Effectiveness Evaluation Model for Frontline Worker Safety Intervention: An Exploratory Case Study of a Construction Prefabrication Company

by

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A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

In

Construction Engineering & Management

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ABSTRACT

Frontline foremen and workers play a critical role in implementing management's safety policies and procedures. Despite the ultimate position in safety organization of frontline foremen and workers, variations in safety competency and acceptance level are often neglected, which leads to diverse perceptions of safety instructions. This study aims to explore practical measures to evaluate how effectively safety programs and techniques are implemented at a frontline level. The challenges associated with evaluating frontline intervention effectiveness are (1) unclear establishment of evaluation criteria for ongoing safety intervention; (2) difficulty in identifying the intervention effectiveness due to infrequency of an incident occurrence; and (3) infeasibility of comparative study due to confounding or effect modifications. Since communication skills as well as competence for hazard awareness and response are fundamental and integral aspects of frontline safety management, pre-task planning and worksite inspection are investigated to determine the effectiveness of intervention implementation. Based on the rare event count data, a Poisson regression model is deployed which takes into account no-lost-time incident cases of 156 workers and their evaluation factors in a construction pre-fabrication company. To achieve statistical homogeneity, some demographic factors (e.g., supervisor seniority, worker experience, craft size, position, shop & shift) as confounding and effect modification variables are applied in each regression test. The results of the factor analyses suggest that increasing content coverage rates, longhand description in the pre-task planning, and safety communication times are critical factors to reduce incident rates. Hazard identification and workplace inspection frequencies are relatively less effective factors. For the evaluation variables subject to effect modifications, it is found through stratum analysis that the longhand description practice is effective for less experienced supervisors (<19 years). The safety communication is helpful to juniors (<35 years) versus seniors (35~71 years). In addition, company-wide time lag analysis demonstrates that hazard identification improves safety performance over the course of a 4-month term.

ACKNOWLEDGEMENTS

First of all, I would like to express my sincere thanks to my supervisors, Dr. SangUk Han and Dr. Simaan M. AbouRizk, for their vision, support, and guidance in the preparation of this thesis.

Thanks are extended to the staff at Waiward Steel Fabricators Ltd., who shared their knowledge and experience and provided data for this research. Their cooperation and support are very much appreciated.

I am also grateful to all members of the Construction Engineering and Management group for their support and assistance during my graduate program.

Finally, I would like to thank my wife, Ajin, and children, Philip and Ella, for their continuous support and encouragement throughout my study at the University of Alberta.

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1. INTRODUCTION

1.1 Background

The safety performance of the construction industry has dramatically improved in recent years, with the Recordable Injury Rate in the United States decreasing by a margin of 74% in the period from 1989 to 2012. Simultaneously, a number of safety interventions have been developed in the construction industry, with their contributions to safety performance underscored by the strong connection between decreased incident rates and implementation of safety interventions. However, the construction industry is still known for higher incident rates than other industries due to its dynamic and physical challenging working environment. Though it accounts for just 8% of the overall workforce among all industries, statistics shows that the construction industry accounts for 25% and 18% of work-related fatalities in Canada and the United States, respectively (Association of Workers' Compensation Boards of Canada 2013; U.S. Bureau of Labor Statistics 2013).

In spite of dramatic improvements in safety performance with sustained efforts over the last three decades, traditional approaches have reached their limit with improvement rates plateauing. Although the adoption and establishment of new safety interventions in a construction site or fabrication facility is a major contributor to injury reduction, effectiveness assessment of these on-going interventions has had less attention.

Top management in an organization establishes safety policy which defines strategic goals and often includes procedures which direct the decision making and discretion to low-level management (Petersen 2003). As per the set procedures, frontline supervisors and workers conduct safety practices associated with their production activities at the lowest level in a company (Zohar 2000). Given the top-down nature of safety management, employers anticipate workers to be cautious of the hazards in their daily tasks and to take appropriate mitigation actions against the risk (Hislop 1999). Contrary to employers' expectations, however, continuous efforts to improve the safety policy and procedures do not always lead to significant enhancement of safety performance in practice. According to Zohar (2000), such discrepancies between management's goals and implementation at the individual worker level are encountered when groups have significant variation in safety competency and acceptance level, which leads to diverse perceptions of safety procedures and policies among individual workers. Through safety climate research, it has been shown that groups with lower safety climate perception scores, have poorer safety records (Guest et al. 1994; Sherry 1991).

To evaluate the effectiveness of frontline safety intervention, it is important to understand the foreman's role and responsibilities with regard to safety-related activities. The foreman plays a key role in establishing and maintaining worker safety on the job as a link between workers and upper management. The upper management usually entrusts the site foreman with the responsibility for site safety (McVittie and Vi 2009). Therefore, significant group variation exists due to varied perceptions between instituted procedures and supervisory styles within each subunit. As an example, a recent study showed that a workgroup under a foreman with strong leadership skill has better safety performance than those under less competent foremen (Van de Voorde 2013). In these respects, effectiveness evaluation of existing interventions is necessary to ensure on-site personnel's ability to achieve effective hazard control, and to increase employees' acceptance of supervisor-administered interventions.

1.2 Objectives

This study aims to explore practical measures evaluating how effectively safety programs and techniques are being implemented at a frontline level. A case study is undertaken to determine appropriate metrics through field observation and to collect relevant data in practice. Consequently, the safety practices of foremen and individual workers are analyzed and compared with each individual's safety records to ascertain recommended practices with the potential to lower incident rates.

It is important to improve safety interventions by filling the gap between implementing techniques and evaluating the implementation through study of frontline practices rather than from a managerial level perspective. One of the most significant challenges in evaluation of safety intervention effectiveness can be determining what should be assessed and which measures should be employed. Systematic evaluation of a variety of elements of accurate assessment of the degree to which safety is being integrated into job-site work practices can be achieved (Hislop 1999). A critical step toward better performance is to focus on evaluating implementation techniques on existing safety programs rather than studying which safety technique and programs are effective.

1.3 Thesis Organization

This thesis begins with an introductory chapter that presents an overview of the entire thesis, including the background, problem statement, research objectives, and methodologies used.

Chapter 2 provides a theoretical background through review of previous studies related to construction safety interventions, safety roles and responsibilities of frontline foreman, and job safety analysis. In construction research and practice, various safety techniques and programs have proposed to identify, evaluate, and mitigate the causes of incidents. The relevant studies on effectiveness evaluation of safety intervention are reviewed and the challenges associated with frontline safety intervention are discussed.

Chapter 3 discusses challenges in evaluating frontline safety interventions. Considering the characteristics of frontline organization and safety programs, three challenges in particular make it difficult to evaluate effectiveness: evaluation criteria of on-going safety interventions; validity and reliability of dependent variables; and effect modification and confounding.

Chapter 4 explores the evaluation variables, defining practically measurable safety practices led by foremen and workers. This chapter presents two processes: selecting existing frontline safety interventions related to workers' and foremen's active participation, and identifying measurable evaluation factors through understanding of the relationships among selected variables.

Chapter 5 explains the general regression model and its utilization in effectiveness studies as a research method. Furthermore, the rationale underlying the use of the

Poisson regression model for this particular study is discussed, and basic knowledge about such regression is introduced.

Chapter 6 demonstrates the regression analysis and represents relative risk for each evaluation variable. Furthermore, additional stratum and time lag analyses are conducted for detailed results.

Chapter 7 concludes the thesis with a summary of what has been practically and theoretically achieved. Some improvements in comparison to previous studies are discussed. Finally, proposed future enhancements are outlined.

2 LITERATURE REVIEW

In construction, researchers and practitioners have proposed various safety techniques and programs to identify, evaluate, and mitigate the causes of incidents. This chapter reviews relevant studies on effectiveness evaluation of safety interventions, and discusses challenges associated with frontline safety intervention.

2.1 Construction Safety Interventions

Generally, a safety intervention can be justified as a trial to improve how tasks are done for better safety performance. In the worksite, there are various types of interventions, such as training programs, engineering practice, or administrative procedures or initiative (Robson 2001). Clinical research often uses intervention studies in laboratories to prove favourable results or negative side effects of drugs or treatments; these studies are considered to deliver the most reliable evidence in epidemiological research.

Safety interventions are grouped as engineering interventions, considering the physical work condition; administrative interventions, focusing on procedures and policies; and personal interventions, pertaining to worker training and behaviour (Zwerling et al. 1997). The types of safety intervention implemented on a jobsite include not only Personal Protective Equipment (PPE) such as hearing protectors (Seixas et al. 2011) and safety glasses (Lipscomb 2000), but also managerial methods such as organizational policy, safety programs, incentives, and legislation (Becker et al. 2001; Darragh et al. 2004; Winn et al. 2004).

Depending on the perspective, safety interventions are applied differently at every level of a workplace safety program. Figure 2.1 illustrates the organizational safety management, which is divided into technical sub-system and human sub-system (Robson 2001). Regardless of the type of intervention, technical sub-systems aim to modify or improve the organization, design, or environment for the given workplace. Human sub-systems, alternatively, are intended to change the individual worker's attitude or behaviour.

Apart from this level of intervention, legislation, regulations, laws and standards are established by government, business, and professional organizations.

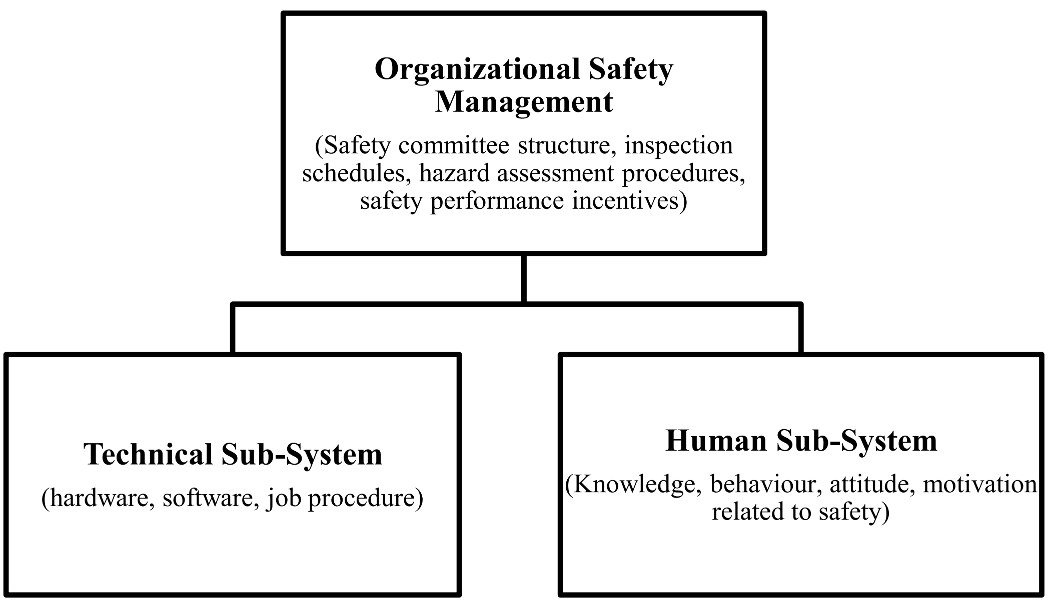


Figure 2.1. Levels of intervention in the workplace safety system (Robson 2001)

Various safety interventions have been examined in previous studies in order to ascertain the effect of safety interventions on safety performance; Table 2.1 summarizes relevant studies corresponding to target interventions and data collection methods, safety outcome measures, and analysis methods. Notably, survey questionnaires (Bailey 1997; DePasquale and Geller 1999; Ray and Frey 1999; Sokas et al. 2009; Vinodkumar and Bhasi 2010; Luria et al. 2008; Oude Hengel et al. 2012; Kapp 2012) and interviews (Kines et al. 2010) have commonly been used as data collection methods to measure and evaluate the effectiveness of safety interventions based on participants' perceptions. Apart from the surveys and interviews that require active participation of human subjects, field observations are carried out to determine the impact of safety interventions on incident rates; herein, here, application rates of safety interventions have been the primary measures of effectiveness, e.g., Haight and Thomas 2003). Comparative studies through literature reviews have also been carried out to determine successful safety interventions (Ray and Bishop 1995; Guastello 1993), while Hammer et al. (2015) utilized a combination of multiple types of data (e.g., survey, quiz score, health assessment) to assess safety performance.

Table 2.1a Analysis methods and target variables in industrial safety intervention research studies

Independent Variable		Target Intervention	Analysis Method	Dependent Variable	Reference
Type	**Input Factors**				
Literature review	Training, feedback & goal setting	Safety training	Statistical review	Safety performance index	(Ray and Bishop 1995)
Literature review	10 types of intervention programs	Accident prevention program	Regression, Meta-analysis	Effect size between target and control group	(Guastello 1993)
Literature review	Various prevention strategies	Various prevention strategies	Meta-analysis	Fatal injury cases & non-fatal injury cases	(Sancini et al. 2012)
Survey	Predicting self-reported involvement variable	Behaviour based safety program	Forward entry regression	BBS score	(DePasquale and Geller 1999)
Survey	leadership, incentives and organization behaviour with 74 question elements	Overall safety program effectiveness	Comparison between ‘good’ & ‘poor’ firms	Recordable accident statistics, compensation costs &frequency/severity ratio	(Bailey 1997)
Survey	Behavioural safety index	Behaviour safety programs	Correlation analysis	Lost-time injury rates	(Ray and Frey 1999)
Survey	Fall & electrical safety pre-post knowledge	Hazard Awareness Training	Logistic regression	Safety climate score	(Sokas et al. 2009b)

Table 2.1b Analysis methods and target variables in industrial safety intervention research studies (continued)

Independent Variable		Target Intervention	Analysis Method	Dependent Variable	Reference
Type	**Input Factors**				
Survey	Perceptions on six safety management practices	Safety management	Structural equation	Safety knowledge and motivation	(Vinodkumar and Bhasi 2010)
Survey	Training application	Two empowerment training sessions	Linear & logistic regressions	Social support and work engagement score	(Oude Hengel et al. 2012)
Survey	Safety-related supervisory score	Supervision based safety	Hierarchical linear modelling	Unsafe behaviours (e.g., PPE violation, walking in permitted area)	(Luria et al. 2008)
Survey	Leadership scales	Levels of transformational and contingent reward leadership	Moderated regression models	Individual perceptions of group safety climate (Compliance score)	(Kapp 2012)
Interview	% of safety related communications of all records	Foremen-worker verbal safety exchanges	Generalized linear & Poisson regression	Safety climate observation	(Kines et al. 2010)
Survey, quiz & health assessment	Supervisor quiz score & behaviour scale	SHIP intervention	Correlation & coefficient	Blood pressure and health outcome	(Hammer et al. 2015)

Table 2.1c Analysis methods and target variables in industrial safety intervention research studies (continued)

Independent Variable		Target Intervention	Analysis Method	Dependent Variable	Reference
Type	**Input Factors**				
Observation	Intervention application rates (Man-hours)	4 intervention categories (Behaviour modification, incentive and awareness; training; job design; & equipment)	Linear regression & exponential non-linear regression	Incident rates	(Haight et al. 2001; Haight and Thomas 2003)
Observation	Intervention application rates (Man-hours)	4 intervention categories (Safety awareness and motivation, skill development and training, new tools and equipment design methods, equipment related activities)	Linear regression & exponential non-linear regression	Incident rates	(Iyer et al. 2004; Iyer et al. 2005)
Observation	Intervention application rates (Man-hours)	5 intervention categories (Leadership & accountability; qualification, selection & pre-job; contractor engagement & planning; work in progress; safety evaluation & verification)	Linear regression & exponential non-linear regression	Incident rates	(Oyewole et al. 2010)

Haight et al. (2001) proposed linear regression model analysis between intervention implementation and incident rate. As a part of collecting input and output variables, Haight et al. designed the Loss Prevention System model, categorized by 4 factors (i.e., behaviour, awareness, motivation; skill development and training; job design; and employment-related work) and composed of 15 intervention variables (e.g., training, meeting, task analysis, hazard analysis, equipment inspection) to be measured in hours. In their study, the regression model and its function showed a significant exponential relationship between the intervention application rates and incident rates (Haight et al. 2001).

Iyer et al. (2004) extended the original framework of the Loss Prevention System model to test generalizability in a power company and verified the mathematical relationship. Their study showed that 6 weeks of carry-over effect occurs in the safety interventions. Following the Iyer et al. study, Oyewole et al. (2010) established a model including 34 safety interventions categorized by 5 factor input variables (e.g., leadership and accountability; qualification, selection and pre-job; employee engagement and planning; work in progress and factor; and evaluation, measurement, and verification) similar to Haight's Loss Prevention System model. The study tested intervention effects based on resource allocations for 31 resource combinations of 5 factors. Their findings showed that qualification, selection and pre-job are not positive effect to incident reduction rather than the other factors.

Shakioye and Haight (2010) developed a more practical model by integrating a dynamic model and an optimization module between the factors and incident rates on the Loss Prevention System model. Their dynamic model is able to repeatedly establish coefficients of an updated relationship between the intervention factors and the incident rate as more data is gathered from the database through day-to-day operations. Then, the optimization module produces the best mix of man-hours for intervention application (Shakioye and Haight 2010).

Statistical trials for an existing model have been conducted with incident data in another case study, where the application of linear regression techniques produced insignificant results, e.g., non-linear regression, correlation check, combination of regressors, and logarithm transformation (AlOmair 2015). Samuel (2012) developed research to show that statistical analyses such as the response surface methodology could be employed to investigate the interactive effects of safety intervention factors using actual data. Samuel's research showed that the allocation of additional resources towards a categorized factor such as qualification, selection, or pre-job would not likely improve the overall safety intervention program, thereby leading to indiscriminate waste of resources and capital. More recently, meta-regression analysis has been developed and used to identify a significant linear relationship between time and risk reduction for fatal injuries, where that evaluation was highly dependent on large scale interventions (Sancini et al. 2012).

2.2 Safety Role and Responsibility of Frontline Foremen

In general, the management framework of a construction project has three layers: strategic, tactical, and frontline operational. Top management, middle management, and supervisor/foremen lead the layers' respective safety management programs in construction projects (Fang et al. 2015). The foreman has a responsibility to control unskilled, semi-skilled, and skilled workers.

In turn, the foreman is supervised by middle management (e.g., supervisor/project manager), and top management (e.g., executives). The foreman liaises between the crafts and top management as a representative of the first line of supervision and is immediately responsible for safety performance on site (Hymel 2012).

A number of guides and manuals support idea of essential interventions and their attributes to measure effectiveness. The construction frontline supervisor's role and responsibility are described in various ways. For instance, the Construction Research Congress listed important safety tasks using a task and position competency matrix through 'A Practical Guide to Safety Leadership'. The four tasks highlighted as 'Full understanding required' are; (1) carry out workplace and task hazard identification, risk assessments and control; (2) facilitate group team discussions and meetings; (3) plan and deliver toolbox talks; and (4) make site visits where the site worker is spoken to directly about HSE in the workplace (Biggs, et al. 2008).

The frontline foreman's safety involvement and initiatives have been found to have a stronger link to overall safety performance than does top management commitment (Simard and Marchand 1995). Although the relationship among top, middle management and frontline workers is important, their behaviour is indirect and conditional. Top management entrusts safety implementation to frontline supervisor/foreman (Swuste et al. 2012).

Safety research investigating construction projects for the London 2012 Olympic Games looked at the relationship between site supervisor competence and effectiveness of safety programs (Cheyne et al. 2011). The authors represented supervisor’s behaviours in companies with high safety performance and observed the following rends: (1) a large time investment on occupational safety topics; (2) participation in developing safety programs and procedures together with workers; (3) involvement in workplace inspection and accident investigation; and (4) responsibility for training of new employees.

