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ASSESSMENT OF CONSTRUCTION WORKERS OCCUPATIONAL
SAFETY COMPETENCIES USING SIGNAL DETECTION THEORY

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ASSESSMENT OF CONSTRUCTION WORKERS OCCUPATIONAL SAFETY COMPETENCIES USING SIGNAL DETECTION THEORY

By

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ABSTRACT

ASSESSMENT OF CONSTRUCTION WORKERS OCCUPATIONAL SAFETY COMPETENCIES USING SIGNAL DETECTION THEORY

By

Bhavin J. Patel

Construction accidents in general and fall accidents in particular are of major concern in construction, as many lives are lost and business suffers. Despite the contribution of construction accident causation models, accidents occur. Most of the models that have been developed stress identification of the underlying causes of accidents and have sided with either management or the workers fault. None of these models could adequately explain the process of construction accident due to their dynamic nature.

A new approach to understand construction accidents has been proposed by Howell et al (2002) based on the work of Rasmussen (1997). One of the aspects of this model is focused on worker training to identify the hazard zone (unsafe condition) beyond which work is no longer safe. The main goal of this research was to develop a methodology by which worker sensitivity to unsafe conditions and risk orientation (the tendency of a worker to work in a condition despite knowing it is unsafe) can be assessed prior to prescribing a training program. This research proposes such methodology based on signal detection theory (SDT), which is used in the manufacturing industry to detect defective component. Application of SDT in the construction industry to determine sensitivity and risk orientation of ironworkers has been explained in this thesis. This would help to design guidelines on how to enhance construction workers' training and also their abilities to identify by themselves the boundary beyond which work is not safe.

DEDICATION

This thesis is dedicated to my mom and dad for their continued support and love.

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INTRODUCTION

1. INTRODUCTION

1.1 Motivation

Over the past three decades, numerous organizations and researchers have focused on investigating construction accidents. The literature on construction safety reveals that much research effort has been directed at examining accident records to categorize the most common types of accidents that occur to a specific trade, and how these accidents happen (MacCollum, 1990; La Bette, 1990; Rietze, 1990; Fullman, 1984; Goldsmith, 1987; Davies and Tomasin, 1990; Culver et al., 1990; Helander, 1991; Culver et al., 1992; Peyton and Rubio, 1991; Hinze, 1997).

As the leading cause of most injuries and fatalities in construction, fall accidents have received much attention. In fact, the Occupational Safety and Health Administration (OSHA) considers reducing falls as a strategic goal for the organization for the next five years. OSHA investigated 7,543 construction related accidents from January 1990 through October 2001, and found that falls accounted for 34.6% of the injuries (Huang and Hinze, 2003). From the statistical analysis it was found that the proportion of falls has increased in past 12 years: the average proportion of falls was 34.1 % during the years before 1996 and increased to 38.4% in the following years (Huang and Hinze 2003). Figure 1.1 shows the breakdown (in percentage) of construction accidents causes.

To examine what time of the day, or month relates to accidents, a study conducted by Huang and Hinze (2003) concluded that most accidents were reported in the month of July with 820 accidents. However, February, with 493 accidents, was the month with the least accidents. Analysis also showed that in winter (December to February) the average proportion of fall accidents and all accidents per month are 7.6 and 6.6% respectively, while in summer (June to August) the average proportion of fall accidents and all accidents are 9.1 and 10.3 %.

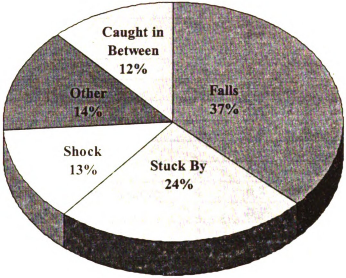


Figure 1.1 Cause of Construction Accidents Investigated by OSHA (Source: Huang and Hinze 2003)

The study conducted by Huang and Hinze (2003) from the available data from OSHA also showed that fall accidents occur more frequently on certain types of projects, beginning with new construction followed by renovation, maintenance and finally demolition work. Table 1.1 shows the breakdown of the count and percentage of fall accidents and all accidents from 1997 to 2001. It can be seen from the table that projects involving commercial buildings and single family or duplex dwellings account for nearly half of the fall accidents from 1997 to 2001 (Huang and Hinze, 2003). Statistics also showed that 60% of falls occurred in new construction or additions (Table 1.2).

Project	Falls		All Accidents	
	Count	Percent	Count	Percent
Commercial building	404	33.3	715	22.8
Other building	212	17.4	412	13.1
Single family or duplex dwelling	211	17.4	503	16
Multifamily dwelling	113	9.3	183	5.8
Manufacturing plant	79	6.5	168	5.3
Tower, tank, storage elevator	71	5.8	103	3.3
Bridge	28	2.3	94	3
Other heavy construction	21	1.7	94	3
Highway, road, street	16	1.3	381	12.1
Sewer/water treatment plant	14	1.2	76	2.4
Power plant	13	1.1	33	1.1
Power line	10	0.8	116	3.7
Contractor's yard/facility	5	0.4	42	1.3
Pipeline	4	0.3	91	2.9
Shoreline development, dam, reservoir	4	0.3	24	0.8
Refinery	3	0.2	21	0.7
Excavation, landfill	2	0.2	63	2
Subtotal	1210	100	3119	100
Not known	5		23	
Total	1215		3142	

Table 1.1 Distribution of Accidents in Project by Type from 1997- 2001 (Source: Huang and Hinze, 2003)

Type of Construction effort	Falls		All Accidents	
	Count	Percent	Count	Percent
New project or new addition	721	59.3	1,640	52.2
Alteration or rehabilitation	219	18	565	18
Maintenance or repair	189	15.6	531	16.9
Demolition	41	3.4	101	3.2
Other	41	3.4	283	9
Subtotal	1,211	100	3,120	100
Not Known	4			22
Total	1,215		3,142	

Table 1.2 Distribution of Accidents by Nature of Construction (Source: Huang and Hinze, 2003)

In the same study conducted by Huang and Hinze (2003), it was determined that from 2,741 accidents reported by OSHA, 81% of them occurred while workers were working on the first to third floor of buildings and the average height of the fall was almost 37 feet. The distribution of fall heights is shown in Figure 1.2. From the figure it could be concluded that 70% of fall accidents occur at 30 feet or less.

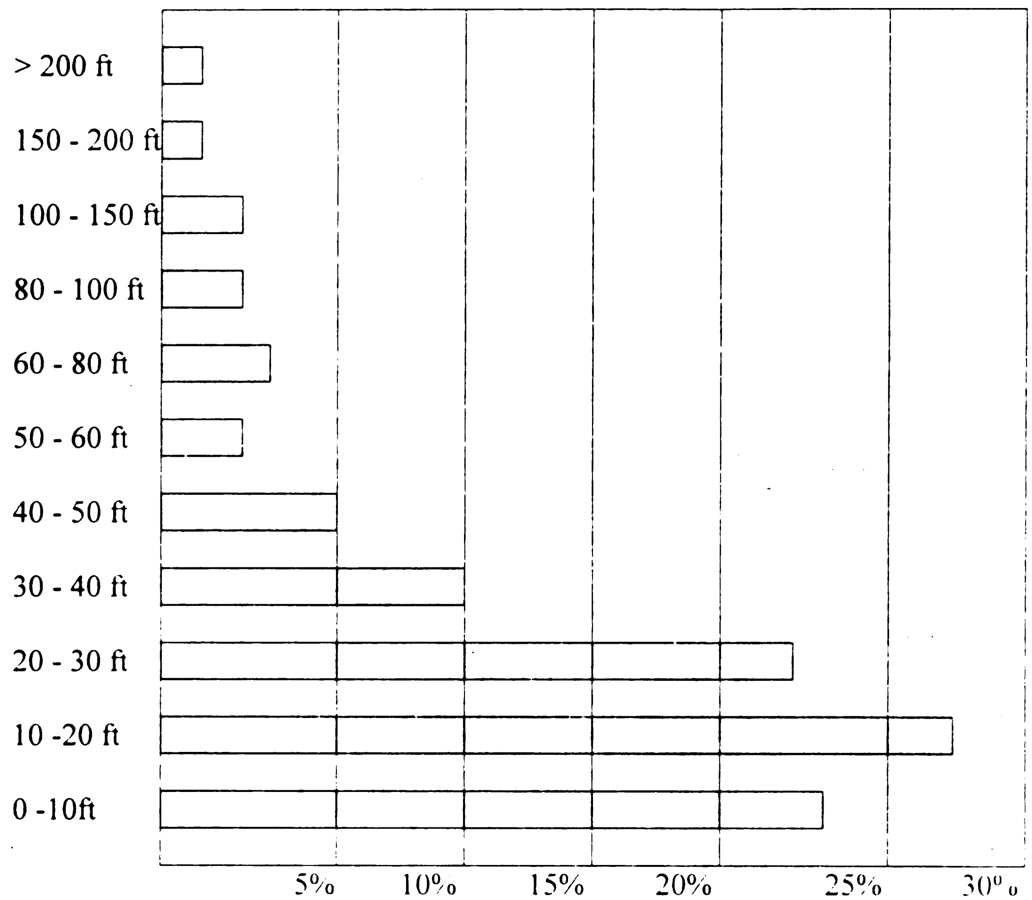


Figure 1.2 Distribution of Height of Construction Fall Accidents from 1997-2001 (Source: Huang and Hinze, 2003)

This study also determined that falls generally resulted due to misjudgment of workers about the hazardous situations, lack of Personal Protective Equipments (PPE) or insufficient safety protection.

Various research studies have found that fall accidents typically occur due to faulty equipment, inadequate fall protection, floor openings, aerial lifts, steel or concrete erection, roofing and/or placing reinforcement. These causes are typically classified under unsafe conditions or unsafe acts and often are due to organizational problems. Identification of root causes to find effective corrective actions could prevent these injuries/fatalities.

1.2 Problem Area

Notwithstanding the progress and improvements made in the safety record, construction work remains hazardous work. The National Safety Council (NSC) reported that, in 2001, construction accounted for 6% of the United States' workforce but claimed a disproportionate 23 % of all occupational fatalities and 10.5 % of all occupational injuries (Injury Facts, 2002). Moreover, the NSC estimated that, in 2001, 15% of the $145 billion spent on occupational injuries, was spent on construction cases.

Accidents in general, and fall accidents in particular, are of major concern in the construction industry, as many lives are lost and business suffers. Much is known about accidents through investigations that provide for the "what" and "how" questions. Despite its necessity as a phase, accident investigation seldom addresses the factors that contributed to the accident causation, i.e., *WHY* the accident occurred. Allan St John (2003) mentioned that fall prevention is far more effective than fall protection, which often involves personal protective equipment and training (Huang and Hinze, 2003). Brown (1995) has argued convincingly that accident investigation techniques should be firmly based on theories of accident causation and human error, which would result in a better understanding of the relation between the "antecedent human behavior" and the accident at a level enabling the root causes of the accident to be determined. Consequently, prevention efforts could be directed at the root causes of accidents and not at symptoms, leading to more potent prevention efforts.

Myriad accident causation models have been proposed over the years. These models provide many explanations for the occurrence of injuries and fatalities to industrial workers. Models are classified into different categories such as management models, behavior models, human factor models, system models, epidemiological models, decision models, etc. (Heinrich, 1980). Most of the models stress identification of the underlying causes of accidents and have sided with either management or with the workers. In general, the overall objective of these models is to provide tools for better industrial accident prevention programs.

Construction accident causation models based on variants of the above models have been introduced in the literature by a handful of researchers (Abdelhamid and Everett, 2000; and Suraji et al. 2001). Despite the contributions of these construction accident causation models in understanding the accident process, none adequately explain the underlying causes of construction accidents. For researchers, many topics related to falls still need to be investigated in great detail.

A new approach to understanding construction accidents has been proposed by Howell et al. (2002) based on the work of Rasmussen (1997). The model suggested recognizes that organizational and individual pressures push people to work in hazardous situations. These pressures defeat efforts to enforce safe work rules, specifically in a changing work environment such as in construction. Therefore, this approach emphasizes the need to train workers to be conscious of hazardous work environments and engage the work with better planning and appropriate protection in a way very similar to how fire fighters engage hazardous situations.

The original model as proposed by Rasmussen is shown in Figure 1.3. As shown, Rasmussen divided the work environment into three zones. Zone I, which is the region enclosed by the "Boundary of Unconditionally Safe Behavior", "Organizational Boundary to Economic Failure", and "Individual Boundary to Unacceptable Work load", is considered the safe zone.

Rasmussen states that due to economic or workload pressures, workers will shift their work along the workload and/or cost gradients, respectively. So as long as workers remain within the safe zone, work activities can be safely performed. Current safety regulations and management practice are directed at keeping the workers in the safe zone. Rasmussen suggests that enlarging the safe zone through proper planning of operations will make the work safer.

The zone encompassed by the "Boundary of Unconditionally Safe Behavior" and the "Irreversible Loss of Control Boundary" is Zone II or the hazard zone. Workers working in the hazard zone are considered to be working at the edge (pushing their luck). Rasmussen believes that, despite regulatory or supervisory efforts, workers will move to the hazard zone for many reasons. He suggested, contrary to current conventional wisdom, that the only effective way to counter these tendencies to work in the hazard zone would be to make visible the boundary beyond which work is no longer safe and teach worker to recognize the boundary.

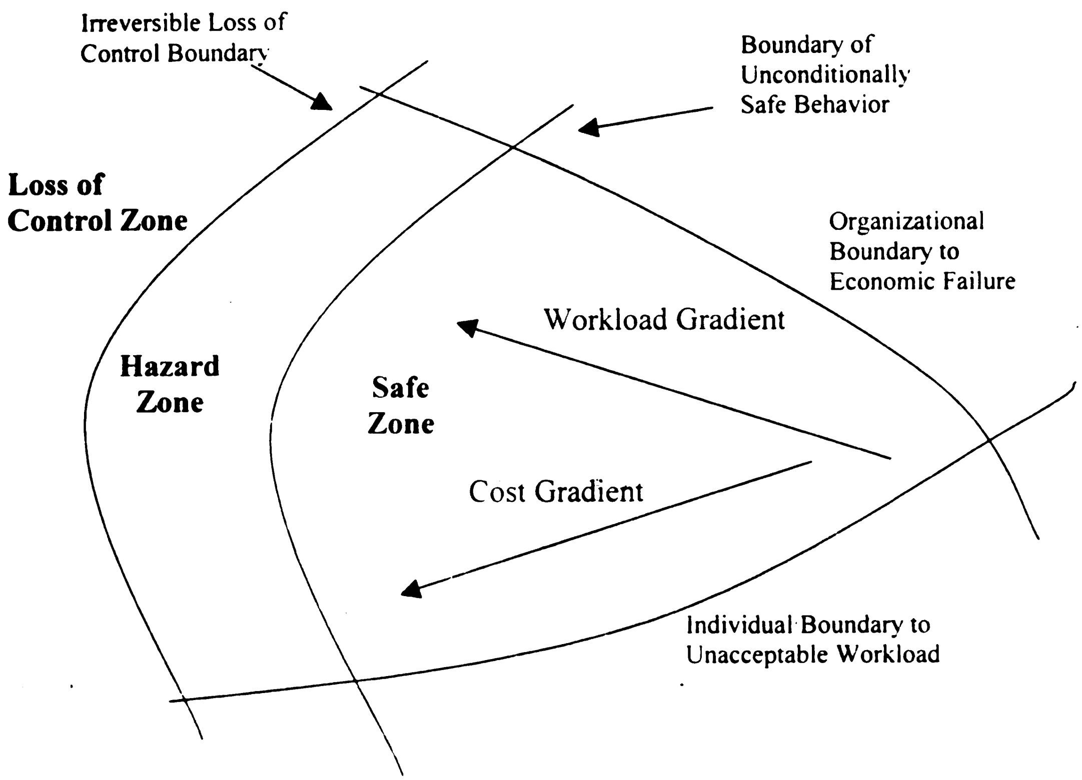


Figure 1.3 Three Zones of Risk
(Source: Howell et al., 2002)

The third and final zone in Rasmussen's model is the loss of control zone, in which accidents occur and control is lost, leading to injuries and/or fatalities. He proposed that workers should be educated on and trained in how to recover from situation in which control is lost. This is very similar to instructing drivers in how to respond to slips on icy roads.

1.3 Goal and Objectives

The acceptance and effectiveness of Rasmussen's approach remains a question that only future research can answer. A number of techniques exist for operations planning that could help to enlarge Zone I. Virtual reality and simulation techniques could be used to train workers in regaining lost control. Teaching workers to recognize that they have stepped into the hazard zone appears to be achievable through intensified and directed training. However, this focus on worker training assumes that workers will always recall what constitutes a safe or unsafe situation as well as respond to perceived or actual risks in the same manner.

The main goal of this research was to develop a methodology by which workers' sensitivity to unsafe conditions and risk orientation (the tendency of a worker to work in an unsafe condition despite knowing it exists) can be assessed prior to prescribing a training program. Due to the high rate of occurrences, fall accidents were considered as case examples. To arrive at this goal, the following objectives were proposed:

1) Develop a technique to assess the sensitivity and risk orientation of workers to unsafe conditions.

2) Design and conduct a survey to determine the sensitivity and risk orientation of workers at risk of fall accidents.

1.4 Proposal Overview

This research report is comprised of five chapters. Chapter 1 provides a general introduction to the state of safety in construction and the motivation behind this research. The goal and objectives of the research are also presented in this chapter. Chapter 2 provides a background on different accident causation models and also introduces signal detection theory, which will be used extensively in this research. Chapter 3 outlines the methods used to achieve the research objectives. Chapter 4 discusses in detail the results achieved using the methods developed in chapter 3. This is followed by chapter 5, which contains summary, conclusions and contributions of the research.

Appendix A contains the questionnaire and interview format developed for surveying ironworkers based on OSHA standards and the case study from NIOSH. This questionnaire was developed to determine the response of ironworkers to unsafe conditions. Appendix B contains the results of the survey. Appendix C contains the results of the analysis of the data for the ironworkers using SDT and ROC. Appendix D contains a normalized SDT table. Appendix E has distribution plots of d' and $\beta_{current}$, followed by Appendix F, with results from the multiple regression analysis.

Chapter 2

BACKGROUND

2. BACKGROUND

For many years, reducing injuries and accidents has been a prime focus of government organizations such as the Occupational Safety and Health Administration (OSHA) and the National Institute for Occupational Safety and Health (NIOSH). Research efforts have focused on developing accident causation models to unearth root causes of occupational accidents. In this chapter, an overview of the different accident causation models and theories is provided.

