases. Therefore, more studies should be conducted to study the impact of identified attributes on non-sever accidents and near misses. Second, there was no reliable information regarding the exposure of the workers to the hazards in the accident reports provided by OSHA IMIS. In order to overcome this problem, the exposure time can be considered as weight. Then, the risk of an attribute can be translated to the risk of a worker by multiplying its value to the exposure time. Third, the impact of injury prevention practices in mitigating risks is not considered in this study. In future studies, the impact of injury prevention practices in reducing risks with their associated costs can be quantified. Forth, the risk values calculated in this study are sensitive towards the severity scale that was used. Sensitivity analysis should be implemented in future studies to investigate the impact of severity scores on quantified risks. Finally, in spite of these limitations, the contribution of this study in introducing a novel method to quantify safety risks in the construction industry is significant.

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CHAPTER 6

PREDICTING SAFETY OUTCOMES USING GENERALIZED LINEAR MODELS

ABSTRACT

It is shown that strategies that occur early in the project development process have great potential to enhance safety in the project. One of the most recent advancement in the preconstruction safety management strategies is to identify fundamental attributes of construction work environments that cause injuries and quantify their safety risks. The goal of this paper was to utilize the attribute-based risk management concept and propose several safety predictive models to determine the outcome of possible injuries in early phases of a project. In order to identify the attributes that contribute to incidents and quantify their relative risks, content analysis conducted on over 1700 injury reports from the National databases. Principal component analysis (PCA) performed on the safety dataset to identify critical safety attributes. Then, the identified principal attributes have been mathematically modelled as independent variables using generalized linear models (GLMs) to predict safety risk profile, frequency and severity of different kind of injuries. The predictive power of the developed models tested using a rank probability score (RPS). The results of this study can be used by safety managers to accurately forecast the potential severity of the accident in a project.

Keywords: Safety risk management, predictive models, principal component analysis, generalized linear models

INTRODUCTION

The construction industry is extraordinarily dangerous. Although the industry employs 6.5% of the workforce in the United States (BLS 2010a), it accounts for 17% of all total work related fatalities (BLS 2010b). In addition to moral or humanitarian concerns regarding the

consequences of construction injuries, it has been established that owners and contractors have a financial incentive to reduce number of accidents (Everett et al. 1996). In fact, Waehrer et al. (2007) estimated that the cost of injuries in the construction industry was about \$11.5 billion in 2002, which was the 15% of the costs for all private industry.

Several studies indicate that preconstruction safety activities are the most effective in reducing injuries (Szymberski 1997) and, consequently, there is a great interest among safety researchers to introduce new practices that can be implemented in early stages of a project. For example, safety can be considered during the design of the permanent facility (Gambatese et al. 2005) and it can be integrated in to the constructability reviews (Hinze and Wiegand 1992) or project schedules (Yi and Langford 2006). The underlying goal of these methods is to identify and control safety hazards before the project begins. Although, these preconstruction strategies have shown great potential to improve safety, they have not diffused through the construction industry due to the lack of robust risk data or predictive models.

Safety risks have been identified and quantified in previous studies; however, there are some chief limitations. First, most of the risk quantification methods are subjective. There are limited studies that quantify risks objectively or use empirical data sources. Second, it is impractical to quantify risk for every potential task or construction object. To address these chief limitations, Esmaili and Hallowell (see chapter 5) proposed an attribute-based risk identification and analysis method that helps practitioners to model the safety risk independently of specific activities or construction objects. In this method, the risk of worker injury is considered to be the direct result of the temporal and spatial interactions among a limited number of fundamental

attributes that characterize the work environment. The main advantage of attribute-based hazard identification is that risk can be quantified for most of the tasks using limited number of attributes in preconstruction phase of the project.

This paper aims to use fundamental attributes identified by Esmaeili and Hallowell (see chapter 5) to serve as predictor variables in probabilistic safety models. In order to limit the scope of the study, we focus on struck-by accidents, which are one of the leading causes of construction fatalities (Hinze et al. 2005). It is expected this approach and the resulting models will drastically improve proactive safety management. Specifically, the predictive models can help practitioners to consider safety during design, choose alternative means and methods of construction, identify high risk periods of project, and select injury prevention practices more strategically.

LITERATURE REVIEW

The literature review focuses on the nature of struck by accidents and the current predictive models in construction safety domain. The salient results of the review are summarized below.

Nature of struck-by incidents

According to OSHA, struck-by injuries are resulted from “forcible contact or impact between the injured person and an object or piece of equipment” (OSHA 2011). Struck-by accidents accounted for 22% of all construction related fatalities between 1985 and 1989, and while the percentage of caught in/between and electrocutions have decreased between 1997 and 2000, the percentage of struck-by accidents has increased slightly since the time (Hinze et al. 2005). Although struck-by accidents are one of the significant proximal causes of injuries, few studies

have examined this topic directly. In one of the early studies, Thomson (1996 cited in Hinze et al. 2005) investigated equipment related injuries and found that majority of accidents occur due to lack of compliance with OSHA regulations and lack of maintenance for equipment. She stated that keeping equipment in full compliance with OSHA safety standards, such as providing functional back alarms, reliable brake systems, roll-over protection systems, and equipment monitoring, will decrease equipment-related injuries and fatalities significantly.

Perhaps the most significant study to focus specifically on struck-by construction injuries was conducted by Hinze et al. (2005). To improve worker training efforts, they investigated the OSHA's IMIS database from 1997 to 2000 to determine causal factors involved in struck-by injuries/fatalities. They found that the salient proximal causes are private vehicles, construction equipment, falling objects, vertically hoisted materials, horizontally transported materials, and trench cave-ins (Hinze et al. 2005). Each of these proximal causes is reviewed in detail below.

Workers struck-by private vehicles

Injuries where workers are struck-by vehicles are classified in to two main categories: struck-by private vehicles and construction equipment (Bryden and Andrew 1999). Struck-by private vehicles injuries typically occur due to vehicle incursions into an active worksite. This risk increases dramatically when work is performed at night (Arditi et al. 2005). In fact, several studies showed that motor vehicle travel through roadway construction areas increases the risk of a vehicle accident (Doerge and Levy 1977, Pigman and Agent 1990, Sorock et al. 1996). Ore and Fosbroke (1997) used a death certificate-based surveillance system to identify 2144 work-related motor vehicle fatalities among civilian workers in the United States construction industry over

the years 1980-1992. They found that construction workers are twice as likely to be killed by a motor vehicle as worker in other industry sectors and injury prevention efforts in the construction have had limited effect on motor vehicle-related death (Ore and Fosbroke 1997). Some studies suggested that devising and following an effective traffic control plan during the early stages of a project is off great importance for work zone safety (Jacks 1987). Other measures, such as, providing better driver warning systems and increasing buffer zones between work areas and roadways were also suggested for reducing these types of fatalities (Wight et al. 1995).

