This is to certify that the
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ANALYSIS OF CONSTRUCTION SAFETY
COMPETENCIES USING FUZZY SIGNAL DETECTION
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Tariq S. Abdelhamid
Major Professor's Signature

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ANALYSIS OF CONSTRUCTION SAFETY COMPETENCIES USING FUZZY SIGNAL DETECTION THEORY

By

Puneet Narang

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ABSTRACT

ANALYSIS OF CONSTRUCTION SAFETY COMPETENCIES USING FUZZY SIGNAL DETECTION THEORY

By

Puneet Narang

Construction is a hazardous industry. The primary focus of this research was to develop a method to quantify workers' ability to identify hazardous conditions on a construction jobsite. This research applied a hybrid model of fuzzy signal detection theory (FSDT) to assess workers' ability to detect unsafe conditions. A survey was designed, with 18 questions, to elicit a worker's detection ability and confidence level in his/her decision. The average sensitivity value (measures the ability to discriminate between safe and unsafe condition) of the sample of 30 ironworkers was found to be above average ($d'=1.52$, with $\sigma=0.69$). The sample had a conservative strategy (bias $\beta=0.40$, with $\sigma=0.25$), whereby they would even consider some of the safe conditions as unsafe, providing a measure of how confident they were of their decision. Results from the sample of 30 ironworkers indicated that there existed no relationship between age/years of experience in the industry and workers ability to identify hazards. Statistical analysis of the same data using conventional or crisp SDT showed an increased sensitivity ($d'=1.81$) with a very high variation ($\sigma=1.30$). The same sample's bias was found to be $\beta=0.70$, also with a higher variation $\sigma=0.48$. The disparity is attributed to the fact that there is loss of information when the real world signals are forced into binary sets in crisp SDT. These results illustrated that fuzzy SDT model was a better fit, when compared to crisp SDT, for analyzing the safety competencies of construction workers.

Dedicated to my family, who during the course of this work
welcomed a new member,
my wife.

It is the relentless support and selfless love of these five people that keeps me going.

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This thesis could only take shape because I was guided, supported and directed by my advisor Dr. Tariq Abdelhamid to see things so much more clearly. His in-depth understanding of concepts, practical experience and academic knowledge were the foundations on which this project was launched. And it was his eye for detail, desire for continuous improvement and constant encouragement that saw it through.

I would like to express my thanks to Dr. Mohammad Najafi and Dr. Joanne Westphal for their timely and valuable inputs, which make this research so much more meaningful.

Professionals like Mr. Lawrence Kruth and Mr. David Hannah from the steel construction industry, gave the practical edge and the primary purpose of improving safety training seems achievable. They were kind enough to grant access to their jobsites, to collect critical data that helps justify the model.

I would also like to extend my sincere gratitude to all the professors and staff who helped me at various stages during the course of my graduate study here at Michigan State University.

I am indebted to friends and co-workers with whom I interacted, exchanged thoughts and ideas, sometimes even disagreed, constantly evolving and giving every day of academic life a new meaning.

Above all else, a big thanks to my family for everything and thank you God!

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INTRODUCTION

1. INTRODUCTION

Construction work is potentially dangerous, and to be able to render any job-site 100% safe is not an easy job. In order to attain such high levels of safety, one must understand the very nature of safety implementation efforts and the perspective of workers themselves towards what constitutes safe/unsafe conditions. A large number of researchers have focused on different aspects of worker safety and a number of resulting theories have been suggested (McClay, 1989; Hinze, 1997; Abdelhamid and Everett, 2000; Suraji et al., 2001; Toole, 2002; Howell et al., 2002; Abdelhamid et al., 2003).

1.1 Motivation

Construction remains one of the high-risk industries and occupations over a long period of time. This is despite continuous efforts across the industry to reduce the occupational hazard rate associated with it. The BLS data shows that in 2003, there were 1,131 fatal occupational injuries in construction and 408,300 nonfatal injuries and illnesses, according to data from the Injuries, Illnesses, and Fatalities program (Bureau of Labor Statistic, 2005). A look at the national occupational injuries data, as shown in Figure 1-1, indicates that the year 2004 actually saw an increase in the rate of fatal work injuries, which went up to 4.1 fatalities per 100,000 workers from 4.0 in 2003. The BLS (2005) stated that, "This was the first increase in the overall national fatality rate since 1994".

Construction as an industry is responsible for almost 6% of the nations workforce (National Safety Council, 2001), but claims a disproportionate 23% of all occupational fatalities and 10.5% of all occupational injuries (Injury Facts, 2002).

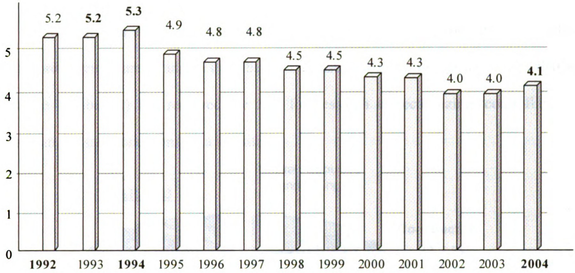


Figure 1-1 Rate of fatal work injuries per 100,000 workers, 1992-2004
(Source: U. S. Department of Labor, Bureau of Labor Statistics,)

Table 1-1 below, provides an industry breakdown for the number of fatalities in the last two years, and it indicates a clear increase from 2003 in the share of injuries attributed to the Construction industry (up by 2% in one year).

Industry	**2003**		**2004**	
	# Of Fatalities	%	# Of Fatalities	%
Natural Resources and Mining	850	16.9%	811	16.1%
Construction	**1131**	**22.4%**	**1224**	**24.3%**
Manufacturing	420	8.3%	459	9.1%
Wholesale Trade	191	3.8%	203	4.0%
Retail Trade	344	6.8%	372	7.4%
Transportation and Warehousing	808	16.0%	829	16.4%
Utilities	32	0.6%	51	1.0%
Information	64	1.3%	54	1.1%
Financial Activities	129	2.6%	115	2.3%
Professional and Business Services	453	9.0%	448	8.9%
Education and Health Services	143	2.8%	157	3.1%
Leisure and Hospitality	275	5.5%	245	4.9%
Other Services	203	4.0%	204	4.0%
Total	5043		5172	

Table 1-1 Fatal occupational injuries in the Private industry - All United States
(Source: U. S. Department of Labor, Bureau of Labor Statistics 2005)

According to BLS, "Fatal work injuries involving construction laborers accounted for nearly one out of every four private construction fatalities in both 2003 and 2004". The prominent share of injuries attributed to construction and its upward trend (also see Figure 1-2 below) has renewed the zeal for research in recognizing, controlling and reducing unsafe conditions on a job site.

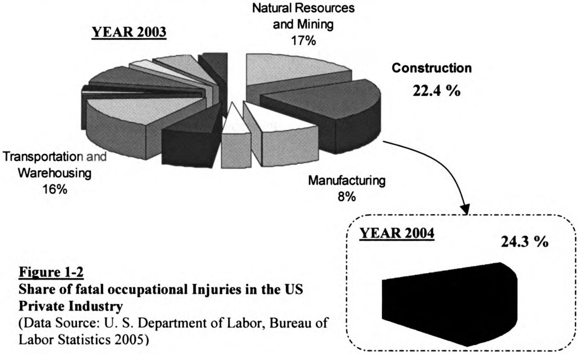


Figure 1-2
Share of fatal occupational Injuries in the US Private Industry
(Data Source: U. S. Department of Labor, Bureau of Labor Statistics 2005)

The U.S. Department of Labor classifies construction as a high-risk occupation, because of the high incidence of occupational injuries and fatalities that occur in the construction industry sector. A further investigation within the industry yields a picture that concurs with the advancements in the construction methods, and at the same time points towards the primary area responsible for the increase in the number of accidents. For example, Steel Construction has become a very important part of commercial construction and there has been a lot of innovation in the means and methods of steel erection, but with that also came a lot of risks. As reported by a construction safety specialist there were 16 fatalities in the year 2005 in the state of Michigan, and 9 out of these were due to falls. A similar situation exists in the residential sector where most of the accidents are due to falls. Ironworkers, carpenters and to some extent the other trades, i.e. painters, electricians and plumbers are always exposed to the occupational fall hazard. In the state of Michigan, only about 4% of the workforce is employed in construction, however, construction fatalities account for more than 40% of all fatal workplace accidents, and falls are the single leading cause (MIOSHA Press Release September 22, 2005). The scenario presents a challenging situation for those involved in construction safety to try and reduce the risk of accidents.

1.2 Problem Area

The disparity in the proportion of construction workforce and the accidents related to it is a clear indication of an existing problem. To analyze construction worker safety on a job-site, it is important to understand the mechanics of safety implementation efforts. If we take any construction jobsite as an example, there are a myriad of inherent conditions that could lead to accidents. Of-course there is gap between the accident actually occurring, and an existing condition i.e. potential for an accident. How wide or narrow this gap is, depends upon how well are the management and workers prepared to handle a dangerous situation. The first point of contact is inevitably the worker, who is performing his/her job and often needs to make a decision that would result in the potential condition transforming into a dangerous one and eventually into an accident. The worker's action simply would release the hazard, or create one for another worker. Hazard identification is probably the most critical aspect in successfully implementing safety regulations and guidelines. While not the primary focus of this research, other factors like adequate safety equipment, proper worker training with the means and methods, company policies and mandatory guidelines are also important. There are external or physical directives that are employed in the form of written instructions, formal training – both off and onsite, visual aids, video recordings and via the use of actual safety gear & equipments as the job commences. These industry wide guidelines and statutes are constantly evolving and form the foundation for all safety training. This thesis, however deals with the other, less popular side, that of analyzing the construction worker's perception of hazards. To analyze the safety competency of a given worker it is imperative to understand and quantify worker hazard identification under different situations.

Before a detailed discussion on the assessment of worker's hazard identification ability, it is important to look at prior research on asserting the root cause behind construction accidents. The objective of these root cause models is to provide tools for better accident prevention programs, which could offer a better understanding of assessment of hazard identification abilities. For example Heinrich's Domino theory (1930, 1959) was one of the first efforts and presents an accident as one of the five factors in a sequence that results in an injury. The five dominoes in his model are i) ancestry and social environment, ii) fault of person, iii) unsafe act and/or mechanical or physical hazard, iv) accidents and v) injury. The model suggested that through inherited or acquired undesirable traits, people might commit unsafe acts or cause the existence of mechanical or physical hazards, which in turn could cause injurious accidents. So if one domino toppled (occurred) the others would follow.

A number of other theories and models were proposed in the coming years, not all would be relevant for this research, but the ones mentioned here hint at the variety and complexity of this domain. McClay's 'universal framework' (1989) model identified three key elements of accidents: hazards, human actions and functional limitations that are exceeded in the case of an accident. Hinze's distraction theory (1996) suggests that the probability of accidents increase when workers are distracted from thinking about their safety due to stress of work or other factors. Abdelhamid and Everett (2000) in their root cause analysis model argue that management deficiencies and/or workers' actions create unsafe conditions in the workplace, and when faced with unsafe conditions workers either fail or succeed in identifying them. Suraji et al. (2001) developed the constraints-response model that attributes accidents to distal and proximal factors, which cause workers to respond in an incautious manner. Toole (2002) suggests eight root causes: lack of proper training, safety equipment not provided, deficient enforcement of safety, unsafe equipment, method or condition, poor safety attitude and chance deviation from prescribed behavior.

Howell et al. (2002) proposed a new approach in understanding construction accidents by providing a link between all the above-mentioned models and uniting them under the Rasmussen model. Jens Rasmussen (1994) in his theory of "Cognitive System Engineering" argues that there are no objective stop rules for tracing the cause of events. According to this theory, the analysis stops when an explanation makes sense from the analyst's perspective. He lays down five different perspectives and the point at which each of them is satisfied, limiting the range of potential causes of the error/accident. Rasmussen's framework offers a clear understanding of the relationship between individual work environment, and of the primary factors that lead to accidents. He defines the three zones of risk and explains how a work migrates across these boundaries, leading to loss of control and resulting in an accident. Rasmussen's model explaining the different zones and primary factors leading to loss of control can be viewed in Appendix C. An important conclusion from this model was that workers must be trained to recognize hazards, because only when they are able to identify safe and unsafe conditions, they would respond to perceived and actual risk in the correct manner.

Abdelhamid et al., (2003) and Patel (2003) further explored the need for an assessment of the process of identification. They argued the need for a methodology to assess worker ability to clearly identify hazards. They proposed the application of another significant model, Signal Detection Theory (SDT), in assessing construction workers occupational safety competencies. SDT is a robust theory with industry wide acceptance that provides a precise language for analyzing a decision making process. There are two important parameters in this analysis: sensitivity and bias of the observer, and these help quantify the assessment process. Abdelhamid et al. (2003) and Patel (2003) proposed a methodology that was based on the Rasmussen model, but used signal detection theory to assess construction worker sensitivity and their bias towards a risky strategy leading to an accident. Although the proposed application of SDT provides a very good initial understanding of the identification process, there is a high potential to improve this assessment process. Construction, like many other industries, is a real world setting, which is not devoid of its share of uncertainties. As explained in the following chapters, the SDT model fails to capture all the information because of its intrinsic binary structure. SDT works on a yes/no paradigm and in assimilating data as black and white;

there is critical information that gets lost. To provide an accurate assessment of construction safety competencies, there is a need to improve the model that is used for this assessment.

1.3 Thesis Overview

Signal Detection Theory (SDT) as developed by Tanner, Swets and Green in 1954, further structured in 1966 and 1969, formalized the properties of detection of signals and noise and developed a mathematical approach to the evaluation of the accuracy of diagnostic systems, whether machine or human based. Almost all reasoning and decision-making takes place in the presence of some uncertainty and it takes a certain level of competency, in that given area, to be able to make the right decision. There is always a relationship between physical stimuli and sensory response; Signal Detection Theory provides a basis to measure this. It is a well-developed psychophysical approach to measure performance.

SDT can be considered one of the most robust and useful quantitative theories given its evolution over the years (Swets, 1977, 1996; Swets and Pickett, 1982; Sorkin and Woods, 1985) and the variety of its application in fields like manufacturing, medicine and aviation. The concept is strongly based on a binary division of the states of the world to a signal or a noise, and a resulting binary system for detection.

Traditional set theory talks about crisp sets, where members belong to a particular set, since a clear boundary exists between set members and non-members. This is the same in SDT where there is clear-cut segregation of both the signal (or noise) and the response. Fuzzy logic, on the other hand, provides an alternative to the traditional set theory. Lotfi Zadeh in 1965 proposed the basic postulates of Fuzzy Logic and since then there have been many extensions and versions of Fuzzy Set theory, but none were as widely accepted and incorporated into scientific research as the original.

The act of assigning non-binary membership degrees to a previously binary definition is referred to as fuzzification (Parasuraman et al., 2000). Fuzzy SDT increases the applicability of conventional SDT analysis to many real world settings, including construction worker safety competencies, where the definition of a signal event is far less dichotomous than in a controlled laboratory environment. The fact that real world situations are not always clearly defined, every decision making task has uncertainties involved, and construction is no exception, use of a more customized model namely fuzzy SDT is clearly justified.

1.4 Goals and Objectives

The primary goal of this research is to develop a method to quantify construction workers' ability to identify hazards on site. The following objectives were proposed to reach the goal for this research:

1. Develop a method to investigate and measure a construction worker's ability to detect and identify unsafe conditions.
2. Design and conduct a survey based on fuzzy SDT to assess construction workers' perception of safety, specific to the risk of fall accidents.

1.5 Research Scope

The purpose of this research is not to figure out 'why' or 'how' the accident occurred, but to understand the workers perspective, his or her perception of threat and to correctly assess their ability to identify an unsafe situation. It is not investigating a causal model for construction occupational accidents; neither does it attempt to suggest a method to prevent such accidents. The research aims to understand construction workers' perception of safety. It focuses on ironworkers to demonstrate the use of the method developed for this research.

1.6 Summary

Chapter one of this thesis illustrated the contribution of construction fall accidents to the national fatalities and occupational hazards. There is a high disparity in the percentage of workers employed in the field of construction (6%) and its share of injuries (23%). This is an indication of an existing problem and the need for further investigation is clear. There are a number of causes responsible for the high accident rate. This research is focused on analyzing how a construction worker perceives safety, because he/she is the first point of contact, whenever a hazard is released on any jobsite.

This chapter briefly introduced the concepts of signal detection theory and fuzzy logic, which are presented as a combined hybrid model in the following chapters. It also presented the goal and objectives for this project and outlined a brief scope for this research.

Chapter 2
BACKGROUND

2. BACKGROUND

Most of the research pertaining to assessment of safety competencies revolves around understanding the root cause of the accident (Heinrich, 1980; McClay, 1989; Hinze, 1996; Abdelhamid and Everett, 2000; Suraji et al., 2001; Toole, 2002; Howell et al., 2002). Much research has been conducted to develop numerous accident causation models, but this research is concerned with the first instance when a worker encounters an unsafe condition. It is the process of detection, the worker's ability to comprehend whether the situation he/she is in, is potentially dangerous or not. Abdelhamid et al. (2003) and Patel (2003) have studied the occupational safety competencies of workers by focusing on the Rasmussen model and applying the principles of SDT in assessing worker sensitivity and bias during the detection process. This chapter provides an overview of the detection process and classical threshold theory. It further details the SDT framework and the calculation of sensitivity and bias. Then it goes on to introduce fuzzy logic, which is fundamentally different from the binary concepts of SDT. The hybrid model of fuzzy SDT is explained towards the end, which provides the ideal tool to correctly assess the worker's sensitivity and bias while making decisions pertaining to safety on site.

2.1 Mechanics of Detection

In order to understand the hazard identification process, it is important to understand how the worker would identify or mentally detect an unsafe condition. Detection can be defined as the perception that something has occurred or that some state exists. The process of detection itself involves the presence of some physical stimulus/stimuli, to which the observer's brain reacts by producing a response. This process can be further broken down as shown in Figure 2-1 below.

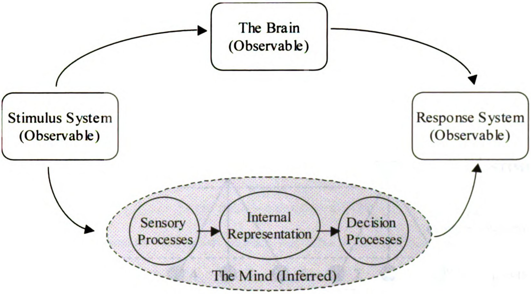


Figure 2-1
The Process of Detection - I
(Harvey, 2004)

The stimulus system, the brain and the response system (refer figure) are easily perceivable parts for this process. The actual inference can be broken down as 1) the sensory process and 2) the decision process. These would be explained in detail further in the chapter.

What happens in the 'internal representation' stage is actually a simple association exercise. *Each response belongs to one stimulus class*, and while inferring various responses are to be associated with its corresponding and correct stimulus class.

STIMULUS ⟶ **RESPONSE**

The observer whose performance is being studied is either presented with, or encounters, a certain set of stimuli of different types and must assign a distinct response to each. Every time a stimulus is presented, i.e., in every trial the observer attempts to match his/her response to the correct stimulus. As shown in Figure 2-2, each response belongs to only one stimulus class; responses 1, 2 and 3 belong to stimulus class A; 4, 5 and 6 belong to class B and so on.

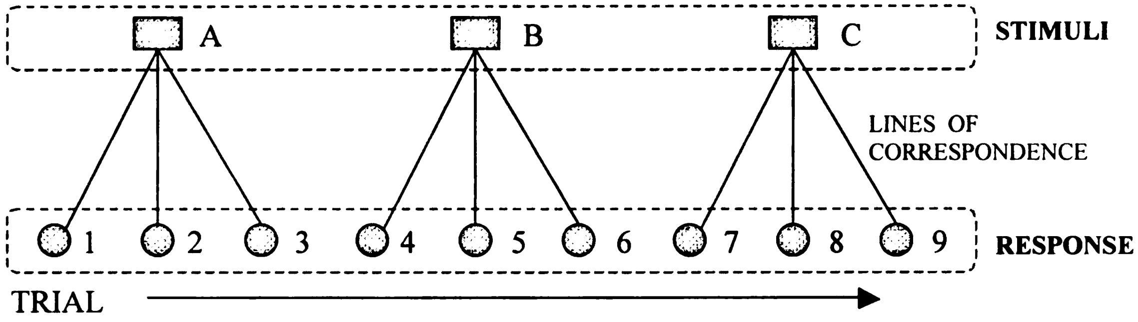


Figure 2-2
Internal Representation or the Correspondence Process – showing correct correspondence

In this research proposal only the simplest correspondence, that of "One Interval Design" is discussed. There are only two stimulus classes and the observer has to choose between them. In "Two-alternative forced-choice design", both stimuli are presented on every trial, in a random spatial or temporal order. This is better understood as order discrimination, because the observer's response indicates which stimulus occurred in which order. When more than two stimuli are represented it is referred to as multi-alternative forced-choice design (Macmillan and Creelman, 1991). When 'one interval design' is considered, as illustrated in Figure 2-3, a single stimulus drawn from one of the two stimulus classes is presented and the observer's generated response has to correspond to its correct class. This experiment setup is often referred to as the Yes-No classification because there are two stimuli classes to choose from in each trial and the response either belongs to one or the other. This is a simple discrimination process – the ability to tell two stimuli apart.

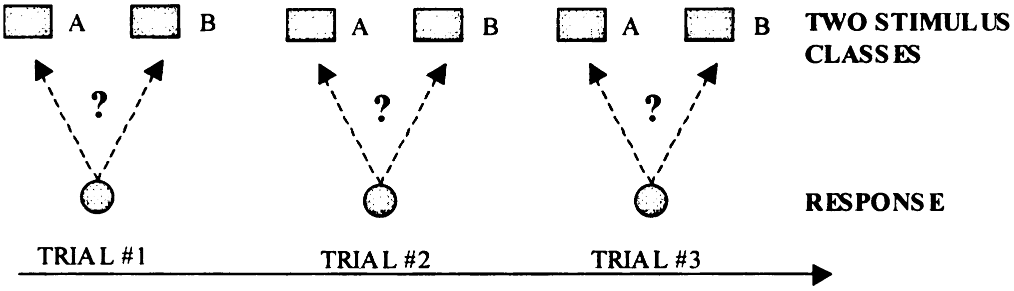


Figure 2-3
Event trials – one interval design

If one of the two stimulus classes contains a null stimulus e.g. "tone" versus "background", this is referred to as *Detection.* If neither stimulus class is null, it is a *Recognition* exercise. As the experiment involves two stimulus classes, A and B, the response to each trial can be simplified further as 'Yes' for Class A and 'No', when it is not Class A. This leads to four possible outcomes: –

1. Stimulus A, Response Yes (Hit)
2. Stimulus A, Response No (Miss)
3. Stimulus B, Response Yes (False Alarm)
4. Stimulus B, Response No (Correct Rejection)

These possible outcomes form the basis for signal detection theory, which will be introduced shortly.

2.2 Threshold Model

Rendering a condition hazardous or not is a part of an observer's decision-making process. This process itself has undergone close examination and extensive research while evolving from the classical High Threshold Model to the more widely accepted Signal Detection Theory. Threshold was considered as a stimulus level that would mark the point in time for the observer to perform one of the following tasks at some criterion level: –

- Detection
- Discrimination
- Recognition
- Identification

As shown below in Figure 2-4, these tasks have two primary psychological components (Krantz, 1969; Harvey, 2004): –

1. Sensory Process – this transforms the physical stimulation into internal sensations
2. Decision process – this decides on a response based on the output of the sensory process

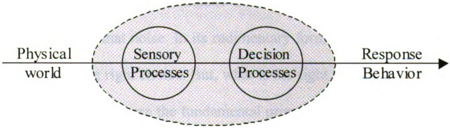


Figure 2-4
The Process of Detection – II
(Harvey, 2004)

HTM – High Threshold Model

From as early as 1860 the classical concept of a stimulus threshold resulting in 'detection' was the predominant model. Being a property of the sensory process, the HTM was based on identifying a stimulus level below which the stimulus has no effect (as if the stimulus was not there) and above which the stimulus causes the sensory process to generate an output. All psychophysical measurements of thresholds were designed to infer the stimulus value corresponding to the theoretical threshold from the observed detection performance data (Harvey, 2004). The high threshold model of detection assumes that the sensory process contains a sensory threshold. Then in the 1950s a major theoretical advancement was made, when the existing threshold model was combined with a new theory of detection.

2.3 Signal Detection Theory

Signal Detection Theory (SDT) is a method of assessing a decision making process when a person or a machine has to detect or recognize a stimuli and respond accordingly. The sensory process does not have a threshold in the SDT model, instead it is assumed to have a continuous output based on random Gaussian noise[1], and whenever a signal is present it combines with that noise. In its rudimentary form, SDT can simply be viewed as the ability to make the right choice. But, what is the right choice and how well can an individual make that choice – are the fundamental principles from where SDT derives its

---

[1] A normal distribution in a variate X with mean μ and variance σ^2 is a statistic distribution. While statisticians and mathematicians uniformly use the term "normal distribution" for this distribution, physicists sometimes call it a Gaussian distribution and, because of its curved flaring shape, social scientists refer to it as the "bell curve."

roots. The earliest application of SDT was the quantification of the performance of electronic receivers for detecting noisy radio signals (Peterson et al., 1954). Tanner & Swets (1954) extended this to describe human detection of threshold-level signals. But it was in 1966 that David Green and John Swets, in their book Signal Detection Theory and Psychophysics, described the modified theory and laid the foundations of widespread application of SDT to a variety of perceptual and cognitive tasks involving decision-making (Parasuraman et al., 2002).