2.1 Overview of Accident Causation Models

The American industrial accident prevention movement started in 1892 when the safety department of Joliet works of the Illinois steel company was formed. This was followed by formation of the National Safety Council in 1913 (Zeller, 1986). Industrial safety or the concept of safety started with a common objective in mind: the desire to reduce injuries and to save lives and properties. With this objective in mind, a series of theorems was developed in the 1930s to define and explain accidents.

One of these theorems is that proposed by Heinrich in his 10 axioms on industrial safety, which helped many researchers to understand the accident process for the first time. The first and most famous axiom stated that: "The occurrence of an injury invariably results from a completed sequence of factors, the last one of these being the accident itself. The accident in turn is invariably caused or permitted directly by the unsafe act of a person and/or a mechanical or physical hazard." (Heinrich et al., 1980).

This axiom was the foundation for developing the "Domino Theory" which, suggested that, to reduce injuries, fatalities, and property damage, the factors leading to an accident must be prevented. Heinrich proposed the following five dominoes (see Fig.2.1):

Ancestry and social environment: According to Heinrich, factors like recklessness, stubbornness and avariciousness are inherent, and the environment in which one is brought up also may develop undesirable traits.

Fault of person: Fault or errors of person are due to a violent temper, nervousness, ignorance of safe practices, etc., which are inherent factors. These could lead to unsafe acts or the existence of mechanical or physical hazards

Unsafe act and/or mechanical or physical hazard: Heinrich believes unsafe acts performed by a worker or the existence of mechanical or physical hazard directly leads to accidents. These unsafe acts could be starting machinery without warning, removal of safeguards, etc.

Accident: According to Heinrich, an accident is an unplanned event that leads to an injury, which is due to an unsafe act.

Injury: Fractures, lacerations, etc., are injuries that result directly from accidents. According to Heinrich, these factors are sequentially dependent and, if this sequence is interrupted by eliminating one factor, the occurrence of injury may be prevented.

Heinrich also defined accident prevention as "an integrated program, a series of coordinated activities, directed to the control of unsafe personal performance and unsafe mechanical conditions, and based on certain knowledge, attitudes, and abilities."

(Heinrich et al., 1980). Until recently, the Domino Theory was universally accepted as the real description of the accident process (Heinrich et al. 1980).

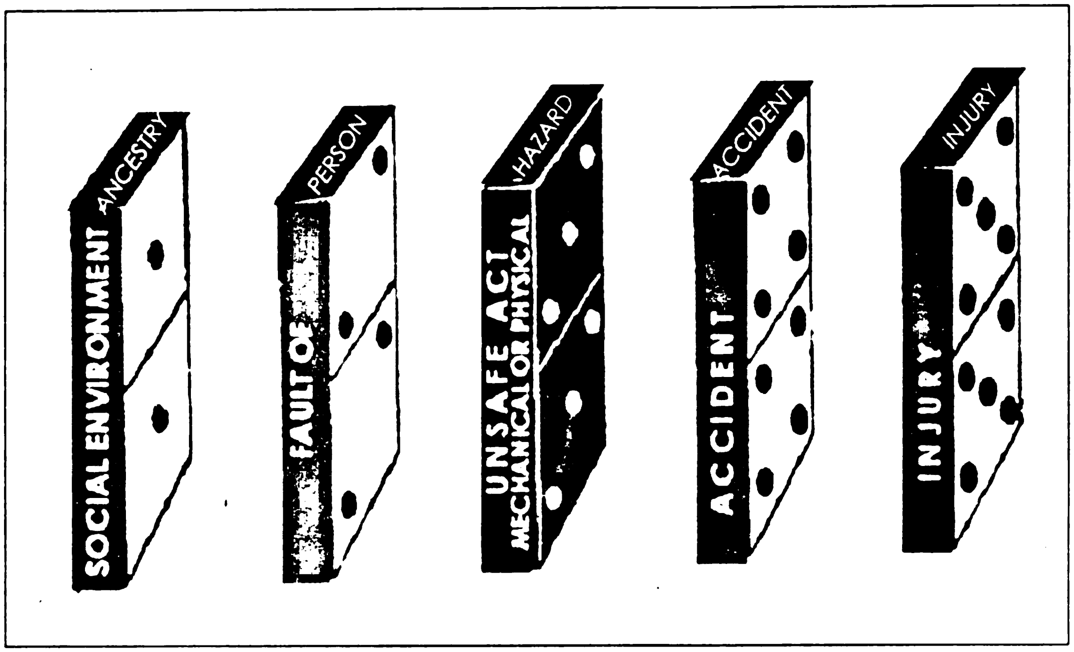


Figure 2.1: The Five Factors in the Accident Sequence
(Source: Heinrich, Petersen, Ross 1980)

Heinrich's views were criticized for oversimplifying the control of human behavior in causing accidents and for some statistics he gave regarding the contribution of unsafe acts versus unsafe conditions (Zeller, 1986). Nevertheless, his work was the foundation for many others. Over the past thirty years the domino theory has been updated with an emphasis on management as a primary cause in accidents, and the resulting models were labeled as management models or updated domino models. Other models have evolved separate from the domino theory but were still based on Heinrich's work. These models are classified into different categories such as behavior models, human factors models, system models, epidemiological models, decision models, etc. (Heinrich, 1980).

Management models hold management responsible for causing accidents, and the models introduced try to identify failures in the management system. Examples of these models are the Updated Domino Sequence (Bird, 1974), the Adams Updated Sequence (Adams, 1976), the Weaver Updated Dominoes (Weaver, 1971), and the Energy Release model (Zabetakis, 1975). Two other accident causation models that are management based the Stair Step model (Douglas and Crowe 1976) and the Multiple Causation (Petersen 1971).

Human error theories are best captured in behavior models and human factor models. Behavior models picture workers as being the main cause of accidents. This approach studies the tendency of humans to make errors under various situations and environmental conditions, with the blame mostly falling on the human (unsafe) characteristics only. As defined by Rigby (1970), human error is "any one set of human actions that exceed some limit of acceptability." Many researchers have devoted great time and effort to defining and categorizing human error (e.g., Rook et a., 1966; Recht, 1970; Norman, 1981; Petersen, 1982; McClay, 1989; DeJoy, 1990; Reason, 1990; Wagenaar et al., 1990; and O'Hare et al., 1994).

The foundation of most behavior models is the accident proneness theory (Klumb, 1995). This theory assume that there exist permanent characteristics in a person that make him or her more likely to have an accident. The theory was supported by the simple fact that when considering population accident statistics, the majority of people have no accidents, a relatively small percentage have one accident, and a very small percentage have multiple accidents. Therefore, this small group must possess personal characteristics that make them more prone to accidents (International Labor Organization

1983). Other theories and behavior models include the Goals Freedom Alertness Theory (Kerr, 1957), the Life Change Unit Theory (Alkov, 1972), and the Motivation Reward Satisfaction Model (Peterson, 1982). For other behavioral models see Krause et al. (1984), Hoyos and Zimolong (1988), Dwyer and Raftery (1991), Friend and Kohn (1992), and Krause and Russell (1994).

The human factors approach holds that human error is the main cause of accidents. However, the blame does not fall on the human unsafe characteristics alone, but also on the design of the workplace and tasks that do not consider human limitations and may have harmful effects. Therefore, these models study the effect of a particular situation or environment on human performance, and the limitations humans have in performing tasks are also addressed. Cooper and Volard (1978) states: environment and human characteristics (both physical and psychological) as factors that contribute to accidents and to human error. They have also briefly discussed the concept of overload, which is when an individual is subjected to more than he or she can handle (Peterson 1975). These ideas are common to the field of human factors engineering. Examples of human factor models include the Ferrel theory (Ferrel 1977), the Peterson model (Peterson 1982), the McClay model (McClay 1989), and the DeJoy model (DeJoy 1990).

A system model recognizes the strong interaction between individuals, their tools and machines, and their general work environment. Examples of such models are the Firenze Model (Firenze, 1971) and the Ball model (Ball, 1973). Other examples are also covered in Roland and Moriarty (1990), and Vincoli (1993). Epidemiological models came about after the safety research community considered an accident to be an epidemic. Epidemiology is the search for causes associated between diseases or other biologic processes and specific environmental experiences. In 1961, Suchman proposed an epidemiological model that suggests that an accident phenomenon is an "unexpected, unavoidable, and unintentional act resulting from the interaction of host, agent, and environmental factors within situations which involve risk taking and perception of danger" (Suchman, 1961). Surry developed a decision model based on the epidemiological model of Suchman (Surry, 1974).

Based on the above-mentioned models a fishbone model was proposed by Nishishma (1989) for understanding the process of accidents. According to his model the four factors, which generated unsafe behaviors and unsafe states are: 1) human, 2) equipment, 3) work and, 4) management (Suraji et al., 2001). Reason (1990) proposed the tripod model, which represent the interconnection between accident, unsafe acts and resident pathogens. In his study, the resident pathogens are latent failure such as error, violation or technical failure.

Construction accident causation models based on variants of the above models have been introduced in the literature by a handful of researchers. McClay (1989) identified hazards, human actions, and work overload as the three key elements of an accident. The study conducted by Whittington et al (1992) stated that poor management decision-making and inadequate management control are major contributors to accidents. Hinze (1996), in another study, stated risk of accidents might be generated by workers' distraction, caused by physical or mental distraction. This theory of his is known as the distraction theory. In this study of distraction he attributes accidents to production pressures or other stress factors that distract workers from hazards and increase the probability of accidents. Hinze et al (1998) developed a coding system that would facilitate the categorization of injuries and fatalities. They believed if accidents were categorized carefully, this categorization would provide a viable basis for implementing on effective accident prevention program. Based on the OSHA causation code they further classified it for modification. For example, fall accidents were coded in two categories: 1) fall from elevation and 2) fall from ground level. Stuck by accidents were coded in to three categories 1) stuck by equipment, 2) stuck by falling material and 3) stuck by material (other then falling) (Hinze et al., 1998).

In another study by Suraji et al. (2001), a model was proposed which highlighted the underlying complex interaction of factors in the causation process. This model explains the constraints and responses of various parties involved in design and construction, which might lead to an accident. The Accident Root Causes Tracing Model by Abdelhamid and Everett (2000) identifies three general root causes—management deficiencies, training, and workers' attitudes. The 'constraints-response' model (Suraji et al, 2001) suggests that project conditions and/or management decisions may result in an inappropriate selection response on the part of workers, leading to an accident. Another study conducted by Mohamed (2002) explains the relationship between safe climate and safe work behavior in construction site environments. A model was developed based on a hypothesis that safe work behaviors are consequences of the existing safety climate, which in turn is determined by five independent sets of factors identified as management, safety, risk, work pressure and competence. In 2002, Toole identified eight root causes for construction accidents: lack of proper training; lack of safety equipment; deficient enforcement of safety; unsafe equipment, methods, or conditions; poor safety attitude; and isolated deviations from prescribed behavior.

Several past studies focused on preventing fall accidents using various tools and methods. For example a study proposed by Singh (2000) investigated fall accidents occurring on low-rise roofs. From his study, he concluded that no single method or rule of fall prevention would help in preventing falls from low-rise roofs, but stated that prefabrication was one of the most promising method (Huang and Hinze 2003). Another study by Duncan and Bennett (1991) reviewed the performance of various fall protection systems and stated that both active and passive measures are useful in reducing fall injuries. Vargas et al. (1996a, 1999b) developed an expert system that would help to analyze cases of construction falls by using fault-tree analysis and stated that all forms of fall protection can be inadequate in different circumstances.

Most of the above mentioned models are theoretical and they lack details about those factors which make significant contributions, so it's hard to follow or implement these models in real scenarios. Also none of these models consider or address the organizational and operational factors which may increase the risk of accidents. To overcome the above-mentioned problem, Rasmussen proposed a model, which helps to understand the accident process in a more realistic way.

2.2 Rasmussen's Theory of Cognitive System Engineering

Many accident causation models have been developed, as discussed in the above section of this chapter. Despite the contributions of these accident causation models they lack proper understanding of the accident process, none of these models considers the dynamic nature of construction work and that accident scenarios differ in how they occur from site to site. It is not possible to predict every scenario and have rules for each under the dynamic conditions. So a new approach is necessary to represent the system behavior one which does not focus on human errors or violations. mechanical failure or management. but an approach which understands the mechanism of an accident in an actual and dynamic work environment (Rasmussen, 1997). The concept of following preset rules can be applied in a well-structured environment where nothing can go wrong other then some fixed scenario. but this is not possible under dynamic conditions. To include this missing dimension. Howell et al. (2002) proposed a new approach to understand construction accidents based on Rasmussen's theory of cognitive system engineering.

Rasmussen in his theory of "Cognitive System Engineering" argued that there are no fixed stop rules for tracing the cause of events. Rather, in a normal case, the analysis stops when an explanation makes sense from the perspective of the analysts (Howell et al., 2002). Rasmussen identified six common perspectives (Rasmussen 94).

Common sense explanation of what happened: Analysis stops when the act or event that offers reasonable explanations and is familiar to the analyst is identified.

Understanding human behavior: The scientist's perspective. This approach seeks to understand the inner mechanism of human behavior. The stop rule is to identify any actor in the flow of accident events that did not maintain control. even though he or she may not have started the flow. and then to explore his or her cognitive process.

Evaluating human performance: The reliability analyst's perspective. This approach attempts to predict the effects of likely errors on large system performance. This approach is very difficult to apply in less structure scenarios and also is more complex as humans adapt to the situation and often push for performance beyond that predicted by the designer.

Improving performance: The therapist's perspective. The availability of a cure determines when the search for a cause stops. The bias of the therapist will likely affect the selection-trainers will see the problems as a lack of training, while psychologists or safety officers may see it as a lack of motivation or awareness.

Finding somebody to punish: The attorney's perspective. The stop rules are to identify a person who was in control of their behavior, i.e., guilty of the act.

Improving system configuration: The designer's perspective. Here the objective is to find changes in the work system, which will improve its performance. This is tricky business as the systems are "designed" by a number of people with different perspectives, from legislators to machine designers.

The new approach or theory proposed by Rasmussen states that organizational and individual pressures push people to work in hazardous situations. These pressures defeat efforts to enforce safe work rules, specifically in a changing work environment such as in construction. Therefore, this approach emphasizes the need to train workers to be conscious of hazardous work environments and to engage the work with better planning and appropriate protection, in a way very similar to how fire fighters engage hazardous situations.

The framework proposed by Rasmussen, shown in Figure 2.2, explains more clearly the relation between the individual and the work environment. In his theory, Rasmussen stated that the workspace within which the worker can move freely is bounded by administrative, functional and safety related constraints. These constraints push workers to work in the hazard zone, beyond which it is no longer safe and accidents occur.

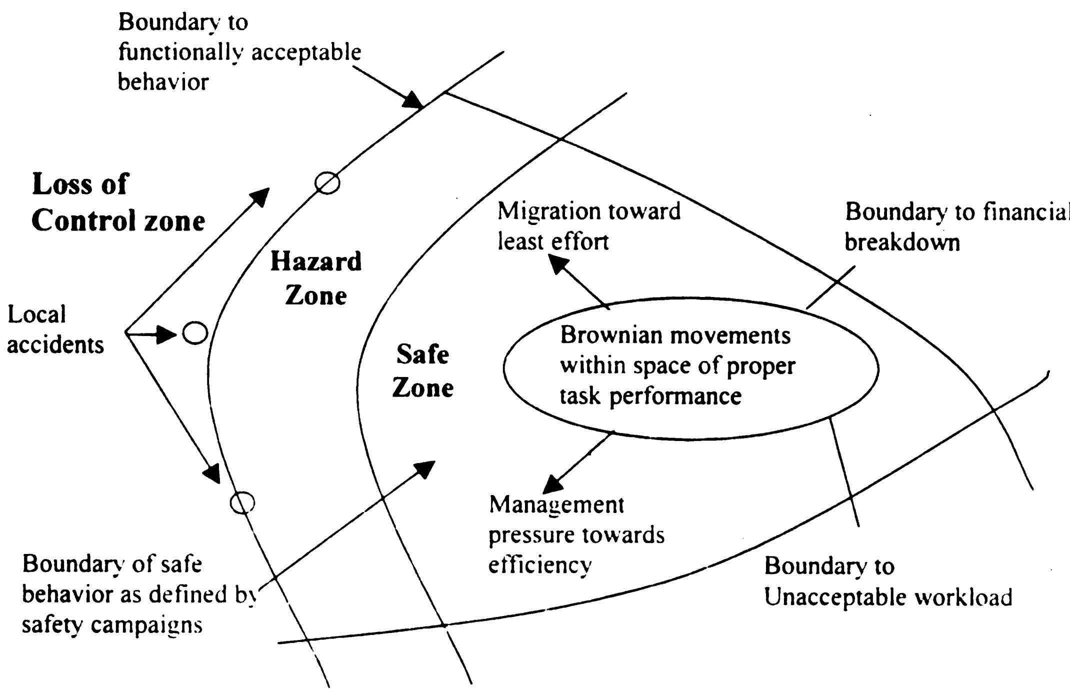


Figure 2.2 Migration of Work Towards Loss of Control (Source: Howell et al., 2002).

Rasmussen's model leads to a three-step approach to safety, as shown in Figure 2.2 (Howell et al., 2002).

Zone 1- The safe Zone. He suggested that one could enlarge this safe zone through proper planning of the operation.

Zone 2 - At the Edge Zone. He suggested that this boundary or zone should be made visible beyond which work is no longer safe and teach workers how to recognize the boundary. He also suggested teaching workers how to detect and recover when hazard is released at the edge of control. This could be done through 'simulators"

Zone 3- Over the edge. This is the zone where accidents occur, so he suggested designing ways to limit the effect of the hazard once control is lost.

According to Rasmussen, accidents result from a "loss of control" when work migrates from the boundary of functionally acceptable behavior to the loss of control zone. He also believed that the worker him/herself is the best person to judge the boundaries of safe work. So instead of forcing workers to follow the rules to stay in the safe zone, Rasmussen suggested that the workers be trained to:

- Identify in which zone they are working,
- Identify hazards,
- Prevent hazard release, and
- Recover when hazards are released.

While counterintuitive, Rasmussen's recommendation to train workers to deal with hazards and recover from scenarios when control is lost recognizes that workers will frequently work in the hazard zone due to various reasons and pressures. Management pressure and seeking less effort are realistic examples of what may push workers to the hazard zone. Rasmussen still maintains that safety and performance will increase if the safe zone is enlarged with proper planning.

Rasmussen's model explains the process of accidents. The following section of this chapter will discuss Signal Detection Theory (SDT), which had been applied mostly in the manufacturing industry to determine the performance of the operator.