Struck-by construction equipment

Another common scenario for a struck-by accident is when a worker on foot is hit by heavy construction equipment (e.g. bulldozer). One of the underlying causes for this type of accident is the lack of visibility in the driver's blind spot (Fullerton et al. 2009). Blind spots can lead to accidents because of the operator's obstructed view and workers in close proximity (Teizer et al. 2010a). Ore and Fosbroke (1997) suggested several measures to avoid this type of accident including: changing machine design to improve the visibility of the operators, redesigning audible back up alarms, and assigning spotters. Recently, there is an increasing interest to employ state-of-the-art technologies such as proximity sensing to identify and remove blind spots around heavy construction equipment. For example, Teizer et al. (2010a) mounted a laser scanner inside the equipment cab to develop an automated tool to detect blind spots by analyzing the 3D point cloud.

Lack of vision of operator or blind spots around the equipments can be exacerbated when the equipment is backing up. In order to overcome this challenge, several researchers investigated

situational awareness of construction workers. Again, automation can play an important role in enhancing safety. For example, Kim et al. (2004) modelled objects and zones that may create hazards in 3D environment using the sparse point cloud approach or Teizer et al. (2007) proposed an automatic three-dimensional (3D) sensing and modelling of job sites in real time. In another study, Teizer et al. (2010b) used radio frequency (RF) remote sensing and actuating technology to provide real-time warning to workers-on-foot and equipment operators when they become too close in distance.

Struck-by objects or materials

Lifting, hoisting, and moving materials are common activities on construction sites. However, in a congested work environment, it is possible that workers are struck-by these moving objects. The hazard of struck-by materials can be escalated when a worker is located under or near a boomed vehicle or tower crane. For example, Aneziris et al. (2008) used a logical model to quantify occupational risk of crane activities. They analyzed recorded accidents and information about safety rules concerning work on cranes to identify sequence of events that lead to an accident in crane activities. They found that falling and swinging loads are some of the critical risk factors that can lead to struck-by accidents. They suggested that to mitigate the effect of these risk factors, a careful attention should be paid to the placement of crane, hoisting system, rigging operations, capacity of crane, and providing personal protective equipments (PPE).

In another study, Tam and Fung (2011) conducted a questionnaire survey and structured interviews to explore the extent of following safety guidelines for the use of tower cranes in the Hong Kong construction industry. They found that workers being struck-by moving objects or

falling objects are the most common reason for the fatalities in Hong Kong. They also found that difficulties in communication among crew members, long working hours (fatigue), and stress from time constraint can cause unsafe tower crane operations. They suggested that better training should be provided, sufficient rest breaks should be arranged, the number of sub-contracting layers should be restricted, proper air-conditioning systems should be provided for operator cabins, communication among local and foreign workers should be enhanced, and proper maintenance should be conducted on tower cranes (Tam and Fung 2011). Furthermore, a careful attention should be paid to the planning of lifting operations and reduce the effect of time constraints.

Safety predictive models

Predicting safety performance and objectively quantifying safety risk is important because proactive measures can be taken to avoid or reduce the hazards. In fact, quantifying the probability of injury under specific conditions is the main step towards proactive safety management. The objective of safety predictive models is to find a relationship between safety performance (dependent variable) and some measurable factors (independent variables) that may contribute to predict safety related outcomes. The relationship can be shown as below:

Safety performance = *Function* (variables that may affect safety)

There are several methods to measure safety performance (i.e., the dependent variable) such as accident statistics, accident control charts, attitude scales, severity sustained by the workers, safe behavior, and identifiable hazards (Brauer 1994, Gillen et al. 2002; Cooper and Phillips 2004,

Esmaeili and Hallowell 2012). A variety of factors have been used to measure the predictor variables such as safety attitudes, practices and characteristics of construction firms, safety program elements employed, and construction trades and activities. Safety predictive models vary according to the nature of these different types of predictive variables. The authors classified predictors into two main categories according to the stage of the project that they can be used: predictors that can be employed in the planning stage and predictors that should be used during the construction phase.

Safety predictive models for the construction phase

Predictive models used in the construction phase mostly assume that the unsafe conditions exist and injuries happen due to unsafe behavior. To improve safety, prevention practices should be employed to foster safe behavior. These models relate safety outcomes (e.g., injury rate) to the factors that affect safe performance (e.g., safety practices). The major characteristic of these models is that they use independent variables that can be measured during construction.

Safety climate is often used to forecast safety performance during construction. Safety climate is considered as a subset of organizational climate and can be defined as the “moral perceptions” that workers share about the importance of safety (Zohar 1980, p96). Researchers have attempted to find empirical evidence of relationship between safety climate and safety performance such as frequency and severity of accidents. In one of the seminal studies, Zohar (1980) successfully predicted safety program effectiveness as judged by safety inspectors in industrial organizations using safety climate dimensions. Glendon and Litherland (2001) distributed safety climate questionnaire to examine the relationship between safety climate and safe behavior. They

assumed that safe behavior leads to less frequent and severe accidents. However, they did not find any relationship between safety climate and the safety performance. Fang et al. (2006) took a different approach by using logistic regression to investigate the relationship between safety climate and personal characteristics (e.g. education level). In one of the most recent studies in this area, Johnson (2007) examined the predictive validity of safety climate and found that safety climate was negatively correlated with the number of lost workdays due to injury.

Some researchers examined other predictive variables, for example, Tam and Fung (1998) studied the relationship between common safety management strategies in Hong Kong and their accident rates using multiple regression analysis. They found that seven variables can explain around 40% of the variance of companies' accident rates. In another study, Gillen et al. (2002) found a relationship between injured construction workers' perceptions of workplace safety climate, psychological job demands, decision latitude, and coworker support and severity sustained by the workers. Their model could explain 23% of the variance in injury severities with these predictors. Cooper and Phillips (2004) also used multiple regressions and found that the perception of importance of safety training can predict the actual levels of safe behavior.

Although predictive models designed for the construction phase can be effective tools in measuring safety status, they have the following limitations: (1) the reported relationship between safety climate and safety behavior is largely dependent on subjective self-reporting instruments (Chen and Yang 2004); (2) these models focus on unsafe behavior and ignore the importance of physical unsafe conditions; and (3) the proposed models cannot be integrated in to

the preconstruction safety activities because during design and preconstruction there is no knowledge of the safety climate or behavioral issues in the project.

Safety predictive models for the preconstruction phase

Predictive models designed for the preconstruction phase are more concerned about the physical unsafe conditions that will occur during construction. These models aim to measure the level of risk before construction in an effort to better understand which risks must be mitigated. Because there is typically no knowledge of the crew members, contractor, or safety program elements, safety performance must be anchored to unsafe conditions associated with the work environment. The main feature of predictive preconstruction safety models is that they use independent variables that can be measured before construction begins.

Researchers have attempted to predict hazard by quantifying risks for different trades (Baradan and Usmen 2006), activities (Hallowell and Gambatese 2009), or loss-of-control events (Rozenfeld et al. 2010). For example, Lee and Halpin (2003) presented a predictive tool to estimate accident risk in utility-trenching operations using training, supervision, and preplanning as predictive variables. In order to assess the condition of predictive variables they used the fuzzy input from the user. Outside of the construction domain, Chen and Yang (2004) used regular observation of unsafe acts and conditions to develop a predictive risk index as an indication of safety performance in the process plant. There are two main limitations of these types of predictive models. First, there are numerous activities and loss-of-control events and quantifying risks for all of them is impractical. Second, in most research, risk has been assessed subjectively thereby limiting the internal and external validity of the estimates. Therefore,

developing predictive models using *empirical* data is important for advancing knowledge in this area. The prominent predictive models in construction safety domain with their associated response and predictor variables are listed in Table 1.