Signal Detection Theory assumes two possible states of the world: signal (s), in which the event of interest is present, and noise (n), in which it is absent (Green and Swets, 1966). As shown in Table 2-1, the observer is faced with the task of identifying one of these two states (stimuli) in the form of two possible responses – yes or no.

	State of the World	
Observer Response	**Signal** *(s)* (Corresponds to stimulus Class A)	**Noise** *(n)* (Corresponds to stimulus Class B)
Yes *(Y)*	Hit	False Alarm
No *(N)*	Miss	Correct Rejection

Table 2-1
Four Outcomes of Signal Detection Theory (Source: Wickens, 1992)

Each of these (yes or no) responses has an associated probability given as –

Probability (Yes, given signal present) = P (Y|s) = Hit Rate (HR)

Probability (Yes, given signal absent) = P (Y|n) = FA Rate (FAR)

Probability (No, given signal present) = P (N|s) = Miss Rate (MR)

Probability (No, given signal absent) = P (N|n) = CR Rate (CRR)

Of the four numbers in the table, only two are needed to provide information about the observer's performance, because:

$$HR + MR = 1 \quad ...(3)$$

$$FAR + CRR = 1 \quad ...(4)$$

The two numbers needed to summarize an observer's performance are called a Hit & False Alarm pair, denoted as an ordered pair e.g. (HR, FAR) = (.8, .4). With this information, it is clear that the observer has a hit rate of 80%, a false alarm rate of 40%, a miss rate of 20% (1.0 – 0.8) and a correct rejection rate of 60% (1.0 – 0.4). At this juncture, it is imperative to introduce the two main components of the decision making process: information acquisition and criterion (Heeger, 1997). The acquisition of information while making a decision depends upon the strength of the stimulus, i.e., a stronger signal will tend to yield a better performance. The second component deals with the minimum level of internal certainty needed for an observer to decide that a signal was present.

To explain these in detail, the distribution shown in Figure 2-5 (next page) will be used. The horizontal axis of the figure represents the event trials, i.e., how the stimuli are presented to an observer. The vertical axis marks the probability of the presented stimuli. The curve (distribution) on the left is for the noise-alone (event of interest absent) trials, and the distribution curve on the right is for the signal (event of interest present) trials. The figure shows that there is a distinct overlap in the two distributions; the stimuli are presented in a continuous manner – the 'signal' stimuli are actually interspersed with the 'noise only' stimuli. The observer, also referred to as the operator, can have a tendency to say 'yes' more often to the presented stimuli, as a result having less number of 'misses',

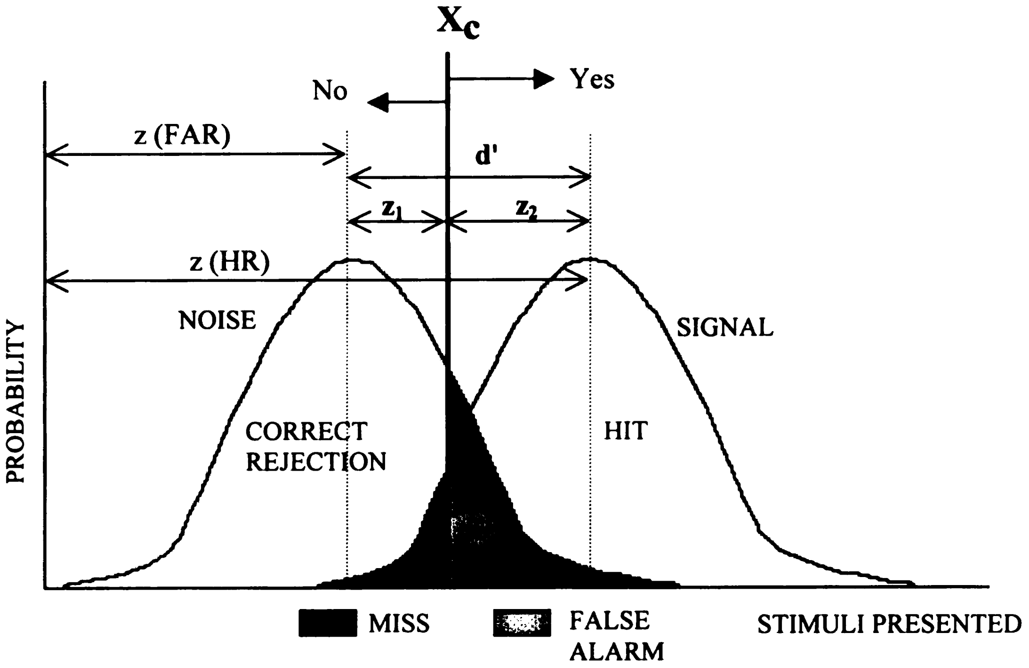


Figure 2-5
Stimuli Distributions (signal and noise): Signal Detection Theory
(Source: adapted from Wickens, 1992)

but also producing higher 'false alarms'. These variations in the operator decisions can be understood by studying the 'sensitivity' and 'response bias'.

2.4 Sensitivity or Discriminability Index (d')[2]

How well a person can discriminate between whether a signal is present or absent is represented by the difference between the means of the two distributions, which is captured by the quantity d' (see Figure 2-5; $d' = z_1 + z_2$). The value d' is the standardized difference between the means of the signal present and signal absent distributions. To calculate d', we only need to know a person's hit and false alarm rates.

$d' = z(HR) - z(FAR)$ ...(5)

---

[2] Pronounced as d-prime

In equation 5, 'z' is the inverse of the normal distribution function. z (HR) and z (FAR) represent the transformation of the hit and false alarm rates to z-scores (see Figure 2-5). The z-transformation converts the hit or false alarm rate to a z score, i.e. to standard deviation units. Assuming normal distribution and making use of the symmetry property of z-scores, a proportion of 0.5 is converted into a z-score of 0. Proportions larger than 0.5 lead to positive scores and those less than 0.5 lead to negative ones.

The quantity d' is a measure of how sensitive an observer is to the difference between the signal and noise stimuli, respectively. A perfectly sensitive observer/operator would achieve a perfect score, HR of 1 and an FAR of 0, i.e., correctly detecting all signals from the noise. This would result in perfect separation on the two distribution/curves, i.e., no overlap. Whereas a completely erroneous observer would not be able to distinguish between the two stimuli, thereby yielding very similar scores for HR and FAR (an imperfect score). In most real life cases there are more hits than false alarms, but performance is not perfect.

When an observer cannot discriminate between signal and noise, HR = FAR and d'= 0. At the other extreme, a perfectly accurate observer would yield an infinite value of d' (based on the cumulative standard normal distribution table, see Appendix F). Realistically when HR = 0.99 and FAR = 0.01 pair results, d' = 4.65, which is considered the ceiling value for d' (Macmillan & Creelman, 1991). An average performance would result in a d' = 1. The worst case scenario in which all signals would be missed and every time a noise stimulus is presented, the observer would respond with a 'yes-signal present' resulting in d' = - 4.65.

It is important to note here that the above measure of sensitivity is based on the two distributions that are assumed to be equal. Stated differently, if the noise distribution has a mean μ_n and standard deviation σ_n and the signal distribution has a mean μ_s and standard deviation σ_s. The explanation of d' so far has been for the case $\sigma_n = \sigma_s$. (equal variance sensitivity).

In more general cases, when $\sigma_n \neq \sigma_s$, the appropriate measure of sensitivity is d_a where

$$d_a = (\mu_s - \mu_n) / \{(\sigma_s^2 + \sigma_n^2)/2\}^{1/2} \qquad \text{(unequal variance sensitivity)} \qquad \ldots(6)$$

Therefore d' is a special case of d_a when both stimuli are distributed equally.

2.5 Criterion (X_c) or the Response Bias (β)

The inclination of a person to say 'Signal Present' in response to a stimulus is captured by the location X_c or the choice criterion, as shown on Figure 2-6. If a stimulus has strength

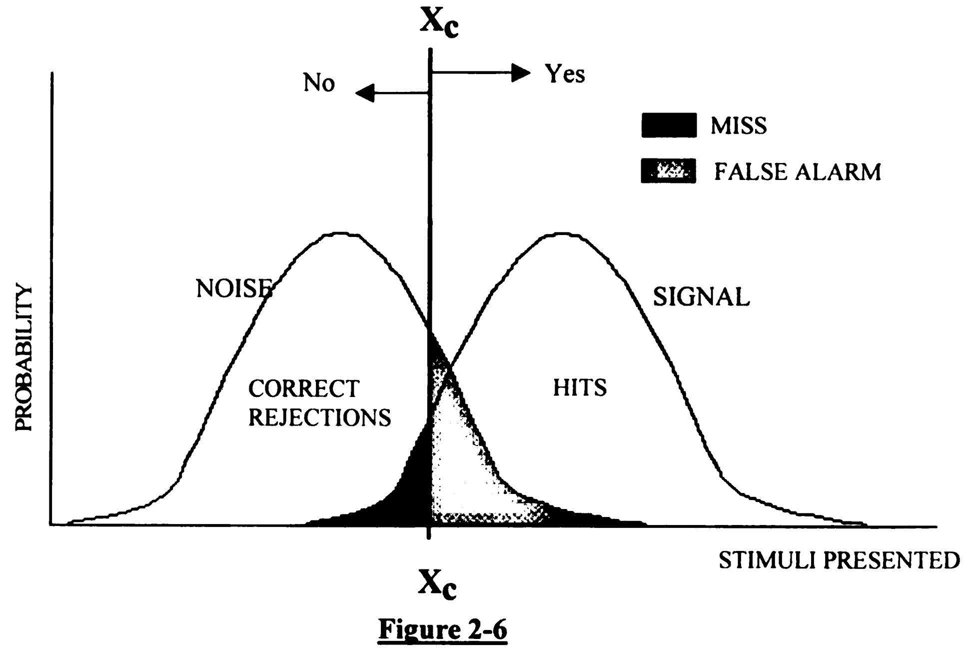


Figure 2-6
Criterion (X_c) or the Response Bias (β): Signal Detection Theory
(Source: adapted from Wickens, 1992)

or 'association' greater than the X_c, then the observer will indicate YES – Signal Present. If a stimulus has strength less than the criterion X_c, then the observer will say NO – Signal Absent. This criterion can be easily understood as a decision threshold associated with the choice of judgments or responses. Change in the position of X_c determines the respective proportions of misses to false alarms (Swets 1996). If the observer has a higher response criterion / bias, X_c would be pushed to the right (consider this as the observers point of conviction; if it takes a lot to convince the observer that the stimulus presents a signal, then the bias would be towards saying 'no' more frequently) thereby increasing the number of misses. Accordingly the false alarm rate and the number of hits would drop. On the other hand, if the response bias were very low, i.e., X_c shifts to the left, then there would be an increase in the false alarms but fewer misses.

This response criterion for the 'decision process' is also denoted by a measure called 'β', referred to as the response bias. Change in this factor affects the observer's tendency to adopt a certain strategy for generating a response, hence the term 'bias'. 'β' is the ratio of the ordinates P (X/s) and P (X/n) for a given level of X_c. Because β is calculated for a particular location of X_c it is referred to as $\beta_{current}$, and it is determined as follows:

$$\beta_{current} = P\,(X/s)\,/\,P(X/n) \qquad \ldots(7)$$

As discussed before, the detection process is broken down into the sensory process and the decision process. Sensitivity, i.e., a measure of the sensory process is usually a stable characteristic. However, it is the decision criterion or the response bias used by an observer that varies over time and from task to task. The main factors responsible for this variability are: -

- Instructions to the observer
- Relative frequency of noise trials and signal trials
- Payoff Matrix – relative cost of making the two SDT errors (False Alarms & Misses) and the relative benefit of making the two SDT correct responses (Hits & Correct Rejections).

Harvey (2004) states that these three factors can cause the observer to adopt very contrasting decision criteria at different times. These changes in the decision criteria can often be confused as changes in sensitivity, if the proper discriminability index is not used.

As expressed in Abdelhamid et al. (2003), evaluating the results of multiple observers requires the normalization of the response criterion because of the high variability between the response criterion of different observers. This is achieved by comparing different observer results ($\beta_{current}$ from each observer) to an optimal value of β which corresponds to a minimum number of errors, i.e., minimum misses & false alarms. This optimal value of β is the ratio of the probability of noise, P (N), and the probability of a signal, P (S):

$$\beta_{optimum} = P\ (N) / P(S) \qquad \ldots(8)$$

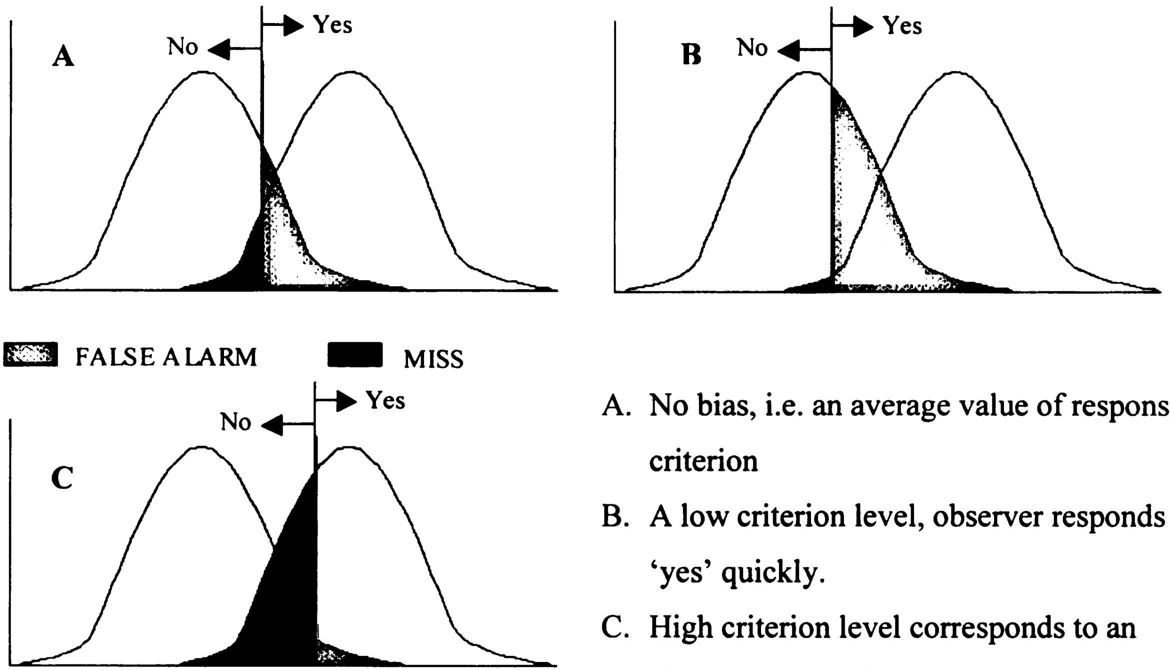
Now the ratio between the optimum and the current β's ($\beta_{\ current} / \beta_{\ optimum}$), provide a normalized value, which can be evaluated as a 'risky' or 'conservative' observer strategy. The definition of the observer's detection strategy as 'risky' or 'conservative' depends upon the setup, the field/domain/industry in which the experiment is being performed. What is construed as a conservative strategy while detecting defective motor parts in an assembly (manufacturing process), could very well be a risky strategy if applied to the aviation industry when scanning for hazardous & abusive substances. The most important factor is assigning or classifying the definition of 'noise' and 'signal' stimuli. For all practical purposes if $\beta_{current} > \beta_{optimum,}$ it is referred to as a conservative strategy due to higher misses, and the reverse $\beta_{current} < \beta_{optimum}$, as a risky one resulting in higher false alarms.

2.6 Detection: A Dynamic Process

The operator adopts a criterion location, i.e. a β value and with each presented stimuli provides a response. Whenever the internal response is greater than this criterion they respond 'yes', otherwise 'no'. An important point to note here is that the sensitivity for the experiment is fixed (constant value of d').

Fluctuations in 'Response Bias' / Criterion (β)

As mentioned before, a low level of β indicates that the observer has a lower threshold; resulting in a Yes response for a lot of trials, as shown below in case B of Figure 2-7. This would yield a very low Miss Rate, but the rate of False Alarm will be very high.



A. No bias, i.e. an average value of response criterion
B. A low criterion level, observer responds 'yes' quickly.
C. High criterion level corresponds to an observer not saying 'yes' very easily.

Figure 2-7
Fluctuations in Criterion (X_c) or the Response Bias (β)
(Source: adapted by author from Wickens, 1992)

A high level of β indicates that the observer has a high threshold; resulting in a No response for a lot of trials. This would yield a very low False Alarm Rate, but the probability of scoring a Miss will be very high. This corresponds to case C in the figure. The average observer, who understands the detection process at hand, would adopt a fairly moderate value of β, resulting in low rates of both misses and false alarms. This is case A in Figure 2-7.

Fluctuations in 'Sensitivity' or the 'discriminability index' (d')

As discussed earlier, d' measures how many standard deviations the signal distribution mean is from the noise distribution mean. The higher the d' value, the higher is the sensitivity or ability to discriminate between signal and noise. If the 'criterion' for a number of trials is kept constant[3] and the separation of the distribution of signal and noise is varied, the scenarios (A and B) presented below in Figure 2-8 can be studied.

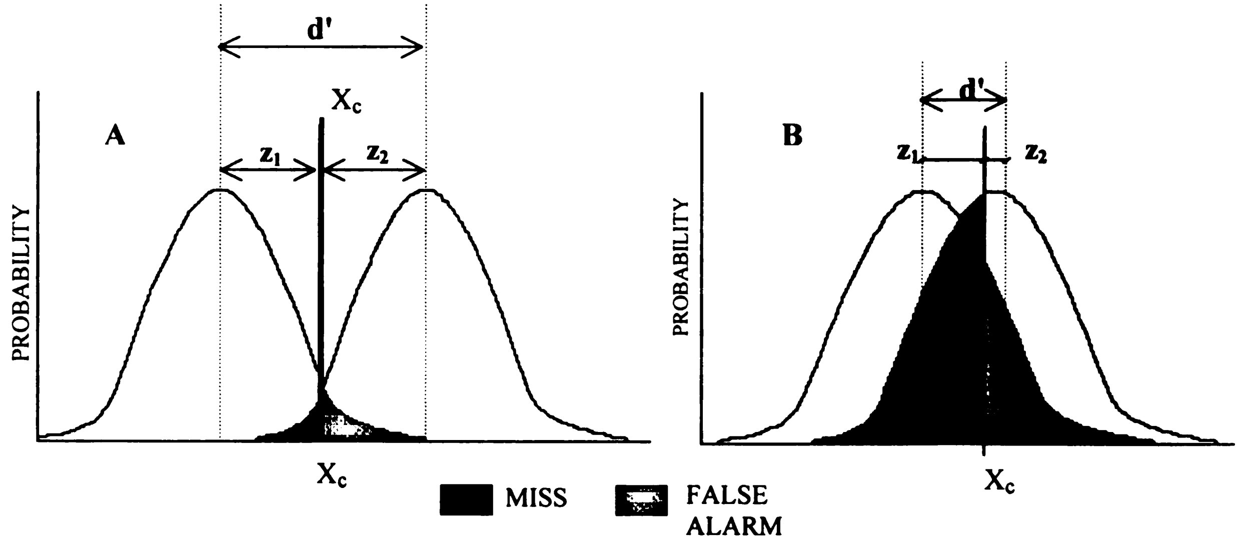


Figure 2-8
Fluctuations in discriminability index (d')
(Source: adapted by author from Wickens, 1992)

In Figure 2-8, case A shows a good separation between the signal and noise distributions. This means the operator can distinguish between the signal and noise, and produce a

---

[3] This can be achieved by keeping the same operator (assuming that his/her response bias does not change over a number of trials) or by using different operators with identical response bias.

good (HR, FAR) pair. The small overlap in case of A indicates that that it is inevitable to have some misses and false alarms. Case B in the same figure, provides a high degree of overlap in the two distributions, indicating that the operator has less ability to detect a signal from the noise. Accordingly, there would be a high number of misses and false alarms. It is important to note that an operator's choice of a high or low bias, would not improve the outcome. The shift in X_c would only affect the type of error, a low criterion would mean high FAR, and a high criterion would result in increased misses.

There is another aspect of the distribution that affects the operator's ability to detect the signal. Even if the separation between the noise and signal densities stays the same, the actual spread of the distribution can lead to remarkably varying degrees of detection. Figure 2-9 illustrates two such cases, where case B represents two distributions that have a very low variation. The response bias is set at the ideal location between the means of the two distributions, resulting in a very good set of readings. There would be a high number of hits and correct rejections. The almost insignificant overlap would mean hardly any misses or false alarms. Case A on the other hand represents an identical

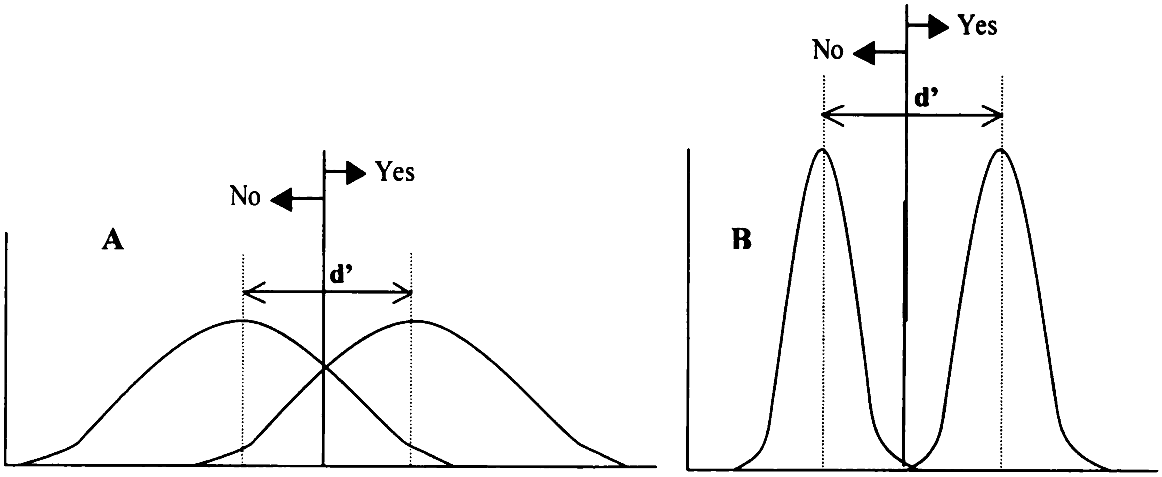


Figure 2-9
Fluctuations in spread (intensity) of noise and signal distribution with d' constant

sensitivity and the same ideal location of X_c, but would yield a considerable amount of false alarms and misses.

It is interesting to note here that although case B yields very low FA's and M's, even a very small shift in the operator's response bias (location of X_c) would result in a sudden increase of FA's or M's (depending upon which side X_c shifts). A similar scenario for case A would not result in any drastic changes in the four possible outcomes. Case A appears to be a more stable configuration. Also real world situations are more likely represented by case A. Distributions like those represented in case B are generally attributed to artificial or laboratory setups.

To better understand these fluctuations in d' (sensitivity or discriminability index) presented below in Table 2-2 are a set of random sample observations in the form of (HR, FAR) pair and their respective d' values.

(HR, FAR) pair	**z (HR)**	**z (FAR)**	**d'** *z (HR) - z (FAR)*
.99, .01	2.33	-2.32	**4.65**
.99, .30	2.33	-0.52	2.85
.99, .50	2.33	0	2.33
.99, .75	2.33	0.67	1.66
.80, .50	0.84	0	0.84
.50, .10	0	-1.28	1.28
.50, .50	0	0	**0**
.50, .80	0	0.84	-0.84
.50, .90	0	1.28	-1.28
.10, .50	-1.28	0	-1.28
.10, .90	-1.28	1.28	-2.56
.05, .95	-1.64	1.65	-3.29
.01, .99	-2.32	2.33	**-4.65**

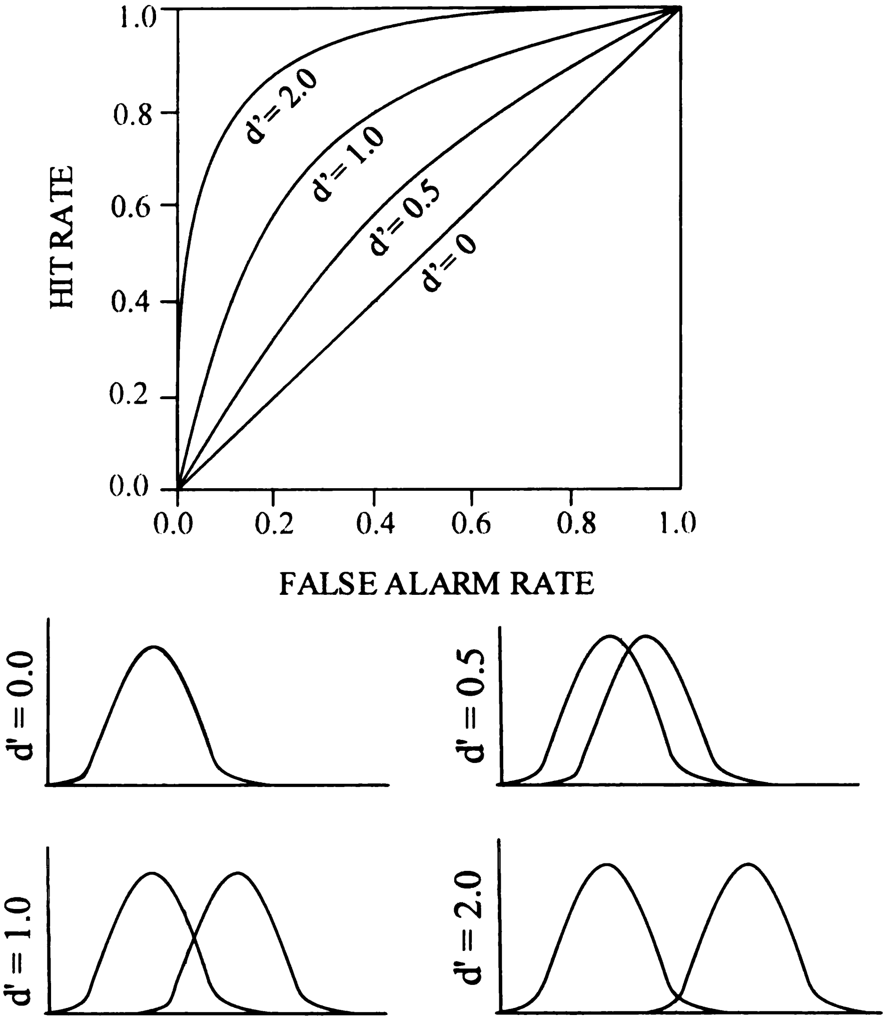
Table 2-2
Sample observations of sensitivity derived from various HR-FAR pairs

As clear from Table 2-2, the wider the gap between the HR and FAR (with a higher HR and lower FAR), the higher is the discriminability index. As explained earlier in section 2.3, for all practical purposes d' = 4.65 is considered the ceiling and the worst case for the lower value is -4.65. It is interesting to note how the varying d' would relate to the operator's bias. A very good model that explains this relationship and has also found acceptance across many fields that involve assessment of a decision making process is the receiver operating characteristic (ROC). The next section explains in detail the concept and functioning of the ROC space.