Consequently, the front-line foreman is the key staff responsible to conduct safety activities in addition to scheduling, coordination, and quality assurance. Although the foreman’s primary responsibility is production-related tasks, they must be familiar with the overall safety program, and must be held responsible for the safety of the workers under their supervision. Psychology and economics research conducted by the Mercatus Center has evaluated the behavioural effects of regulatory overload on businesses (McLaughlin and Williams 2014). This study found that *numerous and detailed regulations can reduce compliance, discourage innovation, and fuel uncertainty* (McLaughlin and Williams 2014). It is complicated and subjective to judge whether safety interventions have the result of overloading the worker. However, it is the case that workers tend to bypass safety rules due to increased cognitive failure and stress, leading to higher-risk behaviour (Mapp 2007).

2.3 Job Safety Analysis

Job safety analysis (JSA) is 'an analytical process which helps integrating accepted safety and health principles and practices into a particular task' (CCOHS 2006). Although there are numerous safety practices for frontline worker and foreman, ultimately most of these practices are included in or related to JSA both technically and conceptually. JSA gives detailed instructions to workers before the start of a given task. In order for it to be effective, though, all crew members must participate, and must assist in identifying hazards and corrective actions.

JSA, also known as Job Hazard Analysis (JHA), is used at most construction companies under a variety of names, including job analysis, task analysis, or pre-task planning. Although these terms are used in various situations and industries, they either have very similar meanings to or are interchangeable with JSA (Glenn 2011).

The most influential resource in shaping the format of these analyses has been the National Safety Council's (NSC) three-column form, which is broadly utilized in risk assessment practice (Table 2.2). A JSA also comprises three main stages (Chao and Henshaw 2002) which are named differently, but conceptually constitute the same process as NSC's standard form and any other risk assessments.

(1) Identification – selecting a specific task and generating each activity step, and identifying any hazards which may occur during the work.

(2) Assessment – evaluating the relevant level of risk for each hazard.

(3) Control – putting in place sufficient measures to reduce or eliminate assessed hazards.

Table 2.2. Job Safety Analysis format of National Safety Council

Sequence of Basic Job Steps	***Potential Hazards***	***Recommended Action Procedure***
Examining a specific job by breaking it down into a series of steps or tasks, will enable you to discover potential hazards employees may encounter. *Each job or operation will consist of a set of steps or tasks. Be sure to list all the steps needed to perform the job. Some steps may not be performed each lime; an example could be checking the casters on the hand truck. However, if that step is generally part of the job it should be listed.*	*A hazard is a potential danger. The purpose of the Job Safety Analysis is to identify ALL hazards- both those produced by the environment or conditions and those connected with the job procedure.* *To identify hazards, ask yourself these questions about each step:* *Close observation and knowledge of the job is important. Examine each step carefully to find and identify hazards-the actions, conditions, and possibilities that could lead to an accident. Com- piling an accurate and complete list of potential hazards will allow you to develop the recommended safe job procedures needed to prevent accidents.*	*Using the first two columns as a guide, decide what actions or procedures are necessary to eliminate or minimize the hazards that could lead to an accident, injury, or occupational illness.* *List the recommended safe operating procedures. Give a recommended action or procedure for each hazard. Serious hazards should be corrected immediately. The JSA should then be changed to reflect the new conditions.* *Finally, review your input on all three columns for accuracy and completeness. Determine if the recommended actions or procedures have been put in place. Re-evaluate the job safety analysis as necessary.*

In practice, the Construction Owners Association of Alberta has proposed Field Level Risk/Hazard Assessment as a tool similar to JSA, but specifically designed for frontline workers; hazard and control measures are thus developed for company- or project-specific JSAs. This can help individuals and crews to eliminate or minimize potential losses during the course of performing their work (Hudson 1998). FLHA is at the base of the hierarchy of company risk assessment procedures (Figure 2.2). It is distinct from risk assessment practices in the higher levels of the hierarchy because focus group is related to frontline workers.

Figure 2.2 Risk assessment structure in organization (Hudson 1998)

In addition to its original purpose, JSA is a useful tool for maintaining a safety program by influencing employee knowledge and behaviour. Foremen are able to use JSA to train and provide safety knowledge, especially with regard to non-routine processes and frequently occurring hazards. Since JSA is more focused on particular tasks, it is a useful training resource for introducing company procedures or legislations in a practical context. JSA records contribute to work place inspection and incident investigation as useful information for reviewing hazard and control measures, and provide insight into how incidents occur.

Since JSA involves a significant amount of human effort, it tends to have practical problems associated with methods and tools. Studies in the literature have discussed some of the pitfalls associated with implementing JSA on site (Lyon and Hollcroft 2012).

- Lack of consultation with or involvement from employees with practical knowledge of the task to be assessed and communication of management;
- Failure to identify all hazards associated with a particular activity and all possible outcomes;
- No follow-up actions based on the results of the assessment;
- Poor assessment and control which fails to assign subject matter experts for particular risk assessments or to account for job analysis bias;
- Systematic problems: insufficient time and resources; customary practices among incumbent; improper form; absence of review and verification process;
- Insufficient identification of the hazards associated with a specific task;
- Analysis not based on statistical data;
- No connection between hazards and risk controls; and
- No involvement of workers in decision process.

3 PROBLEM STATEMENT

Previous studies provide insight into the effectiveness of safety programs and their relationships with safety outcomes. When such programs and managerial activities are applied to on-site practice, however, the following challenges make it difficult to evaluate safety program effectiveness in front-line management.

3.1 Evaluation Criteria of Ongoing Safety Interventions

In practice, evaluation criteria for ongoing safety interventions often are not clearly established, with the result that the evaluation comes to rely on subjective judgement in the intervention procedure. For instance, the manager's handbook published by the Construction Owners Association of Alberta describes an evaluation criterion as an abstract clause such as "how well are forms filled out?" or "assign specific people to gather and analyze Field Level Risk Assessment data to solve the identified problem" (Hudson 1998).

Similarly, the Job Safety Analysis (JSA) by Canada's National Occupational Health & Safety only emphasizes a supervisor's accountability to establish follow-up activities for monitoring the effectiveness, without providing any practical guideline (CCOHS 2006). Technical issues may arise from the fact that the monitoring and evaluation of safety practice now depends on the ability of each individual (e.g., supervisor) who implements such interventions.

With these unclear and subjective instructions, WorkSafe New Zealand reported that 80% of employees could not accurately complete a hazard report, 49% of supervisors and team leaders fall into the middle or lowest group in reading company health and safety procedure properly, and 20% of supervisors also struggled with health and safety paperwork, making it difficult for them to communicate the information to employees (Workbase 2013). Consequently, the ambiguities involved in evaluation criteria may cause difficulties in data collection.

It could be argued that obligatory regulatory interventions are just organizational interventions to commit to or by which to compel workers to reduce injuries. Especially for pre-task planning such as JSA, if the job analyst misunderstands the objective of the process or does not have enough skill to conduct the task, company resources are wasted as a result (Dessler 2015).

The ambiguities involved in evaluation criteria may also cause difficulties in data collection. Alternatively, various measurement techniques such as audits, perception surveys, and cost-benefit analyses have been proposed and applied to measure the quality of successful interventions. These methods play a role in better understanding respondents' perceptions of the research topic (Needleman and Needleman 1996; Denzin and Lincoln 1994); however, such methods typically require more time and cost to continuously collect data over a long period in order to allow for the tracking and in-depth understanding of causality in the given case.

Haight and Thomas (2003) provided a comprehensive literature review to determine a scientifically supported method to evaluate safety and health programs. As mentioned, many measurement techniques, such as audits, perception surveys, and cost-benefit analyses, have been used by previous researchers. Although these studies have helped to define the qualities of successful interventions for practitioners, they fail to represent the magnitude of effectiveness with relative or absolute values.

Both Hogg (2005) and Zou and Sunindijo (2015) discussed difficulties related to experimental research on workplace safety. Due to the complexity of on-site environments, self-reporting questionnaires and surveys are much more accessible and easier to organize. In addition, such research requires a good deal of attitudinal measurement, which is difficult to obtain by experiments. Further analysis in these studies revealed that survey questionnaires were the main methods used for data collection in quantitative research, and that more than half of qualitative research used interviews as the main qualitative research method. Such approaches tend to deliver intentionally distorted perspectives rather than actual situations. Although Needleman (1996) and Denzin (1994) emphasized that such qualitative research methods play a role in better understanding how interventions operate in the worksite, they still only function as a supportive factor in quantitative studies. In actual practice, the practitioners responsible for safety in a given company may adjust their interventions through subjective decisions.

Recently, various approaches to evaluating safety intervention effectiveness have been conducted. Qualitative methods have been used to evaluate individual intervention implementation, such as interview, survey, observation and document analysis. Quantitative methods, in turn, rely on numerical variables with statistical approaches by survey or cost benefit analysis (Haight and Thomas 2003). However, most mathematical approaches have only considered intervention application rates in comparison to incident rates as an outcome variable. These do not bring any practical intuition about implementation with craft-level workers, since workers are not in the position to select a given intervention but rather are limited to focusing on how to effectively conduct them within the context of a given application.

With regard to the evaluation of safety intervention implementation, looking at how practitioners deliver a certain intervention to the workplace, for instance, is not sufficient. In spite of numerous intervention-related research studies having been conducted, less attention has been paid to safety interventions in the lower levels of an organization (i.e., frontline). Even when company safety interventions are well prepared and clearly presented to subunits, there can be significant variation between groups, resulting in different perceptions of company procedures and supervisory practices among the various subunits. Past studies have, for instance, identified differences in the safety climate of different role type subunits (Glendon and Litherland 2001). Others have noted the difference between safety profiles by age group in a single organization and proposed targeted safety strategies accordingly (Mason 1998).

Many of the issues observed are to the fact that safety interventions are implemented by considering their acceptability to employees rather than their actual effectiveness (Zwerling et al. 1997). For example, a supervisor who instructs workers to ignore certain safety procedures whenever production falls behind schedule creates a distinction between company procedures and subunit practices (Zhang and Yu 1998). One study on safety climate identified discrepancies among the safety climates of different subunit (Glendon and Litherland 2001). For these reasons, this study analyzes safety intervention effectiveness strictly within the scope of the front-line of an organization.

3.2 Validity and Reliability of Dependent Variables

Due to the relative infrequency of safety incidents, the lack of available data hinders identification of the causal relationship between evaluation items and incidents in data analysis. In reality, the majority of workers within a given workplace can usually remain uninjured despite a high incident rate; for example, a non-fatality rate of 149.6—which is the rate of the U.S. construction industry in 2010—indicates, by definition, 149.6 out of 10,000 full time employees were injured (CPWR 2013). In this regard, safety analysis is often focused on the at-risk circumstances and attributes leading to an incident rather than ordinary conditions. Researchers tend to elaborate on the circumstances of an incident rather than ordinary conditions. Lost-time injury data has flaws, since the datasets of small organizations are out of balance and infrequent (Qiu et al. 2013; Spangenberg et al. 2002). The analysis of these discrete events may be confounded by the rare appearance of safety incidents over long time periods, particularly where safety interventions are effective (Lee et al. 2001). Perhaps for this reason, self-reporting surveys and interviews have been widely applied in safety research (Hogg 2005; Zou and Sunindijo 2015). Although these proxy measures are regarded as more reliable than incident rates, the loose relationship between intermediate outcomes and incidents (Robson 2001) or the low validity of measurement (Esmaeili et al. 2015) are issues that may factor in. Therefore, the appropriate selection of data types and investigation subjects is a key to gaining in-depth understanding of the relationship between frontline intervention effectiveness and safety performance.

Low injury rate is not a sufficient predictor of severity potential. For instance, regarding the Texas City refinery explosion of 2005, the Chemical Safety and Hazard Investigation Board reported that "A very low personal injury rate at Texas City gave BP a misleading indicator of process safety performance" (Chemical Safety and Hazard Investigation Board (CSB) 2007). In a presentation at the International Association of Oil and Gas Producers Offshore Safety Forum, it was noted that total recordable injury rate is not fully able to predict the potential escalation to single and multiple fatalities. It is thus necessary to shift the focus toward recurring incidents equal to the escalation (Zijlker 2005).

The use of lost-time injury cases as a common outcome variable has flaws, since the incident datasets of small organizations are imbalanced and the probability of an event is relatively low. On the other hand, logistic regression has been widely used to test binary outcome variables as a classical classification. Although some studies have proposed large-scale logistic regression, it is still limited with regard to analysis of rare events due to bias in application with large-scale datasets (Qiu et al. 2013).

3.3 Confounding and Effect Modification

Concerning difficulties related to data acquisition, it should be noted that the characteristics of individuals and tasks affecting the likelihood of incidents are often neglected in data analysis. Consequently, effect-modification and confounding variables can randomly influence the accuracy of the evaluations; that is, various levels of inherent risk of subunits (e.g., those working at heights, younger workers, and workers in heavy industries) and concurrent use of several safety programs (e.g., in-house training and government campaign simultaneously) can lead to over- or under-estimates of the effectiveness of certain intervention (Robson 2001).

Effect-modification and confounding can influence the accuracy of the evaluations, especially case control studies. Effect modification occurs when the effect size of the exposure between input variable (e.g., occupation, task, safety practice) and output variable (e.g., injury) is different in the level of third variable (e.g., age, gender, experience).

As an example of effect modification, the statistics on disorder rates of low back pain by occupation in construction show that, overall, bricklayers (41.5%) had higher injury rates than painters (26.8%) (Stürmer et al. 1997). If these results are adjusted by age (effect modification), painter (57%) shows higher rates than bricklayer (47%) because the proportion failing into the senior cohort, generally more vulnerable to back pain, is higher among bricklayers than painters (Stürmer et al. 1997). In this case, the age can become a confounding variable if it affects both occupational choices (e.g., painter or bricklayer) and injury rates. Third variables—for instance, the age in this case—works as the effect modifier or confounding variable, where understanding of the actual relationship between the disorder and occupation is hindered when it is not considered.

Confounding is similar, but distinct from, effect modification; it occurs as a result of imbalance between the exposed and unexposed groups with respect to input variables (independent risk variables) and output variable (the incident of interest). Unlike with effect modification, confounding is related to both input and output variables.

The difference between ordinary and confounding-considered results can be seen through a recent study about relationships between learning disabilities, conducted by the Canadian Community Health Survey (CCHS). The target interests were attention-deficit/hyperactivity disorder (ADHD) and risk of occupational injury among young workers. Multivariate logistic regression analysis was conducted to assess occurrences of medically attended work injuries. The crude odds ratio regardless of any demographic factors in the analysis represents the likelihood of work injury with ADHD as 2.7. However, with considering personal demographic variables as confounders, fully adjusted odds ratio indicates 1.9 which referring to lower ADHD effect size than crude ratio. This means that researchers accept over- or under-estimated ADHD effect in injury occurrence, unless the additional analysis with confounding variables conducted (Breslin and Pole 2009; McNamee 2005).

To reduce effect modification and confounding effects, confounding effects can be controlled through proper preparations. However, it requires the logistical limitations of the effectiveness evaluation design such as short term and small population, which is not feasible for frontline organizations. Moreover, most safety studies are dependent on historical data rather than pre-designed assessment. Instead, the other statistical correction method (e.g., stratification, regression analysis) can adjust estimated results to consider the effects of exposure. Historically, the most common statistical approach for dealing with confounding has been stratification; the standardized mortality ratio is a popular indicator to control age confounding.

4 RESEARCH SCOPE

For the identification of practical measures to evaluate the effectiveness of ongoing safety interventions, a case study is conducted in a steel prefabrication shop located in Edmonton, Canada, in order to determine the effectiveness of different types of safety interventions and relevant performance indicators through field observation and data acquisition. The observation is mainly focused on frontline safety practices where foremen communicate and interact with workers, and the workers under each foreman are identified in order to evaluate frontline supervisory effectiveness among foremen. This approach allows for the fair comparison between study groups (i.e., foremen) with the assumption that top management or other latent variables equally influence frontline employees within an organization.

In particular, the job and personal information of individual employees (e.g., task type, experience, and seniority) is collected to account for effect modification and confounding, and the entire population, including those without injury records, is involved in the data analysis to avoid over-estimation of the relationship between measures and safety records. To model the skewed data (e.g., the majority of workers in the dataset may not have any injury), a Poisson regression technique is applied for discovering and assessing the resulting risk levels associated with measures representing safety-related practices. The selection processes to determine the effectiveness of various safety interventions and measures and analytical methods are further described in this chapter.

4.1 Selection of Frontline Safety Interventions and Measures

This section represents the process of exploring the evaluation variables. Since frontline workers and supervisor are the target interest as the lowest organizational level in this study, the focus is on those safety tasks which are initiated by these personnel.

Figure 4.1 represents essential safety interventions by project phase and responsible organization level. As shown in the graph, in the early stages prior to construction/production, no safety activities are initiated by frontline supervisor and workers, despite some involvement as reviewers at these preliminary stages. Although most of the listed safety programs are directly or indirectly related to frontline workers, global programs controlled at the management or project team level are excluded in this research because they are equally provided through a frontline workplace without variance.

Consequently, it is mainly supervisory activities that are considered in this analysis, since supervisors are responsible to implement safety policies and interventions as the lowest managerial role (Heinrich 1950).

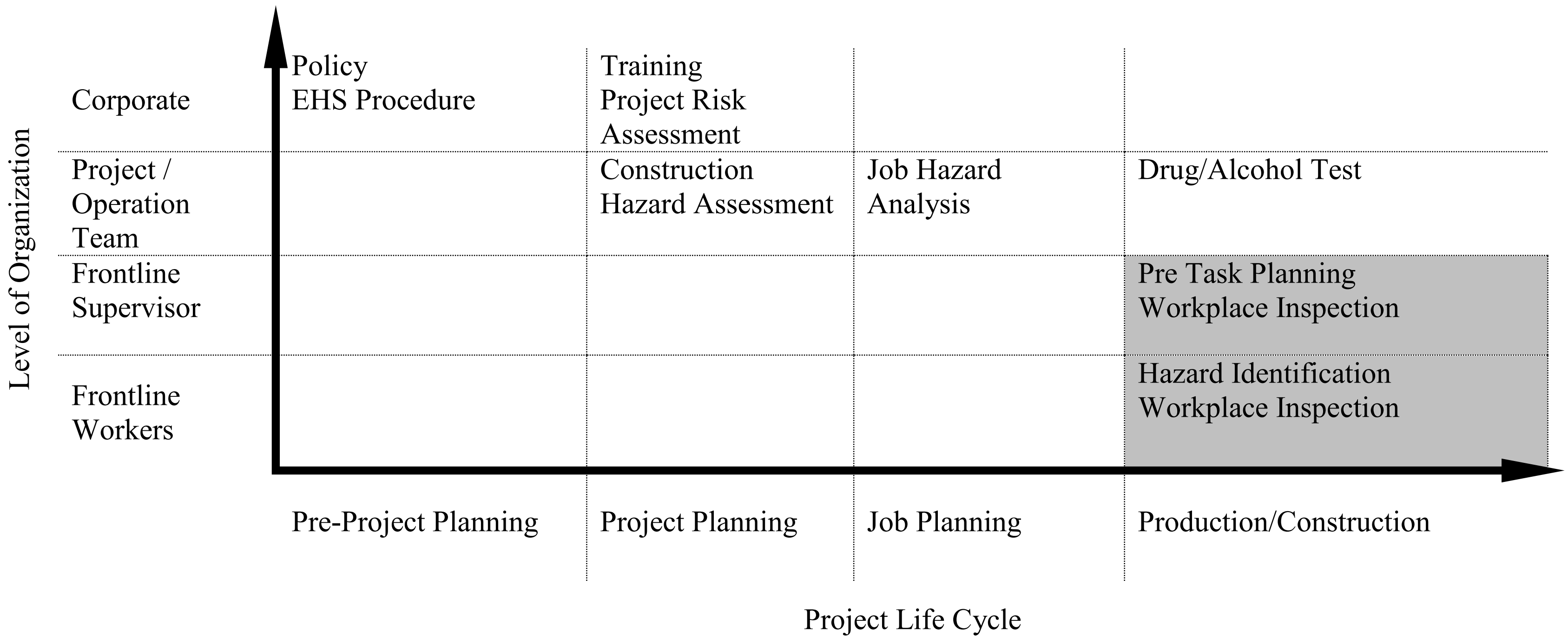


Figure 4.1. Safety interventions responsibilities by level and project life cycle

In this case study, the major focus is placed on those safety interventions requiring active participation of and interaction between frontline workers and supervisors in the processes of risk identification, evaluation, and mitigation. Communication skills as well as competence for hazard awareness and response are fundamental and integral aspects of frontline safety management (Carter and Smith 2006; Albert et al. 2014a).