2.3 Signal Detection Theory

In the manufacturing industry, quality inspections are performed on products to reject defective ones. A perfect quality inspection process would be able to identify and reject all the defective products. This is seldom attained despite the use of sophisticated equipment to perform the inspection instead of using human inspectors. The inspection problem is also found in other industries or job situations such as a radiologist detecting a tumor on an X-ray plate, airport security guard detecting weapons, and for the purposes of this research construction workers determining if the work conditions are safe or unsafe.

The number of defective products, diseases, or weapons, etc. that escape detection (misses) and non-defective ones that are rejected (false alarms) gives a measure of the effectiveness of an inspection process. These two measures have also become the basis for characterizing the sensitivity of the operator performing inspection. Researchers have dubbed the framework leading to such characterization as "Signal Detection Theory" (SDT).

SDT is applicable in situations where two discrete states of the world (signal and noise) cannot be easily discriminated. In such situations, a human operator (or machine) is faced with the task of identifying one of the states. If the state of the world is a signal, e.g., a defective product, the response of the operator (or machine) is either 'yes' the product is defective (a HIT), or 'no' the product is not defective (a MISS). If the state of the world is noise, e.g., the product is not defective, the response of the operator (or machine) is either 'yes' the product is defective (a FALSE ALARM), or 'no' the product is not defective (a CORRECT REJECTION). These situations are represented as shown in Table 2.1. Clearly, a perfect result would not have any false alarm or misses, but in real life this is not possible.

		State of the World	
		Signal	Noise
Response	Yes	Hit	False Alarm
	No	Miss	Correct Rejection

Table 2.1 The Four Outcomes of Signal Detection Theory (Wickens, 1992).

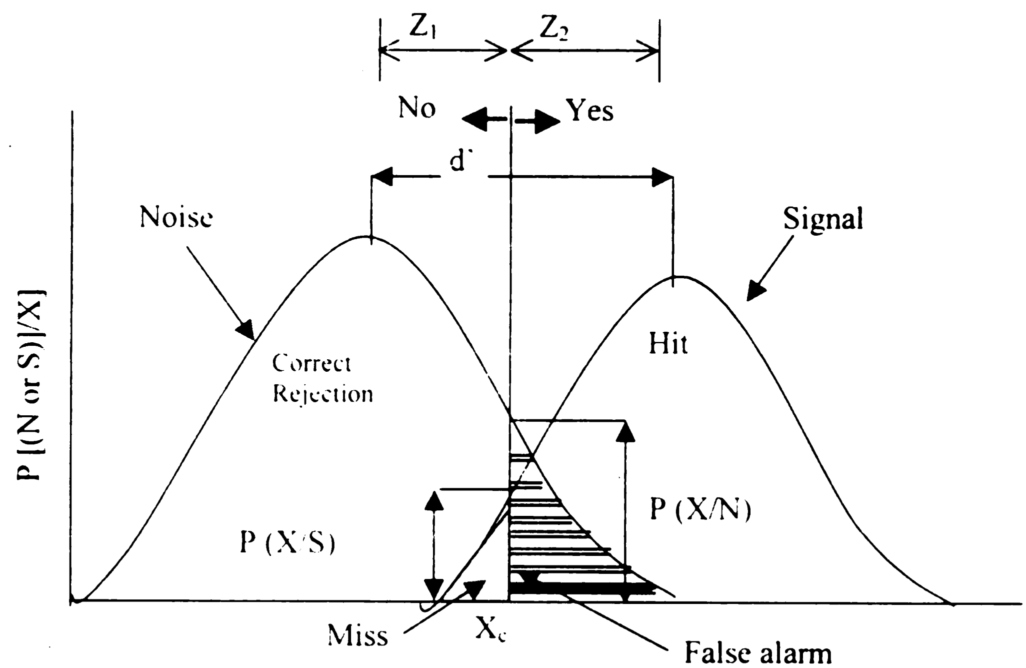
In a signal detection task, operators sometimes have response bias and are prone to say 'yes' more often than they should, thereby detecting most of the signal but also producing many false alarms. As other response could be conservative by saying 'no' and producing few false alarms but missing many of the signals (Wickens, 1992). Depending on the task, a conservative approach with fewer false alarms may be better than not missing any signals while having many false alarms.

Assuming that a signal indicator or strength has a normal distribution, the information in Table 2.1 could be graphically represented as shown in Figure 2.3. Xc, shown in Figure 2.3, represents the critical level where an observer decides the nature of a signal. In other words, Xc represents the "mental" cut-off the observe uses to decide whether to say 'yes' there is a signal (a hit), or 'no' there is noise (correct rejection).

In Figure 2.3, the shaded portion on the left of Xc represents the signals missed by the observer. The striped portion to the right of Xc represents the signals the observer incorrectly considered as hits, i.e., false alarms. The change in the position of Xc determines the respective proportion of misses to false alarms. For example, if Xc cuts more into the signal side, then most responses will be 'no' resulting in numerous misses and fewer hits and false alarms. This strategy is considered conservative. If Xc cuts more to the left, most responses will be "yes" resulting in fewer misses but more of false alarm. This indicates a risky strategy.

Figure 2.3 Distribution of Detection Theory

(Wickens, 1992)



The tendency of an observer to follow a conservative or risky strategy is measured using a parameter termed the response criterion or likelihood ratio, and denoted $\beta_{current}$. This parameter has also been termed the judgment or decision criterion of the observer. Mathematically, as shown in Figure 2.3, $\beta_{current}$ is the ratio of the ordinates

P (X/S) and P (X/N) for a given level of Xc. P (X/S) and P (X/N) represent the conditional probability of Xc given a signal and the probability of Xc given noise, respectively.

$\beta_{current}$ is calculated using Equation 2.2 (Wickens, 1992).

$$\beta\ current = \frac{P(X/S)}{P(X/N)} \tag{2.2}$$

A high value of $\beta_{current}$ indicates a high number of misses, whereas a lower one will generate more false alarms. Because of inter-observer variability with respect to the choice of Xc, evaluating the results of multiple observers requires normalization of the value of $\beta_{current}$ or comparison to an optimal value. The optimal value of β has been taken as the value corresponding to a minimum number of errors, i.e. minimum misses and false alarms. Mathematically, this value is the ratio of the probability of noise, P (N), and the probability of a signal, P (S). Equation 2.3 (Wickens, 1992) gives this ration.

$$\beta\ opt = \frac{P(N)}{P(S)} \tag{2.3}$$

After finding the value of $\beta_{current}$ and β_{opt}, the pair are compared to determine whether an observer is following a risky or conservative strategy. If $\beta_{current}$ is greater than the value of β_{opt}, then Xc is positioned more to the right, resulting in fewer false alarms and more misses. According to the SDT literature, observers with such a mental-cutoff require more evidence to say 'yes' a part is defective or a tumor exists. Under SDT, this is considered a conservative strategy for operators to adopt because of the consequences and actions triggered after a false alarm results, such as rejecting a non-defective product or performing unnecessary medical procedures. When $\beta_{current}$ is less than β_{opt}, then Xc is positioned more to the left, resulting in more false alarms and fewer misses. Based on SDT, this indicates that the observer needs less evidence to say 'yes' a part is defective or a tumor exists. Therefore, this strategy is considered a risky strategy.

Another important measure of an observer's performance in signal detection tasks is sensitivity to the signal and the noise. This is measured by the degree of separation between the means of the two distributions shown in Figure 2.3, denoted as d'. A high value of d' indicates a high degree of separation and, thus, high observer sensitivity. Data from myriad tasks indicate that d' ranges in value from 0.5 to 2.0.

The value of d' is determined by adding the two values Z_1 and Z_2 shown in Figure 2.3. Z_1 and Z_2 represent the value of the standard normal variable corresponding to the probability of a false alarm and probability of a hit, respectively. The values are readily available from standard tables. The application of SDT will be demonstrated using an example of a typical inspection process.

Example 2.1:

A manufacturer produces DC motors using a process that generates 5% defectives. In response to increasing customer complaints, the manufacturer institutes a final inspection system that finds 80% of the defective motors at the expense of falsely rejecting 1% of the good motors. Determine the sensitivity of the operator and the strategy adopted.

Solution: From the information given, the following probabilities can be deduced:

P (Noise) = P (product is not defective) = 0.95

P (Signal) = P (product is defective) = 0.05

P (Hit) = 0.80 P (Miss) = 1-P (Hit) = 0.20

P (FA) = 0.01 P (CR) = 1- P (FA) = 0.99

Table 2.2 represents the inspection process with its possible outcomes.

		State of the World	
		Signal (Defective Product)	**Noise (Good Product)**
Response (Is motor defective?)	**Yes**	HIT = 80%	FALSE ALARM = 1%
	No	MISS = 20%	CORRECT REJECTION = 99%

Table 2.2 The Four Probabilities

Calculation of the sensitivity, i.e., the value of d' involves the standard normal values Z_1 and Z_2. Using P (FA) and P (Miss), the values of Z_1 and Z_2 are:

$$Z_1 = 2.326 \text{ and } Z_2 = 0.842$$

$$\because d' = Z_1 + Z_2$$

$$\therefore d' = 2.376 + 0.842 = 3.168.$$

This indicates a high degree of separation between the signal and the noise distribution, i.e., the inspector has high sensitivity.

As indicated by Equation 2.2, calculating $\beta_{current}$ requires the determination of

P(X/S) and P(X/N). However, Figure 2.3 indicated the following:

P(X/S) = Ordinate corresponding to Z_2

P(X/N) = Ordinate corresponding to Z_1

Using the tables.

Ordinate corresponding to $z_2 = 0.28$

Ordinate corresponding to $z_1 = 0.027$

$\therefore \beta_{current} = 0.28 / 0.027 = 10.37$

Using Equation 2.3, β_{opt} is easily calculated as:

$$\beta\ opt = \frac{P(N)}{P(S)} \Rightarrow \beta\ opt = \frac{0.95}{0.05} = 19$$

Clearly $\beta_{current} < \beta_{opt}$ which indicates a risky strategy. This means that the inspector's cut-off level, Xc, is positioned more to the left, i.e., cuts more in the signal distribution.

The above example illustrates how the sensitivity and risk orientation of a worker can be determined using SDT. This information sets a benchmark against which the effectiveness of new training can be assessed. Essentially, this information would make it possible to determine if a worker's sensitivity and risk orientation to safe and unsafe conditions increased, decreased, or remained unchanged. Ultimately, the use of SDT will result in increasing workers abilities to judge the boundary beyond which work is no longer safe.

The next section will discuss another approach to representing the analysis of SDT, the ROC curve. The ROC curve helps to understand the joint effect of sensitivity and response bias

2.4 ROC Curve

This method of graphical representation is known as the Receiver Operating Characteristic (ROC) curve and is helpful to portray the equivalence of sensitivity across changing levels of bias, i.e., to understand the joint effects of sensitivity and response bias on the data from a signal detection analysis experiment (Wickens, 1992). The ROC curve is plotted on a single graph using the values of P(Hit) and P(FA) obtained from the SDT analysis. When the same experiment is repeated several times and each time the response criterion is changed, a series of different points are produced. When these points are connected a ROC curve emerges as shown in Figure 2.4. For more sensitive worker the ROC curve will be more curved as compared to other workers. This is a theoretical representation because it is hard to repeat the same experiment to get different points in real life.

The alternative way of plotting the curves shown in Figure 2.4 is by plotting the curve on probability paper, as shown in Figure 2.5 (Wickens, 1992). This representation has its advantage, as the bowed lines of Figure 2.4 now become straight (Wickens, 1992). The Value of P(Hit) and P(FA) could be replaced with Z scores, standard value or scores from the standard SDT table know as Z(Hit) and Z(FA) respectively. For any given point, d' (sensitivity) is equal to Z(H)- Z(FA) (Wickens, 1992).

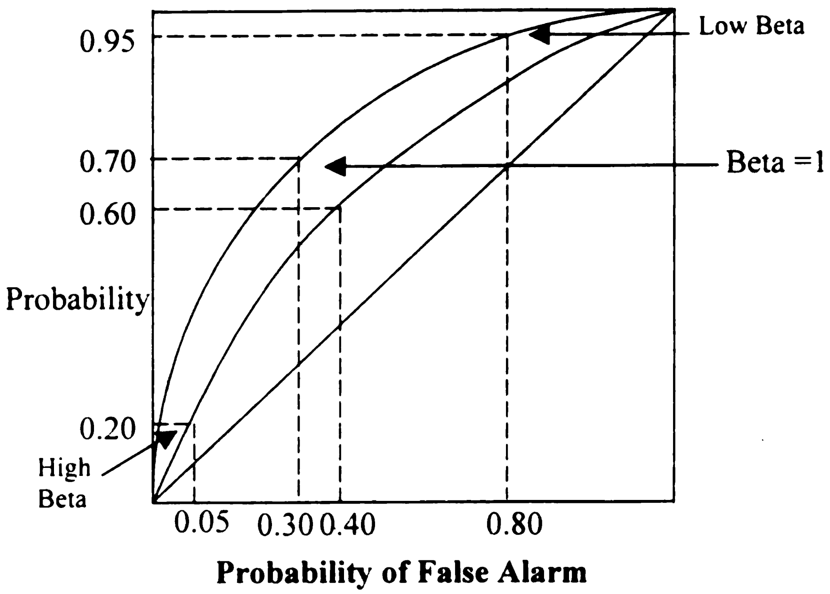


Figure 2.4 Theoretical Representation of the ROC Curve (Wickens, 1992)

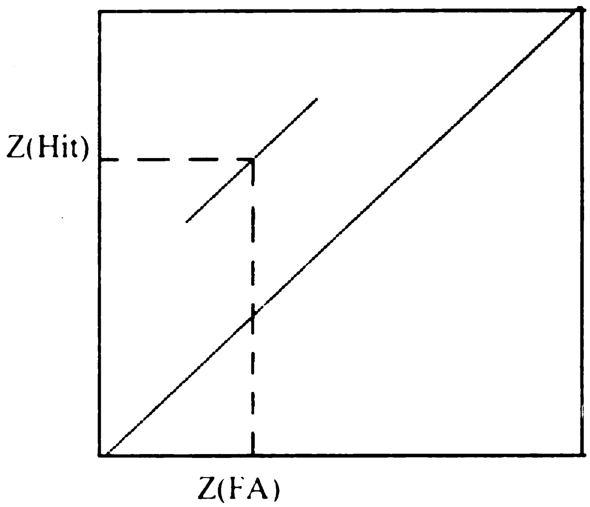


Figure 2.5 The ROC Curve on Probability Paper (Wickens, 1992)

It is important to understand the difference between the theoretical representation of the ROC curve discussed above and the actual empirical data collected in an SDT experiment. The representation shown in Figures 2.4 and 2.5 is continuous and smooth, while actual data collection provides discrete points, or due to some limitation it might not be possible to get more then one point. In such circumstances, a measure called P(A), representing the area under the ROC curve, is an alterative which can be used to measure sensitivity as shown in Figure 2.5 (Wickens, 1992). This area under the ROC curve represents the area to the right and below the line segments connecting the lower left and upper right corners of the curve as shown in Figure 2.6. The area represented by the formed triangle is Δ and P(A) represents the sensitivity (d') of the respondent. The area P(A) is calculated using equation 2.4 (Wickens, 1992).

$$P(A) = \frac{P(Hit) + [1 - P(FA)]}{2.0} \tag{2.4}$$

Equation 2.4 (Wickens, 1992) was used to determine the P (A) for the example discussed in section 2.3 of this chapter, which produced a value of 0.9. This value of P (A) represents the sensitivity (d') for the operator. The sensitivity calculated using standard SDT is 3.16. The difference between the two values of d' is caused by the fact that the ROC curve portrays the joint effects of response bias and sensitivity

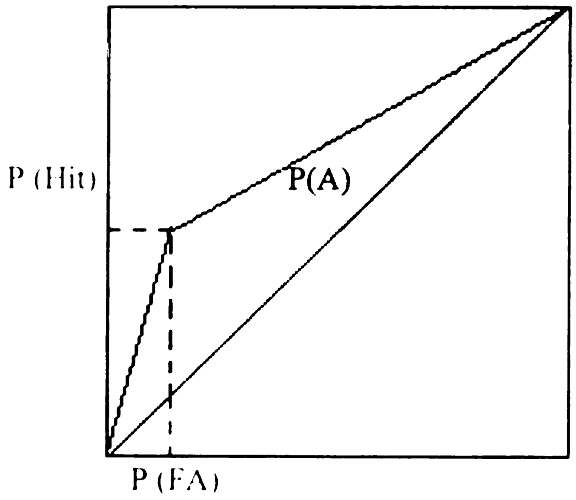


Figure 2.6 Example of Measure of P(A) (Wickens, 1992)

Chapter 3

METHODOLOGY

3. METHODS

The first chapter of this thesis gave an overview of construction fatalities and the contribution of fall accidents to these fatalities. The problem area, goal and objectives of the research were also discussed in this chapter. In Chapter 2, the history and evolution of accident causation models and theories were discussed. The new approach to accident causation, as proposed by Rasmussen, was presented. Signal detection theory was also introduced which will be further utilized in this research. In this chapter, methods to achieve the objectives of the research will be discussed. The application of signal detection theory will also be demonstrated.

3.1 Introduction

The main goal of this research was to develop a methodology by which workers' sensitivity to unsafe conditions and risk orientation (tendency of a worker to work in a condition despite knowing its unsafe) can be assessed prior to prescribing a training program. Due to the high rate of occurrences, fall accidents were considered as case examples. To achieve the research goal, the following objectives were articulated:

1) Developing a technique to assess the sensitivity and risk orientation of workers to unsafe conditions.

2) Designing and conducting a survey to determine the sensitivity and risk orientation of workers at risk of fall accidents.

In the following sections of this chapter, these objectives will be discussed in detail

3.2 SDT and Unsafe and Safe Construction Conditions (Objective 1)

An assessment of the construction workers sensitivity and their risk orientation to unsafe conditions was performed, after some modifications to the signal detection theory (SDT). SDT is used in this research because of the fact that there is similarity between the response of the operator in identifying defective and non-defective parts and the construction worker's response in identifying safe and unsafe conditions on site. Also, SDT is the only method that will help to determine both the sensitivity and risk orientation of the construction worker, with some modifications to the theory. Once performed, this assessment could be used to give guidance to workers on how to enhance their abilities to identify the boundary beyond which work is no longer safe. Signal detection theory was discussed in detail in chapter 2. In this section, application and tailoring of the theory will be presented.

Similar to a detection task in other industries, construction workers are expected to identify whether the conditions under which they are working are safe. In SDT, the state of the world is represented by signal and noise. From a construction safety standpoint, the state of the world is either a "Safe condition" or an "Unsafe condition" which correspond to the noise and signal states of SDT.