2.7 Receiver Operating Characteristic

The Receiver Operating Characteristics (ROC) of an operator/subject shows his/her performance as a trade off between selectivity and sensitivity. Selectivity can be understood as the response criterion or the response bias. As shown below in Figure 2-10, the ROC plots the Hit Rate (y-axes) against the False Alarm Rate (x-axes) for a given criterion (β) and sensitivity (d'). ROC plots illustrate all possible values of the response bias (criterion) for a given sensitivity. Each value of d' corresponds to a different ROC curve. Both HR and FAR range from 0 to 1, resulting in all ROC curves to lie within the unit square space, also referred to as the *ROC space*.

We already know that if the criterion is high, then both the false alarm rate and the hit rate will be very low. If we move the criterion lower, then the hit rate and the false alarm rate both increase. Notice also that for any reasonable choice of criterion, the hit rate is always larger than the false alarm rate, so the ROC curve is bowed upward. It is possible to do worse than random, and this is when the curve plots below and to the right of the chance line.



Corresponding distributions (indicative)

Figure 2-10
The ROC Space and different curves for varying observer sensitivity
Macmillan and Creelman, (1991). Corresponding distributions are adapted by author.

As mentioned earlier, the higher the sensitivity, the easier it is for the observer to distinguish between signal and noise, which results in a stronger arched curve in the ROC space. When there is zero sensitivity, the ROC curve falls on the major diagonal, where the hit and false alarm rates are equal. It is for this reason that this straight line is also referred to as the 'chance line' (Macmillan & Creelman, 1991). When HR = 1 and FAR =

0, the observer is said to produce perfectly accurate results and the ROC curve would then shift to the upper left corner. In general, the ROC curves are a clear indicator that an observer yielding a particular HR and FAR pair that lies on a specific ROC, should be able to exhibit any other pair on the same curve. Hence when studying any decision making process and analyzing a performer's ability, the ROC provides a perfect model to compare between different operators. It also helps track the strategy adopted by the operator, when the value β moves along a particular curve, representative of a fixed sensitivity.

As explained in the preceding pages of this chapter, sensitivity and bias are the two parameters that measure the sensory and decision making process respectively. These two together explain how an operator would detect a stimulus and respond. These are the basic principles of signal detection theory. As SDT evolved into a robust and well-established method for the assessment of the accuracy of diagnostic systems, it has also been extensively used in the analysis of decision making performance in a wide range of applications, including aviation, military command and control, weather prediction, medicine and personnel decisions. In particular SDT has been widely accepted in the manufacturing industry, where quality inspections are performed to identify and reject (remove) defective products. Listed below are a few applications in various industries.

1. A defective product in a line for quality inspections - Manufacturing.
2. Presence of a medical condition (e.g. tumor in a CT scan or a fracture in an X-Ray report) - Medicine.
3. Weapon/Abusive substance detection –Security/Travel.
4. Judicial Testimony, evidence recognition – Justice.

5. Air traffic control – Aviation.
6. *Occupational worker safety – Construction*

This is an ever-expanding list because every industry has perceptual and cognitive tasks involving decision making at some level.

An important aspect of the goal of this research was to effectively analyze how workers on a construction site identify hazards. It is interesting to note here, that the framework, on which SDT is based, requires the presence of a signal and noise (absence of a signal). The following section investigates the presence of a clear signal and noise, because only if this clear separation exists can the principles of SDT be applied for assessing a performer's ability.

2.8 Fuzzy Signals, Fuzzy Responses

The very basis of Signal Detection Theory is the binary division of the 'states of the world' into Noise and Signal. The two stimuli classes are considered to be non-overlapping, seemingly drawing from the mathematical expression: $A \cap A' = 0$ (Parasuraman et al., 2000). Everything that is a subset of A is not a part of set A'. Set A' denotes the complementary set for original set A. Even the response to the presented stimuli in the SDT model, is of a binary nature; 'yes, signal is present and no, signal is not present'. This binary classification is typically based on pre-set rules; the enclosed laboratory conditions make it suitable for the physical trial to be categorized strictly as either a signal or a noise. However in real life settings, studies of perception, memory and cognition – focusing on the signal and the resulting response - are not always based on clearly defined parameters. Real world signals are actually fuzzy.

When we use the notation $A \cap A' = 0$, it means that something either is or is not. There is a precise boundary or a definition that separates two classes. Any member that belongs to one class or set cannot belong to its complementary set. This statement is not true for most of the real world settings (Parasuraman et al., 2000) and especially, when decision-making processes involve a cognitive response in the presence of one or many physical stimuli. In situations where there is an explicit boundary, it is only due to the pre-determined rules and the context, which plays a dominant role in the perception of the signal as binary.

Figure 2-11 explains this difference between binary and non-binary classification. Assuming that there are two defined stimuli classes, the responses generated in an enclosed laboratory setup, where the process is closely monitored, would be very definitive and easily associated to the correct class. The graphic pattern in the stimuli and response boxes is indicative of the ease of this classification.

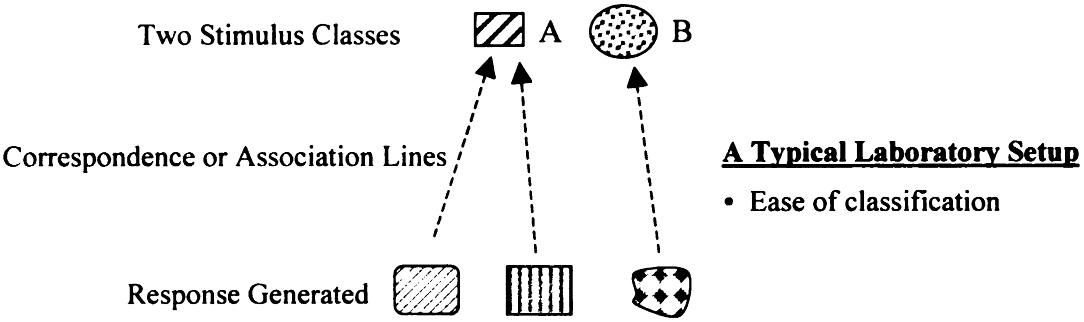


Figure 2-11
Detection process in a laboratory setup

As these stimuli are transferred to real-life settings, i.e., start representing physical day-to-day conditions, their definition starts to blur. Actual stimuli and the responses that they invoke are not so well defined. This is illustrated in Figure 2-12, where the two different stimulus classes, A and B, are not defined clearly. There is evidently a difference, but their blurry boundaries do not indicate a crisp definition.

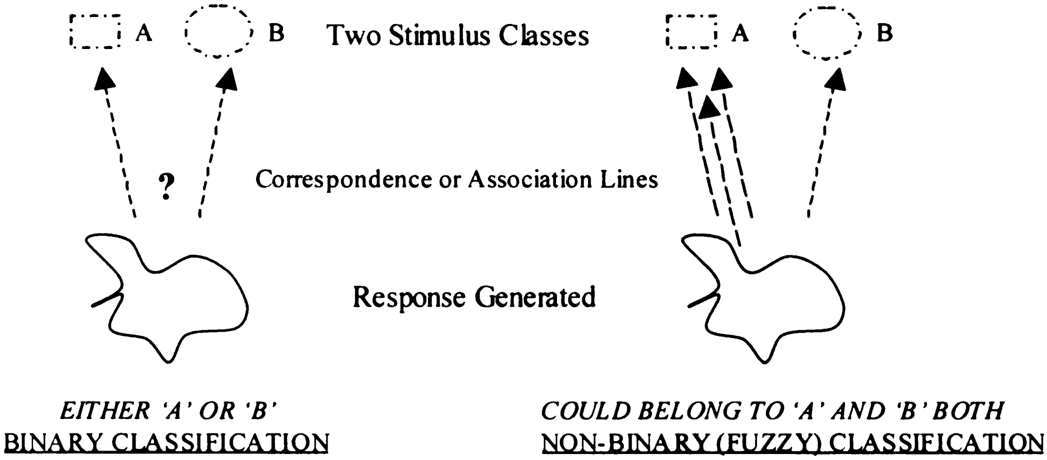


Figure 2-12
Real world setting – Blurred definitions of stimuli and response

In real-life settings the definition of the response and even the stimulus class is not explicit. Nonetheless, the act of detecting a signal, i.e., correspondence of the response to its correct class must take place. In situations where this correspondence would not be evident, the binary model will, in any case, associate the response to one out of the two classes. Under the non-binary, or in other words the fuzzy model, a response could belong more to a particular stimulus class, but some part of it would also belong to the other class. This is the fundamental difference in the two models. And because the fuzzy model captures all that information, which gets lost in binary classification, it is a more advanced model to be applied in real world assessments of performance.

A very good example of how arbitrary this binary categorization can be is the US Air Traffic Control regulations for an aircraft in flight (Masalonis and Parasuraman, 2003). The regulation states that there should be a stipulated separation of 1000 ft vertically and 5 nautical miles (nm) horizontally between any two aircrafts, for a controller to give it a 'signal present' status, i.e., the two planes are regulation compliant. Clearly anything from 0.1 nm to 4.9 nm at the same altitude does not present identical safety implications.

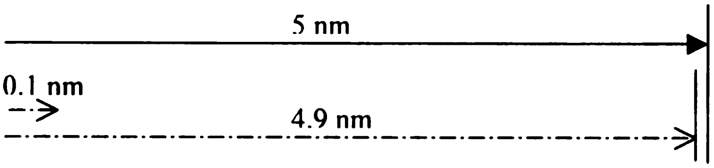


Figure 2-13
ATC horizontal separation regulations for aircrafts in flight

On the other hand, if it were not for the pre-defined 5nm criterion, a 4.9 nm separation would be considered as a very similar event as to that of a 5.1 nm separation (Figure 2-13). This is a clear example of how the context and the designed framework are responsible for the binary definition of a signal, which is inherently a continuous or varying signal, or, in other words, fuzzy.

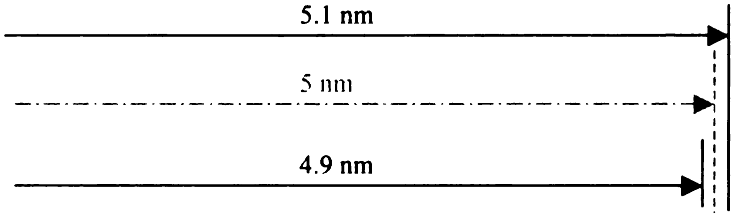


Figure 2-14
ATC horizontal separation regulations for aircrafts in flight

If we remove the framework as shown in Figure 2-14, i.e., abandon the 5 nm separation definition; these two are almost equally dangerous situations. The controller's decision to call signal present or not is dependent on a lot of other external factors. The nature of the sector being controlled, individual perception of the controller, controller's job-risk/pressures at that instance, are all very important parameters that have a bearing on his/her decision. A controller in a sector with high air traffic volume may consider a value such as 8 nm to be the cut-off. This would act as a self-created criterion by the operator (controller), which from time to time would be breached depending upon the controller's perception of whether the separation would increase or decrease. Another important factor, in labeling a stimulus a signal, is the variability in time of the stimulus and the operator's perception of the signal strength.

In the binary language of SDT there is noise and there is signal. The contextual and temporal variability and operator perception discussed above are the primary reasons for a signal being fuzzy. Similarly, the result of a conflict in a detection task or any other decision making process, i.e., the response of the operator is subject to these factors – yielding a fuzzified response. There can be varying degrees of operator confidence when presented with an identical stimulus at different times. Added to these there can also be variation in internal response of the operator (Heeger, 1997) leading to uncertainty; the state of the mind and the neural activity at the instance the stimulus is presented can fluctuate leading to an inherently fuzzy response.

Fuzzy logic as developed by Lotfi A Zadeh in 1965 was combined with SDT by Parasuraman et al. (2000). This allows the event to be somewhere in between, without forcing the binary categorization that can result in the loss of useful information and a less sensitive analysis.

Before moving on to the application of fuzzy logic to conventional Signal Detection Theory it is important to understand the following concepts: –

- *Real world signals are actually of a continuous nature. There is loss of information if these variations are not captured.*
- *Traditional Set theory: Assignment of membership of events to sets, wherein elements either do or do not belong to a given set. These traditional sets are also referred to as Crisp Sets, as there exists a clear boundary between set members and non-members.*
- *Fuzzy logic presents an alternative method to this traditional set theory.*

2.9 Basic Elements of 'Fuzzy SDT'

Signal detection theory is a good tool for assessing cognitive decision-making tasks in a controlled setup with defined classes to choose from, but real world situations rarely present themselves in crisp and precise classes. The combination of fuzzy and SDT enables, rather, enhances its application as a tool for assessment of a decision making process in real world settings. Fuzzy SDT allows the answer to the question 'is this a signal/response' to fall somewhere in between yes and no, i.e., between 1 and 0.

The signal and noise events of the conventional (Crisp) SDT are fuzzified. An event or a trial can belong to the set Signal with some degree between 0 and 1. Similarly a response can belong to a set Response with some degree between 0 and 1.

's'= degree to which an event is a signal; varies from 0 to 1

'r'= degree to which a 'yes' (signal present) response was made; varies from 0 to 1 ...(9)

All possible states of the world (SW) and each possible response value (RV) must be evaluated before assigning degrees of membership to the signal and response sets. Based on a set of variables (these would be different for different applications and depend on the event of interest) that describe the SW, there would be a mapping function required to derive a signal value and a response value.

2.10 Mapping Functions and SDT parameters in the Fuzzy framework

Mapping of the signal and response functions is the first and a very critical step in the fuzzy SDT analysis. The signal mapping function is constructed according to the nature of the data and the needs of the analysis, and it maps those variables that describe the state of the world into the set signal (s) with some membership degree in the range 0 to 1. Therefore, if a particular event has variables that present a signal to a large but not complete degree, 's' would take a value of say 0.85. An event that is not so signal-like may result in 's' = 0.30. The response mapping function generates a value for 'r', depending upon the judgment of confidence that a signal was present, or on how critical is the presence of a signal in that context (Masalonis and Parasuraman, 2003).

Whenever there are a finite number of discrete states of the world and responses, the mapping functions are derived using:

$$s = s_S \text{ for } SW = 1 \text{ to } n_S$$
$$r = r_R \text{ for } RV = 1 \text{ to } n_R \qquad \text{...(10)}$$

SW = each possible value of the state of the world

RV = each possible response value that could be made

n_S = number of possible discrete SW values

n_R = number of possible discrete RV values

s_S and r_R are the discrete mapped functions for signal and response sets.

For continuous states of the world and responses, where the original variables representing SW and RV are continuous, taking infinite values, the mapping functions are derived using:

$$s\,(SW) = f\,(SW)$$
$$r\,(RV) = g\,(RV) \qquad \text{...(11)}$$

SW = original value of the variable representing state of the world, on an interval scale

RV = original value of the variable representing response value, on an interval scale

$f(.)$ and $g(.)$ = functions defined according to the needs of the analysis being conducted and included within $[0, 1]$.

The continuous states of the real world need to be mapped in such a way that the resulting values can form a part of the fuzzy sets. Parasuraman et al. (2000) provide a generic conversion where two distinct functions can be used to convert the continuous states of the world and responses into values of 's' and 'r' respectively, that range between 0 and 1. The most significant difference and striking feature of fuzzy SDT is that a given 's' and 'r' pair is mapped to one or more of the four traditional SDT categories (hit, miss, false alarm and correct rejection). For instance a given event pair can belong to more than one of the four categories with varying degree. In conventional SDT each event falls completely in one and only one of the four categories.

The membership values for the four event trials are defined by the following functions (Parasuraman et al., 2000):

Hit: $H = \min(s, r)$

Miss: $M = \max(s - r, 0)$

False Alarm: $FA = \max(r - s, 0)$

Correct Rejection: $CR = \min(1 - s, 1 - r)$ ...(12)

These equation set is easily applicable and the following Table 2-3 illustrates an example using a few hypothetical s-r pairs.

Signal (s)	Response (r)	Hit	False Alarm	Miss	Correct Rejection
.8	.9	.8	.1	0	.1
.2	.2	.2	0	0	.8
.5	.2	.2	0	.3	.5
.1	.9	.1	.8	0	.1

Table 2-3
Example of typical values from the Truth Table for Fuzzy SDT
(Source: Parasuraman et al.. 2000)

A few interesting points to note from the results obtained using these formulas are:

- There is always at least one zero value among the four categories, unlike crisp SDT where only one category gets populated with a 1 and the remaining three get zeroes.
- When s = r, both Miss and FA have a value of zero
- Sum of all values i.e. H + M + FA + CR is always equal to 1.

Although fuzzy SDT permits $A \cap A' \neq 0$, the sum of the four mutually exclusive outcomes should be 1, because even in fuzzy SDT the four categories represent the full universe of possible outcomes.

"In Fuzzy SDT (FSDT), either *s* or *r or* both must be continuous variables in the range [0, 1]. One of the two may be binary i.e. $\in \{0, 1\}$. However, *s* and *r* cannot both be binary, for this would then reduce FSDT to crisp SDT." (Parasuraman et al., 2000)

The equivalent standard SDT measures when calculated for fuzzified 's' and 'r' values are as follows:

$HR = \Sigma (H_i) / \Sigma (s_i)$ for $i = 1$ to N

$MR = \Sigma (M_i) / \Sigma (s_i)$ for $i = 1$ to N

$FAR = \Sigma (FA_i) / \Sigma (1 - s_i)$ for $i = 1$ to N

$CRR = \Sigma (CR_i) / \Sigma (1 - s_i)$ for $i = 1$ to N ...(13)

In equation13, 'i' is the trial number, N is the total number of trials, 's', is the degree to which an event is a signal, H_i is the degree of Hit for trial 'i', M_i is the degree of Miss, FA_i is the degree of False Alarm and CR_i the degree of Correct Rejection for trial 'i'.

Conventional SDT equations of –

$HR + MR = 1$ and $FAR + CR = 1$, still hold in Fuzzy SDT.

Equation Sets 12 and 13 together can be used in the application of Fuzzy SDT where the degree to which an event / stimulus is a signal varies in a continuous manner from zero to one.

2.11 Sensitivity and Criterion in Fuzzy SDT

In fuzzy signal detection theory (FSDT), the variability of the signal and the response is initially captured with the very definitions of 's' and 'r'. With very little examination it becomes clear that the mapping procedure of FSDT is cognizant of the worker's sensitivity and decision bias. When determining the memberships in the two sets of signal and response, the Wickens (1992) model of noise and signal probability distribution is used. The value of 's' is directly proportional to the sensitivity (d') of the worker; it's his or her ability to tell the two distributions apart. The value of 'r' is directly proportional to the response criterion or bias (X_C) of the worker; it explains where the worker is placing his/her bias (location of the vertical divide between the noise and signal distributions) for giving a 'yes' signal present response. This explanation suggests the use of the fuzzy SDT model for real world settings, as against the conventional one.

From the four possible outcomes calculated using equations 12 and 13, the sensitivity and the response bias can be calculated as follows:

$$d' = z(HR) - z(FAR) \quad . \qquad ...(14)$$

The Criterion measure β can be calculated as:

$$\beta = Y(HR)/Y(FAR) \qquad ...(15)$$

In equation 15, Y(.) represents the ordinate of the normal distribution. This can be expressed as follows:

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2} \qquad ...(15a)$$

2.12 Summary

Chapter two focused on the relevant theories introduced the framework for two important models, SDT and Fuzzy. It explained the two parameters, sensitivity and bias, that quantify the decision-making processes. It was also suggested that the combination of the two models, i.e., Fuzzy SDT would be the appropriate tool in studying construction workers' perception of safety on site.

Chapter 3

METHODOLOGY

3. METHODOLOGY

Chapter three presents the application of Fuzzy SDT (FSDT) model and the adjustments that were required to make it a potential tool that facilitated the objectives of this research.

3.1 Objective # 1

To develop a framework to correctly investigate and measure a construction worker's ability to detect and identify unsafe conditions.

Research Method

Signal detection theory in its crisp form has been applied in assessing construction worker safety competency (Patel, 2002). When the principles of fuzzy logic are combined with conventional SDT, the hybrid model captures vital information, that is present in the form of uncertainties, thereby providing a comprehensive approach in studying hazard identification on a jobsite. The construction worker is inevitably faced with situations where he or she has to make a call, decide whether to go on working in the same manner as he/she has been before that instance. It is at this point in time that the fuzzy SDT model comes into play. The two states of the world, noise and signal do not present themselves as crisp, defined sets, from which the worker can easily pick one. In most scenarios there is a distinct overlap, the stimuli does fall into one category, but not without some degree of membership in the other.

Unlike the 'production line' of manufacturing, where the operator inspects the product and each unit is considered a stimulus, the construction jobsite has a unique framework. Each project being a 'one-off', there is never an identical situation that repeats for a worker. The product itself replaces the 'production line'; the worker is physically adding value by executing his/her trade within the product, which in this case is the physical built space. The product stays stationary and the worker moves through it. The stimuli on a construction jobsite is the physical site condition, the response comes from the worker in the form of detection, whereby he/she takes a decision and depending upon that either carries on work or takes appropriate measures to perform his job in a safer way.

Hence from the construction industry standpoint, the two overlapping states of the world are "safe condition" and an "unsafe condition". Because it is important that the worker identifies an unsafe condition, it is given a "signal" classification. Accordingly, the normal day-to-day safe working conditions are treated as "noise". When a worker is faced with an unsafe condition (signal present), he or she can give two possible responses, 1) 'yes – signal present' scoring a Hit and 2) 'no – signal absent' scoring a Miss. And when faced with a safe condition (signal absent), the remaining two possible responses can be, 3) 'no – signal absent' scoring a Correct Rejection and 4) 'yes – signal present' scoring a False Alarm (Patel, 2002).

In the conventional SDT model, the worker would respond in a binary manner, either saying yes, signal present, and would stop work or would respond no (signal absent) and carry on work. Both the signal and the response only take binary values. Even if the worker is uncertain, there is always a binary response generated. Table 3-1, provides a truth table for conventional SDT, wherein for all possible conditions the worker would yield a value that would populate only one out of the four outcomes, and the rest would have zero membership.

Signal **'s'**	**Response** **'r'**	Hit	False Alarm	Miss	Correct Rejection	**Σ** **H+FA+M+CR**
0	0	0	0	0	1	1
1	0	0	0	1	0	1
0	1	0	1	0	0	1
1	1	1	0	0	0	1

Table 3-1
Possible outcomes of crisp SDT

Fuzzy SDT, on the other hand, recognizes that the worker response is subject to an overlapping membership in the two sets of 'yes' and 'no'. Not all responses are clear black and white, just like not all stimuli are clear black and white. There is a degree to which an event is a signal, i.e., an unsafe condition, and a corresponding degree (for the same event) to which it is a safe condition. Accordingly there is a degree to which a signal present response (or, yes this is an unsafe condition) is made, and a smaller degree to which the same response would be no, signal is absent.

Even in the fuzzy SDT framework the concepts of Hit, Miss, False Alarm and Correct Rejection are valid; it is their binary characteristic that is discarded because of the loss of valuable information. Hence, each event represented by a stimuli–response pair in FSDT belongs, with some degree, to more than one of the four categories used in SDT. Consequently, it is possible that events would claim nonzero membership in more than one outcome category, as shown below in Table 3-2.