Accordingly, two safety interventions implemented in the organization—pre-task planning and worksite inspection—are investigated in order to evaluate the effectiveness of on-site implementation. Specifically, pre-task planning aims to identify potential hazard and control in each step of an activity and thus necessitates active engagement of frontline workers in the process (Hinze et al. 2012). Among the selected safety interventions involving frontline workers, pre-task planning is an integral aspect of identifying hazards that increase the worker's hazard awareness and control measures (CCOHS 2006). The role of workplace inspection, meanwhile, is to evaluate and control hazards in working environments to ensure compliance with safety procedures and regulations.

Table 4.1 outlines the general roles and responsibilities of foremen and workers (European Agency for Safety and Health at Work 2008; Government of Alberta 2015) with associated evaluation measures, identified through observation and reviewed by safety personnel in the organization. Based on these two practices, variables can be generated to offer evaluation measures of intervention implementation. Since unrecognized hazards constitute missed opportunities to assess and mitigate hazards (Cooke and Lingard 2011; Behm and Schneller 2013), implementation efforts to detect potential hazards are a critical aspect of evaluating safety intervention effectiveness.

Table 4.1. Role and responsibility of hazard recognition and control practices in frontline

Safety Intervention	**Roles and Responsibilities**		**Evaluation Measure**	
	Foremen	Workers	Variable	Unit
Pre-task Planning	• Understand the general approach to assessment • Identify safety and health problems • Assess and prioritize the need for action • Suggest options available to eliminate or reduce risks and their relative merit • Promote and communicate safety and health improvements and good practices	• Participate in the meeting • Alert foremen or employer about perceived risks • Report changes in the workplace • Submit proposal to control hazards • Cooperate to enable the employer to ensure a safe working environment	• Hazard and control measure alignment with Job Hazard Analysis rate • Longhand Description Frequency • Safety Communication Time • Hazard Identification Frequency	• Aligned item/JHA risk items (%) • No of longhand SLRA / total SLRA in research period (%) • Actual time during SLRA meeting (minutes) • No. of reported cases/person (times)
Workplace Inspection	• Investigate and record any new hazards identified • Act to eliminate or control the hazards • Order the workers to stop work or talk to affected workers about both the hazards and controls	• Participate in workplace inspections when requested • Make suggestions for corrective actions to inspectors	• Workplace Inspection Frequency	• No. of reported cases/person (times)

4.2 Company Practice and Work Process Overview

4.2.1 Workplace Inspection

Through critical examination of the workplace, inspections identify and record hazards for corrective action. Joint health and safety committees, foremen, and workers can help to plan, conduct, report on, and monitor inspections. Regular workplace inspections are an important part of the overall quality, health, and environmental management program.

Inspection team members are responsible for (Safe Work Australia, 2011):

1) Recording all hazards identified during inspections and determining the risk associated with those hazards, in consultation with relevant employees and contractors;
2) Determining appropriate controls to manage these risks, in consultation with relevant employees and contractors; and
3) Ensuring that action items have been allocated to proper relevant and competent persons in the workplace.

Planned general inspections should be conducted on a weekly basis for each project or area. The inspection team should include, where possible, representation from both management and the field workforce. The case company's general workplace inspection form is described in Figure 4.2 and 4.3.

Shop Inspection Form

Priority Index: 1. Imminent Danger 2. Serious 3. Minor 4. Acceptable 5. Not Applicable (N/A)

Shop:	**Date:**	**Time:**
Conducted By:	**Shift: Day Night Weekend (circle one)**	

#	Inspected Items:	Priority:	Comments:
1	Practice & procedures compliance		
2	Protection of public		
3	Slip & fall hazards		
4	Emergency phone numbers available		
6	Evacuation procedures in place		
6	First aid attendant readily identified and available		
7	Compressed cylinder flashback arrestors in place		
8	Gas cylinders, hoses & regulators in acceptable condition		
9	Cylinders stored properly		
10	Equipment log books are current and available at each crane		
11	Confined space safety compliance		
12	Extreme weather safety		
13	Proper lifting compliance		
14	Cables, ropes & chains in acceptable condition		
15	Mandatory PPE in place		
16	PPE in good condition		
17	Fire extinguishers in place, inspected for the month and align with NFSA Requirements		
18	Fire extinguishers tagged & sealed recently		
19	Fall protection compliance		
20	Waste disposal & housekeeping		

1

Figure 4.2. Workplace inspection form example (front)

Shop Inspection Form

#	Inspected Items:	Priority:	Comments:	
21	Certification of Equipment Operators in Place			
22	Compliance in Use, Storage & Maintenance of Tools			
23	Welder Safety Compliance			
24	Lighting in Shop Adequate			
25	Pinch Point Awareness			
26	Proper Rigging Compliance			
27	Condition of Slings			
28	Compliance of Smoking in Restricted Areas			
29	Compliance in Materials Storage & Handling			
30	WHMIS Compliance			
31	Tripping Hazards			
32	Lock-out/Tag-Out Procedures in Place			
33	Safety for Loading & Unloading of Trucks (Guard rails in place)			
34	Equipment Guards in Place			
35	Act, Regulation & Codes readily available			
36	Vehicle & Equipment Operation Compliance			
37	Properly secured ladders			
38	Sufficient ventilation			
39	Welding Screens used appropriately			
40	Lock-out Tag-out (LOTO) is being followed			
41	All workers are following Waiward's Fall Protection Plan			
42	Other:			

Priority Index: 1. Imminent Danger 2. Serious 3. Minor 4. Acceptable 5. Not Applicable (N/A)

2

Figure 4.3. Workplace inspection form example (Back)

4.2.2 SLRA/FLRA

The FLRA/SLRA of the company where the case study is conducted is based on the Construction Owners Association of Alberta-recommended format, which is broadly utilized in Canadian practice. The applicability of FLRA and SLRA depend on whether the activity is being carried out in the field or in a shop area. The FLRA checklist is focused on hazardous situations in installation tasks, permits, and emergency preparedness. On the other hand, SLRA is designed for hazards in a shop environment. SLRA is thus concentrated on hazards related to the use of permanent equipment and routine work. Although these two forms should be differently designed for different types of work and different environments, the case company's practice is to use similar forms for both contexts. In this study, only SLRA is looked at because the target group's workplace is an indoor prefabrication shop.

Generally, SLRA meetings are conducted on a daily basis. However, in addition to any routine sessions, SLRA should be implemented for any of the following four cases;

1) New job or shift
2) Change workers
3) Change of work area or conditions
4) Change in task or plan

The FLRA/SLRA is completed at the task location and should be attended by all workers participating in the task, including sub-contractors. All workers should have input into the identification and controls of hazards. There is no maximum or minimum amount of time required for such sessions. Contractually, a foreman can allow time for approximately 20 minutes since official commencement of daily work for unionized workers is 20 minutes before the start of physical working. Although theoretically the foreman can extend the SLRA meeting, workers prefer not to spend more than the regularly allotted minutes due to the need to meet the production schedule.

As described in Figure 4.4 and 4.5, the SLRA form should be filled out by a facilitator on both the front and back of the form. The front of the form offers a number of critical check boxes to create awareness of hazards, and also provides an area for work task identification. The back of the form comprises commonly used risk assessment items: task, hazards, and control measures. This form includes areas for descriptions of the overall work task with the individual steps and stages of job tasks required to complete the work. Furthermore, hazards are described based on the planned work tasks. Finally, control measures are implemented and risk levels are determined by crew members. The facilitator records all the controls required to eliminate or at least minimize the hazard to an acceptable level. The entire crew has to sign on the form indicating concurrence about the stated risks and controls for each hazard.

Shop Level Risk Assessment

Date: D / M / Y Time:

Shop Department:

Task Location:

Facilitator: Print Initial

Foreman: Print Initial

Daily Tasks & Expectations

Rigging & Hoisting	
☐ Certified	☐ Inspected
☐ Rigging meeting SLRA for specialty lifts	

Fall Protection/Overhead Hazards	Y/N/NA
Barricades & Signs in Place	
Hole Coverings Identified	
Harness/Lanyard Inspected	
100% Tie-off w/Harness	
Falling Items are secured	
Hoisting or Moving loads in Work Area	
Tools and Materials Secured	
Is Access Below Barricaded	
Removing Barriers or Guardrails	
Areas that Require 100% Tie-off Identified	
Areal Work Platform	

High Hazards	
☐ Congested work area	☐ Heavy lifting*
☐ Dropping objects	☐ Repetitive motion
☐ Confined space	☐ Housekeeping
☐ Working at heights	☐ Moving equipment
☐ Line of fire	☐ Ladder use
☐ Spills / Water	☐ Other people in area
☐ Slips, trips & falls	☐ Warning ribbons
☐ Loud noise	☐ Pinch points
☐ Heat / Cold stress	☐ Lock outs identified
☐ Overexertion	☐ Electric shock
☐ Working alone	☐ PPE requirements
☐ Vehicle movement	☐ New workers identified
☐ Fire or spark	☐ First time tasks

Consider mechanical lift before adding manual effort

Shop Safety Assessment	Y/N
Is everyone fit for duty	
Is everyone competent to perform their duties	
Were there any incidents on the previous shift	
Are there any workers on modified duty	
Have the hazards been reviewed by all workers	

Area Team Members sign below;

1. Print Initial
2. Print Initial
3. Print Initial
4. Print Initial
5. Print Initial
6. Print Initial
7. Print Initial
8. Print Initial
9. Print Initial
10. Print Initial
11. Print Initial
12. Print Initial
13. Print Initial
14. Print Initial
15. Print Initial
16. Print Initial
17. Print Initial

Figure 4.4. SLRA form example (front)

Shop Level Risk Assessment

Work Description

Tasks	List all **hazards** associated with tasks	List all **controls** for all listed hazards	Low	Med	High

Figure 4.5. SLRA form example (back)

4.2.3 Work Process Overview

This research focuses on the safety performance of the modular/prefabricated building construction sector during both manufacturing and on-site processes. More specifically, the target company's operation is steel pre-fabrication of modules for industrial construction projects. Prefabricated construction, it should be noted, entails the manufacturing of building components in an off-site fabrication facility.

The fabrication process broadly comprises a course of operations including detailing, fitting, welding, and surface processing. The detailing process is divided into subtasks, such as cutting, grinding, drilling, and burning. Surface processing includes painting, sand blasting, and fireproofing, depending on the customer's design requirement (Figure 4.6).

The entire operation is categorized by material weight and complexity, resulting in four shops. Each shop has basically the same process, with frequent overlaps in production schedule and urgent orders.

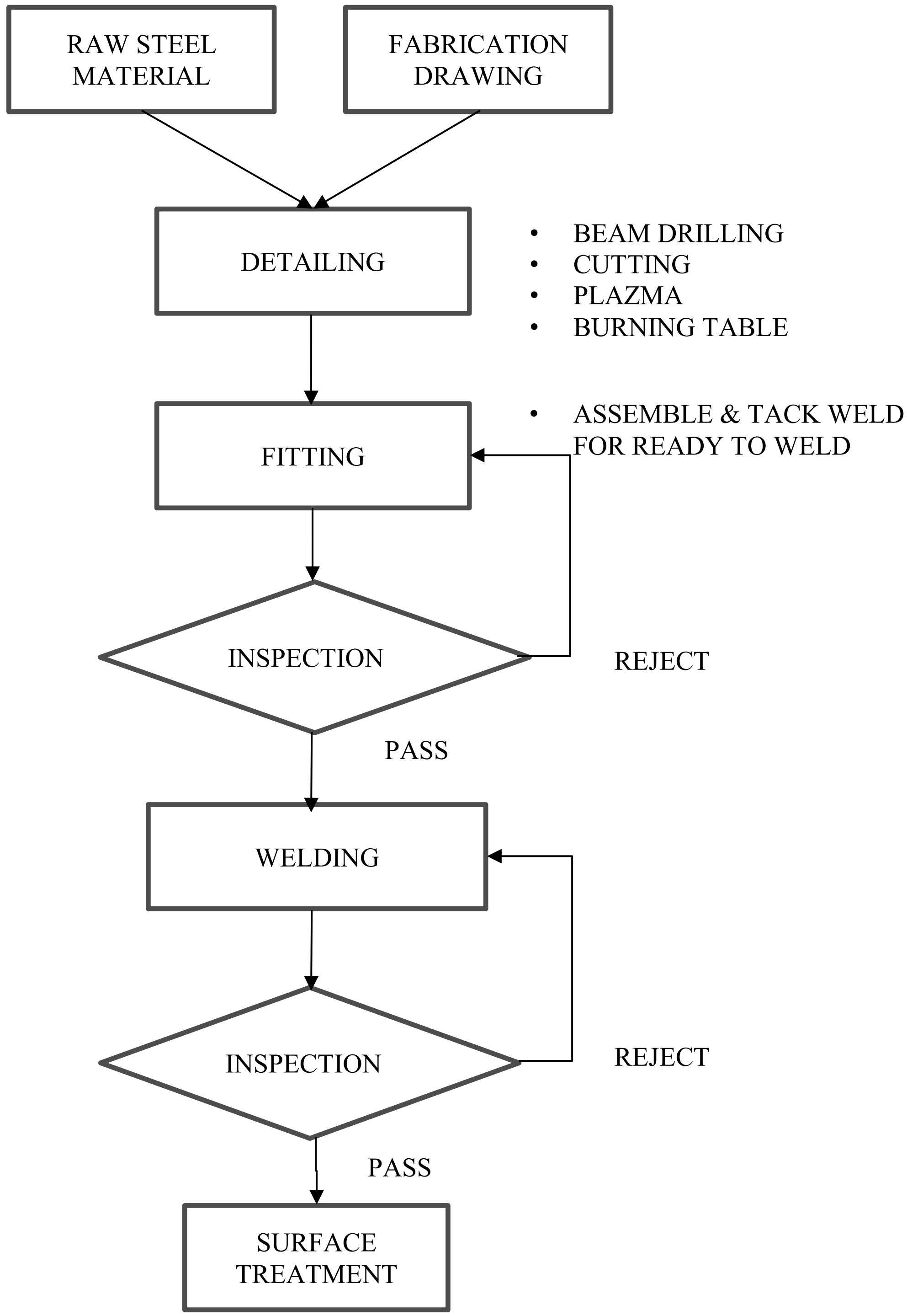


Figure 4.6. Work process map

4.3 Measurement of Evaluation Variables

Technically, to avoid statistical limitations, only measurable and countable evaluation criteria are developed, e.g., bias, internal validity, sample heterogeneity (Robson 2001). Each type of variable has a numerical and continuous value, such as the numbers of cases or percentages to be suitable for statistical analysis.

In respect to each variable as an evaluation element, first, a content coverage rate is associated with the quality of hazard identification during pre-task planning (a.k.a., SLRA). In the organization, JHA is conducted by middle managers such as superintendents and safety managers in conjunction with foremen on a yearly basis for a thorough review of potential hazards throughout the company's operations, while SLRA is performed and led solely by frontline foremen to review and communicate potential hazards in daily practice. Thus, the alignment between reviewed hazards in SLRA and JHA represents the extent to which the potential risks identified through JHA are covered during the SLRA meeting as recommended by the organization policy and standard operation procedure, which eventually affect incident occurrence (Hudson 1998). The alignment is measured based on how many hazards and associated control measures in JHA are discussed in each SLRA report. Such alignment helps bridge gaps in the hierarchical management systems by bringing risk reviews by upper management to daily discussions on the nature of the work being performed (Roughton and Crutchfield 2008).

Longhand description refers to manual writing of the SLRA form as opposed to shorthand (e.g., typing). Interestingly, a high rate of SLRA reports are observed in the organization where the descriptions of tasks and hazards have been written by typing. From the behavioural standpoint, the most significant aspect of descriptions in longhand practice is that it is rarely observed that information is repeated, i.e., copying-and-pasting previous hazard generations and control measures. In contrast, shorthand practice repeats the same checklists and hazard generation and controls over 3 months to 6 months. In particular, the back of the page requires more narration than the front-left blank space on the shorthand assessment. Theoretically, people who write by hand generally have better learning and conceptual understanding than those typewriting (Mueller and Oppenheimer 2014; Mangen 2010), and though writing longhand can slow the reporting process it may help to prevent distractions during writing (Yamamoto 2007). In this regard, the frequency of longhand reporting may shed light on the degree of time and effort as well as cognitive learning and understanding required for foremen to fill in the form as a "living document" and implement effective hazard assessment. This variable is measured in percentage terms of longhand practice throughout the study period.

Third, safety communication is one of the important factors to enhance safety exchange, followed by safety climate. For safety management, communication between supervisor and workers is not only the key element that enhances knowledge sharing and worker involvement, but also an indicator of successful risk assessment (Simard and Marchand 1994). Here communication and participation are associated with leader-member exchange levels of safety information (Kines et al. 2010; Zhou and Jiang 2015). In particular, when provided an opportunity to participate in a decision making process, workers tend to become more receptive to the decision made (Roughton and Crutchfield 2008). This measure is thus quantified with actual time spent for any instruction, review, or discussion among crafts during a SLRA meeting, usually 20 minutes in length.

Fourth, hazard identification refers to the process of ensuring that the level of risk is consistently recognized and controlled within acceptable ranges of risk tolerance. When not appropriately performed, such processes are closely correlated to the occurrence of injury and illness, as workers can remain in the at-risk conditions without any safety control. Previous studies have investigated the relationship between hazard identification and injury rate and revealed that the relevant measure can be utilized as a leading indicator for workplace safety (Manuele 2009; Albert et al. 2014b). In the case organization, hazards are identified by individual frontline workers; hence the number of reported cases per employee is used as an input variable to investigate the relationship with incident records.

Finally, workplace inspection is regularly performed to identify potential hazards associated with working conditions on a jobsite. The inspection has a significant influence on the reduction of injury rate (McLeod et al. 2014), and as part of an auditing program, worker's involvement in jobsite safety inspection is a critical factor affecting injury prevention, thus serving as a performance indicator (Hinze et al. 2012). For the case organization in particular, the purpose of workplace inspection is not only to monitor site conditions, but also to identify any hazard missed and uncontrolled from the pre-task planning. In this research, the number of inspection reports per worker is measured as a variable representing worker participation and involvement in risk mitigation activities.

5 METHODS

This chapter discusses general regression model and its utilization in effectiveness studies. Furthermore, this chapter discusses why Poisson regression model is required for this particular study, and introduces basic knowledge about general regression.

5.1 Evaluation Outline

The effect of practice measures (e.g., content coverage rate) on safety enhancement is assessed using a regression model built for the datasets collected in the case study. Regression has been widely used as a statistical tool which allows for modelling the relationship between variables and predicting the outcome on the basis of the model. In construction, regression analysis has been applied to various research areas including cost and scheduling (Lowe et al. 2006; Hwang 2009; Duffy et al. 2011), project dispute resolution (Cheung et al. 2010), change orders (Anastasopoulos et al. 2010), and safety management (Tam and Fung 1998; Fang et al. 2006; Cooper and Phillips 2004; Sokas et al. 2009a; Oude Hengel et al. 2012).