On the one hand, a worker faced with a "safe" condition and asked whether the condition is unsafe has one of two possible responses, namely 'yes' the condition is unsafe (false alarm), or 'no' the condition is safe (correct rejection). On the other hand, a worker faced with an "unsafe" condition and asked whether the condition is unsafe has one of two possible responses, namely 'yes' the condition is unsafe (hit), or 'no' the condition is safe (miss). Figure 3.1 shows the SDT matrix for these scenarios.

The ideal scenario for a given number of safe and unsafe conditions is for a worker to correctly identify them all. This may happen for some workers but certainly not for all. Some workers will incorrectly consider a condition safe while it is unsafe, and vice versa. Signal detection theory allows the determination of the sensitivity of workers to unsafe conditions as well as their inclination (bias) to consider a situation as unsafe while it is not. For construction workers, it is desirable to minimize the number of misses (considering a condition safe while it is unsafe), at the expense of having more false alarms (considering a condition unsafe while it is safe). This is because a miss is more likely to lead to serious injury or death.

		State of the World	
		Unsafe Condition (Signal)	**Safe Condition (Noise)**
Response (Is condition unsafe?)	Yes	HIT	FALSE ALARM
	No	Miss	Correct Rejection

Figure 3.1 The SDT Matrix for Detection of Unsafe Conditions in Construction

As explained before, worker sensitivity to unsafe and safe conditions as well as the inclination to regard a condition as a safe or unsafe can be assessed using the SDT parameters d' and $\beta_{current}$ High values of d' indicate high sensitivity in differentiating between safe and unsafe conditions. Conversely, low values of d' indicate that a worker needs more training to better differentiate between safe and unsafe conditions. Regardless of the value of d', the mental cutoff used by a worker to decide the state of a condition is given by the value of $\beta_{current}$ with respect to β_{opt}. However, considering the implementation of SDT is construction, a modification is necessary in interpreting the values of $\beta_{current}$ and β_{opt}. As discussed before, if the value of $\beta_{current}$ is greater than that of β_{opt}, then fewer false alarms and more misses will result; in manufacturing industry, SDT usual application this strategy is considered conservative. However, in construction, the cost of a miss could result in a fatality or a serious injury. Therefore, it is a more risky strategy to have fewer false alarms and more misses. Similarly, a value of $\beta_{current}$ smaller than β_{opt}, indicating that more false alarms and fewer misses result, will be considered a risky strategy in STD normal field of use. For construction, this would be considered a conservative strategy.

Undertaking the assessment of worker sensitivity to unsafe and safe conditions as well as the inclination to associate a condition with a safe or unsafe requires the determination of SDT responses (hit, miss, false alarm, and correct rejection) to a number of safe and unsafe conditions. The second objective of this research addresses this issue.

3.3 Survey Development and Its Analysis Using SDT

Assessing worker performance in detecting unsafe and safe condition in real time is both dangerous and infeasible. The alternative is to design a survey (questionnaire) that places the worker in know hypothetical safe and unsafe conditions and asking the worker to identify whether the condition is safe or unsafe. This survey was developed by referring to OSHA standards and case studies of construction fall accidents reported in a NIOSH report. The survey contains 21 questions involving conditions where fall hazards may exist. To keep the scope reasonable, the survey was performed on ironworkers only. This choice is primarily based on the fact that ironworkers (see Chapter 1) suffer from fall accidents more than any other trade.

The questionnaire developed for the survey is shown in Appendix A. For each question, the worker has to choose from one of three responses: 1) An Unsafe Condition or 2) A Safe Condition or 3) I Don't Know. From the response of the worker it would be determined how the worker would react if he/she encounter typical safe or unsafe conditions.

Based on the responses of the worker, the number of hits, misses, false alarms, and correct rejections were determined and converted to probabilities. This facilitated the determination of the sensitivity to unsafe conditions and the risk orientation of the workers.

To illustrate how a response was mapped to a hit, miss, false alarm, or a correct rejection, a sample question is shown below which depicts a safe condition. If the worker's response to this was "An Unsafe Condition" or "I Don't Know", then this indicates that the worker incorrectly considered the condition as unsafe or was not sure of what it was, i.e., – a "false alarm". The response "I Don't Know" is considered a miss if the condition portrayed by the question was unsafe.

INTERVIEW QUESTIONS

Please choose one of the classifications that fit the following Conditions:

1) Working on a scaffold 8 feet above the lower level without a guardrail system.

[X] An Unsafe Condition

[ ] A Safe Condition

☐ I Don't Know

To illustrate further the type of analysis that was performed based on the response of the worker to a 30 question survey, with 24 safe condition scenarios and 6 unsafe condition scenarios. Table 3.1 shows hypothetical responses from one of the workers who participated in the research.

		State of the World	
		Unsafe Condition (Signal)	**Safe Condition (Noise)**
Response (Is condition unsafe?)	Yes	Hit = 4	False Alarm = 3
	No	Miss = 2	Correct Rejection = 21

Table 3.1 Sample Survey Analysis Results

Note that:

P(Noise) = P(safe conditions) = 24/30 = 80%

P(Signal) = P(unsafe conditions) = 6/30 = 20%.

P(Hit) = 4/6 P(Miss) = 1-P(Hit) = 2/6

P(FA) = 3/24 P(CR) = 1- P(FA) = 21/24

Calculation of the sensitivity, i.e., the value of d', involves the standard normal values Z_1 and Z_2. Using P(FA) and P(Miss), the values of Z_1 and Z_2 are:

Z_1 = 1.21 and Z_2 = 0.440

and $\because$ $d' = Z_1 + Z_2$

$\therefore$ $d' = 1.21 + 0.440 = 1.65.$

This is indicates a moderate degree of separation between the signal and noise distributions, i.e., the worker has moderate sensitivity. In this scenario, for a perfect score of 12 "hits' and 9 "CR," the value of ideal $d'_{SDT} = 4.6$, and in the worst case scenario of no "hits" or "CR," the value of $d'_{SDT} = -4.6$

Ordinate corresponding to $Z_2 = 0.362$

Ordinate corresponding to $Z_1 = 0.194$

Using Equation 2.2. $\beta_{current} = 0.362 / 0.194 = 1.865$

Using Equation 2.3 $\beta_{opt} = P\,(Noise) / P\,(Signal) = 0.8/0.2 = 4$

Clearly $\beta_{current} < \beta_{opt}$, which indicates a conservative strategy. Despite that with this strategy causing the worker will have more false alarms, fewer misses will result.

3.4 Analysis with ROC

The above section discusses how SDT is used to analyze the result of the survey. This section will discuss how the responses of the workers participating in the research would be analyzed using ROC. This will be illustrated with the help of the same example as is found in the previous section.

$P\,(Hit) = 4/6 = 0.67$ $P\,(Miss) = 1\text{-}P\,(Hit) = 0.33$

$P\,(FA) = 3/24 = 0.125$ $P\,(CR) = 1\text{-}\,P\,(FA) = 0.875$

From Equation 2.4: P (A) = 0.77

As discussed in chapter 2, section 2.4, P (A) represents the sensitivity (d') for the worker. The sensitivity calculated using standard SDT is 1.65. The difference between the two values of d' is caused by the fact that the ROC curve portrays the joint effect of response bias and sensitivity.

It is worth noting that in an ideal scenario with perfect scores of 12 "hits" and 9 "CR", the value d'_{ROC} = 1 represents an ideal value, and in the worst-case scenario with no "H its" or "CR" the value of d'_{ROC} = 0. Thus, a score of 0.77 is quite high with respect to the ideal. This will be further discussed in chapter 4.

Chapter 4

SURVEY RESULTS AND ANALYSIS OF DATA

4. SURVEY RESULTS AND ANALYSIS OF THE DATA

4.1 Introduction

In this chapter, survey data are presented and analyzed. The analysis of the data uses SDT calculations to determine the sensitivity and risk orientation of ironworkers. The data is analyzed following the steps discussed in section 3.3 and 3.4.

4.2 Data Collection

As discussed in chapter 3, construction accidents, and fall accidents in particular, are of major concern in the construction industry, as many lives are lost and business suffers. Many construction accident causation models have been developed, but accidents still occur with fall accidents representing a significant percentage of the whole. Therefore, this research focuses on understanding the risk orientation of ironworkers to unsafe condition such that worker specific training could be developed. The ironworkers were selected because of their high risk of fall accidents.

Using Signal Detection Theory (SDT), a survey was developed to investigate how an ironworker assesses a hypothetical scenario that portrays either an unsafe or a safe condition. The survey describes 21 scenarios, which are developed based on OSHA fall protection regulations and steel erection codes and also on fall accident cases reported by NIOSH (NIOSH, 2000 "case repot on workers' death by fall"). The developed survey is found in Appendix A.

There was no restriction on age, years of experience or any other criteria for the ironworkers who volunteered to participate in this survey. All the ironworkers were familiar with the OSHA standards and have been through formal training. All 42 ironworkers who participated in this research were members of local 25 (Lansing, MI). In this research, an effort was made to survey at least 30 ironworkers, as using 30 or more sample points allows the use of the normal distribution for results.

The ironworkers were asked to select one of three responses to each question on the survey. The responses were then compared to the correct responses and further analyzed using SDT to determine the sensitivity and risk orientation of each ironworker.

4.3. Sensitivity and Risk Orientation of the Ironworkers by SDT

The response of each ironworker (i.e. a hit, miss, false alarm or correct rejection) is provided in Table 4.1. Survey details are provided in Appendix B (Table B.1).

The survey had 21 scenarios with 12 unsafe and 9 safe conditions. If the ironworker correctly identified an unsafe condition as "An Unsafe Condition" then this was considered a "HIT" and is represented by "H" in Table 4.1. If he or she incorrectly identified an unsafe condition as " A Safe Condition" or as "I Don't Know" then it was considered as a "MISS" and is represented by "M" in Table 4.1. Similarly, a "correct rejection" represented by "CR" in Table 4.1. results when the ironworker correctly identified a safe condition. A "false alarm" represented as "FA", was assigned if the condition was safe but the worker identified it as "An Unsafe Condition" or "I Don't Know".

Q. No.	Workers																					
	W1	w2	w3	w4	w5	w6	w7	w8	w9	w10	w11	w12	w13	w14	w15	w16	w17	w18	w19	w20	w21	w22
Q 1	H	H	M	H	H	H	M	M	H	H	H	H	H	H	H	H	H	H	M	H	H	H
Q 2	FA	FA	CR	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	CR	FA	FA	FA	FA	FA	FA
Q 3	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA
Q 4	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	M	H	H	H
Q 5	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H
Q 6	H	M	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	M	H	M	M	H
Q 7	H	M	H	M	H	H	M	H	H	H	H	H	H	H	H	H	H	M	H	M	M	M
Q 8	H	H	H	M	H	H	M	M	H	H	H	H	H	H	H	H	H	M	H	H	M	M
Q 9	H	M	H	H	H	M	M	H	H	H	H	H	H	H	H	M	H	H	H	H	M	H
Q 10	CR	CR	CR	CR	CR	CR	CR	FA	CR	CR	CR	FA	FA	FA	FA	CR	FA	CR	CR	CR	CR	CR
Q 11	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR
Q 12	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	M	H	H	H
Q 13	H	H	H	H	M	H	H	M	M	M	M	M	M	M	M	H	M	M	M	M	H	H
Q 14	CR	CR	CR	CR	CR	CR	CR	FA	CR	CR	CR	CR	CR	CR	FA	CR	FA	CR	CR	CR	FA	CR
Q 15	M	H	M	M	M	H	H	H	H	H	H	H	M	M	H	M	H	M	H	H	H	M
Q 16	CR	CR	CR	CR	FA	CR	CR	FA	FA	CR	CR	FA	FA	FA	FA	FA	FA	CR	CR	CR	FA	FA
Q 17	M	H	H	H	H	H	H	H	M	H	M	M	M	H	H	H	H	M	H	H	M	H
Q 18	FA	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR
Q 19	FA	FA	FA	FA	FA	FA	FA	FA	CR	FA	FA	FA	FA	FA	FA	CR	FA	FA	FA	FA	FA	FA
Q 20	FA	CR	CR	CR	CR	CR	FA	FA	CR	CR	CR	FA	FA	FA	FA	CR	FA	CR	CR	CR	FA	FA
Q 21	H	H	H	H	H	M	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H

Table 4.1 Results of the Survey of the Ironworkers

Q. No.	Workers																			
	w23	w24	w25	w26	w27	W28	W29	W30	W31	W32	W33	W34	W35	W36	W37	W38	W39	W40	W41	W42
Q 1	H	H	H	M	M	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H
Q 2	FA	FA	FA	FA	FA	FA	FA	FA	CR	CR	FA	CR	FA	FA	FA	FA	CR	FA	FA	FA
Q 3	FA	FA	FA	FA	CR	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA
Q 4	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H
Q 5	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	M	M	H	H
Q 6	H	H	H	H	H	H	H	H	H	M	M	H	H	H	H	H	H	H	H	H
Q 7	H	H	H	H	H	H	H	H	H	M	M	H	H	H	H	H	M	M	M	H
Q 8	H	H	H	M	H	H	H	H	H	H	M	H	H	H	H	H	M	M	M	H
Q 9	H	H	H	H	H	H	H	H	M	M	H	H	H	H	H	H	H	H	H	H
Q 10	FA	FA	FA	FA	CR	FA	CR	CR	CR	CR	FA	CR	CR	FA	CR	FA	CR	CR	CR	CR
Q 11	CR	CR	FA	FA	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	CR	FA	CR	CR	CR	CR
Q 12	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H
Q 13	H	M	H	M	H	M	M	M	H	H	M	M	M	M	M	M	M	M	H	H
Q 14	FA	FA	CR	CR	CR	CR	CR	FA	CR	CR	FA	CR	CR	FA	CR	CR	CR	FA	FA	CR
Q 15	H	M	H	H	H	H	H	M	M	H	M	H	H	M	H	H	H	H	H	H
Q 16	FA	FA	CR	FA	FA	FA	CR	FA	CR	CR	FA	CR	CR	FA	CR	CR	CR	FA	FA	FA
Q 17	H	H	H	H	H	M	H	M	H	H	M	H	H	H	M	H	H	H	M	H
Q 18	FA	CR	CR	FA	CR	CR	CR	CR	CR	CR	CR	CR	CR	FA	FA	CR	CR	FA	CR	CR
Q 19	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA	FA
Q 20	CR	FA	FA	CR	CR	FA	CR	FA	CR	CR	FA	CR	CR	CR	FA	FA	CR	CR	CR	FA
Q 21	M	H	H	M	H	H	H	H	H	H	H	H	H	H	H	H	M	H	H	H

Table 4.1 Results of the Survey of the Ironworkers (Continued)

To illustrate the additional analysis performed on the collected data for each worker, the results of worker "w1" are used. As shown in Table 4.1, "w1" had 10 "Hits" and 5 "False Alarms." This indicates that this particular worker correctly identified unsafe conditions 10 times out of total 12 possible hits, and that he or she incorrectly considered 5 out of 9 safe conditions as unsafe. Based on this information, the corresponding number of hits, misses, false alarms and correct rejections are listed as shown in Table 4.2.

		State of the World	
		Unsafe Condition (Signal)	**Safe Condition (Noise)**
Response (Is condition unsafe?)	Yes	HIT = 10	FALSE ALARM = 5
	No	Miss = 2	Correct Rejection = 4

Table 4.2 Matrix Showing the Responses for Worker w1

From Table 4.2, the probability of a hit, a miss, a false alarm and a correct rejection can be calculated as follows:

Note that:

P(Noise) = P(safe conditions) = 9/21 = 0.43

P(Signal) = P(unsafe condition) = 12/21 = 0.57

P(Hit) = 10/12 = 0.83   P(Miss) = 1-P (Hit) = 0.17

P(FA) = 5/9 = 0.56   P(CR) = 1- P (FA) = 0.44

After obtaining the probabilities. the sensitivity (i.e., the value of d') and the risk orientation (i.e., $\beta_{current}$) may be calculated. From the normalized SDT table (Appendix D) normal devastation values. Z_1 and Z_2, are determined based on P (FA) and P (Miss), respectively.

For P (FA) = 0.56 : Z_1 = −0.15 ; for P(M) = 0.17 : Z_2 = 0.95

Θ d' = $Z_1 + Z_2$

$\therefore$ d' = −0.15 + 0.95 = 0.80

Compared to the ideal d' of 4.6, this d' indicates a low degree of separation between the signal and noise distribution, i.e., the worker has low sensitivity. To determine the risk orientation of the ironworker, the ordinates corresponding to Z_1 and Z_2 are determined from the same normalized SDT table (see appendix D).

Ordinate corresponding to Z_1 = 0.394

Ordinate corresponding to Z_2 = 0.253

Using Equation 2.2. $\beta_{current}$ = 0.253 / 0.394 = 0.64

Using Equation 2.3 β_{opt} = P (Noise) / P (Signal) = 0.43/0.57 = 0.75

Because $\beta_{current} < \beta_{opt}$, this indicates a conservative strategy. With this strategy worker will have more false alarms and fewer misses.

To determine the sensitivity (d') of the ironworker while taking into account the effect of the response bias, the ROC curve will be used. The area under the ROC curve is obtained from the following formula:

$$P(A) = \frac{P(Hit) + [1 - P(FA)]}{2.0} \quad (4.1)$$

As an example for using Equation (4.1), consider the response of worker w1, shown in Table 4.1. Using P (Hit) = 10/12 and P (FA) = 5/9, the

$$P(A) = \frac{0.83 + [1 - 0.56]}{2.0} = 0.64$$

The value given by P (A) will be denoted as d'_{ROC}. Again, compared to the ideal d'_{ROC} of 1, this d'_{ROC} indicate a moderate degree of separation between the signal and noise distributions, i.e., the worker has moderate sensitivity. The value of d' obtained by the ROC curve and SDT is different as the ROC determines the sensitivity of ironworkers by portraying the effect of the response bias on sensitivity.

Similar calculations to those shown for worker "w1" were performed for all the ironworkers. The results are summarized in Table 4.3 below. Details for each worker can be found in Appendix C. Also, Table 4.4 summarizes the number of "Hits", "FA", "CR" and "False Alarm" for each question based on response of all 42 ironworker.