's'	'r'	H	FA	M	CR	Σ H+FA+M+CR
0.8	0.9	0.8	0.1	0	0.1	1
0.2	0.2	0.2	0	0	0.8	1
0.5	0.2	0.2	0	0.3	0.5	1
0.1	0.9	0.1	0.8	0	0.1	1

Table 3-2
Possible outcomes of Fuzzy SDT

To apply FSDT to a construction worker on a jobsite, it is important to understand how the worker perceives the situation. This must then be transformed into values / quantifiable data. When faced with a hazardous situation, the construction worker mentally determines the strength of the stimuli. The first step is the mapping of these stimuli according to the variables that describe the state of the world into the signal set – 's', with some degree of membership varying from zero to one. In the context of a construction site, these defining variables are the severity of the state that point towards an unsafe condition. For example, an unprotected/exposed drop of more than 6 feet, a protruding rebar without protective caps, a crane operation in close proximity to power lines, a faulty steel connection, etc., are some common stimuli - generating situations that a worker faces. The variable in each of these situations would be 'how afflictive or grave is this situation'. Each situation that the worker is faced with is equivalent to mapping between 0 to 1, but there is no such single variable that could be globally used to convert a signal strength to an 's' value. This mapping is given by the following equation:

$$s\,(SW) = f\,(x) \qquad ...(16)$$

In equation 16, the value of 's' is calculated as a function of the severity of unsafe state. Since the severity, or how critically unsafe is a situation, does not depend upon any one single on-site variable, it is not possible to propose an overall function that includes all possible unsafe states. The proposed solution in this research is a linear scale ranging from zero to ten, where ten would be the most severe. For example, a 'ten' would be a condition that would lead to a fatality; and a 'zero' would mean a completely harmless condition. It is important to note here that on a normal construction job-site, it would be almost impossible to prove any condition absolutely harmless. But, this condition (zero rating) has been included in the survey to provide the workers a complete range. The intention is to provide the two extremes, as this would help generate a more realistic answer to the questions. The intermediate values can only be whole numbers. The continuity of the evidence variable is not sacrificed and the range from 0 to 10 helps collate the worker's hazard detection ability. To transform this into an 's' value, i.e., to determine its membership in the signal set, a factor of 0.1 would be used.

The response generated by the worker also needs to be mapped to the 'r' set with a membership ranging from 0 to 1. The response value (RV) is dependent upon the worker's conviction in giving a 'yes – signal present' response. The sole variable here is the level of conviction, and the equation is given as:

$$r\,(RV) = f\,(y) \qquad \ldots(17)$$

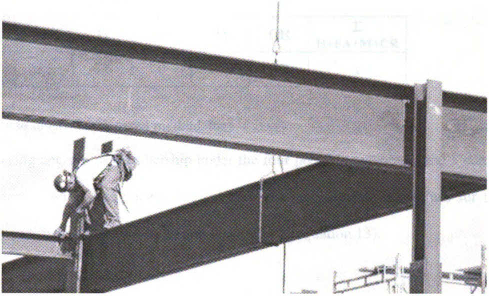
In equation 17, the value of 'r' is calculated as a function of the worker's level of conviction. For the fuzzy SDT model to perform effectively it is desirable to define both 's' and 'r' on similar (if not identical) scales, hence a linear scale similar to 's' was used that would produce the variable value ranging from 0 to 10. The factor used for transforming this into its r-membership is also 0.1.

Illustrated below is an example, where a construction worker is faced with a stimulus during his/her normal course of work on a job-site. The site condition, in the example, shows an ironworker connecting 4th floor beams, with an unprotected edge with no decking in place on the lower floors, protected by conventional fall protection (fall arrest). This condition is presented to a subject in the form of a visual as shown in Figure 3-1 (next page), who is asked two questions and is required to answer them using the rating system as explained earlier. He/she would then select one answer from the eleven possible values under each question.

The first question (How safe is this?) involves the strength of the signal, where the worker has to tell the two states apart – noise and signal. By expressing how safe the situation is the worker provides a value to the ease of signal detection, i.e., the sensitivity or the discriminability index.

The second question (How sure are you about your answer?) deals with the level of conviction the worker has in his/her answer. This can be easily understood as the location of the response criterion divide on the two-bell distribution curve, also referred to as the bias.

An ironworker connecting 4th floor beams, with an unprotected edge with no decking in place on the lower floors, but protected by conventional fall protection (fall arrest).



How safe is this?

Absolutely Safe ↑ | *Injurious* ↑ | *Fatal* ↑

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	●	○	○	○

How confident are you about your answer?

Completely Uncertain ↑ | *Moderately confident* ↑ | *Absolutely Sure* ↑

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	●	○	○	○	○

Figure 3-1
Example to illustrate proposed methodology: Ironworker making initial connections

Supposing the worker selects 7 for the first question and 6 for the second one. Using equations 16 and 17, the values for ‘s’ and ‘r’ are 0.7 and 0.6, respectively. The s and r pair would yield the following truth table for the four outcomes, as calculated from equation 12:

s	r	H	FA	M	CR	Σ H+FA+M+CR
0.7	0.6	0.6	0	0.1	0.3	1

Table 3-3
Example to illustrate proposed methodology

The varying degrees of membership under the four possible outcomes, and a cumulative score from a set of such questions, are then used to calculate the values for the two primary parameters, the sensitivity and bias (refer to equation 13).

There are three important components in the proposed mapping functions stated above (Parasuraman et al., 2000, Tsoukalas and Uhrig, 1997):

1. The proposed mapping function is of the continuous kind because the variables representing the state of the world (severity) and the response value (worker's confidence for a 'yes-signal present' response) are both continuous in nature. If the stimuli under investigation presented a finite number of discrete states, the mapping function would reflect discrete ratings of confidence level of response (e.g. yes-very-sure, yes-sure, yes, yes-unsure and so on).
2. The domain of hazard identification in construction allows both 's' and 'r' to be defined on scales that are map-able to each other.
3. The performance of the proposed mapping is fully achieved as the value of 'r' approaches 's'; indicating an equally appropriate response membership as invoked by the membership value in the signal set. For example, if s = 0.8, the optimum degree of response should also be 0.8.

3.2 Objective # 2

Develop and conduct a survey based on fuzzy SDT to assess construction workers' perception of safety, specific to the risk of fall accidents.

Research Method

The ideal method to determine and analyze worker responses would require real time assessment on a construction job-site. The worker, when faced with both states, safe and unsafe, makes a decision based on his/her understanding of the physical context and his/her analysis of the risk involved. Though this approach would yield data in its native state, it is highly dangerous and practically not feasible. Hence the alternative method adopted is a survey that represents various site conditions pictorially.

Based on the safety standards set by agencies like OSHA (Occupational Safety and Health Administration), NIOSH (National Institute for Occupational Safety and Health) and ANSI (American National Standards Institute), there were potential conditions selected that could result in fall accidents. There were other safe conditions also selected to balance the overall survey and provide the subject with a realistic mix of questions.

It was very important to present these scenarios, as close as possible to how a worker encounters them on site. In order to achieve this, the conditions were further short-listed to only retain those that could be presented visually, in the form of real photographs. This would enable the worker to select the most natural answer and capture the true hazard identification ability of the worker.

Assessing worker safety competencies using a survey design for fuzzy SDT is very different from that of crisp SDT, as presented by Patel (2002). The difference lies in the structure of the questions. As explained earlier in chapter 3, the eleven options shown in Figure 3-1, provide a more continuous mapping. Worker sensitivity and bias are captured when the worker makes the selection to the two questions posed, namely, 'How safe is this?' and 'How confident are you about your answer?'. Once a worker answers a given set of questions, the equations of fuzzy SDT are used to calculate the exact values of sensitivity and bias. Table 3-4 gives a sample list of a 12-question survey with hypothetical responses, providing an 's-r' pair for each question. The calculations for arriving at the two parameters, d' and β, are also shown.

Q.	Worker response		Calculations					
	s	r	H min (s, r)	M max (s - r, 0)	FA max (r - s, 0)	CR min (1 - s, 1 - r)	*Sum Check* *H+M+FA+CR*	$(1 - s_i)$
1	0.6	0.4	0.4	0.2	0	0.4	1	0.4
2	0.8	0.5	0.5	0.3	0	0.2	1	0.2
3	0.2	0.1	0.1	0.1	0	0.8	1	0.8
4	0.2	0.1	0.1	0.1	0	0.8	1	0.8
5	0.3	1	0.3	0	0.7	0	1	0.7
6	0	0	0	0	0	1	1	1
7	0.6	0.5	0.5	0.1	0	0.4	1	0.4
8	0.9	0.8	0.8	0.1	0	0.1	1	0.1
9	0.2	0.6	0.2	0	0.4	0.4	1	0.8
10	0.4	0.5	0.4	0	0.1	0.5	1	0.6
11	0.7	0.8	0.7	0	0.1	0.2	1	0.3
12	0.6	0.5	0.5	0.1	0	0.4	1	0.4
Σ	5.5	5.8	4.5	1	1.3	5.2		6.5

HR $\Sigma (H_i) / \Sigma (s_i)$	MR $\Sigma (M_i) / \Sigma (s_i)$	FAR $\Sigma (FA_i) / \Sigma (1 - s_i)$	CRR $\Sigma (CR_i) / \Sigma (1 - s_i)$	*Sum Check* *HR + M*	*Sum Check* *FAR + CRR*
0.82	0.18	0.20	0.80	1.00	1.00

d' = z(HR) – z(FAR)	β = Y(HR)/Y(FAR)
1.76	0.9319

$HR = \Sigma (H_i) / \Sigma (s_i)$ for i = 1 to N $MR = \Sigma (M_i) / \Sigma (s_i)$ for i = 1 to N

$FAR = \Sigma (FA_i) / \Sigma (1 - s_i)$ for i = 1 to N $CRR = \Sigma (CR_i) / \Sigma (1 - s_i)$ for i = 1 to N

Table 3-4: Sample calculations based on worker response ('s-r' pair)

The calculations for d' and β involve the use of the cumulative standard normal distribution table (explained earlier in equation 14 and 15), which can be found in Appendix F at the end of this thesis.

The final questionnaire for the survey is shown in Appendix A. For each question, the worker had to rate the condition suggested by producing the following:

1) A value ranging from 0 to 10 (both inclusive and only whole numbers) according to the severity of the condition being unsafe: 10 for the situation being totally fatal and a 0 for it being completely harmless.
2) A value ranging from 0 to 10 (both inclusive and only whole numbers) according to the worker's level of conviction in giving a response: 10 for total conviction and 0 for absolute disagreement.

Chapter 4

SURVEY RESULTS AND DATA ANALYSIS

4. SURVEY RESULTS AND DATA ANALYSIS

This chapter presents the survey data and its analysis based on the steps discussed in chapter 3. The research focused on ironworkers due to the high risk of fall accidents as explained in chapter 1. The survey presented 18 on site conditions that an ironworker would typically be faced with during the steel erection phase of any project. Because the survey already targeted a specific group (ironworkers), there was no attempt at further short-listing the sample. All ironworkers were randomly approached, with no restriction on age, sex, or years of experience in the industry. All ironworkers were familiar with safety standards and had undergone some form of safety training, pertaining to their company policies. Therefore, it was expected that they had sufficient understanding of the conditions presented.

The fundamental principle of fuzzy SDT is the non-binary characteristic of signal and response. The ironworkers' ability to identify a signal is mapped in the two-step process, represented by the twin questions with each condition. The 18 conditions presented were a good mix of:

i. Absolutely safe conditions, conforming to standards.

ii. Conditions that were clear violations of all safety standards and would lead to a serious accident.

iii. Conditions that violated safety standard but were not so clearly identifiable. These could result in injuries, minor and/or major.

For example, condition # 3 from the survey presents a condition, as shown in Figure 4-1, where the distance between beams tied on a multiple rigging assembly for erection is 6 feet. The required standard separation between beams in a multiple rigging assembly as

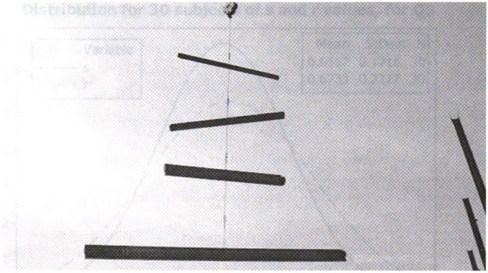


Figure 4-1
Condition 3 from survey questionnaire

set by OSHA is 7 feet. This standard is based on the fact that when an ironworker is standing on a beam and the crane lowers the assembly, the 7 feet distance would avoid getting him hit on the head (when he stands straight) as he lowers the first beam into position. So this is potentially a dangerous condition presented to the ironworkers. As cited by one of the safety professionals interviewed during this research, depending upon how tall each subject was, their perception of threat would vary. Also important is the fact that even if they are aware of the standard (which they were exposed to during their training), how significant (grave) do they feel this condition could be. Table 4-1 and Figure 4-2 present a break up of individual responses and their respective distribution, to this condition.

	Response to Q3 by 30 workers														
w #	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
s	1.0	0.7	0.7	0.8	0.4	0.4	0.7	0.5	0.7	0.7	0.6	0.6	0.7	0.5	0.8
r	1.0	0.8	0.8	0.6	0.7	0.7	0.5	0.8	0.7	0.7	0.2	0.3	0.6	1.0	0.5
w #	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
s	0.9	0.4	0.6	0.5	1.0	0.5	0.6	0.6	0.5	0.7	0.6	1.0	0.7	0.8	0.5
r	0.5	0.6	0.5	0.7	1.0	0.6	0.5	0.8	0.5	0.8	0.3	1.0	1.0	0.8	0.8

Table 4-1
s and r responses by 30 subjects to Q3

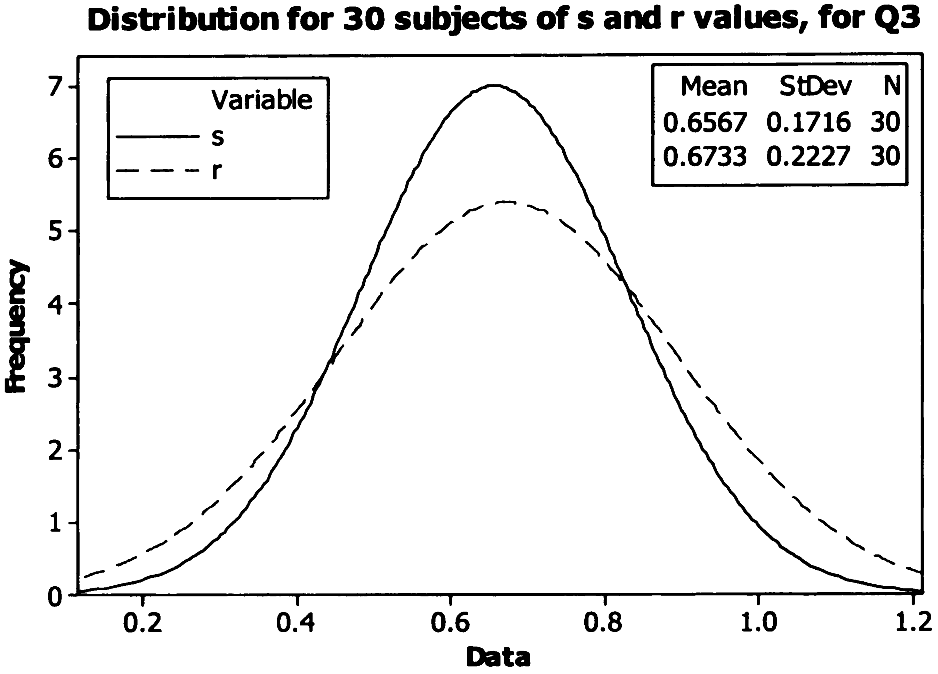


Figure 4-2
s and r distribution for 30 subjects to Q3

The distribution indicates that condition number three from the questionnaire received a mean 's' value of 0.66, mean 'r' value of 0.67, with the 'r' value being slightly more spread out than the 's' value. This gives us an idea of how this group of subjects perceived safety when they would come across such a condition. The true nature of the condition, safe or unsafe, was known from OSHA regulations used for creating the survey. The response of the 30 subjects to each of these conditions can thus be determined, using their responses to the 2 questions asked with each condition.

4.1 Data Collection

Thirty complete surveys were received, which is reasonably large to allow the use of normal distribution to analyze the data. Appendix B lists the survey results for the 30 workers, specifically the (s, r) pairs. The subject would select a value for the two questions on each of the 18 conditions, resulting in the 's' and 'r' pair. The exact 18 conditions can be viewed from the survey attached in Appendix A. Each worker according to his/her understanding first selected a value based on how safe he/she thought the presented condition was. This value is multiplied by 0.1 to yield the membership in the signal set, i.e., 's' value. Similarly the second question (how sure is the worker) calls for a response between 0 to 10, which results in the 'r' value, i.e., membership in the 'Yes-signal present' set.

4.2 Data Analysis

As shown below, Table 4-2 provides an average for each of the questions presented to the ironworker. This table indicates how the subjects responded to the 18 conditions, i.e., how do they interpret a scenario, expressed on a linear scale of 0–10. There could be a scenario where according to the standards, the condition is completely unsafe, but the subjects (as a group) think it is safe. For example conditions presented in questions 5, 6 and 16 are violations of OSHA safety regulations, but on an average the subjects only gives it a 0.5 or less (s-value). Their understanding of the condition is that it would not lead to a serious accident on site. So based on a more widespread study using the same methods described here, feedback could be given to OSHA and these comments incorporated into improving training.

Q #	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Average of 30 workers response to the question "How safe is this condition"																		
s	0.5	0.2	0.7	0.6	0.5	0.5	0.7	0.8	0.4	0.3	0.3	0.8	0.8	0.7	0.4	0.4	0.3	0.3
Average of 30 workers response to the question "How sure are you about your answer"																		
r	0.7	0.8	0.7	0.7	0.7	0.7	0.8	0.8	0.7	0.8	0.7	0.8	0.9	0.8	0.7	0.7	0.8	0.8

Table 4-2
Average (of 30 workers) 's' and 'r' values for each question (condition)

Provided below in Figure 4-3 and 4-4 are the distributions for 's' and 'r' values. This helps formalize the raw data with which there were further calculations performed.

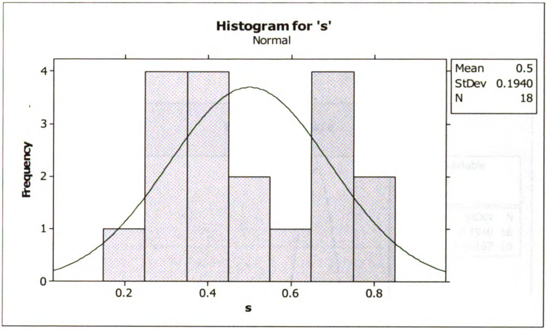


Figure 4-3
Distribution of 's' value for 18 questions

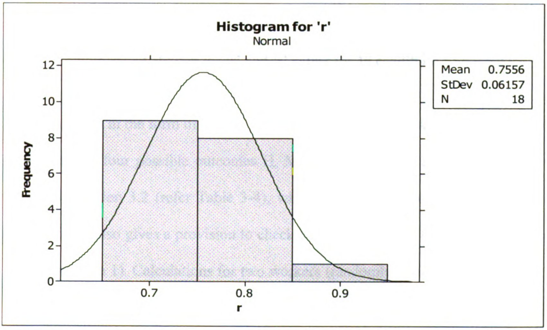


Figure 4-4
Distribution of 'r' value for 18 questions

Figure 4-5 below, provides a comparison of the distributions for s and r values. The combined graph indicates that the 's' values were well spread out (a high variation in the response to the first question - 'how safe is this?'). The distribution for the r-values shows that the subjects were confident of their responses, resulting in a higher mean and reduced spread.

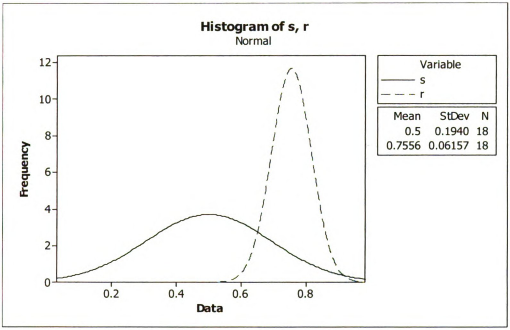


Figure 4-5
Combined distribution for 'r' and 's' values for 18 conditions presented

Once data in the form of 's' and 'r' was determined, the next step was to calculate the value of the four possible outcomes H, M, FA and CR. A sample calculation was presented in section 3.2 (refer Table 3-4), which explains in detail, how each value is determined and also gives a provision to check for any deviations (sum of four outcomes is always equal to 1). Calculations for two workers (randomly selected) are shown below in Table 4-3; the entire set can be found in appendix B.

	Worker 12								Worker 15							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.5	0.9	0.5	0	0.4	0.1	0.5	1	0.6	0.5	0.5	0.1	0	0.4	0.4	1
2	0.5	0.8	0.5	0	0.3	0.2	0.5	1	0.3	0.9	0.3	0	0.6	0.1	0.7	1
3	0.6	0.3	0.3	0.3	0	0.4	0.4	1	0.8	0.5	0.5	0.3	0	0.2	0.2	1
4	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.7	0.6	0.6	0.1	0	0.3	0.3	1
5	0.5	0.6	0.5	0	0.1	0.4	0.5	1	0.5	0.7	0.5	0	0.2	0.3	0.5	1
6	0.3	0.8	0.3	0	0.5	0.2	0.7	1	0.8	0.7	0.7	0.1	0	0.2	0.2	1
7	0.6	0.9	0.6	0	0.3	0.1	0.4	1	0.9	0.8	0.8	0.1	0	0.1	0.1	1
8	0.2	0.5	0.2	0	0.3	0.5	0.8	1	0.9	0.5	0.5	0.4	0	0.1	0.1	1
v	0.3	0.5	0.3	0	0.2	0.5	0.7	1	0.3	0.7	0.3	0	0.4	0.3	0.7	1
10	0.5	0.4	0.4	0.1	0	0.5	0.5	1	0.2	0.5	0.2	0	0.3	0.5	0.8	1
11	0.4	0.5	0.4	0	0.1	0.5	0.6	1	0.3	0.6	0.3	0	0.3	0.4	0.7	1
12	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.9	0.6	0.6	0.3	0	0.1	0.1	1
13	0.8	0.6	0.6	0.2	0	0.2	0.2	1	0.9	1	0.9	0	0.1	0	0.1	1
14	0.5	0.7	0.5	0	0.2	0.3	0.5	1	0.7	0.6	0.6	0.1	0	0.3	0.3	1
15	0.5	0.8	0.5	0	0.3	0.2	0.5	1	0.5	0.9	0.5	0	0.4	0.1	0.5	1
16	0.3	0.7	0.3	0	0.4	0.3	0.7	1	0.3	0.5	0.3	0	0.2	0.5	0.7	1
17	0.1	0.7	0.1	0	0.6	0.3	0.9	1	0.4	0.7	0.4	0	0.3	0.3	0.6	1
18	0.3	0.7	0.3	0	0.4	0.3	0.7	1	0.2	0.7	0.2	0	0.5	0.3	0.8	1
Sum	8.5	12.2	7.9	0.6	4.3	5.2	9.5		10.2	12.0	8.7	1.5	3.3	4.5	7.8	
	Hit Rate =	0.93			FA Rate =	0.45			Hit Rate =	0.85			FA Rate =	0.42		

Table 4-3
Calculation for four possible outcomes – H, M, FA and CR
(Complete calculations for all workers is shown in appendix B)

The s and r distribution corresponding to worker # 15, for all the 18 conditions presented to him/her is shown below in Figure 4-6. Similar distributions can be determined for all other workers, yielding a detailed comparative study for each.

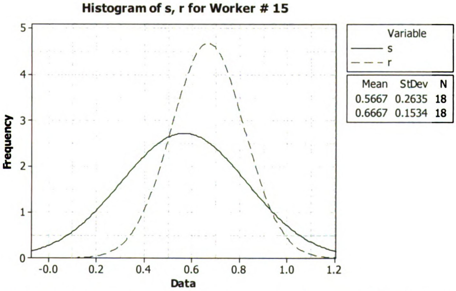


Figure 4-6: Combined distribution of ‘s’ and ‘r’ values for Worker # 15 (18 conditions)

Once the Hit Rate and False Alarm Rate pair is calculated for each worker, the value of sensitivity (discriminability index) and response criterion (bias) is calculated according to equations 14 and 15 as shown in section 2.11. The outcome for the 30 ironworkers is shown below in Table 4-4.