An overview of data analysis is illustrated in Figure 5.1. Five evaluation measures are used as independent variables with effective modifiers or confounders such as seniority (Hymel 1993), experience (Breslin and Smith 2006; Bena et al. 2009), craft size (Burt et al. 2008; Hinze 1981), age (Lander et al. 2016), trade (WorkSafeBC 2014; Bureau of Labor Statistics 2014), and shift (Wong et al. 2011; Ogiński et al. 2000). These secondary variables can potentially affect the safety performance, thereby necessitating statistical adjustment. For the controlling of confounding or effect modification, stratified analysis is carried out to determine the presence of confounding effect and the level of association with the dependent variable. As an output variable representing the safety records, the number of incidents per employee during the case study is recorded and counted in the form of non-negative and discrete numbers. As a result of regression analysis, Relative Risk (RR) is consequently produced and utilized to estimate the influence of each independent variable on the dependent variable.

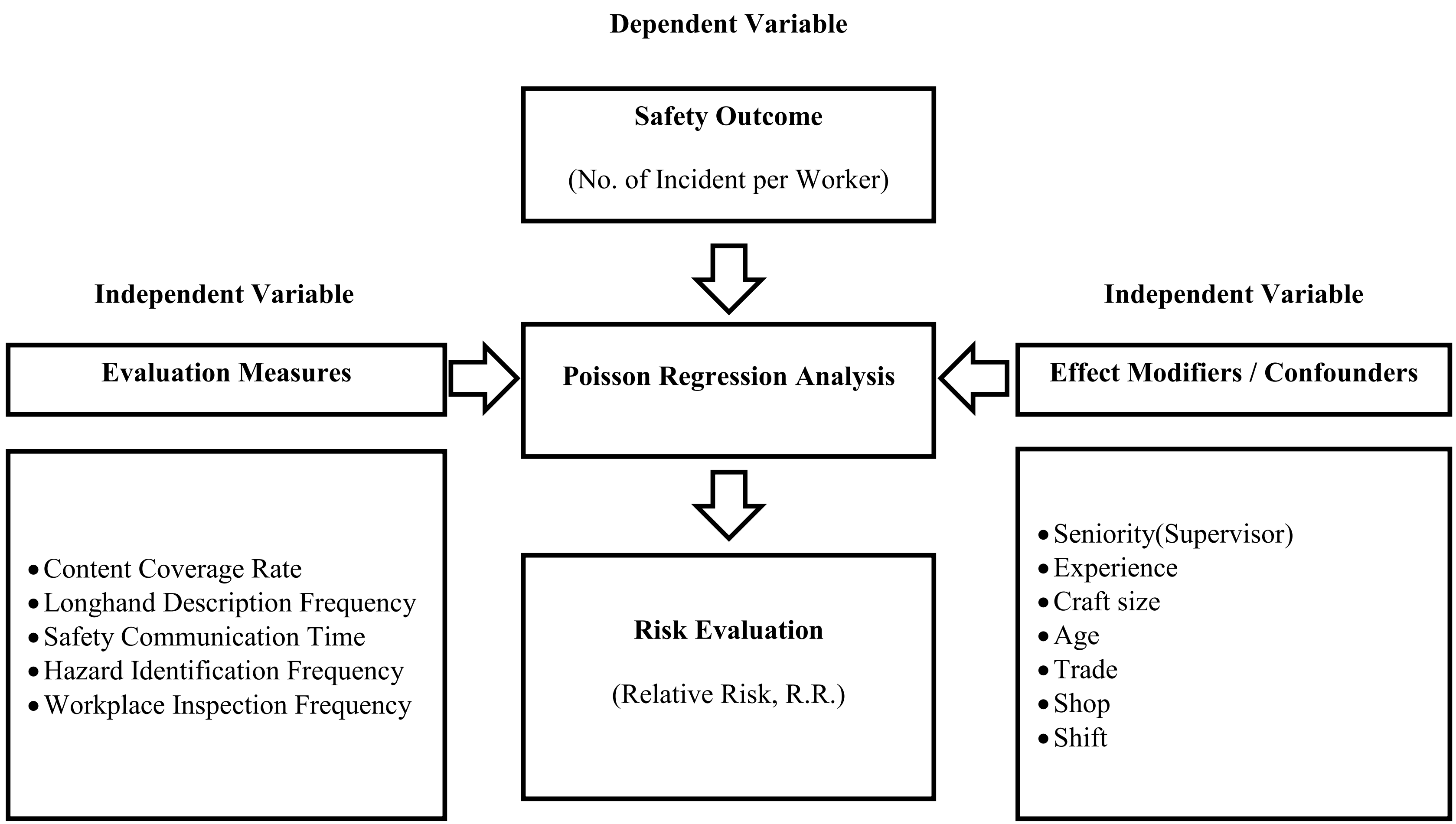


Figure 5.1. Overview of frontline worker safety intervention effectiveness evaluation

5.2 Evaluation Design

Various conceptual designs of effectiveness evaluation in the context of evaluating safety intervention have been introduced. Robson (2001) discussed comprehensive intervention methods from a technical perspective. As described in Table 5.1, effectiveness evaluation designs are divided into three types: experimental, quasi-experimental, and non-experimental.

The experimental design produces the strongest evidence of a causal link between the intervention implementation and observations. Group comparison is conducted by control and intervention groups through an unbiased process, while quasi-experimental design can be considered for non-randomized groups and before-after assessment, which is different approach from the experimental design, in order to overcome logistical limitations (Robson 2001).

In this study, feasible strategies from each design are employed, which allows for target group analysis. Non-randomized control and intervention groups without before-after assessment are applied, whereas reversed evaluation and randomization are excluded due to technical impossibility and the original population limitations in a frontline work site.

Table 5.1. Characteristics of different types of evaluation designs (Robson 2001)

Type of Design	Characteristic of Design			
	Inherent in Design		As commonly used in workplace evaluations	
	Strength of evidence of effectiveness	Randomization of workers/workplaces	Control or compariso n group	Pre-intervention measurements
Non-experimental	Weak	No	Sometimes	Sometimes
Quasi-experimental	Moderate	No	Sometimes	Yes
Experimental	Strong	Yes	Yes	Yes

5.3 Poisson Regression

Regression techniques have been widely used as prediction tools in the construction industry. Regression analysis is one of the strongest statistical methods to calculate an estimation of outcome based on the input parameter. It can be interpreted from plot and correlation coefficient values by computing the dependent and independent variables (Montgomery et al. 2012).

In construction safety management, Tam and Fung (1998) used multiple regression analysis to study the relationship between safety management strategies and site casualty rates. In safety research, Fang et al. (2006) employed logistic regression to analyze the relationship between safety climate and personal characteristics. In addition, safety training interventions were evaluated as an explanatory variable by other researchers in diverse areas (Cooper and Phillips 2004; Sokas et al. 2009b; Oude Hengel et al. 2012). Outcome variables are determined by safety climate or work site inspection, which is easily measured on site. However, such intermediate outcome variables may not guarantee validity due to subjectivity, in spite of higher statistical reliability than injury or fatality rates as the outcome variable.

In general, regression models have been widely utilized to predict safety performance. As listed in Table 2.1 in an earlier chapter, the linear regression method is commonly used to measure intervention effectiveness because it is a strong statistical tool to estimate the parameters expected from a model (Bailey 1997; Ray and Frey 1999; Vinodkumar and Bhasi 2010; Hammer et al. 2015).

Each regression has a different type of dependent variable. When the dependent variable is continuous, linear regression is commonly used. One assumption of linear regression analysis is that the residual errors follow a normal distribution. If the dependent variable is categorical and a binary outcome variable (e.g., fatality, sick/healthy, present/absent), linear regression does not work properly. In such cases, logistic regression can be employed to analyze binary, ordinal, and multinomial outcomes. Among these categorical variables, logistic regression model works for discrete event counting variables, but it produces favourable representation in binary values unless everyone commits only one incident or less in the period.

Poisson regression is also employed to model counting variables. Typically, incident data follow Poisson distribution, which is broadly used in traffic accident analysis (Joshua and Garber 1990; Abdel-Aty and Radwan 2000), political science (Famoye and Singh 2006), clinical trials (Gardner et al. 1995), and property damage assessment (Ismail and Jemain 2007). The dependent variable is assumed to follow a Poisson distribution, and the logarithm of its predicted value can be modelled by a linear combination of unknown parameters. For instance, Amick (2015) conducted Poisson regression analysis to estimate the effect of a unionized environment on safety performance, since unionized construction companies have higher no-lost-time claim rates (RR 1.28, CI 1.23 to 1.34) than nonunion companies. Breslin and Smith (2006) applied Poisson regression to evaluate job tenure and lost-time claim rates. Their study proposed to test a goodness-of-fit statistic from the Poisson model (deviance/degrees of freedom) and they opted to use a negative binomial model since it indicates a better fit than the Poisson model (1.20/8.44). Their analysis showed that the first month claim rates in each worker's tenure are relatively higher (RR 5.56 for contact object, 6.36 for falls, 2.93 for exertion, and 5.28 for exposure to harmful substance), except for cases of repetitive motion-related injuries.

As the dependent variable, No-lost-time incidents, including severe injuries (e.g., lost-time injuries), are employed as an outcome variable, since the use of only lost-time incident rates poses some disadvantages in safety intervention effectiveness research. In this study, all incidents are collected in terms of the parameters set forth by the Workplace Safety and Insurance Board, which specifies lost-time cases as follows (Smith 2010);

1) Worker is absent from regular work
2) Worker earns less than regular pay for regular work
3) Worker requires modified work at less than regular pay

4) Worker requires modified work at regular pay for more than seven calendar days

Cases which require health care but not an absence from work other than the day of injury are referred to as no-lost-time claims, and they are outlined as follows.

1) Less severe injuries (requiring health care but not time off work)
2) Injuries where the worker cannot return to their normal duties the next day, but can do another (less demanding) job, or their current job with modifications.
3) Claims submitted as a result of a chronic work-related condition, after the worker has stopped participating in the labour force (i.e., retired).
4) Claims in which the worker took time off, but was told to submit a no-lost-time claim
5) Claims in which, although the worker could not return to their job, they were forced to return to the workplace the next day

The use of no-lost-time incidents as the dependent variable offers three methodological advantages: (1) higher frequency than lost-time injuries, which delivers a homogeneous distribution; (2) objectivity by avoiding biased self-reporting; and (3) strong connection to lost-time injury rates (Zohar 2000). In addition, as illustrated by the 1-10-30-600 pyramid depicted in Figure 5.2, every 29 minor injuries account for 10 lost-time injuries (Bird and Loftus 1976). Therefore, no-lost-time injuries still play an important role in evaluating comprehensive safety performance within any organization.

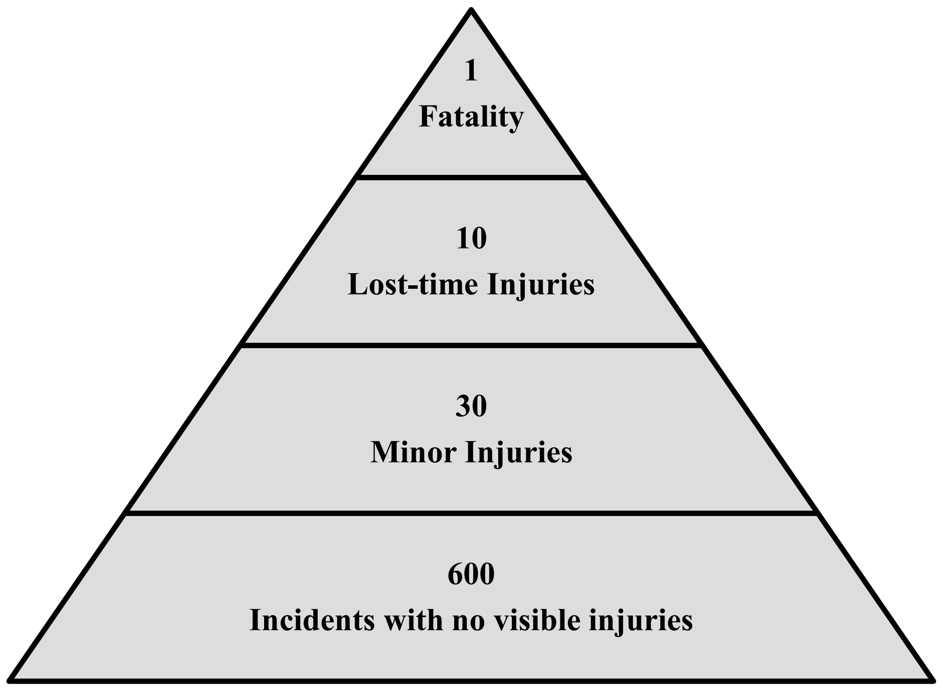


Figure 5.2. Safety accident pyramid (Bird and Loftus, 1976)

As shown in Figure 5.3, the gap trends between lost-time injury and no-lost-time injury of both the case company for this research and Ontario example cases have grown wider over the years. Accepted lost-time claims are found to have declined much more quickly than no-lost-time claims in Ontario from 1991 to 2006 (Smith 2010). In particular, lost-time claims have been extremely rare for the partner company, which makes difficult to use lost-time injuries in the study.

Previous studies have noted that such increasing or stable no-lost-time injury rates versus lost-time injury rates is associated with 'under-reporting' by workers and 'under-claiming' by employers (Safety and Board 2013). Thus, injury rates combining lost-time and no-lost-time are the ideal solution. In this study, no-lost-time cases are used for analysis due to the statistically insufficient amount of lost-time cases.

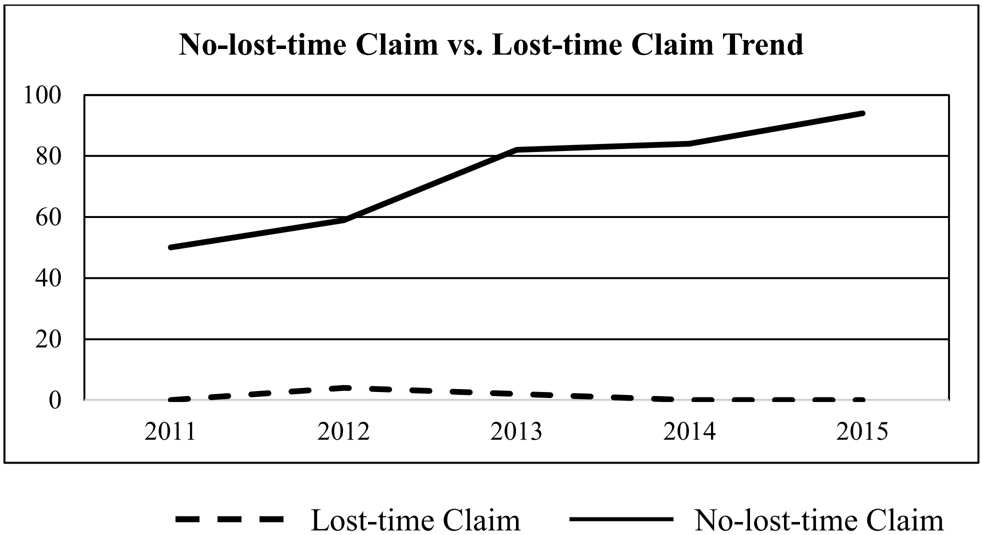


Figure 5.3. Lost and No-lost-time claim trends (the company case study)

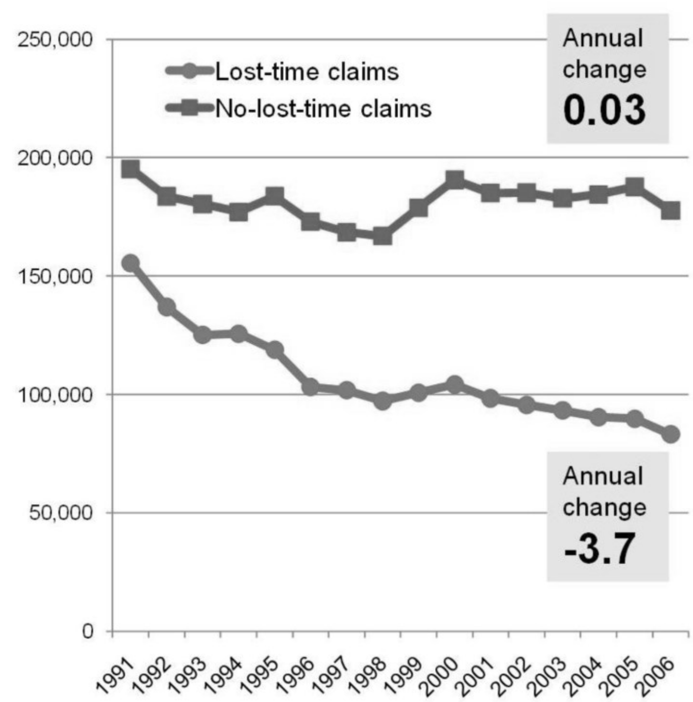
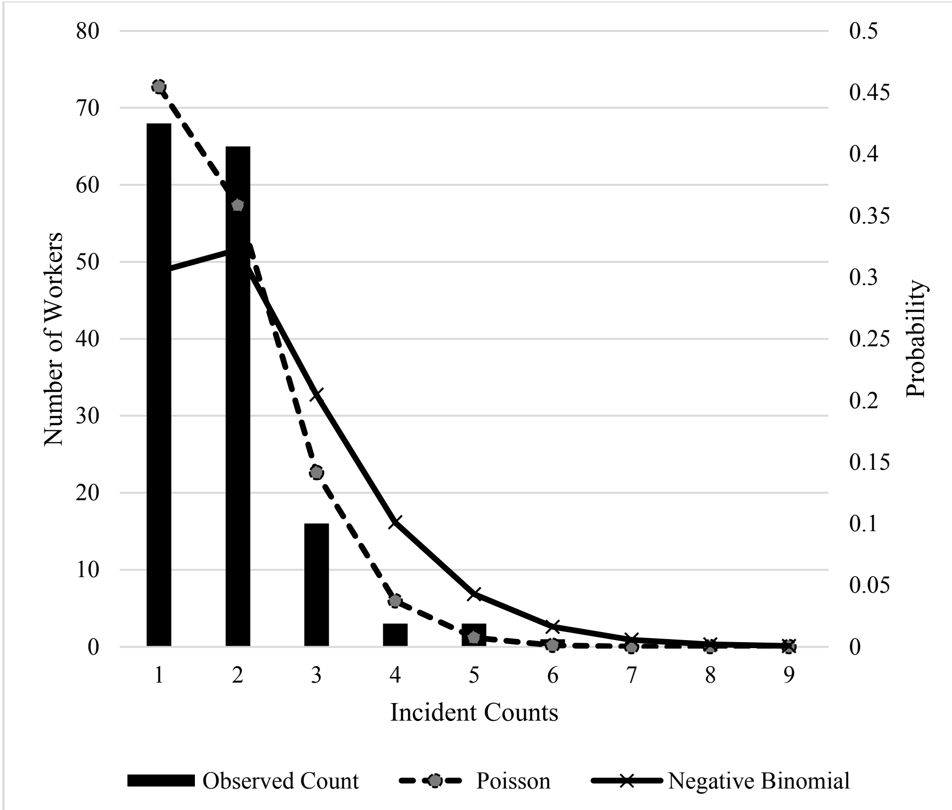


Figure 5.4. Lost and No-lost-time claim trends (companies in Ontario)

To determine the specific regression model, identification and understanding of the data distribution is the initial step in the analysis. The data used as the dependent variable is no-lost-time incident records, including any cases in which the injured employee seeks medical treatment. Compared to lost-time cases or near-miss reports, such data may help to avoid issues related to the rareness of severe injuries and to instances of biased self-reporting (Zohar 2000). Since such incident data includes variables which are discrete and restricted to non-negative integers, a negative binomial or Poisson regression model can be used as a subset of the Generalized Linear models. One of the important decision factors in selecting one of these two models is that conditional mean and variance of data are compared in order to identify over-dispersion and equi-dispersion. The histogram of no-lost-time incidents presented in Figure 5.5 visually illustrates that the distribution has a skewed shape with a skewness ratio of 1.68 (i.e., the normal distribution's ratio is 0); the lines of probability distributions visually show that Poisson distribution has a closer fit to the dataset. The result of a Kolmogorov-Smirnov test (Chakravarti and Laha 1967), which can be used to compare sample datasets with a reference probability distribution, also indicates that the dataset may follow the Poisson distribution (asymptotic significance 2 tailed: 0.967).