Worker	Age	Years of Experience	d'_{SDT}	d'_{ROC}	$\beta_{current}$	$\beta_{optimal}$
w1	32	5	0.8	0.64	0.64	0.75
w2	30	4.5	1.11	0.71	0.88	0.75
w3	22	3	1.73	0.81	0.85	0.75
w4	24	9	1.11	0.71	0.88	0.75
w5	35	2.5	1.11	0.69	0.64	0.75
w6	24	4	1.85	0.79	0.41	0.75
w7	21	1	0.64	0.63	1.08	0.75
w8	26	3	-0.1	0.49	1.1	0.75
w9	24	4.5	1.39	0.75	0.7	0.75
w10	26	5	1.85	0.79	0.41	0.75
w11	30	3	1.39	0.75	0.7	0.75

Table 4.3 Results of Analysis of Survey by Standard SDT and ROC Curve

Worker	Age	Years of Experience	d'_{SDT}	d'_{ROC}	$\beta_{current}$	$\beta_{optimal}$
w12	20	1.5	0.51	0.58	0.7	0.75
w13	31	2	0.23	0.54	0.88	0.75
w14	29	3	0.51	0.58	0.7	0.75
w15	30	7	0.63	0.57	0.51	0.75
w16	36	15	1.73	0.81	0.85	0.75
w17	22	1	0.63	0.57	0.51	0.75
w18	30	3	0.44	0.58	1.1	0.75
w19	25	3	0.88	0.67	1	0.75
w20	19	2	1.11	0.71	0.88	0.75
w21	29	2.5	-0.2	0.46	1.09	0.75
w22	24	2.5	0.52	0.6	0.82	0.75
w23	21	2	0.63	0.57	0.51	0.75
w24	24	1	-0.1	0.49	1.1	0.75
w25	25	6	3.06	0.67	0	0.75
w26	21	1	-0.3	0.44	1.25	0.75
w27	27	6.5	1.85	0.79	0.41	0.75
w28	24	4.5	0.51	0.58	0.69	0.75
w29	25	3	1.85	0.79	0.42	0.75
w30	31	1.5	0.23	0.54	0.89	0.75
w31	23	3.5	1.73	0.81	0.85	0.75
w32	32	7	1.45	0.76	1.08	0.75
w33	19	1	-0.8	0.36	1.38	0.75
w34	29	6	2.18	0.85	0.51	0.75
w35	27	3	1.85	0.79	0.42	0.75
w36	21	1.5	0.18	0.53	0.86	0.75
w37	26	4	0.8	0.64	0.64	0.75
w38	24	2	0.97	0.63	0.42	0.75
w39	24	5	0.97	0.68	1.32	0.75
w40	26	5.5	0	0.5	1	0.75
w41	22	4.5	0.52	0.6	0.82	0.75
w42	33	7.5	1.21	0.68	0.38	0.75

Table 4.3 Results of Analysis of Survey by Standard SDT and ROC Curve (cont.)

Question Numbers	Response			
	Hit	Miss	FA	CR
1	36	6	0	0
2	0	0	36	6
3	0	0	41	1
4	41	1	0	0
5	40	2	0	0
6	36	6	0	0
7	30	12	0	0
8	31	11	0	0
9	35	7	0	0
10	0	0	14	28
11	0	0	3	39
12	41	1	0	0
13	16	26	0	0
14	0	0	11	31
15	29	13	0	0
16	0	0	22	20
17	30	12	0	0
18	0	0	5	37
19	0	0	40	2
20	0	0	18	24
21	38	4	0	0

Table 4. 4 Summary of Response to Each Question

Table 4.4, as discussed before, summarizes the response for each question. The first column of table 4.4 indicates question numbers from the survey, followed by columns indicating the number of responses of each type (Hit, Miss, FA, CR) for each question.

This table will help to determine how the ironworkers as a group interpret each scenario. meaning there might be a condition or scenario, which is unsafe according to OSHA standards. but the group as a whole thinks it, is a safe condition. For example, on question number 13 (see Appendix A). 26 ironworkers out of 42 think the scenario represents a safe condition but OSHA disagrees. Likewise, in question number 19 (see Appendix A). 40 ironworkers out of 42 considered that particular scenario is unsafe. contradicting OSHA standards. So based on this table, feedback could be given to OSHA on what the workers think about the particular scenarios, and such scenarios could be addressed in training to change the approach of the workers.

4.3.1 Relation between d'_{SDT} and d'_{ROC}

This section describes the relation between d'_{SDT} and d'_{ROC}. As discussed in chapter 3. the ideal value of d'_{SDT} is 4.6 and that of d'_{ROC} is 1. However in the worst-case scenario when there are no "hits" or "correct rejections" the worst values that d'_{SDT} and d'_{ROC} assume are –4.6 and 0. respectively. Assuming that the relationship between d'_{SDT} and d'_{ROC} is linear. a theoretical plot is developed as shown in Figure 4.1. In addition. to normalize values of d'_{SDT}, a value of d'_{SDT} of –4.6 (worst case) is considered to be 0% and the value of d'_{SDT} of 4.6 (ideal case) is considered as 100%. It is further assumed that $d'_{SDT} < 60\%$ represents low sensitivity. $60\% \leq d'_{SDT} \leq 80\%$ represents moderate sensitivity. and that $d'_{SDT} > 80\%$ represents high sensitivity.

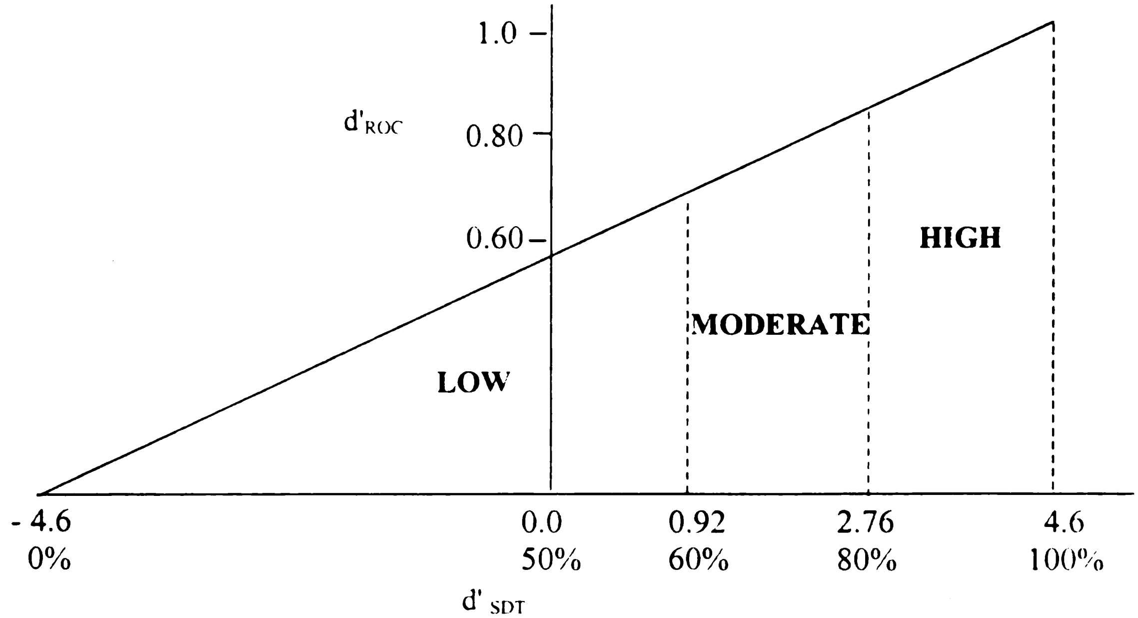


Figure 4.1 Relation between d'_{SDT} and d'_{ROC}

It is important to note that the representation of the relation between d'_{SDT} and d'_{ROC} in Figure 4.1 is only theoretical. To verify whether this assumption is reasonable, the values of d'_{SDT} and d'_{ROC} listed in Table 4.3 were plotted as a scatter plot as shown in Figure 4.2.

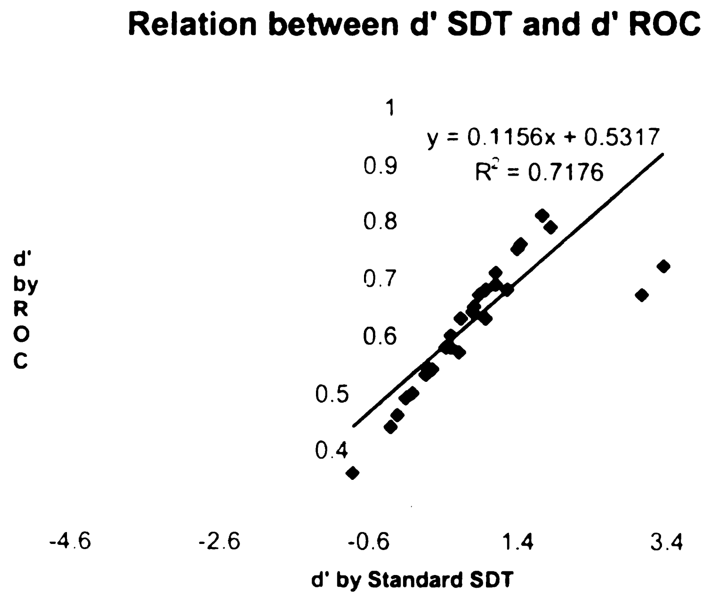


Figure 4.2 Scatter Plot between d'_{SDT} and d'_{ROC}

The plot in Figure 4.2 indicates that the theoretical linear representation is a reasonable approximation of the actual relation. In fact, the high value of the coefficient of correlation (r = 0.847) provides support that d'_{SDT} and d'_{ROC} are indeed linearly related.

4.4 Data Analysis

Sensitivity and response bias analysis results of ironworkers are summarized in Table 4.5. The table provides the value of d' obtained for each ironworker using standard SDT and the ROC curve. Table 4.5 also shows the comparison between beta current and beta optimum, which helps to determine the decision making strategy or risk orientation of each worker. If $\beta_{current}$ is less then $\beta_{optimal}$, then such strategy is considered conservative. If the value of $\beta_{current}$ is greater than $\beta_{optimal}$, then it is considered a risky strategy. The strategy in the last column of Table 4.5.

4.4.1 Average Sensitivity and Risk Orientation of Ironworkers

In this section result from the survey will be discuss in details. First discussing about the decision-making strategy of the ironworkers. The last column of Table 4.5 shows the decision-making strategy for each ironworker. The average strategy of the group of ironworker participated in this research was found to be risky.

The risk orientation of each worker was determined by comparing beta $\beta_{current}$ and β_{opt}. If $\beta_{current} < \beta_{opt}$ then it's a conservative strategy and if $\beta_{current} > \beta_{opt}$ then it's a risky strategy. There are few individuals with very high $\beta_{current}$ value, which shows they are more risky (e.g. w7, w8, w26, etc). The last column of Table 4.5 shows the sensitivity of each ironworker, which is determined based on the d'_{SDT} % as discussed in section 4.4.1.

Worker	Age	Years of Experience	Normalized d'$_{SDT}$ [1]	Normalized d' $_{ROC}$ [2]	$\beta_{current}$	Decision making Strategy	Sensitivity
w1	32	5	58.7	64	0.64	Conservative	Low
w2	30	4.5	62.07	71	0.88	Risky	Moderate
w3	22	3	68.8	81	0.85	Risky	Moderate
w4	24	9	62.07	71	0.88	Risky	Moderate
w5	35	2.5	62.07	69	0.64	Conservative	Moderate
w6	24	4	70.11	79	0.41	Conservative	Moderate
w7	21	1	56.96	63	1.08	Risky	Low
w8	26	3	48.91	49	1.1	Risky	Low
w9	24	4.5	65.11	75	0.7	Conservative	Moderate
w10	26	5	70.11	79	0.41	Conservative	Moderate
w11	30	3	65.11	75	0.7	Conservative	Moderate
w12	20	1.5	55.54	58	0.7	Conservative	Low
w13	31	2	52.5	54	0.88	Risky	Low
w14	29	3	55.54	58	0.7	Conservative	Low
w15	30	7	56.85	57	0.51	Conservative	Low
w16	36	15	68.8	81	0.85	Risky	Moderate
w17	22	1	56.85	57	0.51	Conservative	Low
w18	30	3	54.78	58	1.1	Risky	Low
w19	25	3	59.57	67	1	Risky	Low
w20	19	2	62.07	71	0.88	Risky	Moderate
w21	29	2.5	47.83	46	1.09	Risky	Low
w22	24	2.5	55.65	60	0.82	Risky	Low
w23	21	2	56.85	57	0.51	Conservative	Low
w24	24	1	48.91	49	1.1	Risky	Low
w25	25	6	83.26	67	0	Conservative	High
w26	21	1	46.74	44	1.25	Risky	Low
w27	27	6.5	70.11	79	0.41	Conservative	Moderate
w28	24	4.5	55.54	58	0.69	Conservative	Low
w29	25	3	70.11	79	0.42	Conservative	Moderate
w30	31	1.5	52.5	54	0.89	Risky	Low
w31	23	3.5	68.8	81	0.85	Risky	Moderate
w32	32	7	65.76	76	1.08	Risky	Moderate
w33	19	1	41.3	36	1.38	Risky	Low

Table 4.5 Summary of Results from SDT and ROC Curve

[1] Normalized d' by Standard SDT = (d' by Standard SDT + 4.6/9.2)
[2] Normalized d' by ROC = (d' by ROC/Ideal d' by ROC) Where ideal d' by ROC = 1

Worker	Age	Years of Experience	Normalized d'$_{SDT}$ [3]	Normalized d'$_{ROC}$ [4]	$\beta_{current}$	Decision Making Strategy	Sensitivity
w36	21	1.5	51.96	53.00	0.86	Risky	Low
w37	26	4	58.70	64.00	0.64	Conservative	Moderate
w38	24	2	60.54	63.00	0.42	Conservative	Moderate
w39	24	5	60.54	68.00	1.32	Risky	Moderate
w40	26	5.5	50.00	50.00	1	Risky	Low
w41	22	4.5	55.65	60.00	0.82	Risky	Low
w42	33	7.5	63.15	68	0.38	Conservative	Moderate
Average	**26.02**	**3.88**	**60.01**	**64.60**	**0.77**	Risky	Moderate
Standard Deviation	**4.34**	**2.66**	**9.22**	**11.58**	**0.30**	**NA**	**NA**
COV [5]	**0.17**	**0.69**	**0.15**	**0.18**	**0.38**	**NA**	**NA**

Table 4.5 Summary of Results from SDT and ROC Curve (Continued)

As shown in Table 4.4, the average age of the 42 participants was 26 years with an average 4 years of experience. The average normalized d'$_{SDT}$ and d'$_{ROC}$ are close at around 60%, indicating a low sensitivity. The average $\beta_{current}$ indicates a risky strategy. As indicated by the COV values, there was more variation in $\beta_{current}$ values compared to sensitivity.

It is also worth noting that 5 workers (worker w8, w21, w24, w26 and w33) had negative sensitivity. Because the sensitivity d' is determined by adding the two normal deviate values Z_1 and Z_2 (see Figure 4.3), a negative d' results only when the overlap between the two curves, the signal and the noise, is more than 50% (shown in Figure 4.4). This could happen in three cases:

[3] Normalized d' by Standard SDT = (d' by Standard SDT + 4.6 / 9.2)
[4] Normalized d' by ROC = (d' by ROC / Ideal d' by ROC) Where ideal d' by ROC = 1
[5] COV: coefficient of variation defined as the ratio between standard deviation and average; provided to give a measure of the amount of variability relative to the value of the average.

1. When P(Miss) is more than P(Hit) in which case Z_1 will have high negative value and d' will be negative.

2. When P(FA) is more than P(CR), that mean Z_1 has high negative value.

3. When both the above conditions are true, causing both Z_1 and Z_2 to be negative.

Referring to Table 4.1 reveals that in all five cases where d' is negative more false alarms were made, which matches case 2 above. This explains why the sensitivity (d') of those workers is negative. To improve their sensitivity, worker specific training should be developed.

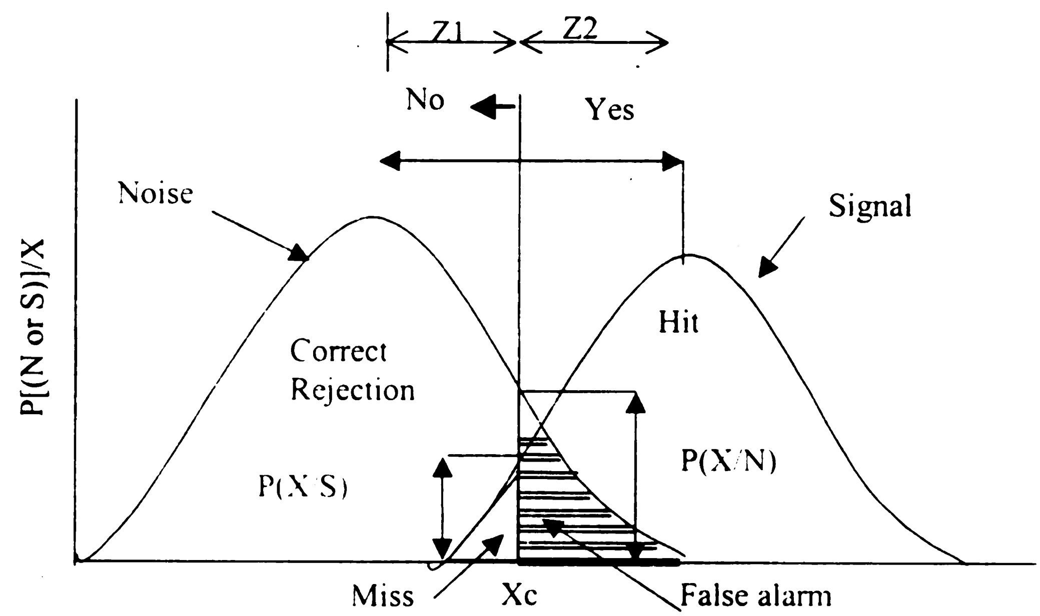


Figure 4.3 Distribution of Detection Theory (Wickens, 1992)

The following section investigates the distribution of d' and $\beta_{current}$ obtained form the survey. This will help to determine whether the distributions for d' and $\beta_{current}$ data are normally distributed

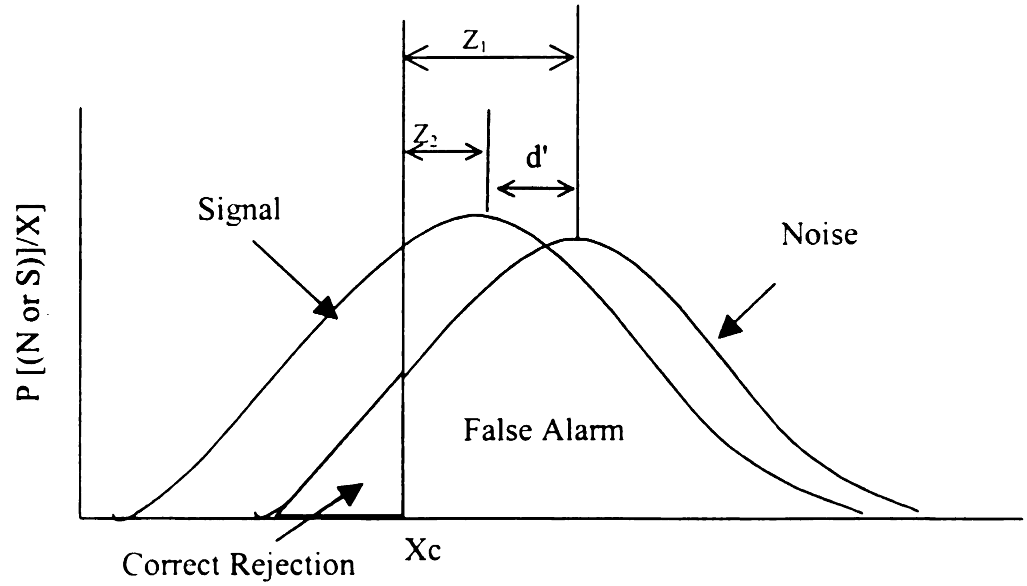


Figure 4.4 Distribution of the Survey Results

The following section investigates the distribution of d' and $\beta_{current}$ obtained form the survey. This will help to determine whether the distributions for d' and $\beta_{current}$ data are normally distributed

4.4.2 Distribution of d' and $\beta_{current}$

To determine whether the data obtained from the survey of 42 ironworkers follow a normal distribution, normal quantile plots were constructed using the statistical software Minitab. A quantile graph is plotted with the standard normal (z) score on the x axis and the data on the y-axis. If the normal quintile plot forms a straight line, then the plot indicates that the data are normally distributed (Moore and McCabe 2002). If there is any systematic deviation from a straight line, then that indicates a non normal distribution.