Worker #	Hit Rate	FA Rate	z (HR)	z (FAR)	**Sensitivity**	Y (HR)	Y (FAR)	**Bias**
	HR	**FAR**			**d'**			β
1	1.00	0.95	3.89	1.62	2.27	0.00	0.11	0.00
2	0.95	0.49	1.61	-0.03	1.64	0.11	0.40	0.27
3	0.94	0.65	1.56	0.37	1.18	0.12	0.37	0.32
4	0.97	0.79	1.84	0.79	1.04	0.07	0.29	0.25
5	0.90	0.40	1.28	-0.25	1.53	0.18	0.39	0.45
6	0.95	0.48	1.67	-0.04	1.71	0.10	0.40	0.25
7	0.98	0.61	2.01	0.27	1.74	0.05	0.38	0.14
8	0.89	0.38	1.25	-0.30	1.54	0.18	0.38	0.48
9	0.95	0.51	1.69	0.01	1.67	0.10	0.40	0.24
10	0.99	0.74	2.29	0.66	1.63	0.03	0.32	0.09
11	0.83	0.24	0.97	-0.71	1.68	0.25	0.31	0.81
12	0.93	0.45	1.47	-0.12	1.59	0.14	0.40	0.34
13	0.87	0.51	1.13	0.03	1.10	0.21	0.40	0.53
14	0.97	0.95	1.94	1.66	0.28	0.06	0.10	0.60
15	0.85	0.42	1.05	-0.19	1.24	0.23	0.39	0.59
16	0.91	0.59	1.37	0.24	1.14	0.16	0.39	0.40
17	0.96	0.55	1.80	0.13	1.67	0.08	0.40	0.20
18	0.94	0.67	1.56	0.45	1.11	0.12	0.36	0.33
19	0.92	0.47	1.42	-0.09	1.50	0.15	0.40	0.37
20	1.00	1.00	3.89	3.89	0.00	0.00	0.00	1.00
21	0.85	0.44	1.04	-0.15	1.19	0.23	0.39	0.57
22	0.86	0.36	1.06	-0.35	1.41	0.23	0.38	0.60
23	0.87	0.40	1.14	-0.26	1.40	0.21	0.39	0.54
24	0.83	0.22	0.97	-0.76	1.73	0.25	0.30	0.84
25	0.93	0.24	1.50	-0.71	2.21	0.13	0.31	0.42
26	0.84	0.28	1.01	-0.59	1.60	0.24	0.34	0.71
27	0.93	0.56	1.49	0.16	1.33	0.13	0.39	0.33
28	0.93	0.71	1.47	0.55	0.92	0.14	0.34	0.40
29	1.00	0.73	3.89	0.60	3.29	0.00	0.33	0.00
30	1.00	0.71	3.89	0.56	3.33	0.00	0.34	0.00
Average	0.92	0.54			1.52			0.40
Min	0.83	0.22			0.00			0.00
Max	1.00	1.00			3.33			1.00
Std. Dev	0.054	0.209			0.668			0.249

Table 4-4: Calculation for Sensitivity (d') and Response Criterion (β) based on FSDT

Based on the calculations of HR, FAR, d' and β of the 30 workers from Table 4-4, shown below in Figures 4-7 to 4-10, are their respective distributions.

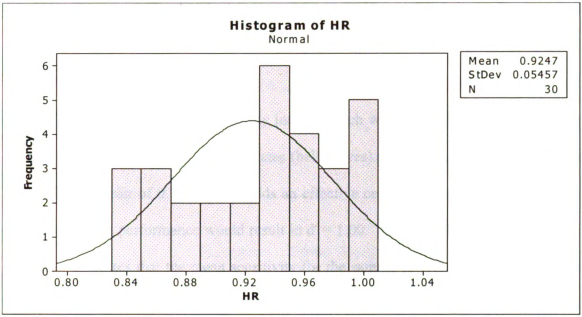


Figure 4-7
Distribution for HR of 30 workers

The average HR is 0.92. This means that 92% of the time, workers correctly spotted an unsafe condition when they saw one. The HR alone does not give enough information; it

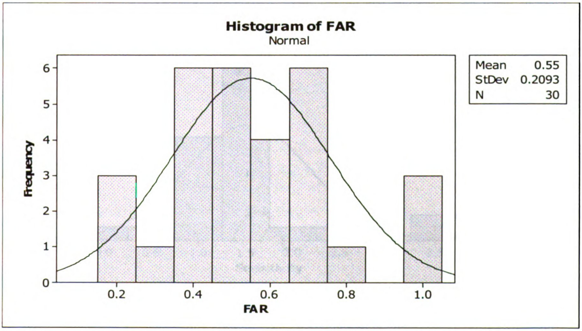


Figure 4-8
Distribution for FAR of 30 workers

is very important to look at the number of false alarms, to get the complete picture.

The mean FAR value from Figure 4-8 for 30 subjects was 0.55. This indicated that 55% of the time, when workers were faced with a safe condition, i.e., noise, they still thought it was unsafe. From the workers' perspective, this reflects a tendency to feel that the conditions are unsafe.

Sensitivity or the discriminability index of each worker can be understood as the extent of separation between the two states (bell curves). As discussed earlier in section 2.4, a HR-FAR pair of 0.99 - 0.01, yields an effective ceiling for sensitivity, where d' = 4.65. An average performance would result in d' = 1.00. A look at Table 4-4 and Figure 4-9 below indicates that the mean sensitivity for the sample is 1.41, which according to the SDT standards is considered above average. There are only three workers (#14, 20 and 28) whose d' value falls below 1.00.

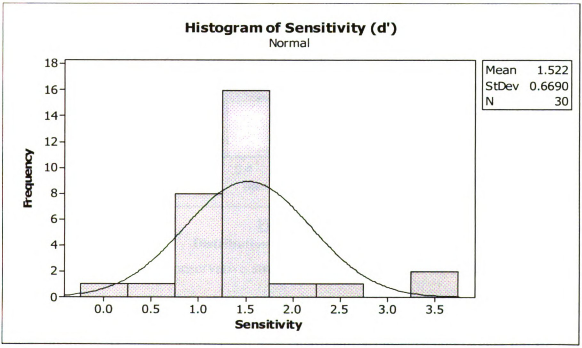


Figure 4-9
Distribution for d' of 30 workers

The decision-making strategy of the workers is reflected by the response criterion or the bias of the group. From the18 questions posed to the subjects, only 7 presented safe conditions, as per the industry safety statutes, resulting in a cut-off value of β = 0.39. Figure 4-10, as shown below gives the β distribution of the 30 subjects, resulting in a mean value of 0.40 with a minimum of 0 and maximum of 1.0. The average strategy of the group of ironworkers who participated in this research was found to be very close, in fact just over the cut-off, and can be considered as conservative. Although they produce a high hit rate, they also produce a high number of false alarms.

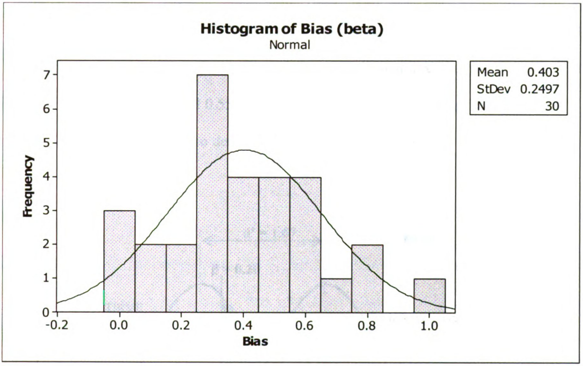


Figure 4-10
Distribution for β of 30 workers

In construction a conservative strategy is definitely better as compared to a risky one, since a risky strategy would result in high misses, which translates to high accident costs, productivity loss and lower morale. This result seemingly contradicts the figures presented in chapter one, where construction accidents are on the increase and annual budgets for safety are on the rise, but it is important to note that the intent of this research is to better understand workers ability to identify unsafe conditions. With the proposed fuzzy SDT approach and gathered data using a well-defined survey, the resulting analysis is an accurate reflection of the way the 30 subjects perceive safety on site.

The average bias of the sample was very close to the cut-off, indicating that there is a need to improve safety training, so that workers produce a high HR and also, more importantly, a low FAR. That would result in an ideal scenario where the money spent into safety training would result in an improvement of hazard identification.

To further expand on these results and understand the relationship with the noise-signal distributions, data from a single (random) ironworker is analyzed. Subject #17 scored a HR and FAR pair of 0.96 and 0.55 respectively, based on his/her mapping of 's' and 'r' values. This worker's ability to detect unsafe conditions is illustrated below in Figure 4-11.

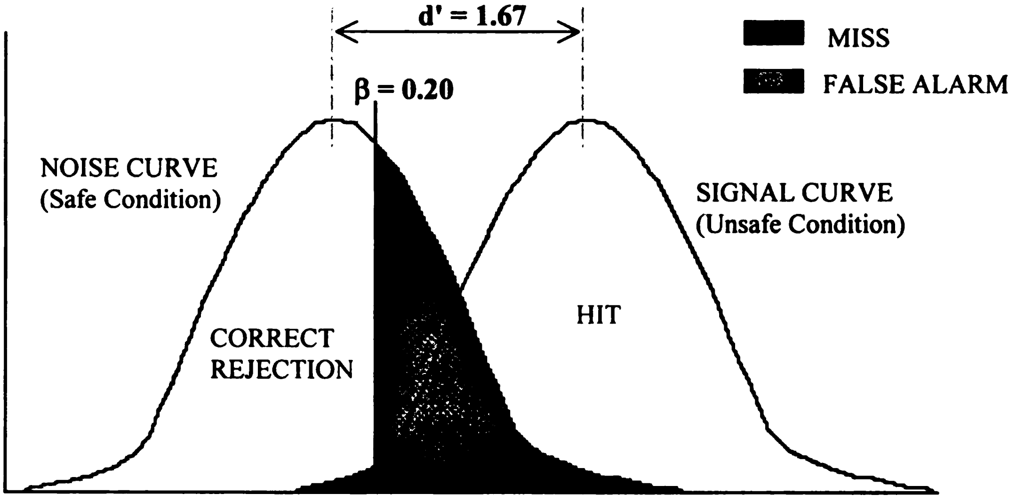


Figure 4-11
Distribution for Worker #17

For the worker's sensitivity (separation between the two bell curves), there is a high Hit Rate recorded, but the False Alarm Rate is also very high, indicative of the conservative strategy adopted by the worker yielding a very low 'response criterion' value (the vertical divide). The conservative bias pulls the divide towards the noise curve and explains the high FAR. In the same manner a distribution could be drawn out for each of the 30 workers that would provide information as to how well they are able to discriminate between the two states (how sensitive they are) and what strategy they adopt (risky or conservative).

4.3 Data Analysis using Conventional SDT

The collected data was further analyzed based on conventional SDT, to explore the possible differences in the two approaches (Fuzzy and Conventional SDT). Survey questions were designed on the basis of industry wide safety regulations, in compliance with OSHA. The survey was designed in such a manner that out of the total 18 conditions presented, 7 were safe and 11 unsafe. Under the conventional or crisp SDT analysis, this binary division forms the platform for further research. The state of the world, or the condition presented to the subject, was now either 'safe' or 'unsafe'. Similar to the methodology followed by Patel (2000), illustrated below in Table 4-5 are the average s-values for the 30 subjects. While analyzing the data using conventional SDT only s-values were incorporated; these correspond to the worker response. There was an important assumption made to convert the continuous 's' values of FSDT for the purpose of conventional SDT analysis. The 0-10 scale was converted into a binary scale; all values from 0 to 3, were regarded as a 'No – Signal Absent' response. Values from 4 to

10 were considered a 'Yes – Signal Present' response. In conventional SDT, the measure of the decision making process, i.e., bias, is determined at the end of the analysis. The r-values of FSDT cannot be used in conventional SDT analysis.

Average for 30 workers							
	Conventional SDT approach						
Q #	**state**	**s**	**Response**	**H**	**M**	**FA**	**CR**
Q1	unsafe	0.5	Yes	☒			
Q2	safe	0.2	No				☒
Q3	unsafe	0.6	Yes	☒			
Q4	unsafe	0.6	Yes	☒			
Q5	unsafe	0.5	Yes	☒			
Q6	unsafe	0.5	Yes	☒			
Q7	unsafe	0.7	Yes	☒			
Q8	unsafe	0.8	Yes	☒			
Q9	safe	0.4	Yes			☒	
Q10	safe	0.3	No				☒
Q11	safe	0.3	No				
Q12	unsafe	0.8	Yes	☒			
Q13	unsafe	0.8	Yes	☒			
Q14	unsafe	0.7	Yes	☒			
Q15	safe	0.4	Yes			☒	
Q16	unsafe	0.4	Yes	☒			
Q17	safe	0.3	No				☒
Q18	safe	0.3	No				☒

Table 4-5: Data Analysis using Conventional SDT

An example, with the same subjects and responses used in FSDT data analysis (worker # 12 and 15), is shown below in Table 4-6. Only one out of the four possible outcomes got populated with a one, leaving the other three with zeroes. Calculations for conventional SDT were based on:

HR = Yes | unsafe condition = Sum of Hits / Signals

FAR = Yes | safe condition = Sum of False Alarms / Noise

Worker 12							Worker 15						
s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
0.5		1	0	0	0	1	0.6		1	0	0	0	1
0.5		0	0	1	0	1	0.3		0	0	0	1	1
0.6		1	0	0	0	1	0.8		1	0	0	0	1
0.8		1	0	0	0	1	0.7		1	0	0	0	1
0.5		1	0	0	0	1	0.5		1	0	0	0	1
0.3		0	1	0	0	1	0.8		1	0	0	0	1
0.6		1	0	0	0	1	0.9		1	0	0	0	1
0.2		0	1	0	0	1	0.9		1	0	0	0	1
0.3		0	0	0	1	1	0.3		0	0	0	1	1
0.5		0	0	1	0	1	0.2		0	0	0	1	1
0.4		0	0	1	0	1	0.3		0	0	0	1	1
0.8		1	0	0	0	1	0.9		1	0	0	0	1
0.8		1	0	0	0	1	0.9		1	0	0	0	1
0.5		1	0	0	0	1	0.7		1	0	0	0	1
0.5		0	0	1	0	1	0.5		0	0	1	0	1
0.3		0	1	0	0	1	0.3		0	1	0	0	1
0.1		0	0	0	1	1	0.4		0	0	1	0	1
0.3		0	0	0	1	1	0.2		0	0	0	1	1
	0.0	8.0	3.0	4.0	3.0			0.0	10.0	1.0	2.0	5.0	
HR =		0.73		FA Rate =		0.57	HR =		0.91		FA Rate =		0.29

Table 4-6: Example of Data Analysis using Conventional SDT for worker 12 and 15

In Table 4-6 the HR and FAR were calculated as follows:

HR = Sum of Hits / Signals = 8/11 = 0.73

FAR = Sum of False Alarms / Noise = 4/7 = 0.57

As explained earlier in chapter 2, even in conventional SDT sum of the four possibilities is always equal to one. The last column for each worker provides a check stating the sum of H, M, FA and CR. All readings for 30 subjects and 18 conditions are presented in Appendix G at the end of the thesis. After calculating the HR and FAR for all 30 workers there sensitivity was determined using equation 14 (section 2.11) and resulting values are shown below in Table 4-7.

Worker #	Hit Rate	FA Rate	z (HR)	z (FAR)	Sensitivity	Y (HR)	Y (FAR)	Bias
	HR	FAR			d'			β
1	0.36	0.29	-0.35	-0.57	0.22	0.38	0.34	1.10
2	0.91	0.29	1.34	-0.57	1.90	0.16	0.34	0.48
3	0.91	0.00	1.34	0.50	0.84	0.16	0.35	0.46
4	0.91	0.11	1.34	-1.21	2.55	0.16	0.19	0.86
5	0.82	0.44	0.91	-0.14	1.05	0.26	0.40	0.67
6	0.91	0.11	1.34	-1.25	2.59	0.16	0.18	0.90
7	0.91	0.22	1.34	-0.76	2.09	0.16	0.30	0.55
8	1.00	0.35	3.80	-0.39	4.19	0.00	0.37	0.00
9	0.91	0.22	1.34	-0.79	2.12	0.16	0.29	0.56
10	0.91	0.22	1.34	-0.76	2.10	0.16	0.30	0.55
11	1.00	0.48	3.80	-0.06	3.86	0.00	0.40	0.00
12	0.73	0.53	0.60	0.08	0.52	0.33	0.40	0.84
13	0.73	0.25	0.60	-0.67	1.28	0.33	0.32	1.05
14	0.73	0.19	0.60	-0.86	1.47	0.33	0.27	1.21
15	0.91	0.33	1.34	-0.43	1.77	0.16	0.36	0.45
16	0.82	0.47	0.91	-0.09	1.00	0.26	0.40	0.66
17	0.73	0.10	0.60	-1.26	1.86	0.33	0.18	1.84
18	0.73	0.32	0.60	-0.48	1.08	0.33	0.36	0.93
19	0.91	0.00	1.34	0.50	0.84	0.16	0.35	0.46
20	0.45	0.16	-0.11	-0.99	0.88	0.40	0.24	1.62
21	1.00	0.12	3.80	-1.19	4.99	0.00	0.20	0.00
22	1.00	0.71	3.80	0.57	3.23	0.00	0.34	0.00
23	0.91	0.51	1.34	0.03	1.30	0.16	0.40	0.41
24	1.00	0.14	3.80	-1.07	4.87	0.00	0.23	0.00
25	1.00	1.00	3.80	3.80	0.00	0.00	0.00	1.00
26	0.91	0.31	1.34	-0.50	1.83	0.16	0.35	0.46
27	0.82	0.48	0.91	-0.04	0.95	0.26	0.40	0.66
28	0.91	0.00	1.34	0.50	0.84	0.16	0.35	0.46
29	0.73	0.20	0.60	-0.86	1.46	0.33	0.28	1.20
30	0.36	0.16	-0.35	-0.98	0.63	0.38	0.25	1.52
Average	0.85	0.30			1.81			0.70
Min	0.36	0.00			0.00			0.00
Max	1.00	1.00			4.99			1.84
Std. Dev	0.175	0.219			1.30			0.48

Table 4-7: Calculation for Sensitivity (d') and Bias (β) using conventional SDT

The data analysis based on conventional SDT varies from Fuzzy SDT, in the calculation of HR and FAR. The s-values are transformed into binary values as explained above. The resultant sensitivity and bias values of the same subjects using the same conditions are very different as compared to the Fuzzy SDT values. Provided below in Figure 4-12a and 4-12b is a comparison of FSDT d' and β with the same parameters when calculated with conventional SDT, illustrated as a normal distribution.

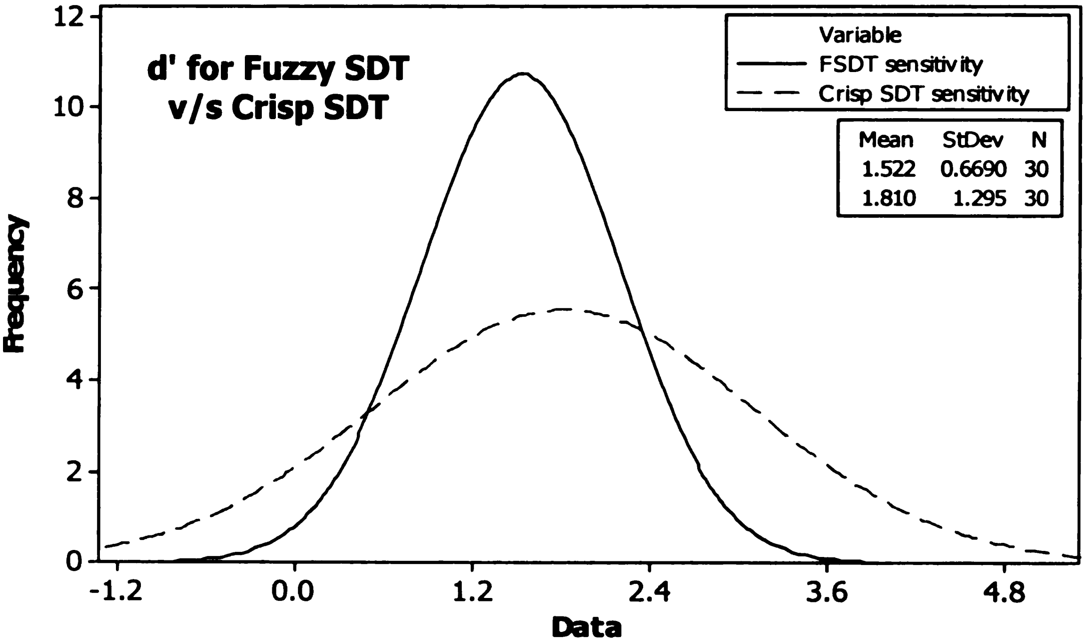


Figure 4-12a: Sensitivity (d') distributions for Fuzzy SDT v/s Crisp (conven.) SDT

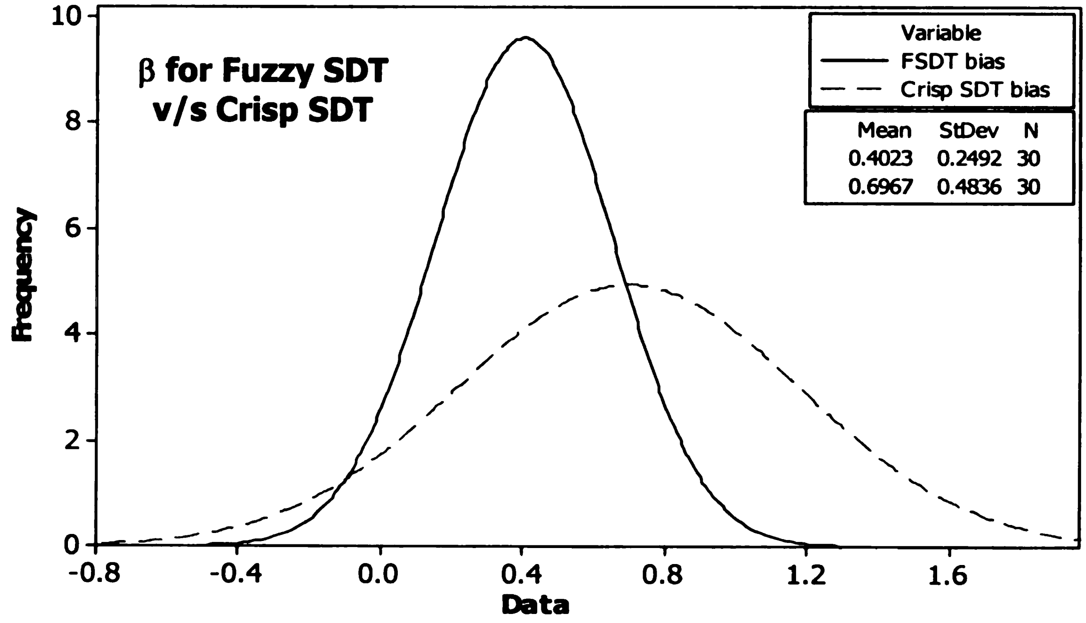


Figure 4-12b: Response bias (β) distributions for Fuzzy SDT v/s Crisp (conven.) SDT

Based on the findings from Figure 4-12a and 1-12b above, there is a distinct difference in the distribution of sensitivity and bias of the same group of subjects with the same set of conditions. The two approaches (FSDT and SDT) provide a contrasting picture. The sensitivity and bias derived using conventional SDT shows a sharp increase in the spread for the 30 subjects. Analysis of d' using fuzzy SDT was subject to normal distribution with a mean (μ) of 1.52 and a standard deviation (σ) of 0.67. Analysis based on crisp or conventional SDT resulted in a mean of 1.81 with standard deviation 1.30. Similarly β, the measure of bias from FSDT model had a mean (μ) of 0.40 and std. dev. $\sigma = 0.25$. With crisp SDT the β values were $\mu = 0.70$ and $\sigma = 0.48$. It is evident that the two models yield very different data, as summarized below in Table 4-8.

Model	**Fuzzy SDT**		**Crisp SDT**	
Value	**d'**	β	**d'**	β
μ	1.52	0.40	1.81	0.70
σ	0.67	0.25	1.30	0.48
HR	0.92		0.85	
FAR	0.54		0.30	

d' = Sensitivity
β = Response bias
μ = average
s = standard deviation

HR = Hit Rate
FAR = False Alarm Rate

Table 4-8: Sensitivity and bias values from fuzzy SDT and crisp SDT

The FSDT model captures the workers sensitivity and bias (in the form of s-r pair) when it asks the two questions – 'How safe is this?' and 'How confident are you about your answer?'. The s-r pair then leads to the HR and FAR which on further statistical treatment results in the d' and β values. In crisp SDT, the binary setup forced the workers response to the same questions into a single outcome set (H, M, FA, CR). It is during this forced classification that the workers' ideal measure of their ability to sense a signal is confounded.

In order to rule out any discrepancy in the results due to the assumption made earlier (binary conversion of the 's' value from the continuous scale based on a cut-off at 3, i.e., 0-3: No, signal absent and 4-10: Yes, signal present), following analysis was performed. All 30 workers' responses to the first question for each of the 18 conditions were converted into crisp SDT model by using two different cut-offs:

a. Cut-off at 2, i.e., 0-2 converted to No, signal absent and 3-10 converted to Yes, signal present.
b. Cut-off at 1, i.e., 0-1 converted to No, signal absent and 2-10 converted to Yes, signal present.

The analysis yielded very similar results with high variation in the d' and β values.

a. For cut-off at 2, mean d' = 2.73 and $\sigma = 1.59$. Mean $\beta = 0.35$ and $\sigma = 0.42$.
b. For cut-off at 1, mean d' = 2.11 and $\sigma = 1.60$. Mean $\beta = 0.16$ and $\sigma = 0.81$.

The detailed tables showing HR and FAR values for each worker and corresponding d' and β values for cut-off at 1 and 2 are presented in Appendix G at the end of the thesis. As proposed earlier in chapter 3, it was with the FSDT model that the true ability of the worker was captured in the s-r pair. The resulting calculations, as shown above, confirmed this hypothesis.

Another important aspect of an efficient data analysis via a survey questionnaire is keeping a check on trends and non-random patterns in the collected data. The survey questionnaire presented identical 18 questions to each worker. There was always a possibility that a given worker would tend to loose interest and his/her responses, as he/she answers subsequent questions, start to show a pattern. The survey results were investigated for the presence of any such systematic trend, namely, a fatigue factor.

Workers' s and r responses were plotted against condition numbers 1 to 18, and the resulting scatter plots with fitted regression lines for 2 workers selected randomly are presented in Appendix H. These plots indicated no relationship between the number of questions and the responses. To further detect any non-randomness of collected data the auto correlation function was plotted. This detects any correlation between subsequent responses from the subject. The resultant scatter plot only indicated white noise, indicating no relationship between how the worker answered every subsequent question. The plots can be found in Appendix H at the end of this thesis.