Mean = 0.790, Std. Deviation = 0.923, Variance = 0.852, N = 156

Figure 5.5. Comparison among histogram, Poisson and negative binomial probability distributions of the number of incidents

In addition, as a major assumption of Poisson regression, equi-dispersion should be checked to determine whether conditional variance is equal to conditional mean. Lagrange multiplier test (Greene 2003) is one of the methods to determine whether equi- or over-dispersion exists in particular data. The null hypothesis assumes that conditional variance exceeds conditional mean; in such a case, negative binomial regression can be appropriate. For the incident data collected, fitting a negative binomial model with ancillary parameter (k = 0) into the Lagrange multiplier test does not yield a statistically significant p-value (0.419 with 95% confidence interval); accordingly, the null hypothesis for over-dispersion is rejected (Cameron and Trivedi 1998). Therefore, over-dispersion (k > 0) should not be an issue when using Poisson regression for the data used in this study.

A Poisson regression model, also known as a log-linear model, is a generalized linear model with the logarithm as the link function; it also includes a Poisson distribution function based on the rate parameter (λ) and independent variable (x). Poisson regression fits linear models to a logarithm (counts of number of events) which looks for group differences. The probabilities of events for a Poisson distribution are defined in Equation (1). In this equation, a random variable Y follows a Poisson distribution with parameter λ; that is, the average number of incidents in a certain period of time is designated by a rate parameter (λ) for an individual employee (i). The rate parameter (λ) is determined with an explanatory variable, also known as an independent variable (x) representing the safety interventions (e.g., content coverage rates, longhand description rates). The Poisson regression model is fitted to log Y; then models of the form can be represented as per Equation (2), whereby we observe the sound theoretical rationale for using logit with binomial and log for the Poisson.

In Equation (3), a regression co-efficient, $exp(\beta)$, represents the expected change in the logarithm of the mean per unit change in the predictor x_i. Increasing $x_i$by one unit multiplies the mean by a factor, $exp(\beta)$ (Cameron and Trivedi 1998).

$$P(Y_i = y_i|x_i) = e^{-\lambda_i}\lambda^{y_i}/y_i! \quad (1)$$

$$\text{Log}\,(\lambda_i) = \beta_0 + x_1\beta_1 + x_2\beta_2 + \cdots + x_k\beta_k \quad (2)$$

$$\lambda_i = exp(x_i\beta) \quad (3)$$

where

y: observed number of occurrences of incidents per individual worker (*0, 1, 2, ...,)*

x: explanatory/independent variable, e.g., safety communication time (0~20)

i: individual worker (1,2, 3… n)

λ: average number of incidents per observed time interval

When x_i is binary, exponential (β) is referred to as an RR ratio. The RR is produced to represent the ratio of the probability of an incident occurring among multiple groups. In other words, RR is the ratio of the probability of event occurrence (i.e., injury rate) of exposed (i.e., treatment) versus unexposed (i.e., control) group. An RR of less than 1.0 reflects a negative relationship (e.g., incident occurrence less likely in exposed than in control group), while a value greater than 1.0 represents positive relationship between the exposed and unexposed group.

The data in this study are analyzed using the statistical computing package, Statistical Package for Social Science (SPSS). In particular, the model-fitted statistics, the summary of the model effects, and the parameter estimates are reviewed as follows:

First, the goodness-of-fit table lists various statistics indicating model-fitness. To assess the fitness of the model, the goodness-of-fit chi-squared test is conducted.

This test evaluates the model form to determine whether or not the Poisson model form fits the input incident data. If the results of the test are found to be statistically significant, this would indicate that the data do not fit the model well. As a second step, Omnibus test whether the explained variance in a set of data is significantly greater than the unexplained variance. Using p-values, the model is tested to find whether or not it yields statistically significant results. Third, the model effects test evaluates each of the model variables with the appropriate degrees of freedom. Finally, the parameter estimates indicate the regression coefficients for each of the variables, along with robust standard errors, p-values, and 95% confidence intervals for the coefficients. Control of Effect Modification and Confounding

Effect modification and confounding are usually involved in causal studies because they provide biased results for exposure magnitude. Generally, to evaluate the relationship between a causal factor and an outcome variable, potential confounders or effect modifiers must be identified since they can lead to misleading outcomes. For the effect modifiers or confounders, stratification is widely used to identify and reduce effect modification and confounding; for instance, the standardized mortality ratio is a popular method to remove confounding by age (Cook, 2007). Some researchers have used confounding and effect modification for the same purpose since these two variables are similar. However, it should be determined whether a given variable is an effect modifier or a confounder in order to prevent a misleading result.

Effect modification relationships among three variables can be represented as in Figure 5.6. Suppose that age is one of the effect modifiers in a study evaluating the efficacy of training to decrease workplace injury. It is certain that training helps to improve not only safety performance but also injury rates. Meanwhile, injury rate is generally higher in younger age groups than in older ones. Consequently, the injury rate will be higher than expected if the trial group covers only younger age. Similarly, age may function as a confounder in other study designs.

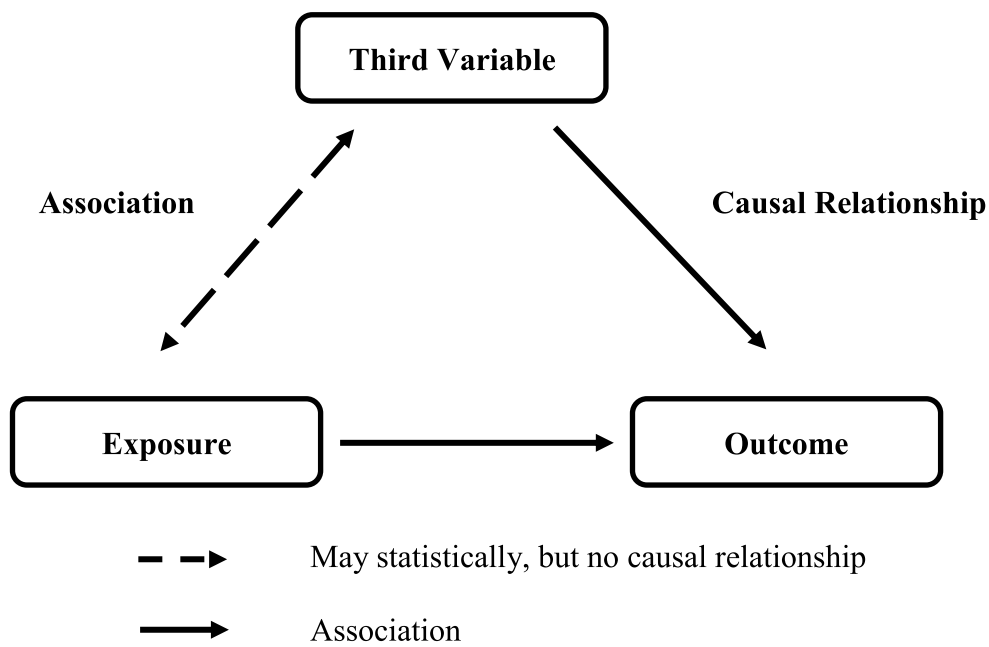


Figure 5.6. Relationship diagram of exposure, outcome and effect modification

In contrast to effect modification, confounding is related to both input and output variables. For instance, a logistic regression model shows that the injury ratio of shift workers is estimated as [Odd Ratio (OR), 2.65]. When considering a third variable such as manual or non-manual work as a confounder, the adjusted OR is lower than in the previous estimation, with a value of 1.73. The reason for this discrepancy is that a larger proportion of manual workers belong to the night shift than to the day shift. These manual workers are more prone to be exposed to risk than are non-manual workers. As mentioned above, manual worker (third variable) is related to both shift work (input variable) and injury ratio (output variable) (Wong et al. 2011a).

For instance, in one study available in the literature the construction worker lost-time injury rate ratio (Denmark/Sweden) is 2.06 for minor injuries in a single organization that has operations in both countries, while the ratio is found to decrease to 1.23 for serious cases, using a regression method which considers sick leave policy differences (Spangenberg et al. 2003). The authors of the study discovered that Swedish workers are reluctant to report minor injuries since the Swedish labour legislation stipulates that the injured worker is responsible to pay for their first day of injury-related absence. In contrast, in Denmark employers are responsible to cover the cost of lost-time from all injuries. Confounding occurs as a result of imbalance between the exposed and unexposed groups with regard to input variables (i.e., independent risk variables) and output variable (i.e., the incident of interest).

The difference between confounding and effect modification can be easily illustrated by the diagram depicting the relationship among exposure, outcome, and a third variable such as effect modifier or confounder (Figures 5.6 and 5.7, respectively). In order for a factor to be considered a confounder, two conditions must be met:

1) the third variable should be associated with exposure without being the consequence of exposure, and
2) the third variable should be associated with outcome independent of exposure, but not as an intermediary.

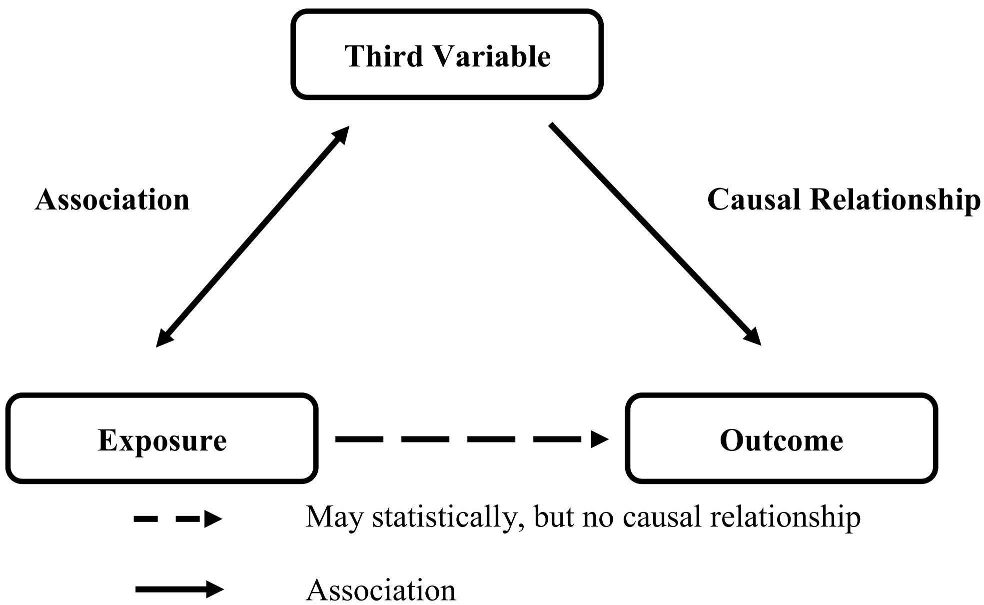


Figure 5.7. Relationship diagram of exposure, outcome & confounding

For example, in verifying the relationship between work at height and fall accident, occupation is a one of the concerns prior to collecting data. Occupation is certainly associated with the frequency of work at height as well as with workplace injury. Construction trade workers are more likely to work at height and also have a dominant fall accident rate (30%) that is higher than for the second highest occupation (e.g., 13% in service workers) (WorkSafeBC 2013). On the other hand, if applying age as a third variable to distort exposure and outcome, it will not be a confounder since there will be no association with work at height. Although fall accidents tend to be more prevalent within the senior age cohort, age is not found to be a major concern with regard to working at height on the industry practice in general.

The most significant difference between confounder and effect modifier has to do with association with exposure variable. As described in Figure 5.5, effect modifier has no link to exposure variable, while confounder has relationships with both exposure and outcome variables.

The rationale for distinguishing between confounding and effect modification is that the approach to achieving final estimation will be different. Effect modification is a demographic phenomenon that should be verified, and therefore stratum-specific estimates are required in order to achieve accurate results. There are several methods of controlling confounding (Swuste et al. 2012);

1) Stratification (report and compare findings for each category or at each level of the confounding factor); this should decrease or eliminate confounding effects by the stratifying factor
2) Standardization or adjustment for an important confounding factor
3) Multiple regression to "adjust" for multiple confounding factors

Stratification is widely used to identify and reduce effect modification and confounding effects; for instance, the standardized mortality ratio is a popular method to remove confounding by age (Cook et al. 2007). The main process of stratification divides the data into subgroups (i.e., strata) according to categories or ranges of a factor, and is used to obtain stratum-specific relative risk. Each stratum-specific relative risk is compared with the crude relative risk. If effect modification exists in the analysis, the relative risks of association in the subgroups differ from one another; this information can in turn be used to identify the magnitude of association among the subgroups based on the adjusted relative risks.

For instance, if a study assesses the effect of wearing a hearing protection device against hearing loss using the regression model, the model first produces crude relative risk in order to represent the effect size for all workers (Table 5.1). However, if age is assumed as an effect modifier, the stratification by young and old groups produces different relative risks for each group. The researcher may conclude that the hearing protection devices prevent worker hearing loss in 40% of cases ($1 - 0.6 \times 100$). When considering the relative risk by age group separately, and comparing relative risk between these two groups ($0.4 < 0.9$), it can be inferred that the use of a hearing protection device is more effective for the younger worker group than for the old worker group. However, older workers are still more vulnerable to workplace noise than are younger workers, even when wearing the hearing protection devices.

Table 5.2. Example of relative risk interpretation in stratification analysis

Hearing Protection Device **Effect Modifier: Age**	**Relative Risk of Hearing Loss**
All group (Crude relative risk)	0.6
Young (Age < 30)	0.4
Old (Age 30+)	0.9

In spite of the simple and straightforward way of carrying out the analysis, stratification is infeasible if dividing several strata or applying multiple confounding variables simultaneously, (which results in a surge of strata containing statistically few or no samples). Alternatively, especially to control for multiple confounding factors at the same time, stratification is often replaced by regression models.

The decision tree in Figure 5.8 gives an idea of how to detect whether confounding or effect modification is available in the model. From steps 1 to 3, crude RR is the main factor by which to estimate the association between the exposure and outcome of interest. Considering an example encompassing the probability of injury in the intervention and non-intervention group, the data is expressed in the 2×2 matrix in Table 5.3.

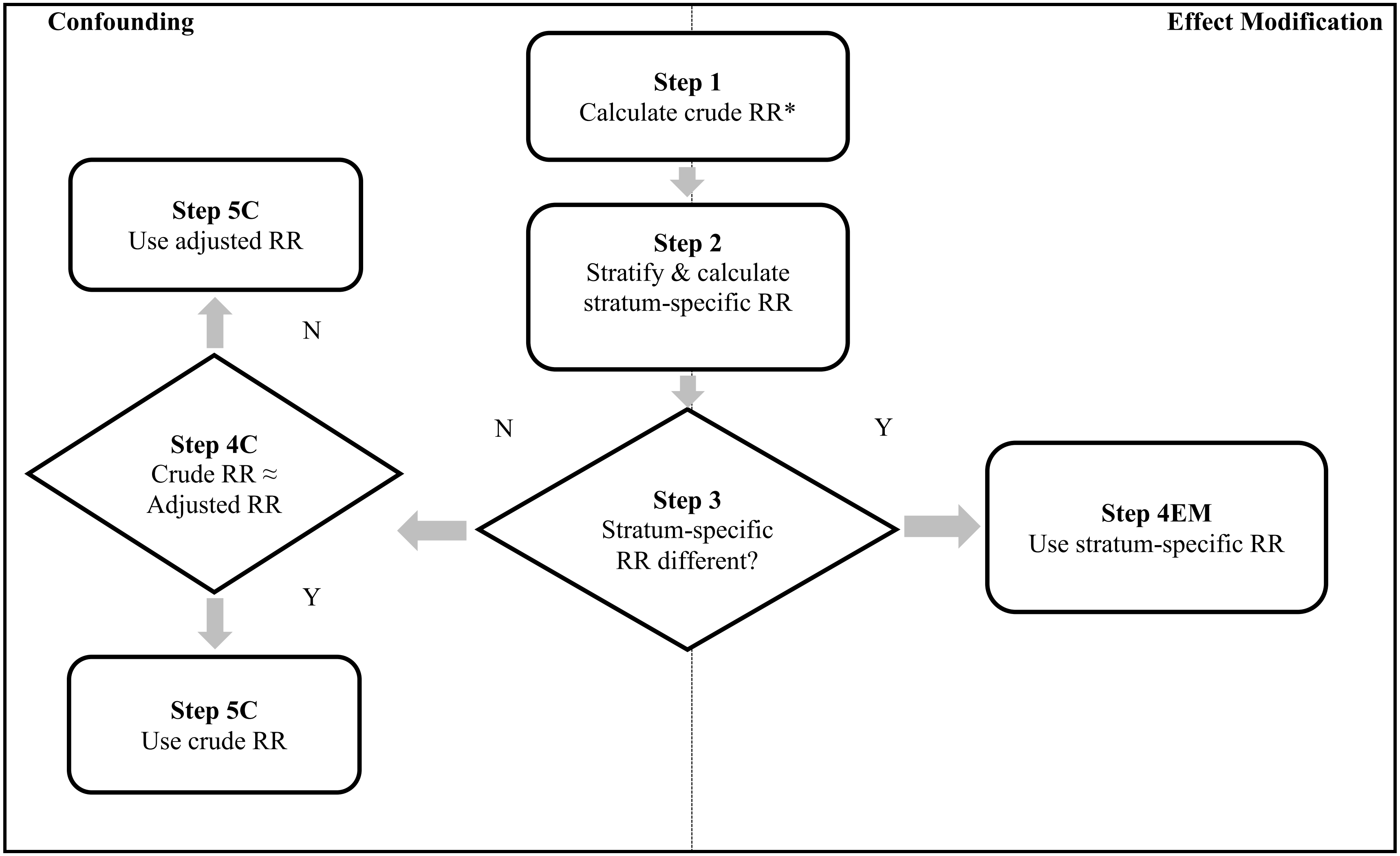
Table 5.3. Example risk ratio 2 × 2 data generation

Risk	Injury occurred	No injury occurred
Intervention	a	b
Non-intervention	c	d

Crude RR is calculated as follows.

$$\text{Crude RR} = \frac{Risk\ of\ incident\ in\ exposed}{Risk\ of\ incident\ in\ unexposed} = \frac{a/(a+b)}{c/(c+d)} \tag{4}$$

This crude RR expresses initial relative risk regardless of any confounders or effect modifiers. Stratification analysis is conducted with potential effect modifiers and confounders by hierarchical sampling such as age, experience, or gender. As a result of stratified RR, if a stratum-specific RR is not different from crude RR, it may be assumed that confounding has an impact on the analysis. This brings us to the next step on the left side of the tree (Steps 4C to 5C) to define crude and adjusted RRs. If this results in significant different from stratum-limited RR, it can be considered as an outcome caused by effect modification on the right side of the tree (Step 4EM). In the case of effect modification, stratum-specific RRs are the final deliverables to give a perspective of the intervention effectiveness of each level (Webb and Bain 2011).



* RR: Relative Risk

Figure 5.8. Decision tree between confounding and effect modification (Webb and Bain 2011)

In terms of confounding controlled analysis, baseline ratios of outcome variable and adjusted RR for potential confounders are produced as described in Step 4C. Change in estimate (CIE) method is employed to remove less effective confounders before comparing crude and adjusted RRs at Step 4C. The CIE procedure deletes potential confounders in a stepwise fashion, with the full model as the starting point. At each step, the covariate that causes the smallest change in the exposure effect estimate, compared with the full model estimate, upon deletion is removed. The process stops when deletion of each of the remaining variables causes a relative change of more than a given cutoff value, usually set at 10%. The idea is that, if the most important confounders are taken into account, the full model estimate will have a low bias, although possibly high variance.