Using the data in Table 4.3, three quintile plots were constructed to determine the distribution of d'_{SDT}, d'_{ROC}, and $\beta_{current}$. All plots exhibited a straight-line confirming that the variables follow a normal distribution. The plots are provided in appendix E.

4.5 Regression Analysis

In this section, regression analysis is used to investigate if age or years of experience are linearly correlated with the sensitivity (d') and risk orientation ($\beta_{current}$) of an ironworker and also to investigate whether age and years of experience together are linearly correlated with the sensitivity (d') and risk orientation ($\beta_{current}$) of an ironworker (by using multiple regression).

Regression analysis is performed primarily to determine the correlation between a dependent (response) variable and an independent (predictor) variable. However, unless an independent variable is controlled and manipulated, a regression model does not imply that Y necessarily depends on X in a "causal" or "explanatory" sense. Such a causal conclusion is only justified in experiments where the independent variable is controlled and the dependent variable is observed. In this research, the regression analysis is based on quasi-experiments, i.e., there was no manipulation of the independent variables. However, while linear correlation results are reciprocal, meaning the math works regardless of which variable is labeled independent, causality is not.

In regression analysis, the coefficient of correlation (represented by r) measures the linear relationship between the response variable and the predictor. The coefficient r is always a number between –1 and 1. A value of r near 0 indicates a very weak linear relationship. The strength of the relationship increases as r moves away from 0 toward either –1 or 1. The extreme values of r = -1 and r = 1 occur only when the points in a scatter plot lie exactly along a straight line. The value of r can be determined using the equation 4.2 (Moore and McCabe 2002).

$$r = \frac{n\sum_{i=1}^{n} XiYi - \sum_{i=1}^{n} Xi \sum_{i=1}^{n} Yi}{\sqrt{\left[n\sum_{i=1}^{n} \mathrm{Xi}^{2} - \left(\sum_{i=1}^{n} Xi\right)^{2}\right]\left[n\sum_{i=1}^{n} \mathrm{Yi}^{2} - \left(\sum_{i=1}^{n} Yi\right)^{2}\right]}} \tag{4.2}$$

After r is determined. hypothesis testing is typically performed to assess the significance of the relation between the two variables under investigation. Usually the null hypothesis is a statement of "not related" or "not effected", etc. The statement of null hypothesis is denoted as H_o: $\rho = 0$. and the statement that will be true if H_0 is not true. the alternative hypothesis and is denoted as H_a: $\rho \neq 0$.

To determine whether the null hypothesis is rejected. a test statistic is determined and computed to a calculate test statistic. The test is designed to check the strength of evidence against the null hypothesis. The less probable the outcome. the stronger the evidence that H_o is false (Moore and McCabe 2002). Assuming the variables have a bivariate normal distribution. H_o: $\rho = 0$ versus H_a: $\rho \neq 0$ is tested as follows:

If $Z_{calc} > Z_{(\alpha/2)}$: H_o is rejected and if $Z_{calc} < Z_{(\alpha/2)}$ H_o cannot be rejected. Z can be calculated using equation 4.3 (Moore and McCabe 2002).

$$Z = \frac{\left(\frac{1}{2}\right)\ln\left[\frac{1+r}{1-r}\right] - \left(\frac{1}{2}\right)\ln\left[\frac{1+\rho_o}{1-\rho_o}\right]}{\frac{1}{\sqrt{n-3}}} \tag{4.3}$$

For the purposes of this research. α of 0.05 is used. Hence. $Z_{(\alpha/2)} = Z_{(0.05/2)} =$ 1.96.

Another common method of performing the hypothesis testing is to use the ***p-value***. The P-value is a statistical quantity that represents the smallest value of α for which the null hypothesis is rejected. Therefore, the p-value represents the statistical significance of the alternative hypothesis. In addition, the p-value can also be used to perform the hypothesis testing itself. If P-value < α: H_o is rejected and if P-value > α: H_o cannot be rejected. The p-value can be calculated using the following equation (Moore and McCabe 2002):

$$\text{P-value} = 2 * P\ (Z > Z_{calc}) \tag{4.4}$$

4.5.1 Regression Analysis for Age

4.5.1.1 Age vs. d'$_{SDT}$

The regression plot of age and d'$_{SDT}$ is shown in Figure 4.5. The value of r for this relation was 0.27. This indicates that the linear relationship between the age of the ironworkers and their sensitivity is quite low.

Testing of the null hypothesis that age and d' are not related versus that they are was conducted as follows using standard SDT:

Using Equation 4.3: $Z = 1.78$ (note $r = 0.27$, $\rho_o = 0$, and $n = 42$)

The rejection region for H_o is when $Z_{calc} > Z_{(\alpha/2)}$; $Z_{(\alpha/2)} = Z_{(0.05/2)} = 1.96$

$\therefore Z_{calc} < Z_{(\alpha/2)}$, hence H_o cannot be rejected.

Using equation 4.4: P-value = 2* P (Z > 1.78) = 0.075 > α. Hence, for any value of alpha less than 0.075, the null hypothesis cannot be rejected.

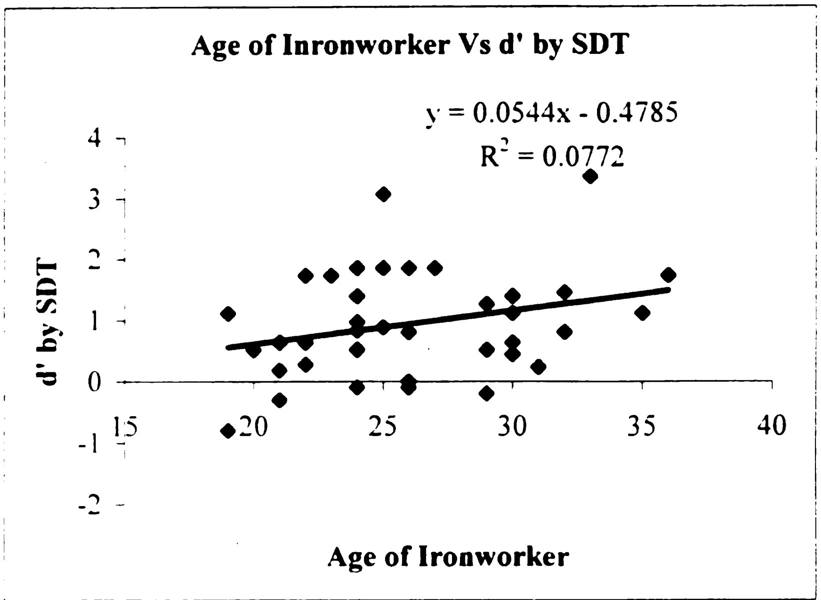


Figure 4. 5 Age of Ironworker vs. d' Using Standard SDT

4.5.1.2 Age vs. d'_{ROC}

Figure 4.6 shows a scatter plot for the sensitivity of the ironworkers using the ROC curve and age. The value of r = 0.256 is close to that obtained for d'_{SDT}. This indicates a low correlation between age and sensitivity. Testing the null hypothesis that age and d' using ROC are not related versus that they are was conducted as follows:

Using Equation 4.3: $Z = 1.64$ (note: r = 0.256, $\rho_0 = 0$, and n = 42); $Z_{(\alpha/2)} = 1.96$

$\therefore\ Z_{calc} < Z_{(\alpha/2)}$, hence H_o cannot be rejected.

Using equation 4.4: P-value = 2* P (Z > 1.64) = 0.101> α. Hence, for any value of alpha less than 0.101, the null hypothesis cannot be rejected.

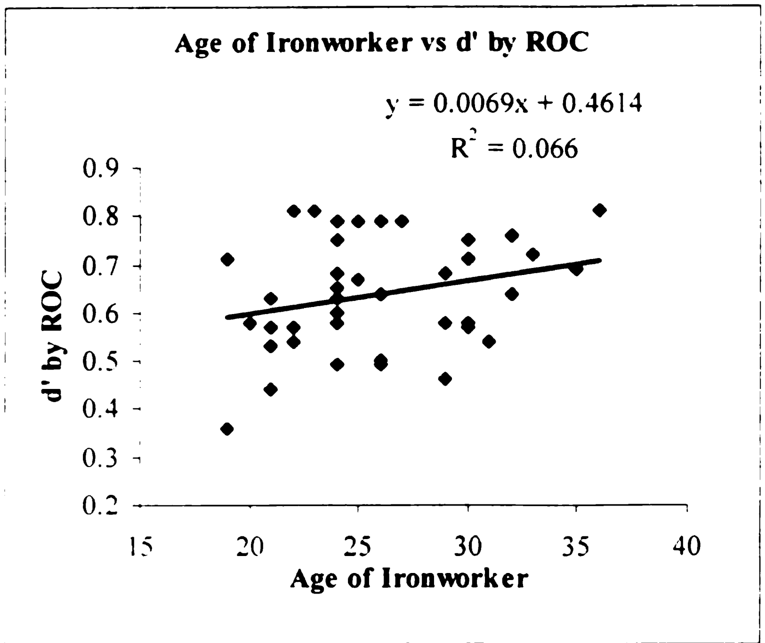


Figure 4.6 Age of Ironworker vs. d' Using ROC

4.5.1.3 Regression Analysis for Age vs. Beta Current ($\beta_{current}$)

In this case, the response variable is risk orientation ($\beta_{current}$) and the predictor is the age of the ironworker. The scatter plot for the two is shown in Figure 4.7. In this case, a value of r = 0.156 was found, which again indicates a low correlation between age and the risk orientation of the ironworkers. Testing the null hypothesis that age and $\beta_{current}$ are not related versus that they are was conducted as follows:

Using Equation 4.3: $Z = 0.985$ (note: $r = 0.156$, $\rho_0 = 0$, and $n = 42$); $Z_{(\alpha/2)} = 1.96$

$\therefore Z_{calc} < Z_{(\alpha/2)}$. Hence H_0 cannot be rejected.

Using equation 4.4: P-value = 2* P (Z > 0.985) = 0.3260 > α: hence, for any value of alpha less than 0.3260, the null hypothesis cannot be rejected. This strongly suggests that there is no correlation between the age of the ironworker and $\beta_{current}$.

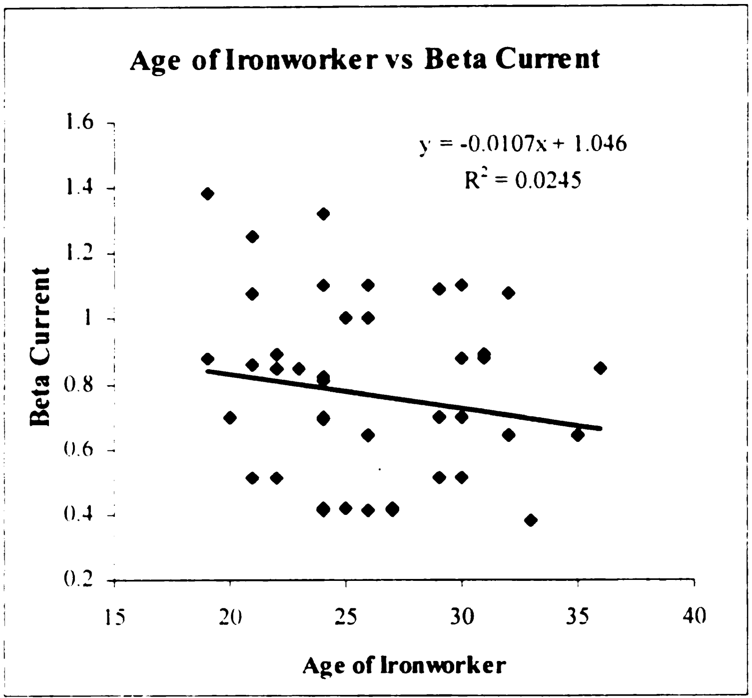


Figure 4.7 Age of Ironworker vs. Beta Current

4.5.2 Regression Analysis for Years of Experience

In this section, a similar analysis to that shown in the preceding section is performed to determine the correlation between the ironworkers' years of experience and the SDT-derived variables. Figures 4.8-4.10 show the scatter plots for years of experience against d'_{SDT}, d'_{ROC}, and $\beta_{current}$.

Table 4.6 shows the results of the regression analysis for experience and the SDT parameters. The results strongly suggest that there is a correlation between the years of experience of the ironworker and sensitivity. However, no correlation was found between the years of experience of the ironworker and risk orientation.

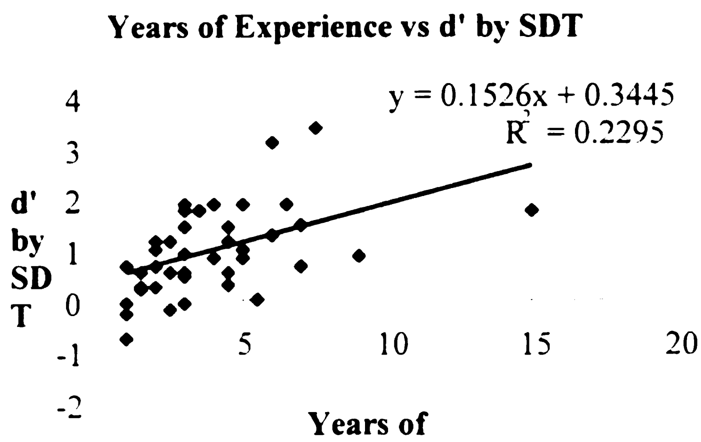


Figure 4.8 Years of Experience of Ironworker vs. d'_{SDT}

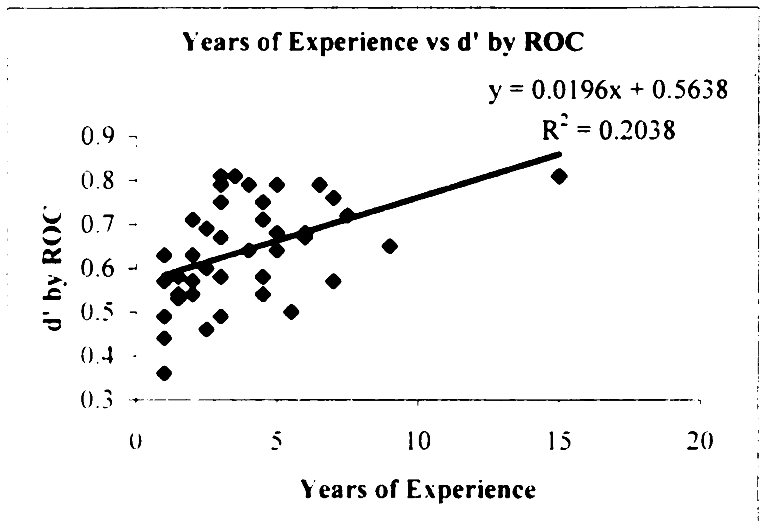


Figure 4. 9 Years of Experience of Ironworker vs. d'_{ROC}

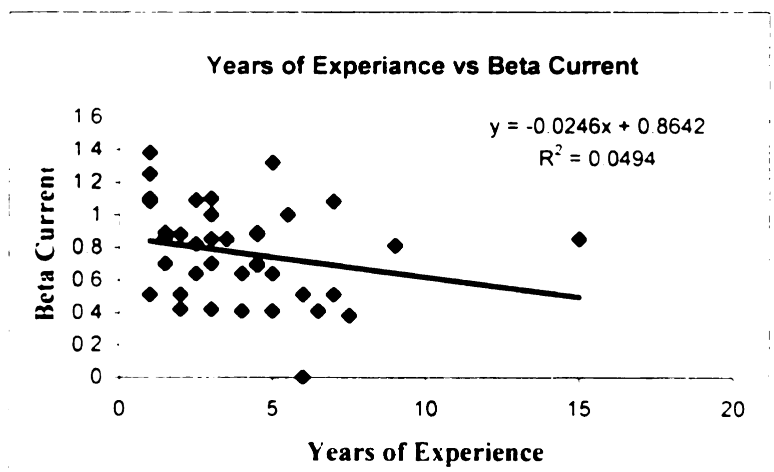


Figure 4. 10 Years of Experience of Ironworker vs. $\beta_{current}$

Regression Variables	R	Z_{calc}	P-Value	Hypothesis Testing Result
Experience and d'_{SDT}	0.48	3.258	0.0012	H_0 is rejected.
Experience and d'_{ROC}	0.45	3.038	0.0024	H_0 is rejected.
Experience and $\beta_{current}$.	0.22	1.411	0.1586	H_0 is cannot be rejected.

Table 4.6 Regression Analyses for Years of Experience

The above section discusses the regression analysis to determine the correlation between age or years of experience Vs the sensitivity (d') and risk orientation ($\beta_{current}$) of an ironworker. Now to determine the combined effect of age and years of experience Vs the sensitivity (d') and risk orientation ($\beta_{current}$), multiple regression analysis is performed and is discussed in the following section.