It was important to consider the quality of data used in this analysis. Because the subject sample was already a focused trade (ironworkers), it was essential to explore whether any characteristics related to the subject sample would have a relationship with the responses received. The next section investigates the existence of any such associations.

4.4 Regression Analysis

This section investigates any relationship between subject age, years of experience in the industry and their corresponding measures of sensitivity and bias. This would help to understand whether a more experienced ironworker (both in terms of age and years in the industry), would identify unsafe conditions better compared to a less experienced ironworker. Table 4-8 below provides a detailed breakdown of the age and industry experience of each ironworker. It also states their sensitivity and bias as calculated earlier.

Worker #	Age	Ind. Exp.	Hit Rate	FA Rate	**Sensitivity**	**Bias**
			HR	**FAR**	**d'**	β
17	21	1	0.96	0.55	1.67	0.20
22	24	4.5	0.86	0.36	1.41	0.60
1	25	6	1.00	0.95	2.27	0.00
11	26	3	0.83	0.24	1.68	0.81
19	26	7	0.92	0.47	1.50	0.37
20	27	8	1.00	1.00	0.00	1.00
4	28	9	0.97	0.79	1.04	0.25
23	28	4	0.87	0.40	1.40	0.54
9	29	8	0.95	0.51	1.67	0.24
10	29	4	0.99	0.74	1.63	0.09
13	29	5	0.87	0.51	1.10	0.53
12	30	5	0.93	0.45	1.59	0.34
21	31	8	0.85	0.44	1.19	0.59
29	31	4	1.00	0.73	3.29	0.00
25	33	4	0.93	0.24	2.21	0.42
26	33	7	0.84	0.28	1.60	0.71
2	34	6	0.95	0.49	1.64	0.27
28	34	10	0.93	0.71	0.92	0.40
3	35	12	0.94	0.65	1.18	0.32
6	35	13	0.95	0.48	1.71	0.25
15	35	7	0.85	0.42	1.24	0.59
5	37	12	0.90	0.40	1.53	0.45
18	37	14	0.94	0.67	1.11	0.33
8	38	11	0.89	0.38	1.54	0.48
16	38	14	0.91	0.59	1.14	0.40
30	38	17	1.00	0.71	3.33	0.00
24	41	18	0.83	0.22	1.73	0.84
7	46	18	0.98	0.61	1.74	0.14
14	49	31	0.97	0.95	0.28	0.60
27	49	25	0.93	0.56	1.33	0.33

Table 4-9
Age and Industry Experience of Ironworkers

The above table provided two independent/predictor variables (age and years of experience) and two dependent/response variables (sensitivity and bias). In an effort to find any relationship between these, each response variable was plotted against each predictor variable and the scatter plots were produced. Figures 4-13 to 4-16 present these scatter plots with a regression line fitted through them.

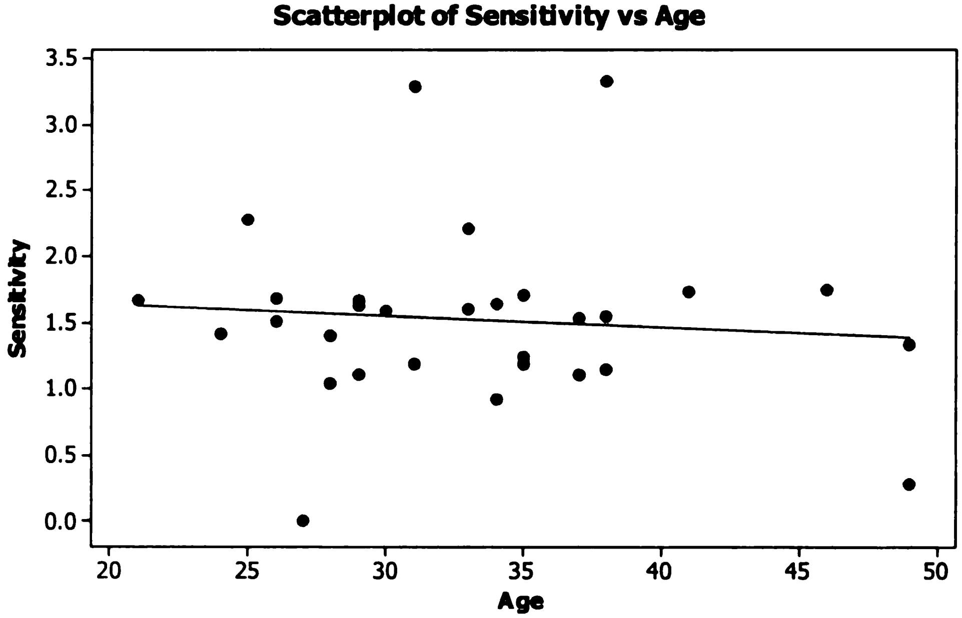


Figure 4-13: Scatter plot with regression line for d' v/s age

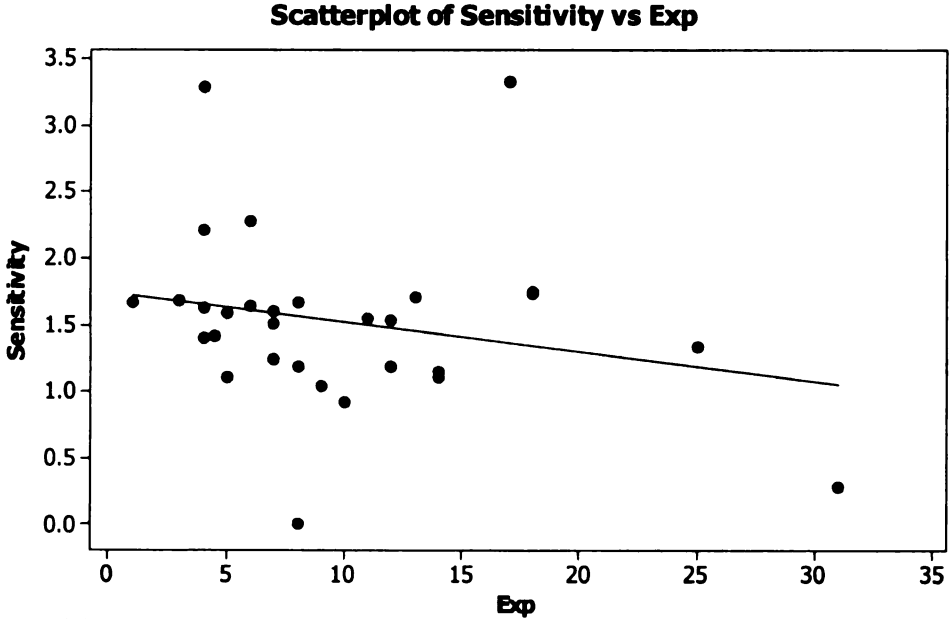


Figure 4-14: Scatter plot with regression line for d' v/s years of experience

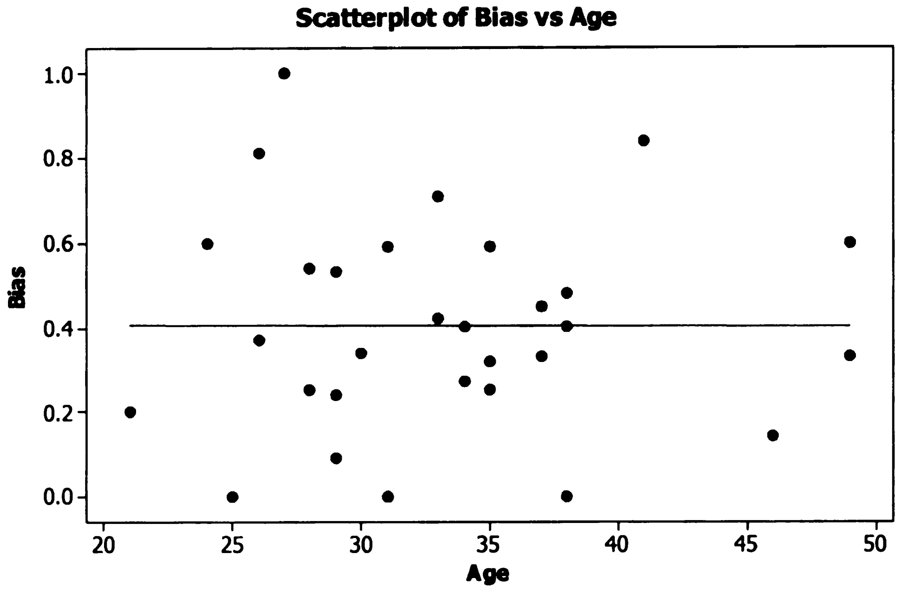


Figure 4-15: Scatter plot with regression line for β v/s worker age

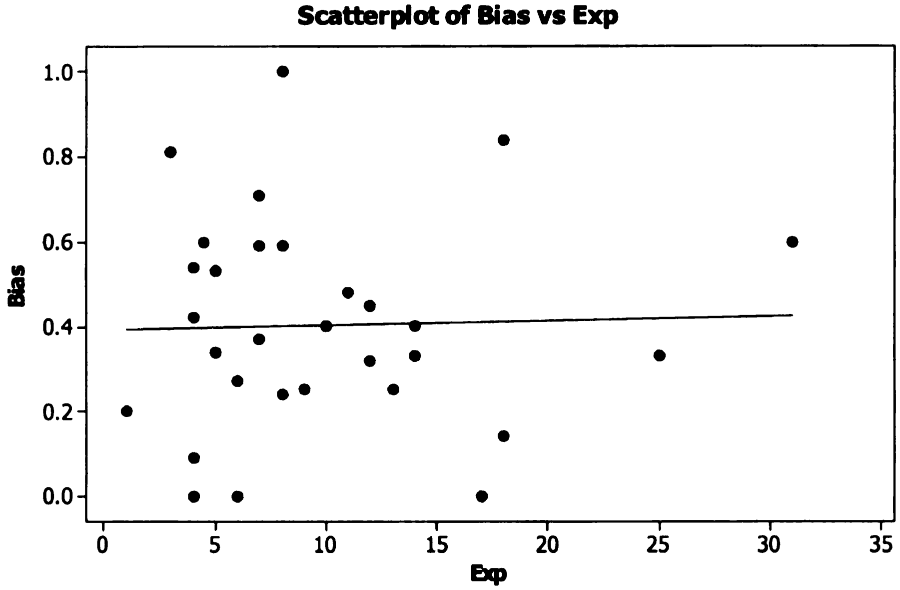


Figure 4-16: Scatter plot with regression line for β v/s years of experience

Based on the four scatter plots, there was no relationship found between any of the predictor variables and the response variables. Data points occurred well spread out and did not seem to follow any set pattern. Detailed results with residual plots for regression analysis when sensitivity was plotted against age of the ironworker are presented below in Figure 4-17. It is clear from the low r-squared values and high p-value, that there exists no correlation between the two.

```
Regression Analysis: Sensitivity versus Age

The regression equation is
Sensitivity = 1.81 - 0.0087 Age

Predictor        Coef   SE Coef       T      P
Constant       1.8102    0.6136    2.95  0.006
Age          -0.00867   0.01810   -0.48  0.636

S = 0.678040   R-Sq = 0.8%   R-Sq(adj) = 0.0%

Analysis of Variance

Source          DF        SS       MS      F      P
Regression       1    0.1055   0.1055   0.23  0.636
Residual Error  28   12.8727   0.4597
Total           29   12.9781
```

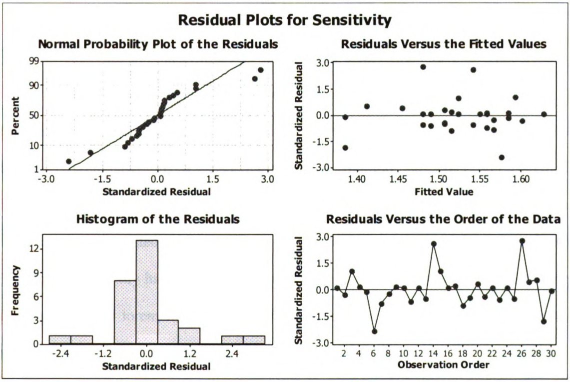


Figure 4-17
Minitab result for regression analysis: Sensitivity and Age of Ironworker

Residual plots and regression results for worker age v/s bias, years in industry (experience) v/s sensitivity and years in industry (experience) v/s bias are presented later in Appendix E. It is clear from the low r-squared values and high p-values, that there exists no correlation between these variables. Hence it was concluded that workers' ability to detect unsafe conditions does not show a direct relationship with their experience/age, when the two parameters of sensitivity and bias are used to measure this ability.

4.5 Interviews and Discussion

There were four construction professionals interviewed from the steel industry in mid and southeast Michigan:

a. Two Steel Erection Foremen from two different steel erection subcontractors.
b. Engineering and Safety Manager for a leading steel fabrication corporation.
c. Safety Director at a job site with a leading general contracting company.

The names of these individuals and companies are not disclosed for confidentiality. The discussions were based on the survey questionnaire. An important observation from these discussions was that an average ironworker on any job-site is debriefed before the start of any project and updated with the most current safety regulations (OSHA, MIOSHA). Each project typically has its own safety and emergency plan drawn out and thoroughly discussed with all foremen, at the start of the project (or when that trade starts on the project).

There was a detailed discussion on the 18 conditions presented in the questionnaire and the following comments were made:

i. Question #3 (Figure 4-18 below) pertaining to multiple lift rigging procedure for erecting beams requiring the separation distance between two beams to be 7 feet. This is not always practiced on site, though if noticed by a safety professional it would account to a violation. The height of the crewmembers actually placing the beam in place is the critical dimension, and a number of times these beams are separated by only 5.5 to 6 feet. This is an acceptable practice amongst the erection crew, but if questioned they would be aware of the code requirement for 7 feet separation.

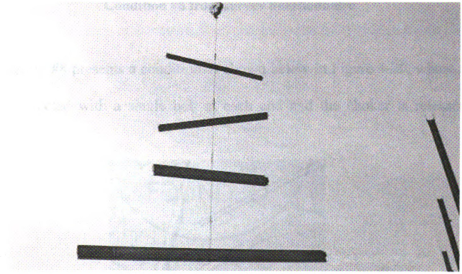


Figure 4-18
Condition 3 from survey questionnaire

ii. Though question #6 presents an unsafe condition per the codes, the erection crew considers it safe to work on an unprotected edge with a drop of more than 3 floors if they are completely tied off and fastened by a fall arrest. This condition is also presented below in Figure 4-19.

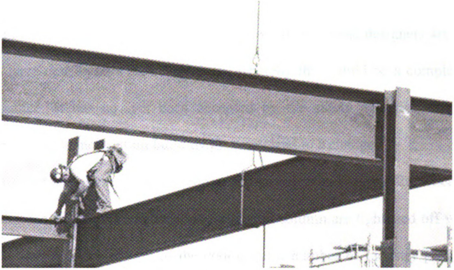


Figure 4-19
Condition #6 from survey questionnaire

iii. Question #8 presents a condition as shown below in Figure 4-20, where a beam is connected with a single bolt at each end and the choker is released (it is

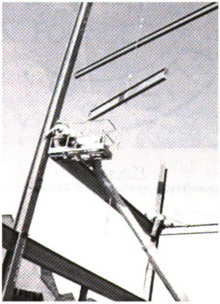


Figure 4-20
Condition #8 from survey questionnaire

detailed[4] in much later). The codes clearly refer to this as a violation. This regulation has been in effect for over 35 years and some designers are believed to have developed a particular detail whereby this would be a completely safe practice. It has not yet been accepted by the safety agencies, but there is considerable momentum building that may lead to a change.

iv. Question #14 presents a condition as shown below in Figure 4-21, whereby only three out of the four anchor rods for a steel column are tightened off with nuts. This again is a violation of the codes, but a number of industry professionals attest to the fact that on the job site, if there is one anchor rod damaged, many a times the column is still erected. They return to the fourth rod and repair it later.

Figure 4-21
Condition #14 from survey questionnaire

All these scenarios are an indication of a gap in the safety regulations/standards and prevalent industry practices for steel erection. These are subtleties and finer nuances of the specialty trade that on numerous occasions transform into a potentially dangerous

---

[4] 'Detailing' in steel erection refers to the process of putting in the remaining nuts and bolts, and tightening the joint up. When the steel piece is set for the first time, it is not completely detailed (only part nuts/bolts are put in place). This process allows for the erection crew to make minor adjustments to plumb the structure up.

situation. Often the ironworker identifies this mismatch, but based on his experience and expertise makes the decision of carrying on with his work. There is an urgent need to bridge these gaps and make safety training more meaningful. The involvement of actual ironworkers and their foreman, a discussion/dialogue between those who define these codes and those, who these codes are designed to protect, could be the first step in this direction.

4.6 Analysis Summary

This chapter presented the data collected for the project and the analysis using fuzzy SDT to determine how well the ironworkers identify an unsafe condition. Based on the fuzzy SDT model, the selected subjects had a conservative approach and had a good discriminability index or sensitivity. For the 30 subjects, the sensitivity measure d' is subject to normal distribution with $\mu = 1.52$ and $\sigma = 0.67$, i.e., $d' \sim N(1.52, 0.67)$. A comparative analysis was performed using the conventional SDT model for the same subject group. Sensitivity (d') distribution for the 30 ironworkers using the crisp SDT model showed a higher mean and a very high spread ($\mu = 2.08$ and $\sigma = 1.95$). The results from fuzzy SDT model were able to better capture the sensitivity of the subjects, confirming that conventional SDT could be improved by combining it with fuzzy, when it is being applied to construction safety assessment. The results of the regression analysis did not provide any correlation between the sensitivity/response bias and the independent variables of ironworker age/industry experience. Detailed tables and values can be viewed in the appendices at the end of this thesis.

Chapter 5

SUMMARY AND CONCLUSIONS

5. SUMMARY AND CONCLUSIONS

5.1 Thesis Summary

The primary goal of this research was to develop a method to quantify construction workers' ability to identify hazards on site. Chapters 1 to 4 present a detailed report on the fundamental concepts, their background, the adopted approach and the results based on a group of ironworkers.

The first chapter provided an introduction to the research area, cited the problem of hazard identification on construction jobsites, addressed the goal and proposed the objectives to reach that goal. It also gave a brief overview of the basic theories that form the primary tool for this research. Chapter two discussed, in detail, the process of detection, earlier models and the advent of signal detection theory and fuzzy logic. It is in fact the hybrid model, namely, fuzzy SDT that provided the ideal framework to study worker hazard perception on a construction site. Chapter three outlined the proposed methods used to achieve the objectives of this research and the predicted outcome. It also explained how this research could lead to innovative safety training design that would eventually result in reducing fall accidents. Chapter four provided an analysis of the data collected from a group of ironworkers and a broad outline of the discussions with safety professionals in the steel construction industry.

5.2 Conclusion

Safety training is only as good as the worker's ability to detect an unsafe condition, as and when he/she is presented with one. This thesis developed an approach to measure how well the worker can identify a hazardous condition. Crisp SDT as implemented by

Patel (2003) provided a very good tool for an assessment of this ability, but had certain shortcomings that limit the resulting assessments. Fuzzy SDT provided the ideal model, on the basis of which the survey questionnaire in this research was designed. This captured useful information, which would have otherwise been lost with crisp SDT, and yielded results that are indicative of a worker's ability in identifying hazardous conditions on a construction jobsite. Overall the approach outlined in this thesis could be used in a variety of real world settings that involve assessment of hazardous construction conditions.

Analysis of the survey data indicated a high variation in the response to the first question - 'how safe is this condition?'. This explains a variation in the manner each of the 30 subjects perceived the 18 conditions presented to them in the survey. Nonetheless the subjects were confident of their responses, which is explained by the higher mean for the response to the second question – 'how sure are you about your answer?'. The average d' value (sensitivity) for the group of ironworkers was found to be 1.52, which shows an above average sensitivity, i.e., they were well able to differentiate and detect an unsafe condition from a safe one. The group had a conservative strategy, whereby they would even consider some of the safe conditions as unsafe yielding a high false alarm rate ($\beta = 0.40$).

The same data when analyzed using conventional SDT resulted in an average d' value (sensitivity) of 2.09 and a high standard deviation of 1.95. This disparity is attributed to the fact that there is loss of information when the real world signals are forced into binary sets in conventional SDT. The hybrid model of fuzzy signal detection theory provided a better assessment of the workers ability to detect a signal, or in other words correctly identify hazardous conditions on a construction jobsite.

The collected data indicated that there was no relationship between the age and experience of the worker and his/her ability to identify hazardous conditions. The results from scatter plots and regression analysis yielded no correlation between the predictor variables age/experience and the response variable sensitivity/bias.

The outcome of the survey proposed in the research could have been very different, based on the sample of ironworkers selected or if the survey questions were altered. The intent of this research was to demonstrate a methodology for the assessment of the workers ability to identify hazards.

During the interviews conducted with construction industry professionals they concurred on how critical safety guidelines were and their implementation on the job-site played a significant role in reducing injuries. At the same time some of the unsafe conditions presented in the survey questionnaire were a point of debate among the practicing professionals. The set of safety guidelines and regulations are constantly evolving. These professionals felt that some of the means and methods for the steel erection trade did not conform to the exact safety guidelines; there was an indication of a gap in the regulations and prevalent practice. In the light of this research and attempt towards improving safety training, this is very significant and once again strengthens the urgent need for a breakthrough in order to reduce construction occupational accidents.

5.3 Limitations of this research

The concepts of signal detection theory, threshold model of detection and fuzzy logic are always evolving, owing to their application in a number of varying fields. Together they provide enough material for years of research, both pure and applied. This thesis attempted to cover only those aspects that would have immediate application for the purposes of identification of occupational hazard in the construction industry. For example, the definition of a signal and the generated response could have temporal and contextual variability, which implies dependence of signal definition on situation specific factors and variation of signal strength over time (Parasuraman et al., 2000). Workers' responses could have variation depending upon what time of the day they answered the survey questions, also, what day of the week and what time of the year it was. These would be important factors that could affect the workers' perception of safety. This research assumes that there is no such variability in the signal.

The survey methodology developed for this research has its own limitations. The issue of construction safety and worker ability to correctly identify unsafe conditions is an important industry wide concern. With a number of national/state agencies constantly trying to improve training and often coming down with heavy fines whenever there is a violation, the subjects for such surveys tend to take a defensive stand. The responses could be indicative more of their intention and not so much of their behavior. This research was only able to measure the perception of a worker towards hazards. The actual behavior of a worker in such circumstances is not known. This needs a third question for each scenario presented to the worker, such as: "How comfortable would you be working in this condition?".

The survey questionnaire attempted to put as much detail, in terms of explaining the physical on site condition, with the help of photographs and text. In a few questions the visuals do not represent the question in its entirety, or may seem to fall short of the condition as explained by the text. For example condition #2 in the survey, as illustrated below in Figure 5-1, shows a condition where the ladder extends 3.5 feet above the landing surface. This by safety standards definition is a safe condition.

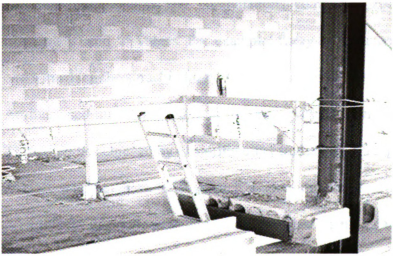


Figure 5-1
Condition #2 from survey questionnaire

The visual in the survey shows another open edge right next to the edge of this landing. The subject while answering the questions for this condition has the tendency to consider this open edge and rate this as an 'unsafe' condition. This was a point brought up during the execution of the survey, and provides some room for improvement. The visual accompanying the text question must be an accurate explanation, leaving no room for the subject to make his/her own assumptions.

The survey was only administered once with the 30 ironworkers. The data from the survey, the resulting analysis and the applied method could be considered sturdy if repeated surveys and results yield results that concur. Repeatability of results is a very important aspect for any survey deployed in research.

5.4 Recommendations for future research

This research will serve as a platform for a lot of further research and investigation. For example, future research should consider:

- Different permutations and combinations could be experimented with when mapping 's' and 'r' values. For example, fuzzy SDT analysis can be extended to cases in which the signal is fuzzy, but the response is discrete or binary.
- An increased number of subjects for the survey, yielding a much larger data set. This could be achieved by exploring other trades and other geographic regions.
- Subject specific characteristics such as previous accident record, frequency and performance of previous training, impact of last training date and education level. These could be investigated for possible association with sensitivity and bias.
- Subject data could include statistics such as worker height and weight. These would improve the analysis of certain conditions from the survey, for example condition # 3 involved spacing between beams and responses would be a direct connection with worker height.
- Different types of accidents could be investigated, for example, accidents due to i) electrocution, ii) hit / struck by iii) trench cave-in (excavations).
- A survey could be designed for the officials who define safety standards, which would help get information as to how well they are aware of industry practices

onsite. This would be an attempt towards bridging the 'gap' as expressed earlier in the research.

5.5 Contributions

This research has developed and demonstrated a methodology to quantify construction workers' ability to identify hazards on site. The main contributions of this research are:

- Application of a relatively new model (fuzzy SDT, originally proposed by Parasuraman et al., 2000) to the construction industry. This provides a breakthrough that would help improve safety-training efforts. Crisp SDT had been applied earlier to assessment of workers' occupational safety competencies. This research further strengthens the analysis by proposing the use of fuzzy SDT. SDT in its original form is as robust a theory as any other. Fuzzy SDT only improves its application.
- The survey questionnaire provides a very valuable tool for assessment of safety competency. It can be used in current safety training across the steel construction industry.
- An approach in reducing accidents on site and a concrete foundation on which safety training could be designed.
- The research identified a gap in how workers and industry professionals perceive certain conditions compared to the standards and safety regulations.