A potential confounder is eliminated at each step if the covariate changes between the baseline and the full model estimate are immaterial. The process finalizes when remaining variables after removing insignificant confounders yield a given minimum point, typically set at 10% change (Budtz–Jørgensen et al. 2007). Consequently, at Step 5C, adjusted RR is accepted when crude and adjusted RRs are over 10% different. On the contrary, only crude RR is used when crude and adjusted RRs are the same or within a 10% range.

5.4 Data Collection and Input

As the quantitative analysis of the safety intervention, variation studies on historical cases of a construction pre-fabrication company based in Alberta, Canada, are conducted. Eighteen months of no-lost-time injury data of 156 workers at all fabrication shops and shifts are collected from the environmental health and safety department. Three documents are used in the analysis—Shop/Field-Level Level Risk Assessment (SLRA) for customized pre-task planning, hazard identification, and workplace inspection reports. Table 5.4 and Figure 5.8 show descriptive statistics of frontline works participating in the research. As highlighted earlier, incident cases are inclined to 0 with low standard deviation up to maximum 5 cases, while age, supervisor seniority, and experience maintain statistical homogeneity. With regard to crew size, three teams have minimum resources due to special nature of work, despite a mean of 12.87. The occupation of "fitter" accounts for the highest proportion of overall positions, and day shift accounts for the majority of jobs. The population of each shop is equally distributed between AB and C, while other shops are varied in distribution due to the unique nature of the work performed.

Table 5.4. Descriptive statistics of participants

Variable	Unit	N	Min.	Max.	Mean	Std. Dev.
Incident	Case	156	0	5	0.79	0.923
Age	Year	156	19	71	44.26	2.870
Supervisor seniority	Year	156	3	23	15.78	7.413
Experience	Year	156	1	23	11.30	7.557
Craft size	Persons	156	3	19	12.87	3.820

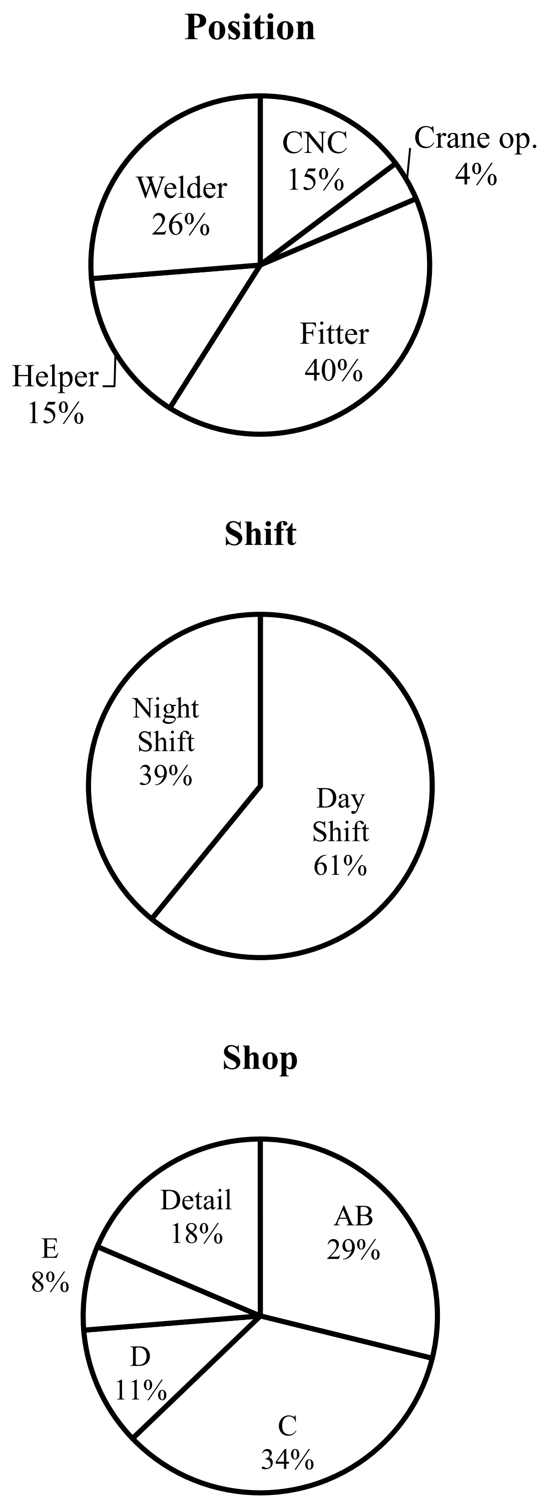


Figure 5.9. Descriptive statistics of participants

It is important to understand the characteristic and demographic distribution of the particular sample organization associated with demographic variables and work nature. Recent research studies have been discussing demographic factors with regard to safety performance (e.g., safety climate, injury rate, worker perception), examining demographic variables as a target interest. In this study, these demographic factors are critical variables to be used as confounders or effect modifiers. Before applying demographic factors into the model, it is beneficial to understand the relationship between demographic variable and incident rate, since it may not be accounted for in the effect modifier or confounder unless any relationships between demographic variables and incident rate are identified.

Previous studies have discussed causal relationships between these demographic factors and incident rates, as outlined below:

1) Age: In general, the younger age group (< 30 years old) has higher injury rates than those older than 30 years old (Lander et al. 2016). Furthermore, it can be seen that injury incidence is approximately two to three times higher for workers below 30 years of age than for those more than 30 years of age. According to a report by the National Institute for Occupational Safety and Health (NIOSH), younger workers (< 25 years old) experience approximately twice as many occupational non-fatal injuries as do older workers.
2) Foreman seniority: Foreman seniority is one of the critical factors to consider in assessing the frontline of an organization since these staff facilitates most of the safety intervention for frontline workers. A previous research study has

indicated that the relationship between foreman experience and injury frequency is a strong inverse correlation and that more injuries are associated with foremen who have less experience (Hymel 1993).

3) Experience: Job tenure is highly related to work injury. Particularly during the first month on the job, workers are exposed to significantly higher risk at workplace. In spite of a decreasing trend in lost-time claim (LTC) rates for work injury and illness in Ontario, for instance, newly employed workers are at greater risk than are more experienced workers (Breslin and Smith 2006b). In another study, workers with fewer than six months' experience show 41% higher relative risk compared with those with job tenure greater than two years (Bena et al. 2013).

4) Crew size – size of workgroup is significantly related to safety climate as well as to workers' safety perceptions. Through a case study of forestry and construction workers, Burt et al. (2008) asserted that social relationships among workgroup members help to cultivate attitudes of being conscientious about and responsible for upholding safety in the workplace safety in the workplace. Hinze (1981) also proved that a smaller workgroup enhances social relationships and reduces instances of workplace injury.

5) Position / Occupation: According to available statistics (e.g., WorkSafeBC 2014; Bureau of Labor Statistics 2014), typically "welder" is the most injury prone occupation in steel fabrication shops. However, no previous studies have strictly divided occupations into one standard because each company's

work process is different than others. Thus, only a conceptual idea can be obtained from the historical statistics.

6) Shift: Night shift workers are subject to a higher rate of workplace injury (Odd Ratio 2.04) than are day shift workers (Wong et al. 2011). Furthermore, a greater proportion of serious injuries occur among night shift workers (Ogiński et al. 2000).

Table 5.5 summarizes all the inputs used for the regression model. The independent variables are logically divided into two groups of effect modification and confounding variables and evaluation measure variables. For the dependent variable, the number of incidents per worker during the 18 months is collected and used for the regression.

Table 5.5. Summary of input variables in regression model

Independent / Dependent Variable	Type of Variable	Sub-type of Variable	Type of Input (Input range)
Independent Variables	Potential Effect Modifier & Confounder	Shop	Categorical (DE, AB, C, D, E)
		Trade	Categorical (CNC, F, W, H, CR) F: Fitter, W: Welder, H: Helper, CR: Crane operator
		Shift	Categorical (N, D) N: Night, D: Day
		Age	Numerical (19~71 years old)
		Foremen Seniority	Numerical (1~23 years)
		Experience	Numerical (1~23 years)
		Craft Size	Numerical (3~19 persons)
	Evaluation Variable	Content Coverage Rate	Numerical (0~100 %)
		Longhand Description Frequency	Numerical (0~100 %)
		Safety Communication Time	Numerical (0~20 minutes)
		Hazard Identification Frequency	Numerical (0~5 times)
		Workplace Inspection Frequency	Numerical (0~9 times)
Dependent Variable		No-lost-time Injury	Numerical (0~5 times)

6 RESULT

This chapter presents the effect size of each intervention evaluation variable and associated effect modification and confounding. As a baseline, effect size is first depicted in crude relative risk (RR), regardless of any confounders and effect modifiers. Then, any variables affected by effect modification are analyzed by stratification, and the ones subject to confounding are described by adjusted RR. Time series analysis is then conducted if the variable shows a less statistically significant result. The reason to require a more significant relationship in the time series analysis than in the group comparison is that the hazard identification practice covers not only individual workers but also the entire workplace; consequently, the practice improves the entire group's hazard recognition level more than the individual worker's.

6.1 Crude Relative Risk for Overall Evaluation Variables

The RRs derived from the Poisson regression are presented in Table 6.1. The table includes evaluated variables, as well as associated coefficient β and crude RR. Crude RR can provide only a basic picture of the probability of an incident occurring before controlling effect modification or confounding. Further analyses are described in the following section.

With a baseline of 1, an RR below 1 indicates that the incident is less likely to occur in the intervention group (e.g., longhand description) than in the control group (e.g., shorthand description). On the other hand, an RR above 1 indicates that the incident is more likely to occur in the intervention group than in the control group. The way to interpret these RRs would be to compute the percent relative effect (the percent change in the intervention group). In this respect, the relative effect of the intervention group can be expressed as a percentage of the no-intervention group (where the no-intervention group is considered to have 100% risk of injury). For example, in the case of RR < 1, those who had the high content coverage rate have a 54% decrease in risk of injury, compared to the group with the low content coverage rate (100%). This example is also represented in the simple calculation expressed below.

$$\% \text{ decrease} = (1 - RR) \times 100, \text{ e.g. } (1 - 0.462) \times 100 = 54\ \% \text{ decrease in incident} \quad (5)$$

On the contrary, when RR > 1, (although such cases are not observed in this study), the group working at height sees a 23% increase in incidents compared to those who do not work at height.

$$\% \text{ increase} = (RR - 1) \times 100, \text{ e.g. } (1.234 - 1) \times 100 = 23\% \text{ increase in incident} \quad (6)$$

Given the RR of each variable, the content coverage is a significant risk reduction variable at 53.8% (RR 0.462 [0.257, 0.830]). It can be interpreted that the group whose SLRA is better aligned with company JHA is less likely to encounter an incident than are less aligned groups.

From the facilitator's behaviour perspective, the longhand description in the SLRA and more safety communication time are recommended practices to improve safety performance. The handwriting application to SLRA is a significant factor, associated with a 59% reduction in incident rate compared to computerized pre-written applications (RR 0.411 [0.245, 0.689]). It can be inferred that the group which has foremen conducting longhand description practice in SLRA is less likely to be injured than the group which does not. Despite advances in and increasing utilization of digital technologies, this result implies that omitting the use of a computer in favour of manually written descriptions in safety documentation leads to improved safety performance.

Safety communication time can reduce incidents by a margin of 13% (RR 0.869, [0.786, 0.962]) compared to groups with less communication, although this has an RR closer to 1 than do previous variables. It can be interpreted that more safety discussion and instruction between foremen and workers can decrease injuries 13% more than the group with less communication

On the other hand, since the hazard identification frequency (Crude RR 0.990 [0.900, 1.089]) represents an RR of approximately 1, it can be inferred that these variables may not be an effective means of decreasing safety incidents. In addition, the hazard identification does not produce statistically significant result (P-value: 0.836). Therefore, further research is required in order to better understand the statistical relationship.

For workplace inspection frequency, in spite of the relatively low risk reduction factor of 7%, the workplace inspection frequency (Crude RR 0.925 [0.857, 0.998]) also helps to reduce safety incidents. It can be interpreted that those in the group that has a relatively high workplace inspection frequency are less likely to be injured than those in the group which rarely conducts workplace inspections.

Table 6.1. Crude Relative Risks and confounders in estimated variables

Evaluation Variable	Coefficient β	Crude Relative Risk[1]	95% CI		Effect modifier	Confounder
			Lower	Upper		
Content Coverage Rate	-0.772	0.462**	0.257	0.830	-	-
Longhand Description Frequency	-0.889	0.411**	0.245	0.689	Supervisor seniority	-
Safety Communication Time	-0.140	0.869**	0.786	0.962	Age	-
Hazard Identification Frequency	0.010	0.990	0.900	1.089	-	Experience
Workplace Inspection Frequency	-0.078	0.925*	0.857	0.998	-	-

** P-value < 0.01, * < 0.05

[1] RR < 1, those in the intervention group are less likely to be injured than those in the no-intervention group

RR > 1, those in the intervention group are more likely to be injured than those in the no-intervention group

6.2 Stratification Analysis by Effect Modification of Longhand Description Frequency and Safety Communication Time

The target group is divided into subgroups by the identified effect modifiers, referred to as strata. Given stratification, the RR of each subgroup is independent from any effect modification related to the stratifying factor. Table 6.2 gives RRs for each stratum. The first observation of note is that handwriting practice in the >19-year experience group is at relatively higher risk (RR 0.823) than are less experienced groups (RR 0.130 and 0.158). This result does not simply mean that foremen with more than 19 years of experience are riskier than those with less than 19 years of experience. Instead, it can be inferred that those working under foremen with fewer than 19 years of experience who conduct longhand practice are less likely to be injured than those working under foremen with more than 19 years of experience. In other words, longhand practice has a greater and more positive impact on the immature than on the comparatively mature foremen group with regard to SLRA implementation.

The second observation is that safety communication time in the 35- age group is associated with relatively lower risk (RR 0.751) than 35~50 and 50+ age groups (RR 1.049 and 1.040) with the same amount of the safety communication time. Similar to the interpretation of longhand description practice, workers under 35 years old who spend the same amount of time on safety communication are less likely to be injured than workers aged 35+. It can also be inferred based on this finding that the younger group is more sensitive to the degree of safety intervention implementation than the more experienced group.

Table 6.2. Stratification analysis of relative risks by effect modifier

Longhand Description in SLRA Stratum: Foremen seniority	RR	95% CI	
		Lower	Upper
All group (Crude)	0.411**	0.245	0.689
<10-year experience group	0.158**	0.039	0.643
10~19-year experience group	0.130**	0.032	0.528
>19-year experience group	0.823	0.455	1.489
Safety Communication Time Stratum: Age			
All group (Crude)	0.869**	0.786	0.962
<35 age group	0.751*	0.380	0.972
35~50 age group	1.049	0.877	1.255
>50 age group	1.040	0.974	1.111

** P-value < 0.01, * <0.05

Due to the detected effect modifications in these two variables, it can be stated that these two practices are affected by the given group of the population and its characteristics. As illustrated in the confounding and effect modification decision tree (Figure 5.8), it is thus necessary to conduct further examination such as stratification analysis.

6.3 Adjusted Relative Risk by confounding for Hazard Identification Frequency

Based on the decision tree and CIE methods, experience is selected as the confounder associated with hazard identification frequency in Table 6.3. In regards to hazard identification frequency, adjusted RR (1.007) delivers the opposite result, implying that an increasing hazard identification frequency leads to increased incident rate. Nevertheless, since these crude and adjusted RRs are not statistically significant, it is considered as the reference factor only, and further mathematical experimentation must be carried out to determine its effectiveness.

Table 6.3. Adjusted Relative Risks and confounders in estimated variables

Evaluation Variable	Coefficient β	Crude RR	Adjusted RR	95% CI		Confounder
				Lower	Upper	
Hazard Identification	0.010	0.990	1.007	0.916	1.108	Experience

6.4 Time Series Analysis for Hazard Identification Frequency

Given the RR of each variable, the hazard identification (adjusted RR 0.990 [0.916, 1.108]) has approximately 1 for RR. Therefore, it can be interpreted into the variance of risk is minimum between frequent and rare incident groups. Nevertheless, the RR is considered as the reference factor only due to the limited statistically reliability as indicated by the high P-value; thus, further mathematical experimentation must be carried out. Due to the statistically insignificant result of the

Poisson regression analysis with regard to hazard identification frequency and incident rate, linear regression is conducted to investigate longitudinal relationship.

The trend graph in Figure 6.1 illustrates the company-wide monthly moving average hazard identification and incident rate for a recent 20-month span using 4-month time lag analysis. It is observed that the number of hazard identification practices is negatively related to incidents 4 months after the time of conducting the practice. Apart from that, the coefficient of determination R^2 indicates that over 63% (R square 0.627) of the variation in the explanatory factors is analyzed by the linear regression model (see Tables 6.4 and 6.5 and Figures 6.2 and 6.3). Therefore, it can be concluded that the hazard identification practice is potentially one of the factors contributing to improved safety performance.

The purpose of hazard identification practice is to detect potential hazards which can lead to uncontrollable situations. Such potential hazards exist when workers do not possess the knowledge and experience identified in the risk analysis or method statement. In this regard, previous studies (Haslam et al. 2005; Carter and Smith 2006) have noted that 33.5% of hazards are not adequately identified and 42% of construction injuries occur due to the lack of hazard identification skills. Therefore, further studies are required to further explore this finding.