Table 1. Safety predictive models in previous literature*

Preconstruction phase		
# Study	Response variable	Predictor variable
1 Lee and Halpin (2003)	Accident risk in utility-trenching operations	Training, supervision, and preplanning
1 Baradan and Usmen (2006)	Safety risk at trade level	Construction trades
2 Hallowell and Gambatese (2009)	Safety risk at activity level	Formwork activities
3 Rozenfeld et al. (2010)	Safety risk at activity level	Loss-of-control events
5 Esmacili and Hallowell (2012)	Safety risk profiles	Highway maintenance and reconstruction tasks
Construction phase		
# Study	Response variable	Predictor variable
1 Tam and Fung (1998)	Accident rates	Safety management strategies
2 Glendon and Litherland (2001)	Percent safe behavior	Safety climate
3 Gillen et al. (2002)	Severity of accidents	Perceived safety climate, job demands, decision latitudes, coworker support
4 Cooper and Phillips (2004)	Safe behavior	Safety training
5 Fang et al. (2006)	Safety climate	Personal characteristics
6 Johnson (2007)	Lost workdays	Safety climate

* Please note that some of the studies were removed from this table because they were not from the construction domain.

CONTRIBUTION TO THE BODY OF KNOWLEDGE

This study departs from the current body of knowledge by developing a novel mathematical model to predict the hazardous situation in early stage of project. For the first time, an objective large accident database was employed to forecast safety related outcomes of accidents using limited number of measurable attributes.

RESEARCH METHOD

Our research objective was to explore attribute-based predictive models that relate the presence of groups of hazardous attributes (predictors) and the probability of various injury types

(response). In order to achieve this objective, we conducted content analysis on 1,771 accident reports. In this process, the fundamental attributes that lead to struck-by accidents were identified as predictor variables and the severity of accidents that caused by these attributes were recorded as response variable. We decided to use injury severity as a dependent variable because estimating the probability of severe accidents based on measurable attributes of a project is more important than predicting infrequent injuries (Lee and Halpin 2003).

Once the attributes were identified and recorded for each injury report, the dimensions of the dataset were reduced using principal components analysis (PCA). Then, generalized linear model were created to analyze the relationship among attributes and injury severity. The specific research methods employed are discussed in detail below. For clarification, the different steps conducted in the study with their goals, inputs, and outputs are summarized in Table 2.

Table 2. Task's description

#	Task Name	Goal	Input	Output
1	Content analysis	To identify principal attributes and quantify the frequency and severity of accidents related to them	Accident reports from OSHA IMIS	List of primary struck-by attributes, frequency tables of attributes, and severity of accidents related to each attribute
2	Principal component analysis	To reduce dimension of the data and remove their colinearity among attributes	Frequency tables of attributes	Principal components
3	Generalized linear model	Finding a linear relationship between the attributes and	Principal components, response variable (severity of accidents)	Predicted β parameters
4	Model pruning	Remove the insignificant variables from the model	GLM model	The best model that contains the right size of variables
5	Evaluation of model skill	Measuring predictive power of the model	Observed events and forecasted probabilities	RPS and RPSS

Database

To structure our present study we used the results from a content analysis conducted in chapter 5. In order to identify fundamental attributes that cause struck-by accidents they conducted content analysis of OSHA's Integrated Management Information System (IMIS). Purpose of their study was to identify attributes that can be identified during the design phase of the project. This chapter uses the database created in chapter 5 which focused on two major groups: (1) building construction general contractors and operative builders and (2) heavy construction other than building construction contractors, which usually have the higher rate of struck by accidents. Table 3 shows the distribution of injury types within these classes. In total, 22 attributes identified that cause struck-by accidents (see Table 4). The output of this research was a matrix which its rows were accident reports and its columns were the safety attributes in which if attribute j contributed to the accident i , then $x_{ij} = 1$, otherwise $x_{ij} = 0$. Several cases were omitted as missing data because they did not have specific accident severity or the description in the report was less than two lines. Due to lack of number of accident reports, SIC 1531 omitted from the analysis.

The severity related to each accident were also recorded and resulted in 26 different types of injury outcomes. Fatality and lost work time (LWT) dominated the accident outcome, which was expected because the IMIS database includes OSHA recordable injuries that have severe consequences. However, this can cause problem for predictive models, because the fatality or LWT will become the most common predicted outcome. In order to solve this problem, the authors categorized the response variables in to the two main groups and conducted the GLM on both of them. In the first group, the response variable dichotomized in fatal and non-fatal

injuries. In the second group, the response variables were categorized in to the three levels: not sever, mild, and severe. The percentage of each injury outcome in different SIC code is shown in Table 5.

Table 3. Accident reports analyzed

	SIC code	Description	Struck-by (%)	Without missing data
Major Group 15:	1521	General Contractors-Single-Family Building	247 (28%)	149
Construction General Contractors And Operative Builders	1522	General Contractors-Residential Buildings, Other Than Single-Family	111 (29%)	71
	1531	Operative Builders	19 (34%)	14
	1541	General Contractors-Industrial Buildings and Warehouses	105 (27%)	86
	1542	General Contractors-Nonresidential Buildings, Other than Industrial Buildings and Warehouses	209 (27%)	178
Major Group 16:	1611	Highway and Street Construction, Except Elevated Highways	501 (65%)	463
Heavy Construction Other Than Building Contractors	1622	Bridge, Tunnel, and Elevated Highway Construction	116 (41%)	104
	1623	Water, Sewer, Pipeline, and Communications and Power Line Construction	280 (34%)	226
	1629	Heavy Construction, Not Elsewhere Classified	183 (40%)	159
Total			1771	1436

Table 4. List of struck-by attributes (predictor variables)

#	Struck-by Attributes	#	Struck-by Attributes
1	Working in swing area of a boomed vehicle	12	Vehicle Accident
2	Workers on foot and moving equipments	13	Flying Debris/objects
3	Lack of vision or visibility	14	Falling objects
4	Flagger on the jobsite	15	Structure collapse
5	Site topography	16	Material storage
6	Working with heavy equipment	17	Lifting heavy materials
7	Falling out from heavy equipments	18	Transporting heavy materials horizontally
8	Nail gun	19	Working at trench
9	Working with power tools/large tools	20	Wind
10	Equipment back up	21	Snow
11	Working near active roadway	22	Temperature

Table 5. Classifying injury types and their distribution for each SIC (in percentage)

Type of injury	Category	SIC Codes								Average
		1521	1522	1541	1542	1611	1622	1623	1629	
First aid	Not severe	10.1	9.9	6.5	9.2	3.0	5.6	2.4	7.0	6.7
Medical case	Mild	20.8	21.0	11.8	8.1	3.6	7.5	7.8	2.9	9.3
Lost work time	Mild	30.8	29.6	35.5	30.8	13.3	23.4	22.4	16.9	24.8
PD*	Mild	8.2	7.4	2.2	6.5	4.2	5.6	3.7	3.5	5.3
Fatality	Severe	30.2	32.1	44.1	45.4	75.9	57.9	63.7	69.8	54.0

* PD means permanent disablement.