APPENDIX A

CONSENT LETTER AND SURVEY QUESTIONNAIRE

Subject Consent Form

IRONWORKER OCCUPATIONAL SAFETY KNOWLEDGE

Principal Investigators: **Tariq S. Abdelhamid, PhD**
Research Assistant: **Puneet Narang**

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 an 18-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. If you are uncomfortable answering parts of the survey, you may leave those parts unanswered. 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 20-25 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 questions or concerns regarding your rights as a study participant, or are dissatisfied at any time with any aspect of this study, you may contact – anonymously, if you wish –Peter Vasilenko, Ph.D., Chair of the University Committee on Research Involving Human Subjects (UCRIHS) by phone: (517) 355-2180, fax: (517) 432-4503, e-mail: ucrihs@msu.edu, or regular mail: 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*

IRB # 05-859
Category: EXPEDITED 2-7
Approval Date: 11/22/2005
Expiration Date: 11/21/2006

SURVEY QUESTIONNAIRE

MSU Member: ____________________________

MICHIGAN STATE UNIVERSITY

Ironworker Occupational Safety Assessment

Date: _________________

Name of the Company: ____

Location of the Job Site: ____

Name / Title of the Person Interviewed: _____________________________________

____

Construction Industry Experience (In Years): _________________________________

Age: ________

INTERVIEW QUESTIONS

Please read the following scenarios and select your answer from the given scale. You can answer by shading/darkening the provided circle under each number.

Example: -

A given scenario: XYZ

How safe is this?

Injurious

↑

3	4	5	6	7
○	●	○	○	○

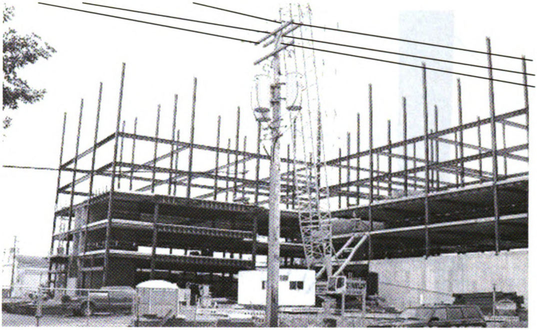
How confident are you about your answer?

Moderately confident

↑

4	5	6	7	8
○	○	○	●	○

1. A crawler crane lifting steel columns, located at 30 feet from a 600 kV power line.



<u>How safe is this?</u>

Absolutely Safe ↑ 0 · *Injurious* ↑ 5 · *Fatal* ↑ 10

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

<u>How confident are you about your answer?</u>

Completely Uncertain ↑ 0 · *Moderately confident* ↑ 5 · *Absolutely Sure* ↑ 10

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

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

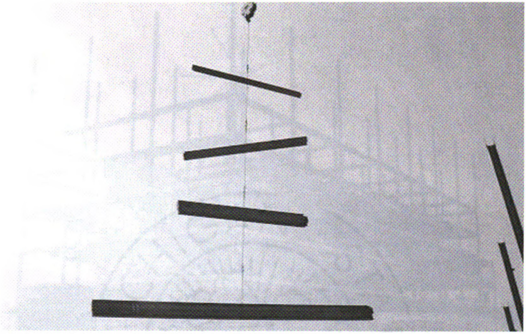
How safe is this?

Absolutely Safe					*Injurious*					*Fatal*
↑					↑					↑
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

How confident are you about your answer?

Completely Uncertain					*Moderately confident*					*Absolutely Sure*
↑					↑					↑
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

3. While erecting steel beams via a multiple lift rigging procedure, the steel members are rigged at 6 feet apart.



How safe is this?

Absolutely Safe *Injurious* *Fatal*

↑ ↑ ↑

0 1 2 3 4 5 6 7 8 9 10

○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○

How confident are you about your answer?

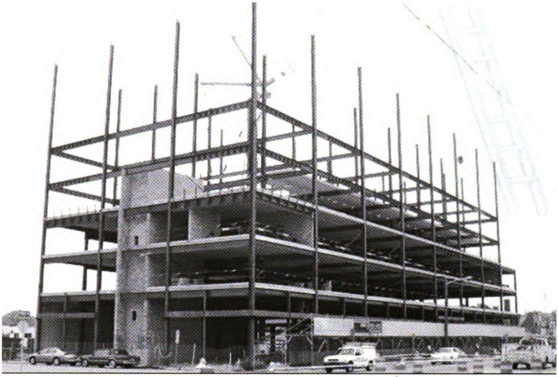
Completely Uncertain *Moderately confident* *Absolutely Sure*

↑ ↑ ↑

0 1 2 3 4 5 6 7 8 9 10

○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○

4. Erecting 7th floor columns, when all the 5th floor planks (precast concrete panels) are not completely in place.



How safe is this?

Absolutely Safe ↑ 0

Injurious ↑ 5

Fatal ↑ 10

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

How confident are you about your answer?

Completely Uncertain ↑ 0

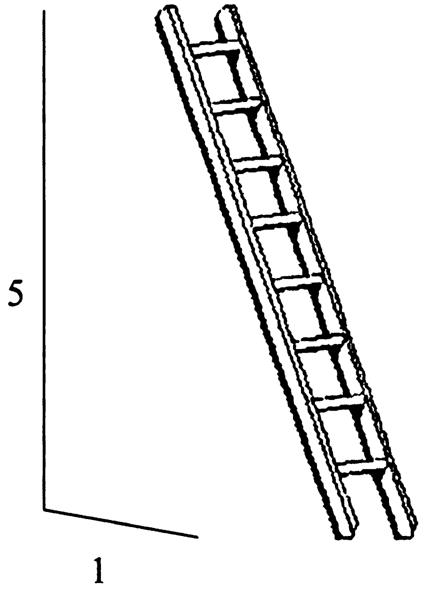
Moderately confident ↑ 5

Absolutely Sure ↑ 10

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

5.

Climbing a portable ladder that is set 1 foot out for every 5 feet climb (as shown in figure).



How safe is this?

Absolutely Safe ↑ 0 · *Injurious* ↑ 5 · *Fatal* ↑ 10

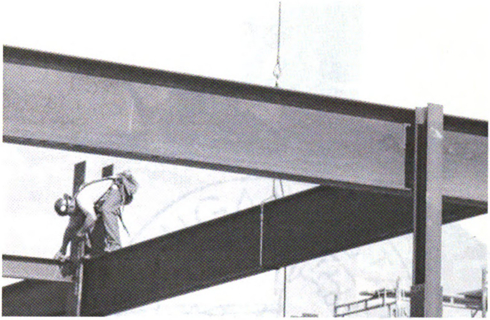
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

How confident are you about your answer?

Completely Uncertain ↑ 0 · *Moderately confident* ↑ 5 · *Absolutely Sure* ↑ 10

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

6. An ironworker connecting 4th floor beams, with an unprotected edge with no decking in place on the lower floors, protected by conventional fall protection (fall arrest).



<u>How safe is this?</u>

Absolutely Safe ↑ — *Injurious* ↑ — *Fatal* ↑

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

<u>How confident are you about your answer?</u>

Completely Uncertain ↑ — *Moderately confident* ↑ — *Absolutely Sure* ↑

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

7. Bolting steel members in place on the 3rd floor, when the temporary bracing is not in place on the lower floors.

How safe is this?

Absolutely Safe *Fatal*

Injurious

↑ ↑ ↑

0 1 2 3 4 5 6 7 8 9 10

○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○

How confident are you about your answer?

Completely Uncertain *Absolutely Sure*

Moderately confident

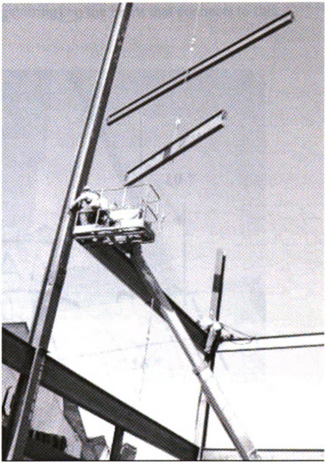
↑ ↑ ↑

0 1 2 3 4 5 6 7 8 9 10

○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○

8.

A 40 feet long beam being attached as a part of a multi-rig assembly is bolted with a single bolt at each end and the choker (cable) is released. The steel beam is detailed into place much later.



How safe is this?

Absolutely Safe ↑ — *Injurious* ↑ (5) — *Fatal* ↑

0 **1** **2** **3** **4** **5** **6** **7** **8** **9** **10**

○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○

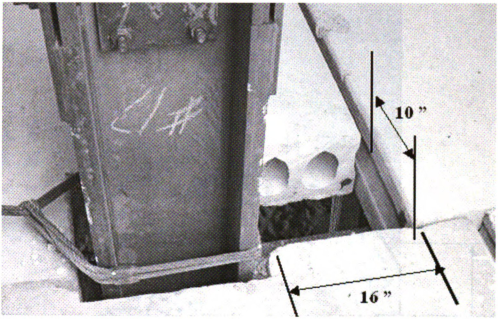
How confident are you about your answer?

Completely Uncertain ↑ — *Moderately confident* ↑ (5) — *Absolutely Sure* ↑

0 **1** **2** **3** **4** **5** **6** **7** **8** **9** **10**

○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○

9. An opening of 16 inches by 10 inches is left uncovered next to column. The concrete planks (precast) are bearing (sitting) on the beam that connects to this column.



How safe is this?

Absolutely Safe ↑ 0

Injurious ↑ 5

Fatal ↑ 10

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

How confident are you about your answer?

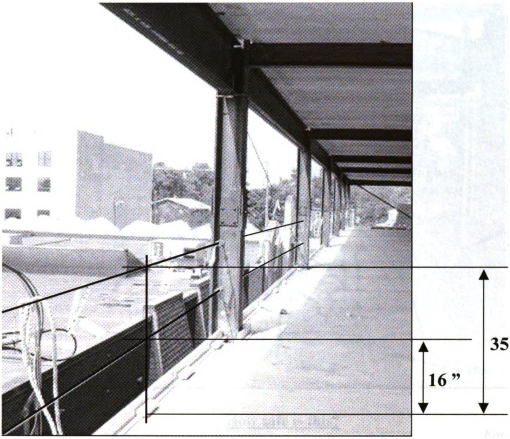
Completely Uncertain ↑ 0

Moderately confident ↑ 5

Absolutely Sure ↑ 10

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

10. Working on the 3rd floor of a building where the top of the perimeter cabling is at 35" and the intermediate cable is at 16" from the floor.



How safe is this?

Absolutely Safe *Injurious* *Fatal*

↑ ↑ ↑

0 1 2 3 4 5 6 7 8 9 10

○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○

How confident are you about your answer?

Completely Uncertain *Moderately confident* *Absolutely Sure*

↑ ↑ ↑

0 1 2 3 4 5 6 7 8 9 10

○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○

11. Operating a forklift on the 4th floor when all perimeter cabling is in place and precast concrete panels are being placed on the 6th floor.

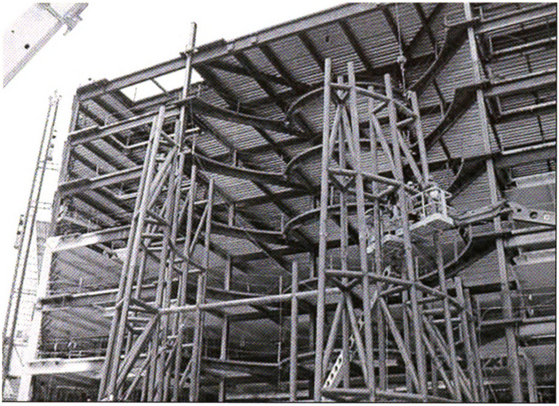
How safe is this?

Absolutely Safe ↑					*Injurious* ↑					*Fatal* ↑
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

How confident are you about your answer?

Completely Uncertain ↑					*Moderately confident* ↑					*Absolutely Sure* ↑
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

12. Beams and decking on the 7th floor are being erected, when the bolting/detailing on the 3rd floor is incomplete.



How safe is this?

Absolutely Safe ↑ *Injurious* ↑ *Fatal* ↑

Absolutely Safe ↑					*Injurious* ↑					*Fatal* ↑
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

How confident are you about your answer?

Completely Uncertain ↑					*Moderately confident* ↑					*Absolutely Sure* ↑
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

13.

Removing the fall protection while transferring from a beam to the hoisting crane.

How safe is this?

Absolutely Safe ↑

Injurious ↑

Fatal ↑

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

How confident are you about your answer?

Completely Uncertain ↑

Moderately confident ↑

Absolutely Sure ↑

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

14.

A column is bolted in place with 3 anchor rods and beams are being connected on the 2^{nd} floor.

How safe is this?

Absolutely Safe ↑   *Injurious* ↑   *Fatal* ↑

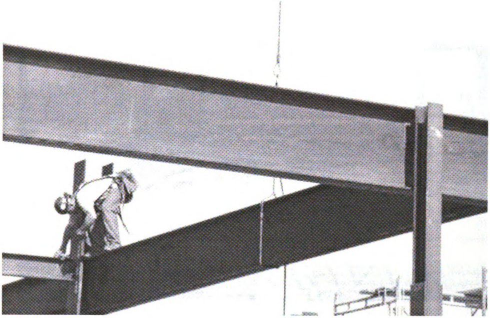
0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

How confident are you about your answer?

Completely Uncertain ↑   *Moderately confident* ↑   *Absolutely Sure* ↑

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

15. Ironworker climbs on the steel beam, when it is held by the crane (tied with a choker), to bolt it in place.



How safe is this?

Absolutely Safe ↑ 0

Injurious ↑ 5

Fatal ↑ 10

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

How confident are you about your answer?

Completely Uncertain ↑ 0

Moderately confident ↑ 5

Absolutely Sure ↑ 10

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

16. Working on 2,500 square feet of decking that has an unsecured connection.

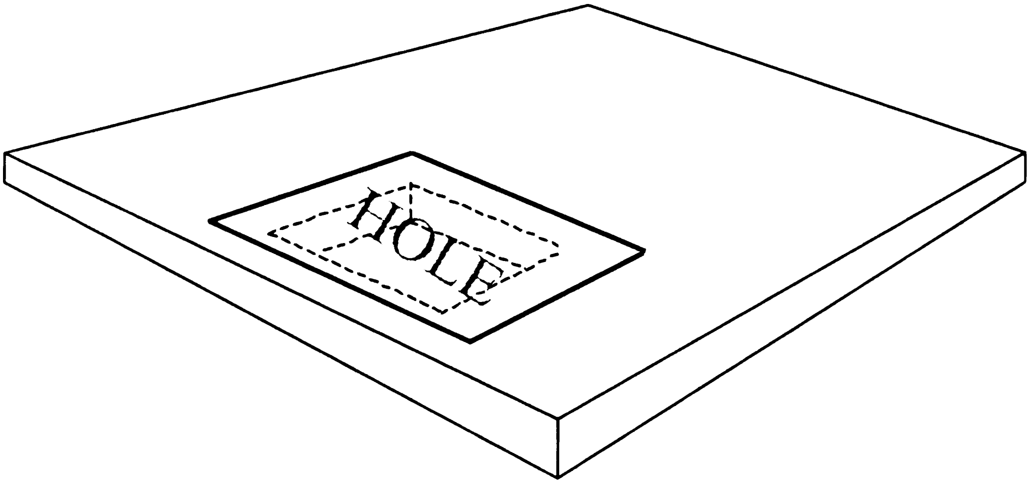
How safe is this?

Absolutely Safe					*Injurious*					*Fatal*
↑					↑					↑
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

How confident are you about your answer?

Completely Uncertain					*Moderately confident*					*Absolutely Sure*
↑					↑					↑
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

17. Shaft opening 3 ft. X 1.5 ft. in size, on the 3rd floor is covered by ¾" ply and painted with high visibility paint and marked with the word "HOLE".



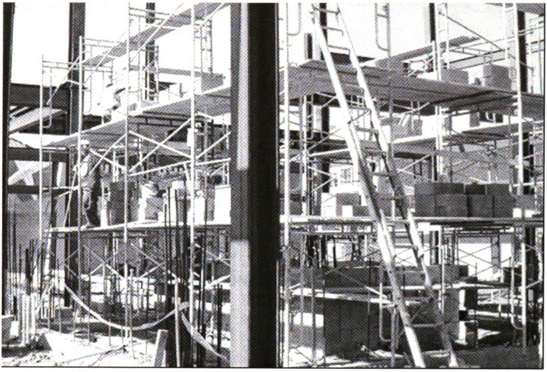
How safe is this?

Absolutely Safe					*Injurious*					*Fatal*
↑					↑					↑
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

How confident are you about your answer?

Completely Uncertain					*Moderately confident*					*Absolutely Sure*
↑					↑					↑
0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

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



How safe is this?

Absolutely Safe ↑ 0

Injurious ↑ 5

Fatal ↑ 10

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

How confident are you about your answer?

Completely Uncertain ↑ 0

Moderately confident ↑ 5

Absolutely Sure ↑ 10

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
○	○	○	○	○	○	○	○	○	○	○

APPENDIX B

SURVEY RESPONSES AND THEIR ANALYSIS

	Worker 1								Worker 2							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.3	1	0.3	0	0.7	0	0.7	1	0.4	0.6	0.4	0	0.2	0.4	0.6	1
2	0	1	0	0	1	0	1	1	0.3	0.9	0.3	0	0.6	0.1	0.7	1
3	1	1	1	0	0	0	0	1	0.7	0.8	0.7	0	0.1	0.2	0.3	1
4	0.5	1	0.5	0	0.5	0	0.5	1	0.7	0.8	0.7	0	0.1	0.2	0.3	1
5	0.6	1	0.6	0	0.4	0	0.4	1	0.6	0.7	0.6	0	0.1	0.3	0.4	1
6	0	1	0	0	1	0	1	1	0.7	1	0.7	0	0.3	0	0.3	1
7	0.3	0.9	0.3	0	0.6	0.1	0.7	1	0.4	0.5	0.4	0	0.1	0.5	0.6	1
8	1	1	1	0	0	0	0	1	0.9	0.7	0.7	0.2	0	0.1	0.1	1
9	0.5	0.9	0.5	0	0.4	0.1	0.5	1	0.3	0.7	0.3	0	0.4	0.3	0.7	1
10	0.9	1	0.9	0	0.1	0	0.1	1	0.2	0.9	0.2	0	0.7	0.1	0.8	1
11	0.1	1	0.1	0	0.9	0	0.9	1	0.3	0.7	0.3	0	0.4	0.3	0.7	1
12	0.1	1	0.1	0	0.9	0	0.9	1	0.8	0.6	0.6	0.2	0	0.2	0.2	1
13	0.3	1	0.3	0	0.7	0	0.7	1	1	1	1	0	0	0	0	1
14	0.2	1	0.2	0	0.8	0	0.8	1	0.6	0.7	0.6	0	0.1	0.3	0.4	1
15	0.2	1	0.2	0	0.8	0	0.8	1	0.4	0.7	0.4	0	0.3	0.3	0.6	1
16	0.2	0.8	0.2	0	0.6	0.2	0.8	1	0.5	0.4	0.4	0.1	0	0.5	0.5	1
17	0	1	0	0	1	0	1	1	0.2	0.8	0.2	0	0.6	0.2	0.8	1
18	0.3	0.8	0.3	0	0.5	0.2	0.7	1	0.4	0.6	0.4	0	0.2	0.4	0.6	1
Sum	6.5	17.4	6.5	0.0	10.9	0.6	11.5		9.4	13.1	8.9	0.5	4.2	4.4	8.6	

Hit Rate = 1.00 FA Rate = 0.95 Hit Rate = 0.95 FA Rate = 0.49

	Worker 3								Worker 4							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.6	0.7	0.6	0	0.1	0.3	0.4	1	0.8	0.9	0.8	0	0.1	0.1	0.2	1
2	0.3	0.6	0.3	0	0.3	0.4	0.7	1	0.2	1	0.2	0	0.8	0	0.8	1
3	0.7	0.8	0.7	0	0.1	0.2	0.3	1	0.8	0.6	0.6	0.2	0	0.2	0.2	1
4	0.5	0.8	0.5	0	0.3	0.2	0.5	1	0.9	0.8	0.8	0.1	0	0.1	0.1	1
5	0.5	0.8	0.5	0	0.3	0.2	0.5	1	0.5	0.5	0.5	0	0	0.5	0.5	1
6	0.7	0.5	0.5	0.2	0	0.3	0.3	1	0.7	0.8	0.7	0	0.1	0.2	0.3	1
7	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.6	0.9	0.6	0	0.3	0.1	0.4	1
8	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.9	0.9	0.9	0	0	0.1	0.1	1
v	0.3	0.7	0.3	0	0.4	0.3	0.7	1	0.3	1	0.3	0	0.7	0	0.7	1
10	0.1	0.7	0.1	0	0.6	0.3	0.9	1	0	0.9	0	0	0.9	0.1	1	1
11	0.1	0.9	0.1	0	0.8	0.1	0.9	1	0	1	0	0	1	0	1	1
12	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.9	0.9	0.9	0	0	0.1	0.1	1
13	0.8	0.5	0.5	0.3	0	0.2	0.2	1	0.8	0.9	0.8	0	0.1	0.1	0.2	1
14	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.9	1	0.9	0	0.1	0	0.1	1
15	0.2	0.8	0.2	0	0.6	0.2	0.8	1	0.5	0.8	0.5	0	0.3	0.2	0.5	1
16	0.1	0.9	0.1	0	0.8	0.1	0.9	1	0.1	1	0.1	0	0.9	0	0.9	1
17	0.1	0.9	0.1	0	0.8	0.1	0.9	1	0.1	1	0.1	0	0.9	0	0.9	1
18	0.2	0.9	0.2	0	0.7	0.1	0.8	1	0.1	0.9	0.1	0	0.8	0.1	0.9	1
Sum	8.4	14.1	7.9	0.5	6.2	3.4	9.6		9.1	15.8	8.8	0.3	7.0	1.9	8.9	

Hit Rate = 0.94 FA Rate = 0.65 Hit Rate = 0.97 FA Rate = 0.79

Table B.1

	Worker 5								Worker 6							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.3	0.5	0.3	0	0.2	0.5	0.7	1	0.6	0.8	0.6	0	0.2	0.2	0.4	1
2	0.4	0.6	0.4	0	0.2	0.4	0.6	1	0.3	0.9	0.3	0	0.6	0.1	0.7	1
3	0.4	0.7	0.4	0	0.3	0.3	0.6	1	0.4	0.7	0.4	0	0.3	0.3	0.6	1
4	0.5	0.8	0.5	0	0.3	0.2	0.5	1	0.7	0.7	0.7	0	0	0.3	0.3	1
5	0.5	0.6	0.5	0	0.1	0.4	0.5	1	0.5	0.8	0.5	0	0.3	0.2	0.5	1
6	0.6	0.5	0.5	0.1	0	0.4	0.4	1	0.3	0.6	0.3	0	0.3	0.4	0.7	1
7	0.7	0.8	0.7	0	0.1	0.2	0.3	1	0.7	0.5	0.5	0.2	0	0.3	0.3	1
8	1	0.8	0.8	0.2	0	0	0	1	0.8	0.8	0.8	0	0	0.2	0.2	1
9	0.4	0.6	0.4	0	0.2	0.4	0.6	1	0.2	0.6	0.2	0	0.4	0.4	0.8	1
10	0.1	0.7	0.1	0	0.6	0.3	0.9	1	0.1	0.7	0.1	0	0.6	0.3	0.9	1
11	0.4	0.4	0.4	0	0	0.6	0.6	1	0.2	0.8	0.2	0	0.6	0.2	0.8	1
12	0.7	0.3	0.3	0.4	0	0.3	0.3	1	0.6	0.5	0.5	0.1	0	0.4	0.4	1
13	0.9	0.7	0.7	0.2	0	0.1	0.1	1	0.8	1	0.8	0	0.2	0	0.2	1
14	0.9	0.9	0.9	0	0	0.1	0.1	1	0.7	0.9	0.7	0	0.2	0.1	0.3	1
15	0.4	0.6	0.4	0	0.2	0.4	0.6	1	0.4	0.5	0.4	0	0.1	0.5	0.6	1
16	0.3	0.5	0.3	0	0.2	0.5	0.7	1	0.7	0.6	0.6	0.1	0	0.3	0.3	1
17	0.3	0.8	0.3	0	0.5	0.2	0.7	1	0.3	0.7	0.3	0	0.4	0.3	0.7	1
18	0.2	0.9	0.2	0	0.7	0.1	0.8	1	0.2	0.6	0.2	0	0.4	0.4	0.8	1
Sum	9.0	11.7	8.1	0.9	3.6	5.4	9.0		8.5	12.7	8.1	0.4	4.6	4.9	9.5	

Hit Rate = 0.90 FA Rate = 0.40 Hit Rate = 0.95 FA Rate = 0.48

	Worker 7								Worker 8							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.6	0.8	0.6	0	0.2	0.2	0.4	1	0.6	0.4	0.4	0.2	0	0.4	0.4	1
2	0.2	0.5	0.2	0	0.3	0.5	0.8	1	0.3	0.8	0.3	0	0.5	0.2	0.7	1
3	0.7	0.5	0.5	0.2	0	0.3	0.3	1	0.5	0.8	0.5	0	0.3	0.2	0.5	1
4	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.6	0.5	0.5	0.1	0	0.4	0.4	1
5	0.5	0.5	0.5	0	0	0.5	0.5	1	0.4	0.6	0.4	0	0.2	0.4	0.6	1
6	0.5	0.9	0.5	0	0.4	0.1	0.5	1	0.8	0.7	0.7	0.1	0	0.2	0.2	1
7	0.9	1	0.9	0	0.1	0	0.1	1	0.6	0.8	0.6	0	0.2	0.2	0.4	1
8	0.8	0.9	0.8	0	0.1	0.1	0.2	1	1	1	1	0	0	0	0	1
v	0.4	0.8	0.4	0	0.4	0.2	0.6	1	0.4	0.5	0.4	0	0.1	0.5	0.6	1
10	0.2	0.8	0.2	0	0.6	0.2	0.8	1	0.3	0.8	0.3	0	0.5	0.2	0.7	1
11	0.1	0.9	0.1	0	0.8	0.1	0.9	1	0.2	0.5	0.2	0	0.3	0.5	0.8	1
12	0.8	1	0.8	0	0.2	0	0.2	1	0.7	0.4	0.4	0.3	0	0.3	0.3	1
13	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.8	0.7	0.7	0.1	0	0.2	0.2	1
14	0.6	0.9	0.6	0	0.3	0.1	0.4	1	0.7	0.9	0.7	0	0.2	0.1	0.3	1
15	0.6	0.7	0.6	0	0.1	0.3	0.4	1	0.5	0.4	0.4	0.1	0	0.5	0.5	1
16	0.2	0.9	0.2	0	0.7	0.1	0.8	1	0.5	0.4	0.4	0.1	0	0.5	0.5	1
17	0.1	0.9	0.1	0	0.8	0.1	0.9	1	0.4	0.7	0.4	0	0.3	0.3	0.6	1
18	0.3	0.5	0.3	0	0.2	0.5	0.7	1	0.1	0.8	0.1	0	0.7	0.2	0.9	1
Sum	9.1	14.3	8.9	0.2	5.4	3.5	8.9		9.4	11.7	8.4	1.0	3.3	5.3	8.6	

Hit Rate = 0.98 FA Rate = 0.61 Hit Rate = 0.89 FA Rate = 0.38

Table B.1...contd.