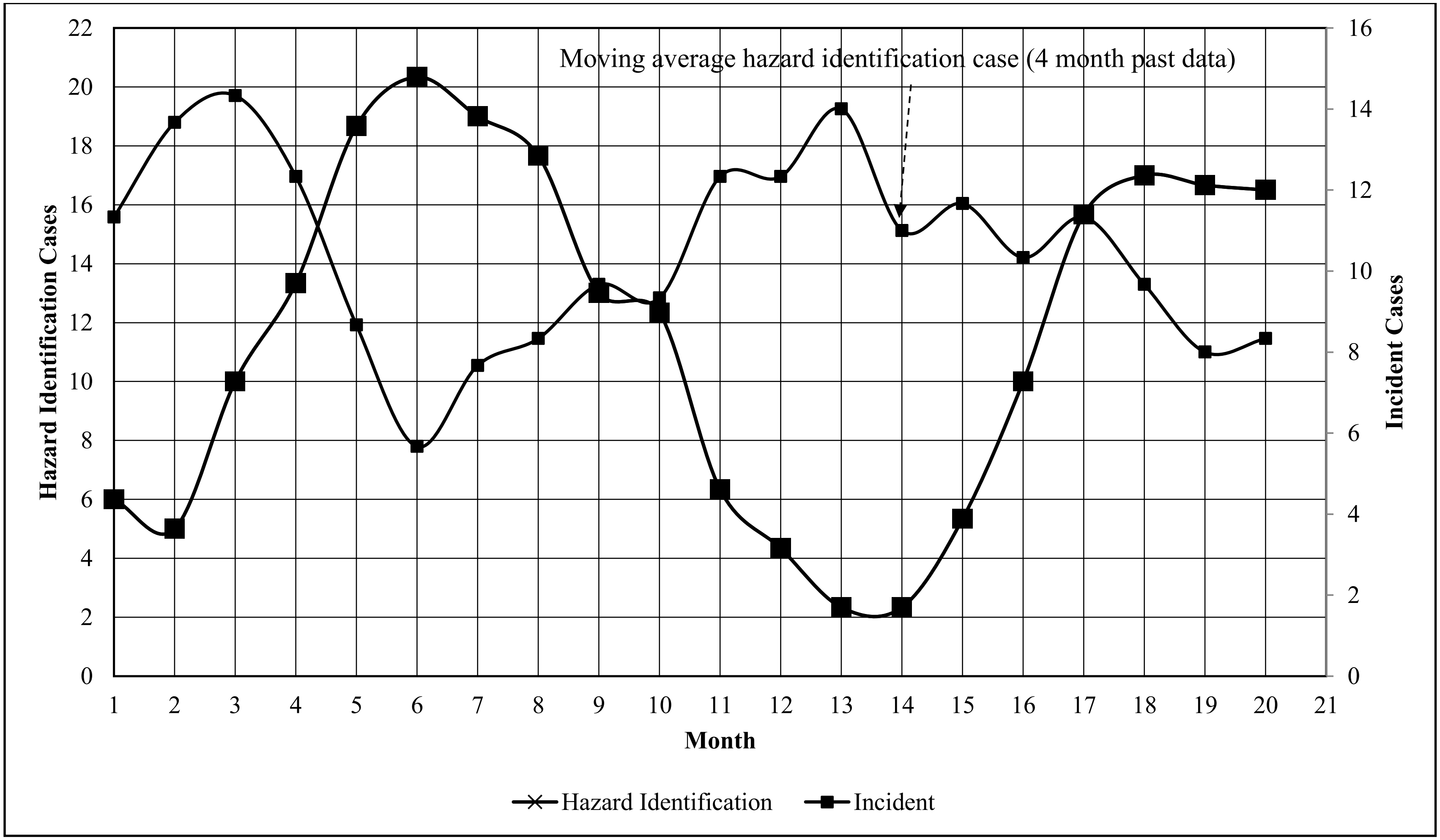


Figure 6.1. Moving average trend of hazard identification and incident rate (4-month lag)

Table 6.4. Linear regression model summary

Model (lag time)	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
4 months	0.792[a]	0.627	0.606	1.46334	1.291
3 months	0.561[a]	0.315	0.277	1.98789	0.974
2 months	0.227[a]	0.052	−0.001	2.33194	0.687
1 month	0.176[a]	0.031	−0.023	2.35751	0.657

a. Predictors: (Constant), Hazard Identification

b. Dependent Variable: Incident

Table 6.5. ANOVA for 4-month time lag case

Model		Sum of Squares	df	Mean Square	F	Sig.
4 mo.	Regression	64.678	1	64.678	30.204	.000[b]
	Residual	38.544	18	2.141		
	Total	103.222	19			

a. Dependent Variable: Incident

b. Predictors: (Constant), Hazard Identification

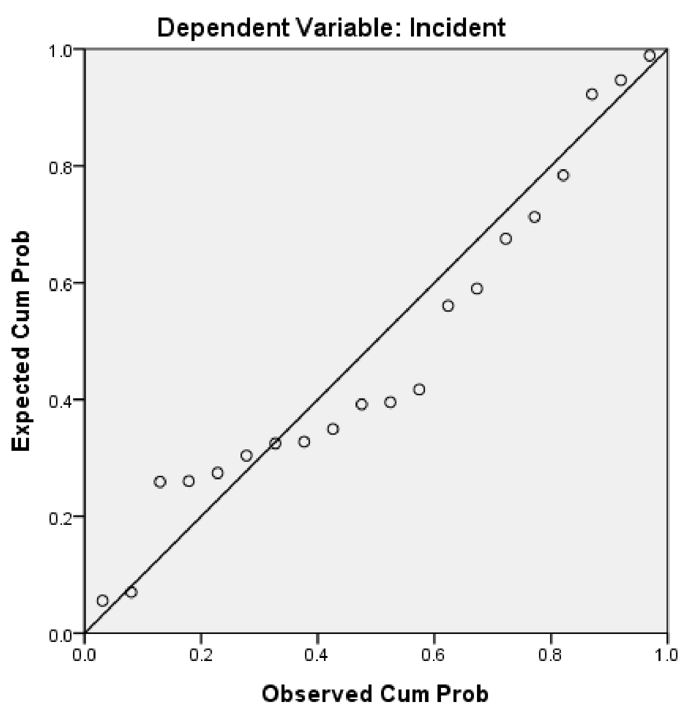


Figure 6.2. Normal P-P plot of regression standardized residual

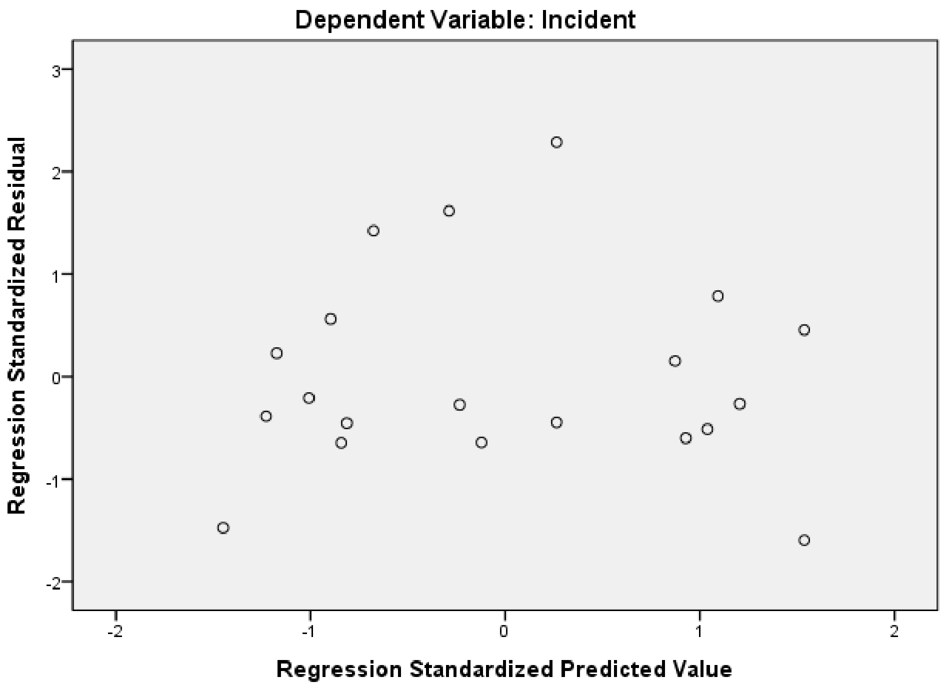


Figure 6.3. Scatter plot

7 CONCLUSION

This dissertation develops a framework of practical measures to evaluate the effectiveness of safety programs and techniques implemented at the frontline level, and reports the findings which have been explored through the case study. The first step toward solving the problem of determining the effectiveness of frontline safety intervention is to find variations in safety competency and acceptance level among individual workers as well as among foremen.

This research highlights three challenges and propose corresponding solutions as follows: (1) objective and measurable evaluation criteria are developed through a comprehensive literature review and site observation in order to eliminate unclear and subjective evaluations of existing frontline safety interventions; (2) regression analysis appropriate to rare event incident data distribution is conducted to increase validity of evaluations of small organizations; (3) confounding control and stratum analysis are suggested to reduce inaccuracy of evaluations resulting from the randomizing effect of confounding and effect modification.

This chapter discusses the differences among and potential improvements to existing safety interventions, and addresses the practical and theoretical implications of the results. Finally, it is proposed that future study explore attributes to measure the effectiveness of other interventions in different work environments, and seek psychological and mathematical studies regarding the relationship between worker behaviour and safety task overload.

7.1 Discussion

On the basis of previous studies, which have primarily explored which interventions are effective, this research investigates approaches that shed light on how to effectively implement interventions. The approaches considered in this study are indicated by quantifiable relative risk (RR) factors in order to assess the relationship between each indicator and safety incidents. This approach gives foremen an opportunity to emphasize relatively important implementation action items in each intervention; accordingly, management can not only encourage workers to facilitate the intervention effectively, but can also evaluate worker competency based on objective criteria found in this research.

Longitudinal study for single groups is widely used in safety intervention research, while latent variables can threaten internal validity. Due to the complex nature of workplace safety, such internal validity occurs when long-time investigation is required, which may involve a number of unintentional organizational events (e.g., specific events between measurements, maturation of tasks, instrument changes, loss of subjects). Alternatively, Poisson regression with confounding and effect modification control is employed to overcome statistical and circumstantial threats. As a result, the fully adjusted RRs associated with confounding effect and stratum analysis related to an effect modification give a wide spectrum of understanding of the magnitude of incident occurrence probability for each intervention variable. This approach helps to illustrate practically that the influence of exposing a population is considerable, and addresses how to pre-determine potential confounders in industrial health and safety studies. Additional factors, such as adjusted RR and stratification, may suggest different perspectives to understand effect size, depending on level or characteristic of the given group. It is also observed that time series analysis is better suited than is group comparison study to company-wide practices such as hazard identification.

7.2 Practical Implications

The findings have valuable practical implications in terms of the identified relative risks of each effectiveness evaluation variable. First, the success of frontline safety management is highly dependent on worker competence, attitude, motivation, and behaviour (e.g., content coverage in SLRA, longhand description in SLRA, safety communication time). Second, some implementation practices deliver better performance in certain age or experience groups. In this study, longhand practice in SLRA is found to be relatively beneficial for the less experienced foremen group, while the younger group is more sensitive to the degree of safety intervention implementation than is the more experienced group.

Safety communication and interactions between frontline foreman and workers during pre-task planning constitute an important behavioural parameter in the implementation of safety interventions. Moreover, hazard and control measure alignment and handwritten pre-task planning, which assesses “content coverage and longhand description”, may be partly related to supervisor attitude in the implementation of the particular safety intervention (Oyewole et al. 2010b). Interestingly, a number of researchers have shown that people who practice writing by hand have better learning and are better able to compose thoughts than those typewriting electronically due to reduced distraction (Yamamoto 2007; Mueller and Oppenheimer 2014). Another study has highlighted the hand's unique relationship with the brain when it comes to composing thoughts and ideas (Berninger et al. 2015). Thus, handwriting practice in safety planning will serve as an indicator of intervention effectiveness and supervisor competency.

In terms of the efficacy depending on the given group's characteristics, it is observed through stratification analysis that longhand description in SLRA is effective for less experienced foremen. In addition, more investment of safety communication time leads to favourable results among younger workers. Correspondingly, these findings provide safety facilitators with valuable practical implications, such as (1) recommending that less experienced foremen use handwriting in SLRA and (2) encouraging younger workers to communicate with foremen about safety issues.

7.3 Theoritical Implications

Although incident rates are commonly used in safety data analysis, a causal relationship can be over/under-estimated due to statistically insufficient incident data. The analysis of these discrete events may be restricted by the infrequency of events over long time periods. The preponderance of rare events in the data suggests that utilization of Poisson count models is appropriate for this analysis. In the construction industry, overall improvement trends in safety performance lead to significant decreases in incidents. In spite of the incident reduction achieved, human reactions to rare events (e.g., workplace injuries) appear to be disproportionate to the objective probability of the events, e.g., overestimate in judgement (Zacks and Hasher 2002; Erev et al. 1994) or underweighting in decision making (Barron and Erev 2003). In this regard, the proposed series of verification processes (e.g., visual representation of incident data distribution, Kolmogorov-Smirnov test for skewness, and Lagrange multiplier test for dispersion) render the selection of appropriate regression model to researchers, especially for handling rare incident data.

In this particular case study, a Poisson regression model is suitable to this data distribution and produces objective estimations to aid management's judgement and decision making with regard to subjective assumptions.

7.4 Limitations

This study identifies implementation factors relating to safety interventions at the frontline level. The research questions posed in this study have been explored and addressed through the quantitative analysis performed as part of the case study. However, the exploratory nature of this study and the justified importance of the construction sector warrant further research in other industries. Furthermore, since this sample case is limited to indoor activities and relies on actual data from the operations being studied, similar research for frontline safety organizations in various industries and environments will be required.

From a documentation analysis standpoint, discrepancies between record and reality are inescapable, (although this research intends to mitigate subjectivity), such that document-focused analysis forms a relatively large portion of this research.

Well-written safety pre-task planning cannot guarantee injury avoidance. However, it can help to define the anticipated behaviour and the implementation of pre-task planning, as well as identify engineering defects (Glenn 2011).

Since this study is based on historical data, it is not possible to take into account group variances resulting from modifications of resources or work generation. New employment in safety management as well as changes in corporate safety strategy has made it difficult to draw conclusions using historical controls. As highlighted by Robson (2001), executing certain interventions and evaluating their effectiveness are tasks that should be designed at the initial stage. In spite of efforts in this research to analyze using objective input data such as numerical incident cases, future study can employ intermediate variables (e.g., climate score, work-site observation checklist, employ survey) for the purpose of validation. Further studies should also be developed to define the relationship between these intermediate variables and injury reduction.

7.5 Recommendations for Future Study

One of the key points of this research is to find measurable injury reduction factors among frontline and micro-size organizations. In practice, worker safety behaviour and safety documentation have little variance within the entire work group, which makes it difficult to measure relationships between certain potential injury reduction factors and incident rates.

In future studies, various mathematical approaches and trials in other circumstances will be used to explorer more attributes of safety intervention effectiveness at the frontline level. This research has evaluated the effectiveness only of hazard recognition and control on/by the frontline of an organization, while other safety interventions (e.g., craft training, equipment inspection, and housekeeping inspection) can be assessed in different sets.

In spite of a number of safety management practices adopted, frontline foremen have a burden to conduct safety activities in addition to scheduling, coordination, and quality assurance, regardless of the effectiveness of the program. In fact, the excessive amount of responsibilities carried by frontline foremen may result in distraction in the workplace. As discussed earlier, it is assumed that workers and foremen tend to ignore safety procedures in case of increased cognitive failure and stress, resulting in higher-risk behaviour. Therefore, any psychological and mathematical studies about safety overload and behaviour would throw light on safety intervention effectiveness.

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APPENDIX A: ANALYSIS PROCESS AND RESULTS

I. Poisson Regression Crude Relative Risk

1) Content Coverage Rate

Model Information

Dependent Variable	Incident
Probability Distribution	Poisson
Link Function	Log

Case Processing Summary

	N	Percent
Included	156	100.0%
Total	156	100.0%

Goodness of Fit[a]

	Value	df	Value/df
Deviance	164.356	154	1.067
Scaled Deviance	164.356	154	
Pearson Chi-Square	158.196	154	1.027
Scaled Pearson Chi-Square	158.196	154	
Log Likelihood[b]	−179.215		
Akaike's Information Criterion (AIC)	362.429		
Finite Sample Corrected AIC (AICC)	362.508		
Bayesian Information Criterion (BIC)	368.529		
Consistent AIC (CAIC)	370.529		

Dependent Variable: Incident

Model: (Intercept), SLRA_RiskCompliance[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
7.613	1	.006

Dependent Variable: Incident
Model: (Intercept), SLRA_RiskCompliance[a]
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	0.403	1	0.526
SLRA_RiskCompliance	6.664	1	0.010

Dependent Variable: Incident
Model: (Intercept), SLRA_RiskCompliance

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test
			Lower	Upper	Wald Chi-Square
(Intercept)	−0.067	0.1052	−0.273	0.139	0.403
SLRA_RiskCompliance	−0.772	0.2990	−1.358	−0.186	6.664
(Scale)	1[a]				

Parameter Estimates

Parameter	Hypothesis Test				
	df	Sig.		Lower	Upper
(Intercept)	1	0.526	0.935	0.761	1.150
SLRA_RiskCompliance	1	0.010	0.462	0.257	0.830
(Scale)					

Dependent Variable: Incident
Model: (Intercept), SLRA_RiskCompliance
a. Fixed at the displayed value.

2) Longhand Description Frequency

Goodness of Fit[a]

	Value	df	Value/df
Deviance	159.459	154	1.035
Scaled Deviance	159.459	154	
Pearson Chi-Square	174.437	154	1.133
Scaled Pearson Chi-Square	174.437	154	
Log Likelihood[b]	−176.766		
Akaike's Information Criterion (AIC)	357.531		
Finite Sample Corrected AIC (AICC)	357.610		
Bayesian Information Criterion (BIC)	363.631		
Consistent AIC (CAIC)	365.631		

Dependent Variable: Incident

Model: (Intercept), SLRA_Longhand[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
12.510	1	.000

Dependent Variable: Incident

Model: (Intercept), SLRA_Longhand[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	0.003	1	0.959
SLRA_Longhand	11.362	1	0.001

Dependent Variable: Incident

Model: (Intercept), SLRA_Longhand

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald Chi-Square	df
(Intercept)	0.006	0.1067	−0.204	0.215	0.003	1
SLRA_Longhand	−0.889	0.2639	−1.407	−0.372	11.362	1
(Scale)	1[a]					

Parameter Estimates

Parameter	Hypothesis Test	Exp(B)	95% Wald Confidence Interval for Exp(B)	
	Sig.		Lower	Upper
(Intercept)	0.959	1.006	0.816	1.239
SLRA_Longhand	0.001	0.411	0.245	0.689
(Scale)				

Dependent Variable: Incident

Model: (Intercept), SLRA_Longhand

a. Fixed at the displayed value.

3) Safety Communication Time

Goodness of Fit[a]

	Value	df	Value/df
Deviance	164.322	154	1.067
Scaled Deviance	164.322	154	
Pearson Chi-Square	161.317	154	1.048
Scaled Pearson Chi-Square	161.317	154	
Log Likelihood[b]	−179.198		
Akaike's Information Criterion (AIC)	362.395		
Finite Sample Corrected AIC (AICC)	362.473		
Bayesian Information Criterion (BIC)	368.495		
Consistent AIC (CAIC)	370.495		

Dependent Variable: Incident

Model: (Intercept), SLRA_SafetyTimeInvest[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
7.647	1	.006

Dependent Variable: Incident

Model: (Intercept), SLRA_SafetyTimeInvest[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	4.380	1	0.036
SLRA_SafetyTimeInvest	7.399	1	0.007

Dependent Variable: Incident

Model: (Intercept), SLRA_SafetyTimeInvest

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test
			Lower	Upper	Wald Chi-Square
(Intercept)	0.788	0.3768	0.050	1.527	4.380
SLRA_SafetyTimeInvest	−0.140	0.0514	−0.241	−0.039	7.399
(Scale)	1[a]				

Parameter Estimates

Parameter	Hypothesis Test				
	df	Sig.		Lower	Upper
(Intercept)	1	.036	2.200	1.051	4.604
SLRA_SafetyTimeInvest	1	.007	.869	.786	.962
(Scale)					

Dependent Variable: Incident

Model: (Intercept), SLRA_SafetyTimeInvest

a. Fixed at the displayed value.

4) Hazard Identification Frequency

Continuous Variable Information

		Std. Deviation
Dependent Variable	Incident	.923
	Hazard Identification	1.89889

Goodness of Fit[a]

	Value	df	Value/df
Deviance	171.926	154	1.116
Scaled Deviance	171.926	154	
Pearson Chi-Square	167.519	154	1.088
Scaled Pearson Chi-Square	167.519	154	
Log Likelihood[b]	−182.999		
Akaike's Information Criterion (AIC)	369.998		
Finite Sample Corrected AIC (AICC)	370.077		
Bayesian Information Criterion (BIC)	376.098		
Consistent AIC (CAIC)	378.098		

Dependent Variable: Incident

Model: (Intercept), HazardIdenti[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
0.043	1	0.835

Dependent Variable: Incident

Model: (Intercept), HazardIdenti[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	4.646	1	0.031
HazardIdenti	0.043	1	0.836

Dependent Variable: Incident

Model: (Intercept), HazardIdenti

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald Chi-Square	df
(Intercept)	−0.226	0.1050	−0.432	−0.021	4.646	1
HazardIdenti	−0.010	0.0487	−0.106	0.085	0.043	1
(Scale)	1[a]					

Parameter Estimates

Parameter	Hypothesis Test		95% Wald Confidence Interval for Exp(B)	
	Sig.	Exp(B)	Lower	Upper
(Intercept)	0.031	0.797	0.649	0.980
HazardIdenti	0.836	0.990	0.900	1.089
(Scale)				

Dependent Variable: Incident

Model: (Intercept), HazardIdenti

a. Fixed at the displayed value.