Principal Component Analysis (PCA)

PCA was introduced by Pearson (1901) and refined by Hotelling (1933). The main objective of PCA is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set. This is achieved by transforming in to a new set of variables, the principal components (PCs), which the first principal component accounts for the largest amount of variance in the data, the second principal component accounts for the next largest amount of variance and is uncorrelated with the first and so on. Several applications have been stated in the literature for PCA such as data reduction (Wold et al. 1987), modeling (Palau et al. 2011), outlier detection (Barnett and Lewis, 1994), variable selection (Jolliffe 2002), clustering (Saitta et al. 2008), and prediction (Salas et al. 2011). PCA is also widely used in climate research where in, a multivariate dataset decomposed into orthogonal patterns using Eigen decomposition (von Storch and Swiers, 1999).

To explain the mathematical algorithm briefly, suppose that the results of content analysis on OSHA IMIS database is stored in matrix X of size N rows by M columns, where N is the number of accident records and M is the number of attributes. Matrix X can be shown as below:

$$X_{(N,M)} = \begin{matrix} \text{Accident\#1} \\ \vdots \\ \text{Accident\#N} \end{matrix} \begin{bmatrix} x_{1,1} & \dots & x_{1,M} \\ \vdots & \ddots & \vdots \\ x_{N,1} & \dots & x_{N,M} \end{bmatrix}$$

In which if attribute j contributed to the accident i , then $x_{ij} = 1$, otherwise $x_{ij} = 0$. The objective is to find a linear transformation as equation below, that transforms:

$$Z_{NM} = X_{NM} \times W_{MM} \quad \text{Equation 1}$$

Where Z is called the score matrix whose k th column is z_k , the k th PC, $k=1, 2, \dots, m$, and W is an orthogonal matrix, called loading, that projects X to Z . The PCA aims to find elements of W in a way that the squared sum of X 's projection on to the PCs direction is the maximum. Jolliffe (2002) showed that the columns of W (w_i) are the eigenvectors of X 's covariance matrix (C_x). Another common approach to find PCs is to use correlation matrix instead of covariance matrix. Chatfield and Collins (1989) stated that PCs obtained from correlation matrix are not the same as PCs obtained from covariance matrix. One of the main drawbacks of using covariance matrix is that PCs obtained from this method are sensitive to the units of measurement used for each variable. It means that variables with largest variance will dominate the first few PCs. In this case, because all measurements are made in the same units, the covariance matrix might be more appropriate.

Selecting number of PCs in the analysis is an important issue. One of the common rules for selecting PCs is to drop any PC with variance less than 1 which is known as Kaiser's rule (Kaiser 1960). One may claim that variables that influencing these PCs can be considered as prioritized

variables. Another method of selecting PCs is to look at the retained variance by them. It is proved that the i th eigenvalue λ_i is a valid measure of variance accounted by the i th PCs (Jolliffe 2002). Therefore, the cumulative variance retained by the first k PC can be determined as below:

$$CumVar_k = \frac{\sum_{i=1}^k \lambda_i}{\sum_{j=1}^n \lambda_j} \quad \text{Equation 2}$$

In applying PCA a careful attention should be paid to the assumptions of the method. As mentioned before, PCA provide a linear transformation of a multidimensional data in to an uncorrelated space. Alternative methods suggested for data that their relationship cannot be explained in a linear (Jolliffe 2002). The authors believed that a linear relationship between attributes is a reasonable assumption.

Although some of the scholars (e.g., Qian et al. 1994) claim that PCA needs multivariate normality, this technique is more descriptive than inferential and it can be used for even a mixture of continues, ordinal, and binary variables (Jolliffe 2002). It is true that a linear function of binary variables is less interpretable than linear functions of continues variables. However, since the main objective of this PCA was to explain the original set of variables with a smaller number of variables PCA can be used regardless of the distribution of the data (Jolliffe 2002). This algorithm is implemented through “prcomp” function in R, which is an open source statistical program,

Generalized Linear Models (GLM)

Regression techniques have been widely used in the construction industry to predict construction demand (Akintoye and Skitmore 1994; Goh 1999), values of total construction activities (Tang et al. 1990), and cash flow (Park et al, 2005). In general, regression techniques aim to model the relationships among variables by quantifying the magnitude that a response variable is related to a set of explanatory variables. The output of the regression model is a forecasting tool that can be used to evaluate the impact of various alternative inputs on response variable (Goh and Teo 2000).

A classical method to evaluate the relationship between predictor and response variable is linear regression. One of the major assumptions of linear regression (LR) is that the response variables come from a normally distributed population. However, in reality, many response variables are categorical and violate this assumption. In order to overcome this barrier, the authors adopted a more general approach that does not have this limitation of LR, called generalized linear models (GLM). This modeling technique provides a very flexible approach to explore the relationships among a variety of variables (discrete, categorical, continuous and positive, extreme value) compared to traditional regression (McCullagh and Nelder 1989). In GLM, instead of modeling the mean, a one-to-one continuous differentiable transformation $g(\mu_i)$, called link function, will be used. Depending on the assumed distribution of response variable (Y), there exist appropriate link functions (McCullagh and Nelder 1989). As mentioned in data gathering section, the response variables in this study are dichotomous (fatality/no fatality) and categorical (severe/mild/non severe), thus a logit link function was used as below:

$$\eta_i = g(\mu_i) = \log \frac{\mu_i}{1-\mu_i} \quad \text{Equation 3}$$

Where μ_i is the expected value of the response variable (injury outcome) and η_i is called linear predictor and transforms the expected value of response variable in a way that:

$$\eta_i = x_i' \beta \quad \text{Equation 4}$$

Where β is the regression coefficient and x is an $N \times P$ matrix called set of predictors and includes N observations (accident reports) and P possible predictor variables (leading PCs). For two categorical variables, the model is logistic regression and for three categorical variables the model is the multinomial regression. Model parameters in GLM will be determined in an iterative process called iterated weighted least squares (IWLS). In summary, this method finds a set of model parameters that maximize the likelihood of reproducing the data distribution of the training set. This algorithm is implemented by default through R's standard GLM libraries such as "MASS", "VGAM", and "nnet". After estimating β , one can predict η and then the values can be transformed in to original response using inverse link function.

Model pruning

One of the common treat to statistical models is over fitting the data set which results in a large number of insignificant variables in the model. Therefore, the predicted variables of the model should be pruned to find a "best model" that contains the right size of variables. To do that, the authors adopted stepwise regression approach that minimizes the Akaike Information Criterion (AIC) instead of likelihood function to evaluate goodness of fit in stepwise search. By

minimizing AIC a balance between the number of parameters and goodness of fit will be built. In fact, this method measures the ability of the predictive model in reproducing the variance of the observations with the fewest number of parameters (Wilks 1995). The AIC value can be calculated from the equation below:

$$AIC = 2K - 2\ln(L) \quad \text{Equation 5}$$

Where k is the number of model parameters and L is the maximized value of the likelihood function for the model. To minimize the AIC, both forward and backward search were conducted in stepwise regression.