4.5.3 Multiple Regression Analysis

Multiple regression analysis in general is performed to determine the correlation of more than one variable. In this research, multiple regression is performed to learn more about the relation between two independent variables, the age and years of experience of ironworkers, and two dependent variables, a) the sensitivity (d') and b) risk orientation ($\beta_{current}$) of ironworkers.

This analysis is performed in Microsoft Excel and the tables obtained from the analysis are provided in appendix F. Based on the value of Adjusted R (Appendix F), Z values and P-values were determined and are summarized in Table 4.7. The results strongly suggest that there is a correlation between the age and years of experience together and the sensitivity of an ironworker. From the analysis in the above section, it was determined that the years of experience of an ironworker alone had a correlation with the sensitivity of the ironworker. However, the results of multiple regression analysis suggest that the age and years of experience of an ironworker together affect his/her sensitivity.

Hence, it could be concluded that the number of years of experience has a strong correlation with sensitivity, and further, it could also be concluded that the number of years of experience along with age affects the sensitivity of a worker with a 95% confidence interval. This means that an older worker with more years of experience will have a higher sensitivity to unsafe conditions.

However, no correlation was found between the age and years of experience of an ironworker (together) and risk orientation. This means that the risk orientation of an ironworker does not change with age or with years of experience. Thus, one may conclude that other variables, such as training or supervision, should be tested to see if they change ironworkers' risk orientation.

Regression Variables	**R**	Z_{calc}	**P-Value**	**Hypothesis Testing Result**
Age & Years of Experience vs. d'_{SDT}	0.437	2.92	0.0036	H_0 is rejected.
Age & Years of Experience vs. d'_{ROC}	0.404	2.68	0.0076	H_0 is rejected.
Age & Years of Experience vs. $\beta_{current}$	0.055	0.342	0.733	H_0 is cannot be rejected.

Table 4.7 Multiple Regression Analysis Results

4.6 Summary

In this chapter, survey data was analyzed using Signal Detection Theory to determine the sensitivity and risk orientation of ironworkers to unsafe condition. The ROC curve also helped to determine the sensitivity of ironworkers by considering the joint effects of response bias and sensitivity (i.e. the joint effects of risk orientation and sensitivity). The results were further analyzed using regression analysis to determine whether the sensitivity or risk orientation of ironworkers is related to their age or years of experience. Also, to determine whether age and years of experience together had any correlation, multiple regression was performed.

The objectives stated in chapter 1 were achieved using the methods and techniques discussed in chapter 3 and chapter 4. Chapter 5 discusses the results and research contributions and concludes with the research limitations and areas of future research.

Chapter 5

SUMMARY AND CONCLUSION

5. Conclusions and Summary

5.1 Conclusions

Construction accidents and specially falls are of major concern for the construction industry and the researchers. Despite the contributions of many construction accident causation models in understanding the accident process, none adequately explain the underlying causes of construction accidents due to its dynamic nature. To over come this limitation a new approach to understand construction accidents has been proposed by Howell et al (2002) based on the work of Rasmussen (1997). The model suggested recognizes that organizational and individual pressures push people to work in hazardous situations. These pressures defeat efforts to enforce safe work rules specifically in a changing work environment such as in construction. Therefore, this approach emphasizes the need to train workers to be conscious of hazardous work environments and engage the work with better planning. So the focus of this research was to develop a model to determine the sensitivity and risk orientation of construction workers, which in turn will help to design worker specific training.

To achieve this goal a survey was developed based on OSHA standard of fall protection and from fall cases reported by NIOSH. With the help of this survey the sensitivity and risk orientation of ironworkers was be determined using SDT. This research focused on assessment of occupational safety and health competencies of construction ironworkers. The result of this research suggest that around 95 % (i.e. 40 out of 42) ironworker who participated in this research have "low" to "moderate" sensitivity toward unsafe condition. This reveals that most workers lack proper safety and health knowledge and require additional training.

The tools presented in this study provide may be used to determine the sensitivity and risk orientation of workers to unsafe conditions. Based on the result of this analysis, worker-specific could be developed to increase the sensitivity and decrease risky behavior towards unsafe conditions.

- In general, based on the analysis performed in this research, the following conclusions are drawn:

- This model could be used as a pre-test and post- test after training for assessing the effect of training.

- Feed back to OSHA on regulation, if for example a particular scenario is always missed or considered safe.

- The whole group of ironworker who participated in this research has risky strategy, which means they should be trained again to change their risk orientation.

- 50% of the ironworkers who participated in the survey have a risky decision-making strategy which means they will have more misses then false alarms. These workers should be trained to change the decision-making strategy from risky to conservative.

- The average sensitivity of the group is moderate when compared to ideal d'.

- The sensitivity and response bias data for the ironworkers follow a normal distribution.

- Regression analysis indicated that sensitivity (d') and risk orientation ($\beta_{current}$) of ironworkers is not linearly correlated to age.

- Regression analysis indicates a moderate dependency between years of experience and sensitivity of the ironworkers ($r = 0.48$, p-value <0.0006). However no linear correlation was found between years of experience and risk orientation of the ironworkers.

5.2 Limitations of this Research

The questionnaire developed for the survey is not based on any company's safety policy or training guides and also just focuses on fall protection. It is based on OSHA fall protection standards and the case studies from NIOSH report only. In this research it is assumed that the worker would react the same as he or she responded in the survey when faced with any of the scenarios portrayed by the survey. Based on this assumption the sensitivity and risk orientation of the ironworker has been determined using Signal Detection Theory.

5.3 Areas of future Research

Future research should consider larger samples as well as other construction trade to determine the sensitivity and risk orientation of the workers. Based on the results. SDT and ROC curve analysis could be performed in a similar way to that performed in this research. Real-time investigation of how workers respond to safe and unsafe condition is also important. Another important area of research is that regarding the design of training after the SDT parameters are determined. Effect of injury history and training frequency should be considered.

5.4 Contributions of the Research

- A technique to determine the sensitivity and risk orientation of the construction workers to safe and unsafe condition was developed.

- A survey allowing the assessment of worker sensitivity and risk orientation to conditions leading to fall accidents was developed.

- Signal detection theory was implanted in construction to determine the sensitivity and risk orientation of workers to unsafe conditions

- The practical application of Rasmussen theory of accident causation in construction was enabled.

- A framework for developing guidelines to design worker specific training

APPENDIX A

Consent letter and Survey questionnaire

CONSENT LETTER

Subject Consent Form

IRONWORKER OCCUPATIONAL SAFETY KNOWLEDGE

Principal Investigators: **Tariq S. Abdelhamid, PhD**
Research Assistant: **Bhavin Patel**

The Construction Management program at Michigan State University is conducting a research project to assess the occupational safety knowledge of ironworkers. The research will help in improving the effectiveness of safety training programs. You are being asked to participate in this project in your capacity as a construction ironworker.

As a participant in this research, you will be asked to complete a 21-question survey on occupational safety rules related to fall protection.

Your assistance is voluntary and you may choose to stop assisting at any time during this project. Your privacy will be protected to the maximum extent allowable by law. Your company or you will not be identified by name. The estimated time for the survey is 30-45 minutes. As a participant, you may request a copy of this consent letter for your records.

If you have any questions about this project, you can do so by contacting Dr. Tariq Abdelhamid, Construction Management Program, Michigan State University at (517) 432-6188. Also if you have any question about your rights as a human subject to a research project, please contact Dr. Ashir Kumar, at University Committee on Research Involving Human Subjects (UCRIHS), Michigan State University at 517-355-2180 (email: ucrihs@msu.edu; 202 Olds Hall, East Lansing, MI 48824).

I voluntarily agree to participate in this study.

Subject Name   Occupation   Signature   Date

Witness Name   Occupation   Signature   Date

SURVEY QUESTIONNAIRE

MSU Member: ______________________

MICHIGAN STATE UNIVERSITY

Ironworker Occupational Safety Assessment

Date: ________________

Name of the Company: ____

Location of Job Site: ____

Name/Title of Person Interviewed: __________________________________

Construction Experience (In Years): _________________________________

Age: _______________

INTERVIEW QUESTIONS

Please choose one of the classifications that fits the following conditions:

1) Working on a 130 foot high coupler scaffold designed by the company foreman.

- ☐ An Unsafe Condition
- ☐ A Safe Condition
- ☐ I Don't Know

2) Working on a scaffold 8 feet above the lower level without a guardrail system.

- ☐ An Unsafe Condition
- ☐ A Safe Condition
- ☐ I Don't Know

3) Working on the 5th floor of a building where permanent bolting/welding on the 1st floor has just begun.

☐ An Unsafe Condition

☐ A Safe Condition

☐ I Don't Know

4) Working on the erection of the 15th floor of a steel structure where the permanent floor decking has been installed up to the 6th floor only.

☐ An Unsafe Condition

☐ A Safe Condition

☐ I Don't Know

5) Working on a scaffold which is 12 feet above the lower level (where permanent decking has been installed) without any fall protection.

☐ An Unsafe Condition

☐ A Safe Condition

☐ I Don't Know

6) Working on a 3.500-sq.ft. decking which has an unsecured connection.

☐ An Unsafe Condition

☐ A Safe Condition

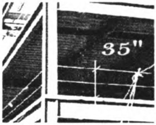
☐ I Don't Know

7) Working on the second floor of a building, which is provided with perimeter safety cables. The top cable is fixed at 35 inches from floor level.

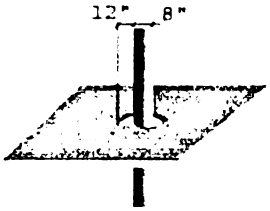
☐ An Unsafe Condition

☐ A Safe Condition

☐ I Don't Know



8) Working on a 37-foot high platform that is provided with a 3.5 foot high steel railing. An 8-foot diameter vent stack runs vertically through the center of the platform, with 12-inch annular space between the vent stack and the platform.



- [ ] An Unsafe Condition
- [ ] A Safe Condition
- [ ] I Don't Know

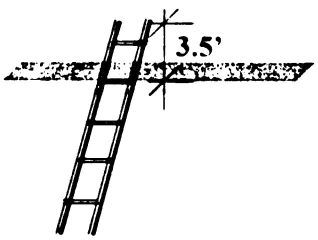
9) A 50-inch square opening was created while working on renovation of a flat roof.

- [ ] An Unsafe Condition
- [ ] A Safe Condition
- [ ] I Don't Know

10) You are working on the 11th floor of a building where permanent bolting/welding on the 9th floor has just begun.

- [ ] An Unsafe Condition
- [ ] A Safe Condition
- [ ] I Don't Know

11) When climbing a portable ladder used for access to an upper landing surface, the side rail extends 3.5 feet above the upper landing surface.



- [ ] An Unsafe Condition
- [ ] A Safe Condition
- [ ] I Don't Know

12) Working on the erection of the 11th floor of a steel structure where the permanent floor decking has been installed up to the 6th floor only.

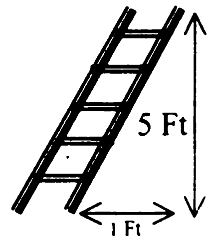
- [ ] An Unsafe Condition
- [ ] A Safe Condition
- [ ] I Don't Know

13) Climbing a portable ladder, which is set 1foot out for every 5 feet, as shown in the figure.

☐ An Unsafe Condition

☐ A Safe Condition

☐ I don't know



14) Working on a scaffold 5 feet above the lower level without a guardrail system.

☐ An Unsafe Condition

☐ A Safe Condition

☐ I Don't Know

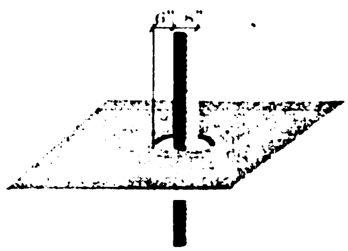
15) Bolting a steel member with a co-worker on the second floor of a building while the ¾ " steel sway bracing rod has not been installed.

☐ An Unsafe Condition

☐ A Safe Condition

☐ I Don't Know

16) Working on a 37 foot high platform that is provided with a 3.5 foot high steel railing. An 8-foot diameter vent stack runs vertically through the center of the platform, with 6-inch annular space between the vent stack and the platform.



☐ An Unsafe Condition

☐ A Safe Condition

☐ I Don't Know

17) Working on a scaffold with a walkway that is 10 foot long, 12 inches wide and is extended over its support by 18 inches.

☐ An Unsafe Condition

☐ A Safe Condition

☐ I Don't Know

18) You are working on a 3,000-sq.ft. decking which has an unsecured connection.

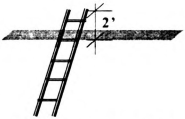
- [ ] An Unsafe Condition
- [ ] A Safe Condition
- [ ] I Don't Know

19) You are working on the 11th floor of a building where permanent bolting/welding on the 9th floor has just begun.

- [ ] An Unsafe Condition
- [ ] A Safe Condition
- [ ] I Don't Know

20) Climbing a portable ladder used for access to an upper landing surface when the side rail extends 2 feet above the upper landing surface

- [ ] An Unsafe Condition
- [ ] A Safe Condition
- [ ] I Don't Know



21) Working on the second floor of a building, which is provided, with perimeter safety cables. The top cable is fixed at 42-inch from floor level.

- [ ] An Unsafe Condition
- [ ] A Safe Condition
- [ ] I don't know

APPENDIX B

Results of Response of Ironworker

Q. No.	Worker 11 Age = 30 Yrs of Exp = 3				Worker 12 Age = 20 Yrs of Exp = 1.5				Worker 13 Age = 31 Yrs of Exp = 2				Worker 14 Age = 29 Yrs of Exp = 3				Worker 15 Age = 30 Yrs of Exp = 7			
	Hit	Miss	FA	CR	Hit	Miss	FA	CR	Hit	Miss	FA	CR	Hit	Miss	FA	CR	Hit	Miss	FA	CR
Q 1	X				X				X				X				X			
Q 2			X				X				X				X				X	
Q 3			X				X				X				X				X	
Q 4	X				X				X				X				X			
Q 5	X				X				X				X				X			
Q 6	X				X				X				X				X			
Q 7	X				X				X				X				X			
Q 8	X				X				X				X				X			
Q 9	X				X				X				X				X			
Q 10				X			X				X				X				X	
Q 11				X				X				X				X				X
Q 12	X				X				X				X				X			
Q 13		X				X				X				X				X		
Q 14				X				X				X				X			X	
Q 15	X				X					X				X			X			
Q 16				X			X				X				X				X	
Q 17		X				X				X			X				X			
Q 18				X				X				X				X				X
Q 19			X				X				X				X				X	
Q 20				X			X				X				X				X	
Q 21	X				X				X				X				X			
Total	10	2	3	6	10	2	6	3	9	3	6	3	10	2	6	3	11	1	7	2
Probability	0.83	0.17	0.33	0.67	0.83	0.16	0.67	0.33	0.75	0.3	0.7	0.33	0.83	0.17	0.67	0.33	0.92	0.08	0.78	0.22

Table B.1 Detailed Results of the Survey Continues

Q. No.	Worker 41 Age = 22 Yrs of Exp = 4.5				Worker 42 Age = 33 Yrs of Exp = 7.5			
	Hit	Miss	FA	CR	Hit	Miss	FA	CR
Q 1	X				X			
Q 2			X				X	
Q 3			X				X	
Q 4	X				X			
Q 5	X				X			
Q 6	X				X			
Q 7		X			X			
Q 8		X			X			
Q 9	X				X			
Q 10				X				X
Q 11				X				X
Q 12	X				X			
Q 13	X				X			
Q 14			X					X
Q 15	X				X			
Q 16			X				X	
Q 17		X				X		
Q 18				X				X
Q 19			X				X	
Q 20				X			X	
Q 21	X				X			
Total	9	3	5	4	11	1	5	4
Probability	0.75	0.25	0.56	0.44	0.92	0.0833	0.56	0.44

Table B.1 Detail Results of the Survey Continues

APPENDIX C

Result of the Analysis of the Data for Ironworkers Using SDT and ROC

Workers	Probability				Z values		Coordinates		d' with SDT	d' with ROC	beta current	beta optimum
	Hit	Miss	FA	CR	Z1	Z2	z1	z2				
w1	0.83	0.17	0.56	0.44	-0.15	0.954	0.39	0.25	0.8	0.64	0.64	0.75
w2	0.75	0.25	0.33	0.67	0.44	0.67	0.36	0.32	1.11	0.71	0.88	0.75
w3	0.83	0.17	0.22	0.78	0.77	0.954	0.3	0.25	1.73	0.81	0.85	0.75
w4	0.75	0.25	037	0.67	0.44	0.67	0.36	0.32	1.11	0.71	0.88	0.75
w5	0.83	0.17	0.44	0.56	0.15	0.95	0.39	0.25	1.11	0.69	0.64	0.75
w6	0.92	0.08	0.33	0.67	0.44	1.41	0.36	0.15	1.85	0.79	0.41	0.75
w7	0.58	0.42	0.33	0.67	0.44	0.2	0.36	0.39	0.64	0.63	1.08	0.75
w8	0.75	0.25	0.77	0.23	-0.77	0.67	0.29	0.32	-0.1	0.49	1.1	0.75
w9	0.83	0.17	0.33	0.67	0.44	0.95	0.36	0.25	1.39	0.75	0.7	0.75
w10	0.92	0.08	0.33	0.67	0.44	1.4	0.36	0.15	1.85	0.79	0.41	0.75
w11	0.83	0.17	0.33	0.67	0.44	0.95	0.36	0.25	1.39	0.75	0.7	0.75
w12	0.83	0.17	0.67	0.33	-0.4	0.95	0.36	0.25	0.51	0.58	0.7	0.75
w13	0.75	0.25	0.67	0.33	-0.4	0.67	0.23	0.54	0.23	0.54	0.88	0.75
w14	0.83	0.17	0.67	0.33	-0.4	0.95	0.36	0.25	0.51	0.58	0.7	0.75
w15	0.92	0.08	0.78	0.22	-0.8	1.41	0.29	0.15	0.63	0.57	0.51	0.75
w16	0.83	0.17	0.22	0.78	0.77	0.954	0.3	0.25	1.73	0.81	0.85	0.75
w17	0.92	0.08	0.78	0.22	-0.8	1.41	0.29	0.15	0.63	0.57	0.51	0.75
w18	0.5	0.5	0.33	0.67	0.44	0	0.36	0.4	0.44	0.58	1.1	0.75
w19	0.67	0.33	0.33	0.67	0.44	0.44	0.36	0.36	0.88	0.67	1	0.75
w20	0.75	0.25	0.33	0.67	0.44	0.67	0.36	0.32	1.11	0.71	0.88	0.75
w21	0.58	0.42	0.67	0.33	-0.4	0.2	0.39	0.36	-0.2	0.46	1.09	0.75
w22	0.75	0.25	0.56	0.44	-0.15	0.67	0.39	0.32	0.52	0.6	0.82	0.75
w23	0.92	0.08	0.77	0.22	-0.77	1.41	0.29	0.15	0.63	0.57	0.51	0.75
w24	0.75	0.25	0.78	0.22	-0.8	0.67	0.29	0.32	-0.1	0.49	1.1	0.75
w25	1	0	0.67	0.33	-0.4	3.5	0.36	0	3.06	0.67	0.01	0.75
w26	0.67	0.33	0.78	0.22	-0.8	0.44	0.29	0.36	-0.3	0.44	1.25	0.75
w27	0.92	0.08	0.33	0.67	0.44	1.41	0.36	0.15	1.85	0.79	0.41	0.75
w28	0.833	0.17	0.7	0.3	-0.4	1	0.4	0.3	0.51	0.58	0.694	0.75
w29	0.92	0.08	0.33	0.67	0.44	1.41	0.36	0.15	1.85	0.79	0.42	0.75
w30	0.75	0.25	0.67	0.33	-0.4	0.67	0.36	0.32	0.23	0.54	0.89	0.75
w31	0.83	0.17	0.22	0.78	0.77	0.954	0.3	0.25	1.73	0.81	0.85	0.75
w32	0.75	0.25	0.22	0.78	0.77	0.67	0.3	0.32	1.45	0.76	1.08	0.75
w33	0.5	0.5	0.78	0.22	-0.8	0	0.29	0.4	-0.8	0.36	1.38	0.75
w34	0.92	0.08	0.22	0.78	0.77	1.41	0.3	0.15	2.18	0.85	0.51	0.75
w35	0.92	0.08	0.33	0.67	0.44	1.41	0.36	0.15	1.85	0.79	0.42	0.75