5) Workplace Inspection Frequency

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
4.266	1	0.039

Dependent Variable: Incident

Model: (Intercept), Inspection[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	1.128	1	0.288
Inspection	4.042	1	0.044

Dependent Variable: Incident

Model: (Intercept), Inspection

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald Chi-Square	df
(Intercept)	0.282	0.2658	−0.239	0.803	1.128	1
Inspection	−0.078	0.0387	−0.154	−0.002	4.042	1
(Scale)	1[a]					

Parameter Estimates

Parameter	Hypothesis Test	Exp(B)	95% Wald Confidence Interval for Exp(B)	
	Sig.		Lower	Upper
(Intercept)	0.288	1.326	0.788	2.233
Inspection	0.044	0.925	0.857	0.998
(Scale)				

Dependent Variable: Incident

Model: (Intercept), Inspection

a. Fixed at the displayed value.

II. Poisson Regression Adjusted Relative Risk

1) Stratification Analysis for Longhand Description Frequency

I. Seniority group (<10-year)

Model Information

Dependent Variable	Incident
Probability Distribution	Poisson
Link Function	Log

Case Processing Summary

	N	Percent
Included	40	100.0%
Excluded	0	0.0%
Total	40	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean
Dependent Variable	Incident	40	0	4	.55
Covariate	SLRA_Longhand	40	.0	.8	.400

Continuous Variable Information

		Std. Deviation
Dependent Variable	Incident	.846
Covariate	SLRA_Longhand	.3870

Goodness of Fit[a]

	Value	df	Value/df
Deviance	37.249	38	0.980
Scaled Deviance	37.249	38	
Pearson Chi-Square	38.105	38	1.003
Scaled Pearson Chi-Square	38.105	38	
Log Likelihood[b]	−36.178		
Akaike's Information Criterion (AIC)	76.356		
Finite Sample Corrected AIC (AICC)	76.680		
Bayesian Information Criterion (BIC)	79.733		
Consistent AIC (CAIC)	81.733		

Dependent Variable: Incident

Model: (Intercept), SLRA_Longhand[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
8.464	1	0.004

Dependent Variable: Incident

Model: (Intercept), SLRA_Longhand[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	0.125	1	0.723
SLRA_Longhand	6.643	1	0.010

Dependent Variable: Incident

Model: (Intercept), SLRA_Longhand

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test
			Lower	Upper	Wald Chi-Square
(Intercept)	−0.087	0.2464	−0.570	0.396	0.125
SLRA_Longhand	−1.842	0.7149	−3.244	−0.441	6.643
(Scale)	1[a]				

Parameter Estimates

Parameter	Hypothesis Test				
	df	Sig.		Lower	Upper
(Intercept)	1	.723	.916	.565	1.485
SLRA_Longhand	1	.010	.158	.039	.643
(Scale)					

Dependent Variable: Incident

Model: (Intercept), SLRA_Longhand

a. Fixed at the displayed value.

II. Seniority group (10~19 year)

Case Processing Summary

	N	Percent
Included	31	100.0%
Excluded	0	0.0%
Total	31	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean
Dependent Variable	Incident	31	0	3	.58
Covariate	SLRA_Longhand	31	.0	1.0	.494

Continuous Variable Information

		Std. Deviation
Dependent Variable	Incident	.720
Covariate	SLRA_Longhand	.3444

Goodness of Fit[a]

	Value	df	Value/df
Deviance	20.064	29	0.692
Scaled Deviance	20.064	29	
Pearson Chi-Square	18.709	29	0.645
Scaled Pearson Chi-Square	18.709	29	
Log Likelihood[b]	−25.835		
Akaike's Information Criterion (AIC)	55.670		
Finite Sample Corrected AIC (AICC)	56.098		
Bayesian Information Criterion (BIC)	58.538		
Consistent AIC (CAIC)	60.538		

Dependent Variable: Incident

Model: (Intercept), SLRA_Longhand[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
8.870	1	0.003

Dependent Variable: Incident
Model: (Intercept), SLRA_Longhand[a]
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.

(Intercept)	0.520	1	0.471
SLRA_Longhand	8.121	1	0.004

Dependent Variable: Incident
Model: (Intercept), SLRA_Longhand

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square
(Intercept)	0.213	0.2961	−0.367	0.794	0.520
SLRA_Longhand	−2.043	0.7167	−3.447	−0.638	8.121
(Scale)	1[a]				

Parameter Estimates

Parameter	Hypothesis Test df	Sig.		Lower	Upper
(Intercept)	1	0.471	1.238	0.693	2.212
SLRA_Longhand	1	0.004	0.130	0.032	0.528
(Scale)					

Dependent Variable: Incident
Model: (Intercept), SLRA_Longhand
a. Fixed at the displayed value.

III. Seniority group (>19-year)

Case Processing Summary

	N	Percent
Included	85	100.0%
Excluded	0	0.0%
Total	85	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean
Dependent Variable	Incident	85	0	5	0.98
Covariate	SLRA_Longhand	85	0	0.9	0.247

Continuous Variable Information

		Std. Deviation
Dependent Variable	Incident	0.988
Covariate	SLRA_Longhand	0.3785

Goodness of Fit[a]

	Value	df	Value/df
Deviance	88.258	83	1.063
Scaled Deviance	88.258	83	
Pearson Chi-Square	85.937	83	1.035
Scaled Pearson Chi-Square	85.937	83	
Log Likelihood[b]	−107.809		
Akaike's Information Criterion (AIC)	219.619		
Finite Sample Corrected AIC (AICC)	219.765		
Bayesian Information Criterion (BIC)	224.504		
Consistent AIC (CAIC)	226.504		

Dependent Variable: Incident
Model: (Intercept), SLRA_Longhand[a]
a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
0.424	1	0.515

Dependent Variable: Incident
Model: (Intercept), SLRA_Longhand[a]
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	0.028	1	0.866
SLRA_Longhand	0.413	1	0.520

Dependent Variable: Incident
Model: (Intercept), SLRA_Longhand

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test
			Lower	Upper	Wald Chi-Square
(Intercept)	0.022	0.1284	−0.230	0.273	0.028
SLRA_Longhand	−0.194	0.3024	−0.787	0.398	0.413
(Scale)	1[a]				

Parameter Estimates

Parameter	Hypothesis Test				
	df	Sig.		Lower	Upper
(Intercept)	1	0.866	1.022	0.794	1.314
SLRA_Longhand	1	0.520	0.823	0.455	1.489
(Scale)					

2) Stratification Analysis for Safety Communication Time

I. Age group (<35-year)

Case Processing Summary

	N	Percent
Included	44	100.0%
Excluded	0	0.0%
Total	44	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean
Dependent Variable	Incident	44	0	5	1.02
Covariate	SLRA_SafetyTimeInvest	44	5.0	10.0	7.500

Continuous Variable Information

		Std. Deviation
Dependent Variable	Incident	1.067
Covariate	SLRA_SafetyTimeInvest	1.8236

Goodness of Fit[a]

	Value	df	Value/df
Deviance	35.698	42	0.850
Scaled Deviance	35.698	42	
Pearson Chi-Square	33.929	42	0.808
Scaled Pearson Chi-Square	33.929	42	
Log Likelihood[b]	−50.984		
Akaike's Information Criterion (AIC)	105.967		
Finite Sample Corrected AIC (AICC)	106.260		
Bayesian Information Criterion (BIC)	109.536		
Consistent AIC (CAIC)	111.536		

Dependent Variable: Incident
Model: (Intercept), SLRA_SafetyTimeInvest[a]
a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
14.418	1	0.000

Dependent Variable: Incident
Model: (Intercept), SLRA_SafetyTimeInvest[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	13.944	1	0.000
SLRA_SafetyTimeInvest	12.580	1	0.000

Dependent Variable: Incident
Model: (Intercept), SLRA_SafetyTimeInvest

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square
(Intercept)	2.404	0.6439	1.142	3.666	13.944
SLRA_SafetyTimeInvest	−0.341	0.0962	−0.530	−0.153	12.580
(Scale)	1[a]				

Parameter Estimates

Parameter	Hypothesis Test df	Sig.		Lower	Upper
(Intercept)	1	0.000	11.070	3.134	39.102
SLRA_SafetyTimeInvest	1	0.000	0.711	0.589	0.858
(Scale)					

Dependent Variable: Incident
Model: (Intercept), SLRA_SafetyTimeInvest
a. Fixed at the displayed value.

II. Age group (35~50 year)

Case Processing Summary

	N	Percent
Included	53	100.0%
Excluded	0	0.0%
Total	53	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean
Dependent Variable	Incident	53	0.0	4.0	0.92
Covariate	SLRA_SafetyTimeInvest	53	5.0	10.0	7.585

Continuous Variable Information

		Std. Deviation
Dependent Variable	Incident	0.978
Covariate	SLRA_SafetyTimeInvest	1.9849

Goodness of Fit[a]

	Value	df	Value/df
Deviance	56.068	51	1.099
Scaled Deviance	56.068	51	
Pearson Chi-Square	54.646	51	1.071
Scaled Pearson Chi-Square	54.646	51	
Log Likelihood[b]	−65.826		
Akaike's Information Criterion (AIC)	135.652		
Finite Sample Corrected AIC (AICC)	135.892		
Bayesian Information Criterion (BIC)	139.593		
Consistent AIC (CAIC)	141.593		

Dependent Variable: Incident
Model: (Intercept), SLRA_SafetyTimeInvest[a]
a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
0.849	1	0.357

Dependent Variable: Incident
Model: (Intercept), SLRA_SafetyTimeInvest[a]
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	0.580	1	0.446
SLRA_SafetyTimeInvest	0.843	1	0.359

Dependent Variable: Incident
Model: (Intercept), SLRA_SafetyTimeInvest

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square
(Intercept)	0.423	0.5553	−0.666	1.511	0.580
SLRA_SafetyTimeInvest	−0.067	0.0732	−0.211	0.076	0.843
(Scale)	1[a]				

Parameter Estimates

Parameter	Hypothesis Test df	Sig.		Lower	Upper
(Intercept)	1	0.446	1.526	0.514	4.532
SLRA_SafetyTimeInvest	1	0.359	0.935	0.810	1.079
(Scale)					

Dependent Variable: Incident
Model: (Intercept), SLRA_SafetyTimeInvest
a. Fixed at the displayed value.

III. Age group (>50-year)

Case Processing Summary

	N	Percent
Included	59	100.0%
Excluded	0	0.0%
Total	59	100.0%

Continuous Variable Information

		N	Minimum	Maximum	Mean
Dependent Variable	Incident	59	0.0	3.0	0.49
Covariate	SLRA_SafetyTimeInvest	59	5.0	10.0	8.203

Continuous Variable Information

		Std. Deviation
Dependent Variable	Incident	0.653
Covariate	SLRA_SafetyTimeInvest	1.7497

Goodness of Fit[a]

	Value	df	Value/df
Deviance	52.792	57	0.926
Scaled Deviance	52.792	57	
Pearson Chi-Square	50.348	57	0.883
Scaled Pearson Chi-Square	50.348	57	
Log Likelihood[b]	−52.505		
Akaike's Information Criterion (AIC)	109.011		

Finite Sample Corrected AIC (AICC)	109.225		
Bayesian Information Criterion (BIC)	113.166		
Consistent AIC (CAIC)	115.166		

Dependent Variable: Incident
Model: (Intercept), SLRA_SafetyTimeInvest[a]
a. Information criteria are in smaller-is-better form.
b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
0.539	1	0.463

Dependent Variable: Incident
Model: (Intercept), SLRA_SafetyTimeInvest[a]
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	0.009	1	0.925
SLRA_SafetyTimeInvest	0.543	1	0.461

Dependent Variable: Incident
Model: (Intercept), SLRA_SafetyTimeInvest

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square
(Intercept)	−0.081	0.8613	−1.769	1.607	0.009
SLRA_SafetyTimeInvest	−0.078	0.1056	−0.285	0.129	0.543
(Scale)	1[a]				

Parameter Estimates

	Hypothesis Test				
Parameter	df	Sig.		Lower	Upper
(Intercept)	1	0.925	0.922	0.170	4.988
SLRA_SafetyTimeInvest	1	0.461	0.925	0.752	1.138
(Scale)					

3) Adjusted Relative Risk for Hazard Identification

Goodness of Fit[a]

	Value	df	Value/df
Deviance	164.843	153	1.077
Scaled Deviance	164.843	153	
Pearson Chi-Square	161.546	153	1.056
Scaled Pearson Chi-Square	161.546	153	
Log Likelihood[b]	−179.458		
Akaike's Information Criterion (AIC)	364.915		
Finite Sample Corrected AIC (AICC)	365.073		
Bayesian Information Criterion (BIC)	374.065		
Consistent AIC (CAIC)	377.065		

Dependent Variable: Incident

Model: (Intercept), HazardIdenti, Experience[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
7.126	2	0.028

Dependent Variable: Incident

Model: (Intercept), HazardIdenti, Experience[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	0.024	1	0.878
HazardIdenti	0.021	1	0.884
Experience	6.393	1	0.011

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square	Hypothesis Test df
(Intercept)	0.021	0.1365	−0.246	0.288	0.024	1
HazardIdenti	0.007	0.0486	−0.088	0.102	0.021	1
Experience	−0.040	0.0158	−0.071	−0.009	6.393	1
(Scale)	1[a]					

Parameter Estimates

Parameter	Hypothesis Test Sig.	Exp(B)	95% Wald Confidence Interval for Exp(B) Lower	95% Wald Confidence Interval for Exp(B) Upper
(Intercept)	0.878	1.021	0.782	1.334
HazardIdenti	0.884	1.007	0.916	1.108
Experience	0.011	0.961	0.932	0.991
(Scale)				

Dependent Variable: Incident

Model: (Intercept), HazardIdenti, Experience

a. Fixed at the displayed value.

APPENDIX B: EXAMPLE OF COMPANY SAFETY DOCUMENT PRACTICE

I. Longhand Case

op Level Risk Assessment

[redacted]

Are You Ready

Date
Sho
Tasi
Faci
Fore [redacted]

Daily Tasks & Expectations
Fitting beams, columns and
frames on bugges
Bugge # 20/28 - Frame - Gary
Bildge # 16 - 1 Beam - John
Bldge # 33 - 4 beams - Udo
Bldge # 34 - 1 beam - Tom
Bldge # 5 - 3 channels - Terry
Bldge # 13 - 6 beams - Yoshi
Bldge # 26/28 - Frame - Jim
Welders - Gratings - Kunt

Rigging & Hoisting	
[x] Certified	[x] Inspected
[ ] Rigging meeting SLRA for specialty lifts	

Fall Protection/Overhead Hazards	Y/N/NA
Barricades & Signs in Place	NA
Hole Coverings Identified	NA
Harness/Lanyard Inspected	NA
100% Tie-off w/Harness	NA
Falling Items are secured	NA
Hoisting or Moving loads in Work Area	Y
Tools and Materials Secured	NA
Is Access Below Barricaded	NA
Removing Barriers or Guardrails	NA
Areas that Require 100% Tie-off Identified	NA
Areal Work Platform	NA

High Hazards	
[x] Congested work area	[x] Heavy lifting*
[ ] Dropping objects	[ ] Repetitive motion
[ ] Confined space	[x] Housekeeping
[ ] Working at heights	[x] Moving equipment
[x] Line of fire	[ ] Ladder use
[ ] Spills / Water	[x] Other people in area
[x] Slips, trips & falls	[ ] Warning ribbons
[x] Loud noise	[x] Pinch points
[ ] Heat / Cold stress	[ ] Lock outs identified
[ ] Overexertion	[x] Electric shock
[ ] Working alone	[x] PPE requirements
[ ] Vehicle movement	[x] New workers identified
[x] Fire or spark	[ ] First time tasks

*Consider mechanical lift before adding manual effort

Shop Safety Assessment	Y/N
Is everyone fit for duty	Y
Is everyone competent to perform their duties	Y
Were there any incidents on the previous shift	N
Are there any workers on modified duty	N
Have the hazards been reviewed by all workers	Y

Area Team Members sign below;

1.
2.
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17 [redacted]

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Work Description

Fitting beams, columns and frames on bugges - cutting, grinding, tacking, turning beams, drilling, stamping.

Tasks	List all **hazards** associated with tasks	List all **controls** for all listed hazards	Low	Med	High
stamping -	pinch points, cuts,	inspect stamps - no mushroom	✓		
	eyes injuries	heads, wear PPE, gloves	✓		
		mandatory, use stamp	✓		
		holder, clamps smaller beams	✓		
		for stamping, housekeeping	✓		
HSE Advisors Report - Youn 04. - respiratory protective equipment					

II. Shorthand Case

Sh Level Risk Assessment

Are You Read

Date:
Shop D
Task L
Facilita
Forema

Daily Tasks & Expectations
909 50C
973 19B / 42B
909 50D
WELDER NUMBERS ON ALL WELDS
TAKE PRIDE IN YOUR WORK
HIGH QUALITY AT ALL TIMES
MIND ON TASK AT ALL TIMES
WORK SAFE
WATCH OUT FOR EACHOTHER
CLEAN CARTS DAILY
HOUSEKEEPING

Rigging & Hoisting	
☒ Certified	☒ Inspected
☒ Rigging meeting SLRA for specialty lifts	

Fall Protection/Overhead Hazards	Y/N/NA
Barricades & Signs in Place	
Hole Coverings Identified	
Harness/Lanyard Inspected	
100% Tie-off w/Harness	
Falling Items are Secured	
Hoisting or Moving loads in Work Area	
Tools and Materials Secured	
Is Access Below Barricaded	
Removing Barriers or Guardrails	
Areas that Require 100% Tie-off Identified	
Areal Work Platform	

High Hazards	
☒ Congested work area	☒ Heavy lifting*
☐ Dropping objects	☒ Repetitive motion
☐ Confined space	☒ Housekeeping
☐ Working at heights	☐ Moving equipment
☒ Line of fire	☒ Ladder use
☐ Spills / Water	☒ Other people in area
☒ Slips, trips & falls	☐ Warning ribbons
☒ Loud noise	☒ Pinch points
☐ Heat / Cold stress	☐ Lock outs identified
☐ Overexertion	☒ Electric shock
☐ Working alone	☒ PPE requirements
☐ Vehicle movement	☐ New workers identified
☒ Fire or spark	☐ First time tasks

Consider mechanical lift before adding manual effort

Shop Safety Assessment	Y/N
Is everyone fit for duty	Y
Is everyone competent to perform their duties	Y
Were there any incidents on the previous shift	N
Are there any workers on modified duty	N
Have the hazards been reviewed by all workers	Y

Area Team Members sign below;
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Work Description

WELDING/GOUGING/GRINDING/CHIPPING/CRANEWORK/HOUSE KEEPING

Tasks	List all **hazards** associated with tasks	List all **controls** for all listed hazards	Low	Med	High
WELDING	FUMES/ARCFLASHES/ SPARKS/BURNS/SLAG	PPE/SCREENS			
GOUGING	FUMES/ARC FLASHES/HOT SLAG SPARKS/BURNS/NOISE	PPE/SCREENS/DOUBLE EAR PROTECTION IF NEEDED IN TOOLCRIB			
GRINDING	SPARKS/NOISE/VIBRATION	PPE/SCEENS/DOUBLE EYE PROTECTION AT ALL TIMES			
CHIPPING	SPARKS/NOISE/VIBRATION/SLAG	PPE/SCREENS/DOUBLE EYE PROTECTION AT ALL TIMES			
CRANE WORK	PINCH POINTS OTHER PEOPLE IN WORK AREA	INSPECTION /COMMUNICATION/FLAG OFF THE AREA/CHECK RIGGING			
HOUSE KEEPING	SLIPS TRIPS AND FALLS EMPTY GARBAGES	WATCH YOUR FOOTING/BEND YOUR KNEES WHEN LIFTING/ALWAYS WEAR YOUR GLOVES/PPE			

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