Evaluation of model skill

After developing the model, the predictive power of that should be measures objectively. The performance of the model has been measured against the observed data through a rank probability score (RPS) which indicates the degree to which the model predicts the observed data. To calculate that, two vectors were constructed: one for forecasted probabilities, P_j , based on the GLM model predictions and another one for observed events, z_j , from the observed data. RPS is computed by dividing injury outcome predictions into number of categories of response variables. Then the cumulative density function of P_j and z_j should be constructed based on the GLM model predictions, resulting in the vectors, $P_{cdf,j}$ and $z_{cdf,j}$.

$$RPS = 1/N \times \sum_{i=1}^j (P_{cdf,j} - z_{cdf,j})^2 \quad \text{Equation 6}$$

Although RPS is quite informative regarding the predictive power of the model, there is a possibility that the observed data be reproduced by pure chance. Therefore, it is necessary to compare the RPS of the model against the RPS of the random process and compare their effectiveness. This is done through the ranked probability skill score (RPSS), which has been used in various climatological contexts to compare model skill in predicting categorical rainfall and stream flow quantities (Regonda et al. 2006). A detailed description of the RPSS method is provided by Wilks (1995). The RPSS is computed by forming a ratio between the average RPS values of the model and chance as shown below:

$$RPSS = 1 - \frac{\overline{RPS}_{Model}}{\overline{RPS}_{Chance}} \quad \text{Equation 7}$$

The RPSS compares the accuracy of model predictions against chance, but rather than simply compare the model against a 50/50 chance for fatality/no fatality (or 33/33/33 chance for three categories response variables), it was compared to the ratio of response variables provided by the original data. In other words, instead of pure chance, the authors used a weighted coin which is a more rigorous test of model performance. The range for RPSS is from minus infinity to one 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.

RESULTS AND ANALYSIS

The frequency of attributes and the severity related to each accident reports obtained. To explore the possibility of reducing the dimensionality of the potential predictor variables (attributes),

PCA was conducted on the dataset. Then, the authors selected number of PCs that should be used in GLM model by visually investigating a scree plot of the variance captured. The scree plot of fractional variance captured for SIC 1521 by the various modes of the PCA is illustrated in Figure 1. As is clear, the fractional variance captured drop rapidly as the number of PCs increases. Notably, over 78% of the fractional variance in the predictor set is captured by the first 5 PCs, meaning that, as expected, there is significant redundancy in the predictor variables. Consequently, by selecting only 5 PCs, the dimension of the data was reduced while only a small portion of the total variance in the original data set was lost.

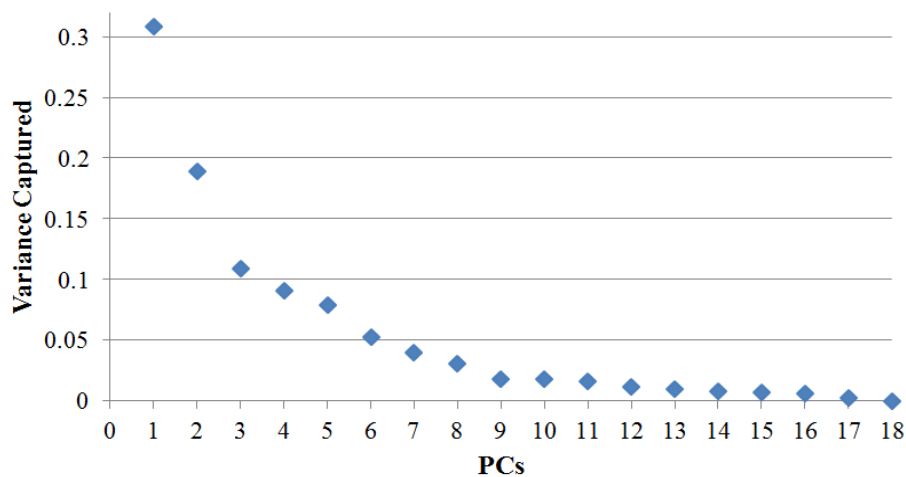


Figure 1. Scree plot of variance captured by each PC for SIC 1521

As mentioned before, PCs are the linear combination of different attributes. The loadings obtained by the PCA can be used to determine the weight of various attributes (variables). The loadings for the first five PCs of SIC 1521 are provided in Table 6. The first PC, which captures approximately 31% of variance, is essentially related to working with tools and struck-by nail guns. This is understandable because SIC 1521 includes general contractors-single-family housing projects in which working with nail guns and power tools are very common activities.

Working with heavy equipment has the highest loads on the second PC. For the last three PCs, struck-by objects related attributes such falling objects, structure collapse, lifting heavy materials, transporting heavy materials horizontally were the most influential attributes. The same procedure was conducted on PCs for the remaining SICs. The selected number of PCs and variance captured for different categories of SIC is shown in Table 7.

Table 6. PCA loadings for the first five PCs of SIC 1521

Attributes	PC1	PC2	PC3	PC4	PC5
1 Working in swing area of a boomed vehicle	0.123	0.201	-0.119	-	-
2 Workers on foot and moving equipments	-	-	-	-0.123	-
3 Site topography	-	0.151	-	-0.179	-0.129
4 Working with heavy equipment	0.247	0.668	-	-0.192	0.145
5 Nail gun	-0.493	-	-0.271	-	-0.138
6 Working with power tools/large tools	-0.531	-	-0.257	-	-0.123
7 Equipment back up	-	-	-	-	0.199
8 Falling objects	0.379	-0.361	-0.462	0.383	0.456
9 Structure collapse	0.310	-0.457	0.471	0.000	-0.473
10 Lifting heavy materials	0.322	-0.202	-0.466	-0.732	-0.112
11 Transporting heavy materials horizontally	0.216	0.285	-0.421	0.447	-0.660
Variance captured (%)	30.9	18.9	10.9	9.1	7.9

Table 7. Number of PCs selected and total variance captured

	1521	1522	1541	1542	1611	1622	1623	1629	Total
Number of PCs	5	5	8	8	13	9	6	9	12
Total variance	0.78	0.75	0.89	0.84	0.96	0.92	0.71	0.88	0.88

Once the PCs were selected, GLMs with a logit link function were fit to the selected PCs to predict the probability of fatality. A stepwise regression approach was used to find the parameter set that minimized the model AIC. The overall results of generalized linear models for two category response variables are shown in Table 8. By adopting stepwise variable selection method, number of PCs were reduced for most of SIC categories. By looking at significant PCs and their related attributes in each SIC group, more insights can be obtained through the critical

attributes that contributes to fatalities. For example, two variables, PC1 and PC2, emphasize the importance of working with power tools (e.g. nail gun) and working with heavy equipment in causing fatality in SIC 1521. The last predictive model in Table 8 includes all data points in the last eight categories and called “Total”.