Table C .1 Summary for Each Worker Who Participated in the Survey

Workers	Probability				Z values		Coordinates		d' with SDT	d' with ROC	beta current	beta optimum
	Hit	Miss	FA	CR	Z1	Z2	z1	z2				
w36	0.83	0.17	0.78	0.22	-0.8	0.95	0.29	0.25	0.18	0.53	0.86	0.75
w37	0.83	0.17	0.56	0.44	-0.15	0.95	0.39	0.25	0.8	0.64	0.64	0.75
w38	0.92	0.08	0.67	0.33	-0.44	1.41	0.36	0.15	0.97	0.63	0.42	0.75
w39	0.58	0.42	0.22	0.78	0.77	0.2	0.3	0.39	0.97	0.68	1.32	0.75
w40	0.67	0.33	0.67	0.33	-0.4	0.4	0.36	0.36	0	0.5	1	0.75
w41	0.75	0.25	0.56	0.44	-0.2	0.67	0.39	0.32	0.52	0.6	0.82	0.75
w42	0.92	0.08	0.56	0.44	-0.2	1.41	0.39	0.15	1.21	0.68	0.38	0.75

Table C .1 Summary for each worker who participated in survey (Continued)

APPENDIX D

Normalized SDT Table

p	Normal Deviation Z	Ordinates
0.01	2.326	0.027
0.02	2.054	0.048
0.03	1.881	0.068
0.04	1.751	0.086
0.05	1.645	0.103
0.06	1.555	0.119
0.07	1.476	0.134
0.08	1.405	0.149
0.09	1.341	0.162
0.1	1.282	0.176
0.11	1.227	0.188
0.12	1.175	0.2
0.13	1.126	0.212
0.14	1.08	0.223
0.15	1.036	0.233
0.16	0.994	0.243
0.17	0.954	0.253
0.18	0.915	0.263
0.19	0.878	0.272
0.2	0.842	0.28
0.21	0.806	0.288
0.22	0.772	0.296
0.23	0.739	0.304
0.24	0.706	0.311
0.25	0.674	0.318
0.26	0.643	0.325
0.27	0.613	0.331
0.28	0.583	0.337
0.29	0.553	0.342
0.3	0.524	0.348
0.31	0.496	0.353
0.32	0.468	0.358
0.33	0.44	0.362
0.34	0.412	0.367
0.35	0.385	0.371
0.36	0.358	0.374
0.37	0.332	0.378
0.38	0.305	0.381
0.39	0.279	0.384
0.4	0.253	0.386
0.41	0.228	0.389
0.42	0.202	0.391
0.43	0.176	0.393
0.44	0.151	0.394
0.45	0.126	0.396
0.46	0.1	0.397
0.47	0.075	0.398
0.48	0.5	0.398
0.49	0.25	0.399
0.5	0	0.399

Table D.1 Normal Deviation and Ordinates for Calculating d' and β

APPENDIX E

Distribution Plots of d' and $\beta_{current}$

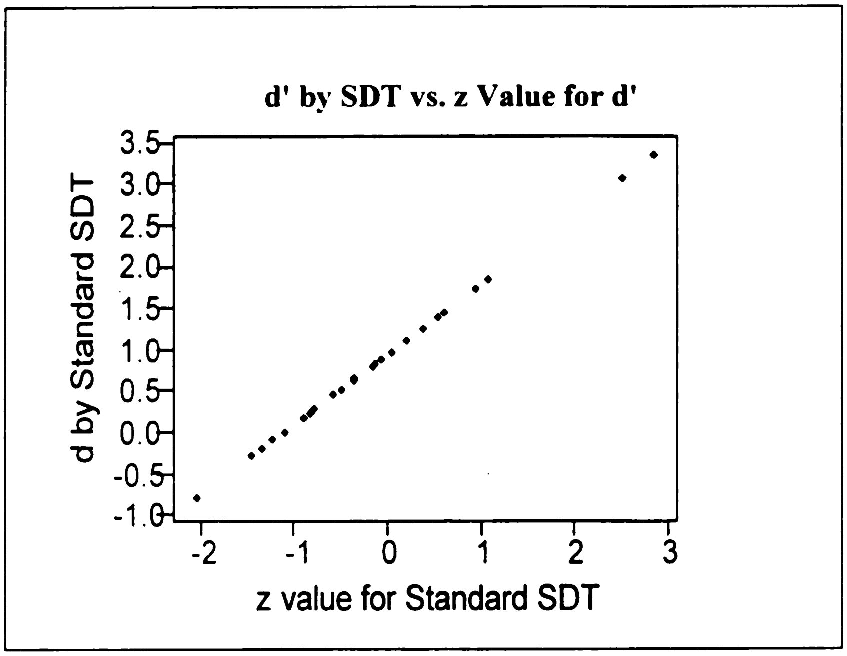


Figure E. 1 Distribution Plot for d' by SDT

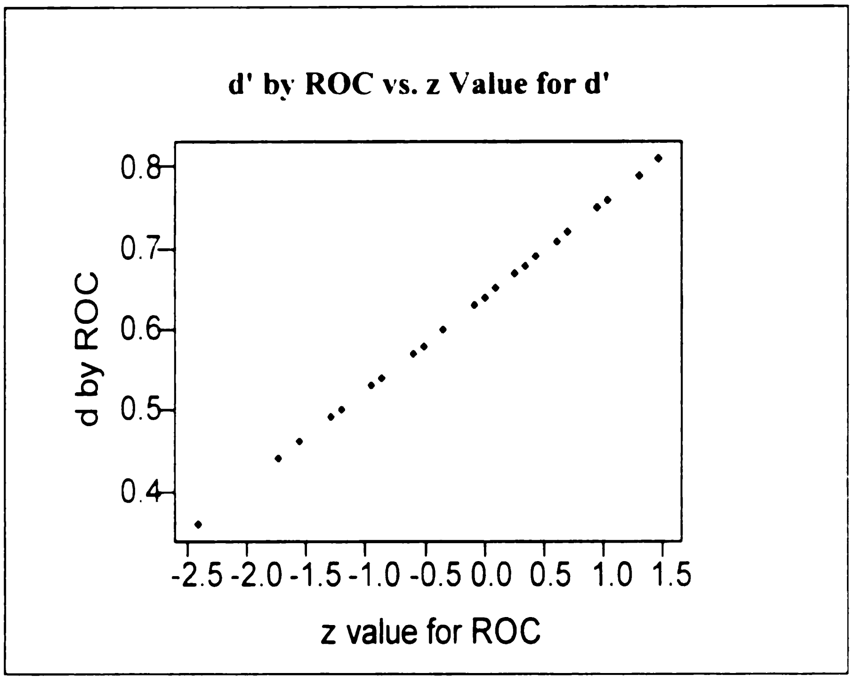


Figure E. 2 Distribution Plot for d' by ROC

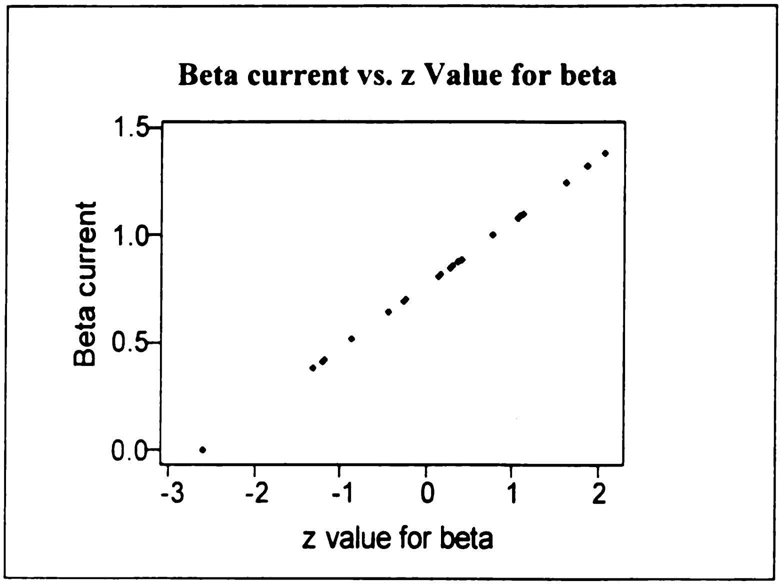


Figure E. 3 Distribution Plot for Beta Current

APPENDIX F

Result of Multiple Regression

Age & Years of Experience vs. Beta Current

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.22736
R Square	0.05169
Adjusted R Square	0.00306
Standard Error	0.29491
Observations	42

ANOVA

	df	SS	MS	F	Significance F
Regression	2	0.18491	0.0924	1.0630	0.35520
Residual	39	3.39200	0.0869		
Total	41	3.57691			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.95165	0.29397	3.237	0.00246	0.357026	1.546	0.357	1.54628
Age	-0.00384	0.01242	-0.309	0.75856	-0.02897	0.021	-0.028	0.02128
Years of Experience	-0.02139	0.02022	-1.057	0.29669	-0.06229	0.019	-0.062	0.01951

Table F.3 Detail Results of Ms Excel Analysis for Age & Years of Experience vs. Beta Current

Age & Years of Experience vs. Sensitivity by ROC

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.4522
R Square	0.2044
Adjusted R Square	0.1636
Standard Error	0.1059
Observations	42

ANOVA

	df	SS	MS	F	Significance F
Regression	2	0.11246	0.056	5.01251	0.01155
Residual	39	0.43753	0.011		
Total	41	0.55			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.5448	0.10558	5.160	7.52E-06	0.33133	0.758	0.331	0.75845
Age	0.0008	0.00446	0.186	0.85304	-0.00819	0.009	-0.00	0.00985
Years of Experience	0.0189	0.00726	2.605	0.01291	0.00423	0.033	0.004	0.03361

Table F.2 Detail Results of Ms Excel Analysis for Age & Years of Experience vs. Sensitivity by ROC

Age & years of experience vs. Sensitivity by SDT

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.4803
R Square	0.2307
Adjusted R Square	0.1912
Standard Error	0.7632
Observations	42

ANOVA

	df	SS	MS	F	Significance F
Regression	2	6.81302	3.406	5.84784	0.00600
Residual	39	22.7184	0.582		
Total	41	29.5314			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.16525	0.76081	0.2172	0.8291	-1.3736	1.704	-1.37363	1.70414
Age	0.00787	0.03214	0.2451	0.8076	-0.0571	0.0729	-0.05715	0.07290
Years of Experience	0.14598	0.05233	2.7893	0.0081	0.04012	0.2518	0.040125	0.25185

Table F.1 Detail Results of Ms Excel Analysis for Age & Years of Experience vs. Sensitivity by SDT

REFERENCES

REFERENCES

Abdelhamid, T. (2003). "Construction Safety and Ergonomics". *Construction research congress.*

Abdelhamid, T. and Everett (2000). "Identifying root causes of construction accidents". *Journal of Construction Engineering and Management.* ASCE, 52-59.

B, Kirwan. (1994), A guide to practical human reliability assessment by Barry Kirwan.

Carlos, A. Vargas (1998). *Investigating Construction Falls using Fault Tree analysis and developing a prototype tool to reduce falls using expert system and computer assisted instruction method.* Ph.D. Diss., Civil Engrg., Ohio State University

Culver, C., and Connolly, C. (1994), "Prevent Fatal Falls in Construction". *Safety and Health* , NSC, Itasca, IL

Culver, C., Hardesty, C., and Anderson, F. (1993). "Ironworker Fatalities in construction". Occupational hazard, 47 pp.

DeJoy, M. (1990). " Towards comprehensive human factors model of workplace accident causation." *Professional Safety,* 35(5), 11-16.

Duncan, C. W., and Bennett, R., III (1991). "Fall protection and debris containment during construction." *Preparing for construction in 21 st century,* L.-M. Chang, ed., ASCE, New York, 97-102.

Heinrich, H., Petersen, D., Ross, N. (1980). *Industrial Accident Prevention.* McGraw-Hill, New York.4 pp

Hinze, J. (1996). "The distraction theory of accident causation." Proc., Int. Conf. An Implementation of safety and Health on Constr. Sites, CIB working Commission W99

Hinze, J., Pedersen, C., and Frdley, J. (1998) " Identifying Root Cause Of Construction Injuties". *Journal of construction engineering and management.,* ASCE, 124 (1), 67-69 pp.

Holt, A. J. (2001). *Principles of construction safety,* Blackwell Science, Malden, Mass

Howell, G. A., Ballard, G., Abdelhamid, T. S., and Mitropoulos, P. (2002). " Working near the edge: a new approach to construction safety." *Proceedings of the 10th International Group for Lean Construction Conference*, Gramado, Brazil. August 5-8, 2002

Huang, X. Hinze, J. (2003). " Analysis of Construction Worker Fall Accidents". *Journal of construction engineering and management.,* ASCE 129 (3), 262-271 pp

Johnson, H., Singh, A., and Young, F. (1998) "Fall protection analysis for worker on residential roofs". *Journal of construction engineering and management.* ASCE, September/October ,418-428.

Johnson, M., Singh, A., and Young, R. H. F. (1998). " Fall protection analysis for worker on residential roofs". *Journal of Construction Engineering and Management.* ASCE, September/October, 124(5), 418-428.

McCam, M. (2000). "Cause of Roofer Death". The center to Protect Workers' Rights. Silver Spring, MD.

McClay, R. E (1989). " Toward a more universal model of loss incident causation- Part II." *Professional Safety,* February, 34-39

Mohamed, S.(2002). " Safety Climate in Construction Site Environments". *Journal of construction engineering and management.,* ASCE, 128 (5), 375-384 pp.

Moore, D. S., McCabe, G. P. (2002). *Introduction to the Practice of Statistics.* W.H. Freeman and Company, New York.

Norman, D.A (1981). " Categorization of action slips." *Psychological Review, 88, 1-14*

National Institute for occupation Safety and Health (NIOSH) 1997. "Construction Safety and Health".

NIOSH & NORA (2000). "National Occupational research Agenda (NORA)" November 2000, NORA fact.

NIOSH (2000). "A summary of Surveillance Findings and Investigative Case Report". *Technical Report November 2000.* U.S. Department Of Health and Human Services

NSC (2000), *National Safety Council,* "Accident facts publication"

O'Hare, D., Wiggins. M., Batt, R., and Morrison, D. (1994). " Cogntive failure analysis for aircraft accident investigation." Ergonomics, vol. 37, no 11, 1855-1869.

Petersen, D. (1982). *Human Error- Reduction and Safety Management.* STMP Press. New York, N.Y.

Pollack, E., and Chowdhury, R. (2001). "Trends in Work-Related Death and Injury Rates among U.S Construction Workers, 1992-98". The center to Protect Workers' Rights. Silver Spring, MD

Rasmussen, J., Pejtersen, A.M., Goodstein, L.P., *Cognitive System Engineering.* John Wiley & Sons, Inc. New York, 1994.

Rasmussen Jens. (1997) "Risk management in a dynamic society: a modeling problem." Safety Science Vol. 27 No.2/3,pp. 183-213, 1997

Reason, J. T. (1990). *Human Error.* Cambridge University Press, New York

Recht, J. (1970). *System Safety Analysis: Error Rated and Cost.* National Safety Council, Chicago.

Rook, L., Altman, J., and Swain, A. (1966). *Human error Quantification.* Sandia

Scott A.Shappell and Douglas A. Wiegmann (2001). "Human factors analysis and classification system (HFACS)". *HFES 45th Proceeding*

Spear, J. (2002) "Incident investigation: A problem solving process" *Professional Safety.* 25-30

Suraji, A. Duff. R, and S J. Peckitt. (2001) "Development of Causal Model of construction accident causation". *Journal of construction engineering and management.* July/ August, 337-344

Toole, M. (2002). "Construction Site Safety Roles". *Journal of construction engineering and management.* May-June, 203-210

Vargas, C., Hadipriono. F., and Larew, R. (1996a). " A fault tree model for falls from a form scaffolding." L. Alves Dias and R. Coble, eds., *Implementation of safety and health on construction sites,* Balkema, Rotterdam, The Netherlands, 291-301.

Vargas, C., Hadipriono, F., and Larew, R. (1996b). " *Cause of falls from floor openings and edges.* " L. Alves Dias and R. Coble, eds., *Implementation of safety and health on construction sites,* Balkema, Rotterdam, The Netherlands, 303-313

Wagenaar. W. A., Hudson, P.T., and Reason J. T. (1990). " Cognitive failure and accidents." *Applied Cognitive Psychology,* Vol. 4, 273-294.

Whittington, C., Livingston. A., and Lucas, D.A. (1992). " Research into management, organizational and human factors in construction industry." *HSE Contract Res. Rep. No. 45.* Her Majesty's Stationery ofc., London.

Wickens, C. (1992), *Engineering Psychology and Human Performance.* HarperCollins Publisher Inc.,24pp.

Zeller, D. (1986) " Heinrich revisited" *professional safety.* April 40-42

Zeller, D. B. (1986). "Heinrich revisited." *Professional Safety,* October. 40-42 Corporation. Albuquerque, New Mexico.