Since the response to be modeled varies binomially, the logit link function was used to transform responses, x , into the linear predictor. By estimating parameters (β), link functions (η_i) can be calculated and by back-transforming link functions with the inverse logit, probabilities of fatalities will be obtained. For example, the underlying formula of model SIC 1521 is:

$$\ln\left(\frac{P_{(Fatality)}}{1-P_{(Fatality)}}\right) = -0.908 + 0.899 \times PC_1 + 1.030 \times PC_2 \quad \text{Equation 8}$$

A similar procedure was used to develop predictive models for three categorical response variables (not severe, mild, and severe). The results of stepwise generalized linear models for these models are summarized in Table 9. The probability of response variables for model SIC 1521 can be calculated from solving the simultaneous equations below:

$$\ln\left(\frac{P_{(Not\ severe)}}{P_{(Severe)}}\right) = 1.396 - 0.165 \times PC_1 + 0.559 \times PC_2 - 1.607 \times PC_5 \quad \text{Equation 9}$$

$$\ln\left(\frac{P_{(Mild)}}{P_{(Severe)}}\right) = 0.745 + 0.796 \times PC_1 + 1.470 \times PC_2 - 1.425 \times PC_5 \quad \text{Equation 10}$$

$$P_{(Not\ severe)} + P_{(Mild)} + P_{(Severe)} = 1 \quad \text{Equation 11}$$

Table 8. Overall results of stepwise generalized linear models for two category response variables

	SIC	Predictor	Estimate	Std. Error		SIC	Predictor	Estimate	Std. Error
1	1521	Intercept	-0.908	0.201	6	1622	Intercept	0.437	0.221
		PC1	0.899	0.310			PC8	-3.243	1.029
		PC2	1.030	0.311			PC9	2.155	1.091
2	1522	Intercept	-0.881	0.295	7	1623	Intercept	0.599	0.141
		PC1	1.294	0.498			PC8	-0.744	0.298
		PC2	0.808	0.470	8	1629	Intercept	1.339	0.294
		PC4	-1.004	0.712			PC1	1.880	0.506
3	1541	Intercept	-0.247	0.228	PC2	0.720	0.506		
		PC2	0.611	0.419	PC3	1.604	0.695		
		PC7	1.931	0.834	PC6	1.805	1.065		
4	1542	Intercept	-0.316	0.158	PC7	2.084	1.145		
		PC1	0.422	0.263	PC8	-1.329	0.679		
		PC2	-0.408	0.271	PC9	-3.026	1.511		
		PC5	-0.818	0.412	9	Total**	Intercept	0.414	0.058
		PC6	-1.057	0.493			PC1	-1.045	0.107
		5	1611	Intercept			1.189	0.114	PC2
PC1	0.442			0.201			PC3	-0.322	0.142
PC2	0.741	0.267	PC6	-0.621	0.179				
PC4	-0.670	0.301	PC7	-0.777	0.200				
					PC8	-0.602	0.203		
					PC10	0.682	0.246		

* All parameters are significant to $p < 0.05$.

**Total includes all data points from 8 SIC categories.

MODEL VERIFICATION

The predictive power of models was measured through two widely used measures for categorical data: rank probability score (RPS) and rank probability skill score (RPSS). As stated before, RPS and RPSS are some of the harshest verification measures. The RPS closer to zero is better and the RPSS can vary from minus infinity (no skill) to 1 (perfect skill). In addition, the expected value of RPSS is less than zero (Mason 2004) which means that any value greater than zero indicate superior performance of the model to the reference forecast. Unfortunately, there is no established acceptable range for RPSS; however, these values can be used to compare the skill performance among different models. For example, the RPSS values obtained here can be used

as baseline to compare the performance of future predictive models in the construction safety domain.

Table 9. Overall results of stepwise generalized linear models for three category response variables

	SIC	Predictor	Estimate	Std. Error		SIC	Predictor	Estimate	Std. Error
1	1521	Intercept-1	1.396	0.281	5	1611	Intercept-1	1.062	0.249
		Intercept-2	0.745	0.309			Intercept-2	2.607	0.224
		PC1-1	-0.165	0.317			PC1-1	-0.156	0.443
		PC1-2	0.796	0.395			PC1-2	0.280	0.407
		PC2-1	0.559	0.498			PC2-1	0.048	0.577
		PC2-2	1.470	0.508			PC2-2	0.756	0.522
		PC5-1	-1.607	0.728			PC4-1	-0.565	0.550
		PC5-2	-1.425	0.766			PC4-2	-1.054	0.484
2	1522	Intercept-1	1.705	0.526			PC5-1	-2.302	0.704
		Intercept-2	0.991	0.580			PC5-2	-1.523	0.648
		PC1-1	-0.401	0.999	6	1622	Intercept-1	1.194	0.361
		PC1-2	1.297	1.147			Intercept-2	1.808	0.341
		PC2-1	1.408	0.742	7	1623	Intercept-1	0.970	0.254
		PC2-2	1.705	0.785			Intercept-2	1.891	0.232
		PC3-1	-1.783	0.960			PC2-1	0.164	0.521
		PC3-2	-0.585	1.038			PC2-2	-0.625	0.482
3	1541	PC5-1	-1.910	1.297	8	1629	Intercept-1	3.884	1.261
		PC5-2	-0.457	1.417			Intercept-2	5.100	1.253
		Intercept-1	0.868	0.340			PC1	5.135	1.545
		Intercept-2	1.044	0.329			PC1	5.777	1.532
		PC2-1	-0.831	0.605			PC6	7.454	3.460
		PC2-2	-0.016	0.584			PC6	7.823	3.436
		PC4-1	-1.422	0.727	9	Total	Intercept-1	0.994	0.102
		PC4-2	-0.418	0.644			Intercept-2	1.739	0.094
4	1542	Intercept-1	0.752	0.220			PC1-1	0.016	0.174
		Intercept-2	0.880	0.216			PC1-2	-1.032	0.165
		PC5-1	0.611	0.557			PC2-1	-0.133	0.174
		PC5-2	-0.331	0.548			PC2-2	-0.636	0.167
		PC6-1	-0.287	0.678			PC3-1	-0.114	0.234
		PC6-2	-1.412	0.685			PC3-2	-0.414	0.222
							PC6-1	-0.068	0.304
							PC6-2	-0.653	0.282
					PC7-1	0.248	0.295		
					PC7-2	-0.567	0.287		
					PC8-1	0.598	0.339		
					PC8-2	-0.166	0.313		

* All parameters are significant to $p < 0.1$.

The results of RPS and RPSS for different categories of SIC are shown in Table 10. The RPS and RPSS values for two and three-category response variable models represent a strong model performance. It is notable that the RPS and RPSS values on average for the two-category response variables models are better than the three-category response variables models. This was expected because the fatalities were the dominant response variable in most of the SIC groups. In addition, dividing non fatal responses in more categories will give a higher weight to the fatality and decrease the predictive power the models. The lowest RPSS values for the two-category response variable models belong to SIC 1611 (0.019), SIC 1623 (0.030), and SIC 1542 (0.076) which have high rate of fatalities, 76%, 64%, and 45% respectively. Similar pattern can be observed in the three-category response variables models and the lowest RPSS values belong to SIC 1623 (0.023), SIC 1542 (0.028), and SIC 1611 (0.034). The best RPSS for both two and three-category response variables belong to SIC 1522 which have 0.216 for two and 0.211 for three categories. In general the results obtained were really good. Also the forecast skill scores were quite reasonable in 0.023-0.216 range.

Table 10. RPS and RPSS values for two and three category response variables

	SIC								Total	Average
	1521	1522	1541	1542	1611	1622	1623	1629		
<i>Two-category response variable (fatality/no fatality)</i>										
RPS (model)	0.367	0.330	0.425	0.446	0.124	0.386	0.438	0.327	0.426	0.363
RPS (chance)	0.432	0.438	0.493	0.489	0.130	0.485	0.460	0.411	0.482	0.425
RPSS	0.149	0.216	0.086	0.076	0.019	0.151	0.030	0.186	0.119	0.114
<i>Three-category response variable (not severe/mild/severe)</i>										
RPS (model)	0.532	0.473	0.523	0.386	0.380	0.487	0.499	0.388	0.571	0.471
RPS (chance)	0.596	0.599	0.622	0.398	0.393	0.546	0.511	0.445	0.624	0.526
RPSS	0.107	0.211	0.159	0.028	0.034	0.108	0.023	0.127	0.090	0.100

PRACTICAL IMPLICATIONS

While the mathematics behind the models is complicated, the findings can be easily used in practice. For example, to calculate probability of fatality for an activity in SIC 1521, following steps should be followed:

- *Step 1:* List of struck-by attributes should be reviewed by a practitioner to decide to which attributes workers are exposed during conducting the activity. Assume that there are three main attributes: nail gun; falling objects; and material storage. The matrix of observation can be constructed by putting one for attributes that exists and zero for attributes that does not exist. The matrix would be like:

$$X = [0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0]_{1 \times 22}$$

- *Step 2:* To find PCs, the matrix X should be multiplied to the loading matrix obtained from PCA as below:

$$Z(PCs)_{1 \times 22} = X(observations)_{1 \times 22} \times W(loadings)_{22 \times 22}$$

$$Z(PCs) = [PC_1 = -0.098; PC_2 = -0.425; PC_3 = -0.690; PC_4 = 0.386; PC_5 = 0.312; \dots]$$

- *Step 3:* At the end, PCs 1 and 2 will be selected to be inserted in to the predictive model for SIC 1521. The probability of fatality can be calculated as:

$$\ln\left(\frac{P_{(Fatality)}}{1 - P_{(Fatality)}}\right) = -0.908 + 0.899 \times (-0.098) + 1.030 \times (-0.425) = -1.434$$

$$\xrightarrow{\text{yields}} P_{(Fatality)} = 0.190$$

There are several practical implications for these results. For example, a designer can see the effect of different design elements on safety and altered the design to provide a safer construction environment. If the hazards cannot be prevented during the design, more attention should be paid to mitigate them during the construction phase. In addition, a project manager can compare alternative means and methods to see which ones provide more hazards for the workers. Furthermore, a supervisor can identify hazardous activities or situations to highlight them during job hazard analysis or tool box meetings.

LIMITATIONS

Though the results of this study have potential to impact current preconstruction safety management, there are several notable limitation related to this study. First, although splitting the data and conducting cross validation is a robust method to check the validity of the model, more studies should be conducted and test the validity of the model in predicting hazards in real projects. In addition, the models were developed using GLM; however, the robustness of the forecasts should be measured against using different forecasting techniques such as artificial neural network (ANN). Second, the external validity of this study is limited because the IMIS database includes only severe accidents that are required to be reported by OSHA regulations. Therefore, the external validity of the study is limited to the accidents with serious outcomes. Future research should be conducted to investigate predictive models for minor injuries and even near misses. Third, the safety risk can be mitigated by implementing different practices. Further study should be conducted to evaluate the effect of implementing the injury prevention practices

on reducing the injuries' outcome. Fourth, this study focused on the safety attributes that can be identified during the preconstruction phase. These attributes mainly address physical unsafe conditions in a project; however, accidents occur due to interaction among unsafe conditions and unsafe behavior. Another study should be conducted to predict the impact of attributes that lead to unsafe behavior on injuries' outcome. Despite several limitations, the proposed predictive models present a practical and easy approach for designers, jobsite engineers and safety managers who are not familiar with extensive mathematical calculations to predict level of hazards in the jobsite reliably.

CONCLUSIONS

One of the main barriers in adopting safety preconstruction activities such as design for safety is a lack of objective tools to identify and quantify the effect of hazards before start of a project. The current study conducted to facilitate adoption of preconstruction safety activities by developing predictive models that forecast severity of possible injuries using fundamental safety attributes. The principal attributes were identified by conducting a rigorous content analysis on 1771 accident reports obtained from OSHA IMIS database. The results subjected to PCA to reduce dimension of the data and remove any possible multicollinearity among variables. Then the influential variables entered in to the GLM model and two series of models were developed. The first model will predict the probability of fatality and the second done will predict the probability of not sever, mild, and sever injuries. To compare the performance of the models, the RPSS of the models were calculated to evaluate performance of the models and cross validation was conducted to check the validity of the models.

The study resulted in several reliable and valid predictive models that can be used by practitioners, managers, supervisors, and researchers to accurately forecast the potential severity of the accident in a project. For the first time, there was a dataset of sufficient size and quality to apply statistical techniques and create mathematical models. It is expected that the predictive models could drastically change the way that potential injuries are considered during planning, project financing, and safety controls.

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CHAPTER 7
CONCLUSION

SUMMARY

The focus of this entire study was on advancement of fundamental safety risk knowledge that will transform hazard identification, assessment, and control. The conceptual overview of different chapters of dissertation is shown in Figure 1. The first paper (chapter 2) investigates the relationship between adoption of traditional safety program elements and deceleration of construction safety improvement since 1998. The results of the study indicate that the construction industry is saturated with regards of current traditional safety program elements. This implies that new injury prevention practices are required.

By considering that the ability to improve safety decreases as the project starts, it is reasonable to develop new safety practices in early stages of project. One of the emerging preconstruction safety practices is integrating safety risk in to the project schedule. The previous attempts to integrate safety risk and project schedule were not successful because there was not a robust safety risk database and the interactions (i.e., compatibility and incompatibility) among tasks were ignored. To address these limitations, second and third papers (chapters 3 and 4) quantify safety risks of common highway construction work tasks and their temporal and spatial interactions using Delphi method. A decision support system (DSS) is also developed to integrate risk database in to the schedule of project using a novel framework. Furthermore, the reliability of the database and developed DSS is measured using multi attribute utility assessment technique and conducting 11 case studies.

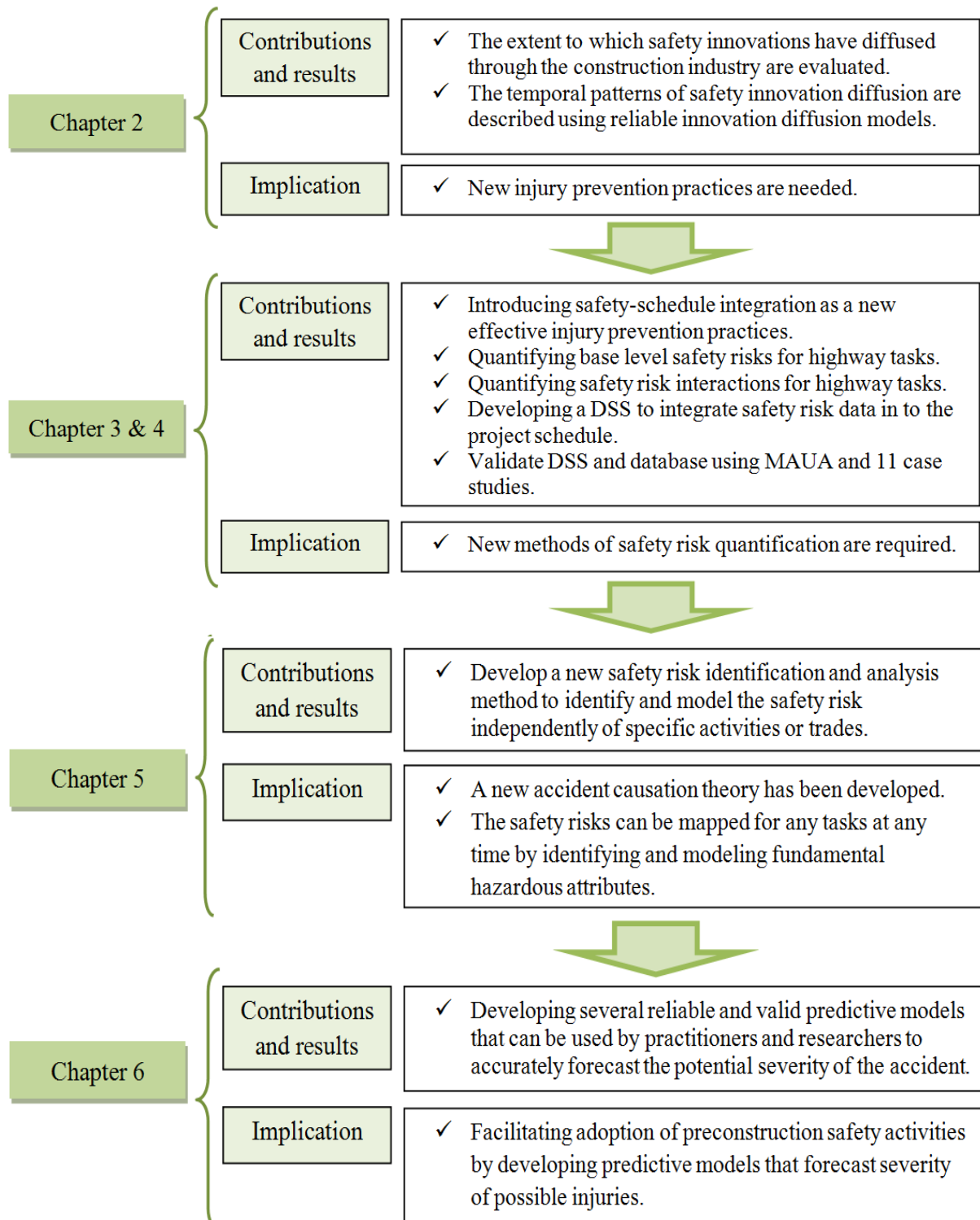


Figure 1. Conceptual overview of dissertation

While the results of previous chapters indicate that safety risk management techniques can be viable and effective tool to improve safety, the rate of adoption of these techniques among practitioners is low. One of the main reasons is that the current risk quantification methods require every new infrastructure feature or task to be individually evaluated which can be laborious activity or even in some cases in practical. To address this gap in knowledge, a new risk identification and analysis method is presented in chapter 5 that enables designers to identify and model the safety risk independently of specific activities or trades.

In order to demonstrate one of the practical implications of the new safety risk management technique, several predictive models are developed in chapter 6. A robust multivariate data analysis, principal component analysis (PCA), is implemented to reduce the dimension of the created safety risk database. Then, the stepwise generalized linear model (GLM) is conducted to find a relationship between PCs (predictor variable) and severity of accidents (response variable). It is expected that the predictive models could drastically transform the current safety practices during planning, project financing, and safety controls.

CONTRIBUTIONS TO THEORY AND PRACTICE

There are several contributions to theory and practice in all chapters of dissertation. In chapter 2, an accurate model of the adoption patterns for safety innovations is presented that helps researchers and practitioners to identify the drivers that lead to higher adoption rate for specific types of safety innovations. In addition, this study revealed that while the rate of improvement in construction safety is decelerated, the construction industry is also saturated by the current safety innovations. This is alarming and indicates the necessity of introducing new injury prevention

practices. Furthermore, the resulted diffusion models can be used to predict the diffusion patterns of new injury prevention strategies through the construction industry. Finally, this study, for the first time, introduces the concept of innovation diffusion theory to the construction safety domain.

Chapter 3 enhances one of the preconstruction safety practices by considering temporal and spatial interactions among tasks. Chapter 4 builds upon the results from chapter 3 and integrates safety risk data in to the project schedule. The output of the model is risk profiles that can be used by safety managers to identify high risk locations and time periods based on the planned sequence and location of tasks. In response, safety managers can plan for extra precautionary measures during these high risk periods, develop customized injury prevention strategies, or inform workers of the tasks and interactions known to cause high risk periods.

While safety risks have been quantified at trade, activity, and loss of control level, no study has identified safety risks at attribute level. This gap in the knowledge is addressed in chapter 5 by analyzing large number of accidents report from national databases and identifying and quantifying safety risks at attribute level. The findings of chapter 5 challenges the traditional reactionary paradigm of construction hazard management by testing the underlying hypothesis that the risk of injury associated with construction objects and work tasks can be broken down into a finite number of fundamental constituent attributes. It is expected that the intellectual deliverables of this study transforms the way that future researchers characterize and model the risk of injuries.

In addition to developing a new risk management technique, the process of conducting content analysis on the accident reports has several implications to the theory. For the first time, a reliable dictionary is developed in an iterative process and multiple coders are used to conduct automated content analysis on accident reports. Similar procedure can be followed by other scholars to conduct automated content analysis.

Finally, the results of chapter 6 is one of the first known predictive model of safety outcomes that is (1) based on a large volume of internally and externally valid empirical data, (2) explored with GLM, an efficient and rigorous technique based on sound science, and (3) robust enough to predict outcomes for any combination of attributes that may be encountered on contemporary worksites.

FUTURE STUDIES

This study reveals several new topics in construction safety that is promising avenues of future research. For example, a follow up research can be conducted for the second chapter to identify enablers and barriers to the diffusion of safety innovations. The results of this study can help practitioners to increase the adoption rate of safety innovations. In addition, because the communication channels can play an important role in spreading information regarding new innovations (Farrell and Saloner 1985), more studies should be conducted to identify communication channels among safety managers that lead to adoption of a new safety innovation.

The most prominent topic of future research emerges from attribute-based safety management. In one of the applications, the new safety risk management technique and created database can be integrated in to the building information models (BIM). There are several safety related feedback and reports that can be created by BIM-based safety management program. For example, by assigning the attributes to the tasks and objects, hazard analysis can be conducted in the planning phase of the project. The hazards identified in this phase can be used by designers to modify their designs and improve safety. If the hazard cannot be mitigated by designer, the contractor can provide necessary measures to decrease the exposure of workers to the identified hazards. Another potential feedback from BIM is safety resource allocation. Using risk profiles provide an opportunity for managers to allocate safety resources in accordance with risk fluctuation in project schedule. Furthermore, different optimization techniques such as genetic algorithm (Goldberg 1989), particle swarm optimization (Kennedy and Eberhart 1995), and ant colony optimization (Colorni 1991) can be used in future studies to optimize the allocated safety resources.

Finally, future studies can be conducted to quantify costs related to different type of injuries resulted from fundamental attributes. These values can be used in a probabilistic model to estimate costs that should be paid for injuries in a project. The contractor can use these estimations to select an appropriate contingency amount.

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