	Worker 9								Worker 10							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.4	0.5	0.4	0	0.1	0.5	0.6	1	0.6	0.9	0.6	0	0.3	0.1	0.4	1
2	0.2	0.8	0.2	0	0.6	0.2	0.8	1	0.1	0.8	0.1	0	0.7	0.2	0.9	1
3	0.7	0.7	0.7	0	0	0.3	0.3	1	0.7	0.7	0.7	0	0	0.3	0.3	1
4	0.8	0.7	0.7	0.1	0	0.2	0.2	1	0.7	0.9	0.7	0	0.2	0.1	0.3	1
5	0.6	0.6	0.6	0	0	0.4	0.4	1	0.6	0.5	0.5	0.1	0	0.4	0.4	1
6	0.6	0.8	0.6	0	0.2	0.2	0.4	1	0.7	0.9	0.7	0	0.2	0.1	0.3	1
7	0.7	0.8	0.7	0	0.1	0.2	0.3	1	0.7	0.8	0.7	0	0.1	0.2	0.3	1
8	0.8	0.8	0.8	0	0	0.2	0.2	1	0.8	0.9	0.8	0	0.1	0.1	0.2	1
9	0.4	0.8	0.4	0	0.4	0.2	0.6	1	0.4	0.9	0.4	0	0.5	0.1	0.6	1
10	0.1	0.9	0.1	0	0.8	0.1	0.9	1	0.1	0.9	0.1	0	0.8	0.1	0.9	1
11	0.2	0.6	0.2	0	0.4	0.4	0.8	1	0.2	0.8	0.2	0	0.6	0.2	0.8	1
12	0.8	0.7	0.7	0.1	0	0.2	0.2	1	0.8	1	0.8	0	0.2	0	0.2	1
13	0.7	0.5	0.5	0.2	0	0.3	0.3	1	0.9	0.9	0.9	0	0	0.1	0.1	1
14	0.7	0.9	0.7	0	0.2	0.1	0.3	1	0.9	1	0.9	0	0.1	0	0.1	1
15	0.3	0.8	0.3	0	0.5	0.2	0.7	1	0.4	1	0.4	0	0.6	0	0.6	1
16	0.2	0.8	0.2	0	0.6	0.2	0.8	1	0.1	1	0.1	0	0.9	0	0.9	1
17	0.2	0.8	0.2	0	0.6	0.2	0.8	1	0	0.7	0	0	0.7	0.3	1	1
18	0.3	0.5	0.3	0	0.2	0.5	0.7	1	0.3	1	0.3	0	0.7	0	0.7	1
Sum	8.7	13.0	8.3	0.4	4.7	4.6	9.3		9.0	15.6	8.9	0.1	6.7	2.3	9.0	

Hit Rate = 0.95 FA Rate = 0.51 Hit Rate = 0.99 FA Rate = 0.74

	Worker 11								Worker 12							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.8	0.5	0.5	0.3	0	0.2	0.2	1	0.5	0.9	0.5	0	0.4	0.1	0.5	1
2	0.2	0.4	0.2	0	0.2	0.6	0.8	1	0.5	0.8	0.5	0	0.3	0.2	0.5	1
3	0.6	0.2	0.2	0.4	0	0.4	0.4	1	0.6	0.3	0.3	0.3	0	0.4	0.4	1
4	0.4	0.3	0.3	0.1	0	0.6	0.6	1	0.8	0.9	0.8	0	0.1	0.1	0.2	1
5	0.5	0.6	0.5	0	0.1	0.4	0.5	1	0.5	0.6	0.5	0	0.1	0.4	0.5	1
6	0.4	0.3	0.3	0.1	0	0.6	0.6	1	0.3	0.8	0.3	0	0.5	0.2	0.7	1
7	0.6	0.5	0.5	0.1	0	0.4	0.4	1	0.6	0.9	0.6	0	0.3	0.1	0.4	1
8	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.2	0.5	0.2	0	0.3	0.5	0.8	1
v	0.3	0.7	0.3	0	0.4	0.3	0.7	1	0.3	0.5	0.3	0	0.2	0.5	0.7	1
10	0.4	0.6	0.4	0	0.2	0.4	0.6	1	0.5	0.4	0.4	0.1	0	0.5	0.5	1
11	0.6	0.3	0.3	0.3	0	0.4	0.4	1	0.4	0.5	0.4	0	0.1	0.5	0.6	1
12	0.6	0.7	0.6	0	0.1	0.3	0.4	1	0.8	0.9	0.8	0	0.1	0.1	0.2	1
13	1	1	1	0	0	0	0	1	0.8	0.6	0.6	0.2	0	0.2	0.2	1
14	0.8	0.8	0.8	0	0	0.2	0.2	1	0.5	0.7	0.5	0	0.2	0.3	0.5	1
15	0.4	0.5	0.4	0	0.1	0.5	0.6	1	0.5	0.8	0.5	0	0.3	0.2	0.5	1
16	0.5	0.2	0.2	0.3	0	0.5	0.5	1	0.3	0.7	0.3	0	0.4	0.3	0.7	1
17	0.4	0.7	0.4	0	0.3	0.3	0.6	1	0.1	0.7	0.1	0	0.6	0.3	0.9	1
18	0.3	0.8	0.3	0	0.5	0.2	0.7	1	0.3	0.7	0.3	0	0.4	0.3	0.7	1
Sum	9.6	10.0	8.0	1.6	2.0	6.4	8.4		8.5	12.2	7.9	0.6	4.3	5.2	9.5	

Hit Rate = 0.83 FA Rate = 0.24 Hit Rate = 0.93 FA Rate = 0.45

Table B.1...contd.

	Worker 13								Worker 14							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.6	0.5	0.5	0.1	0	0.4	0.4	1	0.4	1	0.4	0	0.6	0	0.6	1
2	0.2	0.5	0.2	0	0.3	0.5	0.8	1	0	1	0	0	1	0	1	1
3	0.7	0.6	0.6	0.1	0	0.3	0.3	1	0.5	1	0.5	0	0.5	0	0.5	1
4	0.9	0.8	0.8	0.1	0	0.1	0.1	1	0.4	1	0.4	0	0.6	0	0.6	1
5	0.3	0.8	0.3	0	0.5	0.2	0.7	1	0.2	1	0.2	0	0.8	0	0.8	1
6	0.3	0.9	0.3	0	0.6	0.1	0.7	1	0.2	1	0.2	0	0.8	0	0.8	1
7	0.5	0.6	0.5	0	0.1	0.4	0.5	1	0.5	1	0.5	0	0.5	0	0.5	1
8	0.3	0.8	0.3	0	0.5	0.2	0.7	1	0.5	1	0.5	0	0.5	0	0.5	1
9	0.4	0.7	0.4	0	0.3	0.3	0.6	1	0.5	1	0.5	0	0.5	0	0.5	1
10	0.2	1	0.2	0	0.8	0	0.8	1	0.8	1	0.8	0	0.2	0	0.2	1
11	0.4	0.7	0.4	0	0.3	0.3	0.6	1	0.2	1	0.2	0	0.8	0	0.8	1
12	0.9	0.8	0.8	0.1	0	0.1	0.1	1	1	0.8	0.8	0.2	0	0	0	1
13	0.9	0.8	0.8	0.1	0	0.1	0.1	1	1	1	1	0	0	0	0	1
14	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.2	0.8	0.2	0	0.6	0.2	0.8	1
15	0.8	0.5	0.5	0.3	0	0.2	0.2	1	0.3	0.8	0.3	0	0.5	0.2	0.7	1
16	0.4	0.6	0.4	0	0.2	0.4	0.6	1	0.5	1	0.5	0	0.5	0	0.5	1
17	0.9	0.4	0.4	0.5	0	0.1	0.1	1	0.2	1	0.2	0	0.8	0	0.8	1
18	0.5	0.9	0.5	0	0.4	0.1	0.5	1	0.3	0.9	0.3	0	0.6	0.1	0.7	1
Sum	10.0	12.8	8.7	1.3	4.1	3.9	8.0		7.7	17.3	7.5	0.2	9.8	0.5	10.3	

Hit Rate = 0.87 FA Rate = 0.51 Hit Rate = 0.97 FA Rate = 0.95

	Worker 15								Worker 16							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.6	0.5	0.5	0.1	0	0.4	0.4	1	0.5	0.9	0.5	0	0.4	0.1	0.5	1
2	0.3	0.9	0.3	0	0.6	0.1	0.7	1	0.2	0.8	0.2	0	0.6	0.2	0.8	1
3	0.8	0.5	0.5	0.3	0	0.2	0.2	1	0.9	0.5	0.5	0.4	0	0.1	0.1	1
4	0.7	0.6	0.6	0.1	0	0.3	0.3	1	0.7	0.9	0.7	0	0.2	0.1	0.3	1
5	0.5	0.7	0.5	0	0.2	0.3	0.5	1	0.3	0.9	0.3	0	0.6	0.1	0.7	1
6	0.8	0.7	0.7	0.1	0	0.2	0.2	1	0.5	0.5	0.5	0	0	0.5	0.5	1
7	0.9	0.8	0.8	0.1	0	0.1	0.1	1	0.7	0.9	0.7	0	0.2	0.1	0.3	1
8	0.9	0.5	0.5	0.4	0	0.1	0.1	1	0.9	0.6	0.6	0.3	0	0.1	0.1	1
v	0.3	0.7	0.3	0	0.4	0.3	0.7	1	0.4	0.7	0.4	0	0.3	0.3	0.6	1
10	0.2	0.5	0.2	0	0.3	0.5	0.8	1	0.2	1	0.2	0	0.8	0	0.8	1
11	0.3	0.6	0.3	0	0.3	0.4	0.7	1	0.2	1	0.2	0	0.8	0	0.8	1
12	0.9	0.6	0.6	0.3	0	0.1	0.1	1	0.9	1	0.9	0	0.1	0	0.1	1
13	0.9	1	0.9	0	0.1	0	0.1	1	0.7	0.9	0.7	0	0.2	0.1	0.3	1
14	0.7	0.6	0.6	0.1	0	0.3	0.3	1	0.9	0.8	0.8	0.1	0	0.1	0.1	1
15	0.5	0.9	0.5	0	0.4	0.1	0.5	1	0.4	0.5	0.4	0	0.1	0.5	0.6	1
16	0.3	0.5	0.3	0	0.2	0.5	0.7	1	0.2	0.5	0.2	0	0.3	0.5	0.8	1
17	0.4	0.7	0.4	0	0.3	0.3	0.6	1	0.4	0.8	0.4	0	0.4	0.2	0.6	1
18	0.2	0.7	0.2	0	0.5	0.3	0.8	1	0.4	0.5	0.4	0	0.1	0.5	0.6	1
Sum	10.2	12.0	8.7	1.5	3.3	4.5	7.8		9.4	13.7	8.6	0.8	5.1	3.5	8.6	

Hit Rate = 0.85 FA Rate = 0.42 Hit Rate = 0.91 FA Rate = 0.59

Table B.1...contd.

	Worker 17								Worker 18							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.3	0.8	0.3	0	0.5	0.2	0.7	1	0.5	0.6	0.5	0	0.1	0.4	0.5	1
2	0.3	0.9	0.3	0	0.6	0.1	0.7	1	0.4	0.9	0.4	0	0.5	0.1	0.6	1
3	0.4	0.6	0.4	0	0.2	0.4	0.6	1	0.6	0.5	0.5	0.1	0	0.4	0.4	1
4	0.4	0.5	0.4	0	0.1	0.5	0.6	1	0.9	1	0.9	0	0.1	0	0.1	1
5	0.3	0.6	0.3	0	0.3	0.4	0.7	1	0.3	0.7	0.3	0	0.4	0.3	0.7	1
6	0.7	0.8	0.7	0	0.1	0.2	0.3	1	0.3	0.7	0.3	0	0.4	0.3	0.7	1
7	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.8	1	0.8	0	0.2	0	0.2	1
8	0.9	0.9	0.9	0	0	0.1	0.1	1	0.5	0.9	0.5	0	0.4	0.1	0.5	1
9	0.2	0.8	0.2	0	0.6	0.2	0.8	1	0.5	0.9	0.5	0	0.4	0.1	0.5	1
10	0.1	0.9	0.1	0	0.8	0.1	0.9	1	0	1	0	0	1	0	1	1
11	0.2	0.7	0.2	0	0.5	0.3	0.8	1	0.2	0.9	0.2	0	0.7	0.1	0.8	1
12	0.9	0.7	0.7	0.2	0	0.1	0.1	1	0.9	1	0.9	0	0.1	0	0.1	1
13	0.9	0.8	0.8	0.1	0	0.1	0.1	1	0.8	0.5	0.5	0.3	0	0.2	0.2	1
14	0.7	0.7	0.7	0	0	0.3	0.3	1	0.9	0.8	0.8	0.1	0	0.1	0.1	1
15	0.4	0.7	0.4	0	0.3	0.3	0.6	1	0.4	1	0.4	0	0.6	0	0.6	1
16	0.3	0.5	0.3	0	0.2	0.5	0.7	1	0.1	0.5	0.1	0	0.4	0.5	0.9	1
17	0.3	0.8	0.3	0	0.5	0.2	0.7	1	0.1	0.6	0.1	0	0.5	0.4	0.9	1
18	0.3	0.8	0.3	0	0.5	0.2	0.7	1	0.3	0.9	0.3	0	0.6	0.1	0.7	1
Sum	8.4	13.4	8.1	0.3	5.3	4.3	9.6		8.5	14.4	8.0	0.5	6.4	3.1	9.5	

Hit Rate = 0.96 FA Rate = 0.55 Hit Rate = 0.94 FA Rate = 0.67

	Worker 19								Worker 20			27		8		
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.6	0.7	0.6	0	0.1	0.3	0.4	1	0	1	0	0	1	0	1	1
2	0.3	0.5	0.3	0	0.2	0.5	0.7	1	0	1	0	0	1	0	1	1
3	0.5	0.7	0.5	0	0.2	0.3	0.5	1	1	1	1	0	0	0	0	1
4	0.6	0.3	0.3	0.3	0	0.4	0.4	1	0.5	1	0.5	0	0.5	0	0.5	1
5	0.3	0.6	0.3	0	0.3	0.4	0.7	1	0.7	1	0.7	0	0.3	0	0.3	1
6	0.4	0.9	0.4	0	0.5	0.1	0.6	1	0	1	0	0	1	0	1	1
7	0.5	0.8	0.5	0	0.3	0.2	0.5	1	0	1	0	0	1	0	1	1
8	0.5	0.6	0.5	0	0.1	0.4	0.5	1	1	1	1	0	0	0	0	1
v	0.3	0.5	0.3	0	0.2	0.5	0.7	1	0.5	1	0.5	0	0.5	0	0.5	1
10	0.2	0.6	0.2	0	0.4	0.4	0.8	1	1	1	1	0	0	0	0	1
11	0.1	0.9	0.1	0	0.8	0.1	0.9	1	0	1	0	0	1	0	1	1
12	0.8	0.5	0.5	0.3	0	0.2	0.2	1	0	1	0	0	1	0	1	1
13	0.7	0.8	0.7	0	0.1	0.2	0.3	1	0	1	0	0	1	0	1	1
14	0.7	0.9	0.7	0	0.2	0.1	0.3	1	1	1	1	0	0	0	0	1
15	0.3	0.9	0.3	0	0.6	0.1	0.7	1	0	1	0	0	1	0	1	1
16	0.5	0.5	0.5	0	0	0.5	0.5	1	0	1	0	0	1	0	1	1
17	0.3	0.6	0.3	0	0.3	0.4	0.7	1	0	1	0	0	1	0	1	1
18	0.1	0.6	0.1	0	0.5	0.4	0.9	1	0	1	0	0	1	0	1	1
Sum	7.7	11.9	7.1	0.6	4.8	5.5	10.3		5.7	18.0	5.7	0.0	12.3	0.0	12.3	

Hit Rate = 0.92 FA Rate = 0.47 Hit Rate = 1.00 FA Rate = 1.00

Table B.1...contd.

	Worker 21								Worker 22							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.7	0.3	0.3	0.4	0	0.3	0.3	1	1	0.5	0.5	0.5	0	0	0	1
2	0.3	0.6	0.3	0	0.3	0.4	0.7	1	0.2	0.7	0.2	0	0.5	0.3	0.8	1
3	0.5	0.6	0.5	0	0.1	0.4	0.5	1	0.6	0.5	0.5	0.1	0	0.4	0.4	1
4	0.7	0.4	0.4	0.3	0	0.3	0.3	1	0.7	0.8	0.7	0	0.1	0.2	0.3	1
5	0.4	0.4	0.4	0	0	0.6	0.6	1	0.4	0.5	0.4	0	0.1	0.5	0.6	1
6	0.4	0.7	0.4	0	0.3	0.3	0.6	1	0.6	0.6	0.6	0	0	0.4	0.4	1
7	0.8	0.7	0.7	0.1	0	0.2	0.2	1	0.9	1	0.9	0	0.1	0	0.1	1
8	0.9	0.8	0.8	0.1	0	0.1	0.1	1	1	1	1	0	0	0	0	1
9	0.2	0.7	0.2	0	0.5	0.3	0.8	1	0.4	0.6	0.4	0	0.2	0.4	0.6	1
10	0.21	0.9	0.21	0	0.69	0.1	0.79	1	0.2	0.8	0.2	0	0.6	0.2	0.8	1
11	0.2	0.9	0.2	0	0.7	0.1	0.8	1	0.7	0.3	0.3	0.4	0	0.3	0.3	1
12	0.7	0.7	0.7	0	0	0.3	0.3	1	1	0.7	0.7	0.3	0	0	0	1
13	0.9	1	0.9	0	0.1	0	0.1	1	1	1	1	0	0	0	0	1
14	0.7	0.4	0.4	0.3	0	0.3	0.3	1	1	0.7	0.7	0.3	0	0	0	1
15	0.9	0.7	0.7	0.2	0	0.1	0.1	1	0.8	0.9	0.8	0	0.1	0.1	0.2	1
16	0.6	0.7	0.6	0	0.1	0.3	0.4	1	1	0.8	0.8	0.2	0	0	0	1
17	0.3	0.6	0.3	0	0.3	0.4	0.7	1	0.5	0.5	0.5	0	0	0.5	0.5	1
18	0	0.7	0	0	0.7	0.3	1	1	0.5	0.8	0.5	0	0.3	0.2	0.5	1
Sum	9.4	11.8	8.0	1.4	3.8	4.8	8.6		12.5	12.7	10.7	1.8	2.0	3.5	5.5	

Hit Rate = 0.85 FA Rate = 0.44 Hit Rate = 0.86 FA Rate = 0.36

	Worker 23								Worker 24							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.8	0.6	0.6	0.2	0	0.2	0.2	1	0.8	0.3	0.3	0.5	0	0.2	0.2	1
2	0.3	0.8	0.3	0	0.5	0.2	0.7	1	0.2	0.8	0.2	0	0.6	0.2	0.8	1
3	0.6	0.8	0.6	0	0.2	0.2	0.4	1	0.5	0.5	0.5	0	0	0.5	0.5	1
4	0.5	0.7	0.5	0	0.2	0.3	0.5	1	0.6	0.4	0.4	0.2	0	0.4	0.4	1
5	0.3	0.7	0.3	0	0.4	0.3	0.7	1	0.4	0.4	0.4	0	0	0.6	0.6	1
6	0.6	0.8	0.6	0	0.2	0.2	0.4	1	0.5	0.5	0.5	0	0	0.5	0.5	1
7	0.9	0.9	0.9	0	0	0.1	0.1	1	0.8	0.6	0.6	0.2	0	0.2	0.2	1
8	1	0.8	0.8	0.2	0	0	0	1	0.9	0.7	0.7	0.2	0	0.1	0.1	1
v	0.4	0.7	0.4	0	0.3	0.3	0.6	1	0.2	0.3	0.2	0	0.1	0.7	0.8	1
10	0.4	0.8	0.4	0	0.4	0.2	0.6	1	0.1	0.3	0.1	0	0.2	0.7	0.9	1
11	0.2	0.7	0.2	0	0.5	0.3	0.8	1	0.3	0.5	0.3	0	0.2	0.5	0.7	1
12	1	0.9	0.9	0.1	0	0	0	1	0.8	0.6	0.6	0.2	0	0.2	0.2	1
13	1	1	1	0	0	0	0	1	0.9	1	0.9	0	0.1	0	0.1	1
14	0.6	0.5	0.5	0.1	0	0.4	0.4	1	0.6	0.6	0.6	0	0	0.4	0.4	1
15	0.5	0	0	0.5	0	0.5	0.5	1	0.4	0.6	0.4	0	0.2	0.4	0.6	1
16	0.4	0.2	0.2	0.2	0	0.6	0.6	1	0.6	0.4	0.4	0.2	0	0.4	0.4	1
17	0.4	0.4	0.4	0	0	0.6	0.6	1	0.3	0.5	0.3	0	0.2	0.5	0.7	1
18	0.3	0.7	0.3	0	0.4	0.3	0.7	1	0.1	0.5	0.1	0	0.4	0.5	0.9	1
Sum	10.2	12.0	8.9	1.3	3.1	4.7	7.8		9.0	9.5	7.5	1.5	2.0	7.0	9.0	

Hit Rate = 0.87 FA Rate = 0.40 Hit Rate = 0.83 FA Rate = 0.22

Table B.1...contd.

	Worker 25								Worker 26							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	1	0.7	0.7	0.3	0	0	0	1	0.4	0.5	0.4	0	0.1	0.5	0.6	1
2	0.4	0.6	0.4	0	0.2	0.4	0.6	1	0.3	0.8	0.3	0	0.5	0.2	0.7	1
3	0.7	0.8	0.7	0	0.1	0.2	0.3	1	0.6	0.3	0.3	0.3	0	0.4	0.4	1
4	0.7	0.5	0.5	0.2	0	0.3	0.3	1	0.5	0.4	0.4	0.1	0	0.5	0.5	1
5	0.8	0.8	0.8	0	0	0.2	0.2	1	0.3	0.5	0.3	0	0.2	0.5	0.7	1
6	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.5	0.6	0.5	0	0.1	0.4	0.5	1
7	1	1	1	0	0	0	0	1	0.6	0.5	0.5	0.1	0	0.4	0.4	1
8	1	1	1	0	0	0	0	1	0.7	0.6	0.6	0.1	0	0.3	0.3	1
9	0.4	0.4	0.4	0	0	0.6	0.6	1	0.3	0.5	0.3	0	0.2	0.5	0.7	1
10	0.4	0.6	0.4	0	0.2	0.4	0.6	1	0.3	0.7	0.3	0	0.4	0.3	0.7	1
11	0.7	0.4	0.4	0.3	0	0.3	0.3	1	0.4	0.7	0.4	0	0.3	0.3	0.6	1
12	1	1	1	0	0	0	0	1	0.7	0.5	0.5	0.2	0	0.3	0.3	1
13	1	1	1	0	0	0	0	1	0.7	0.8	0.7	0	0.1	0.2	0.3	1
14	0.9	0.8	0.8	0.1	0	0.1	0.1	1	0.6	0.6	0.6	0	0	0.4	0.4	1
15	0.7	0.8	0.7	0	0.1	0.2	0.3	1	0.4	0.3	0.3	0.1	0	0.6	0.6	1
16	0.9	0.9	0.9	0	0	0.1	0.1	1	0.5	0.1	0.1	0.4	0	0.5	0.5	1
17	0.5	0.6	0.5	0	0.1	0.4	0.5	1	0.4	0.7	0.4	0	0.3	0.3	0.6	1
18	0.5	0.8	0.5	0	0.3	0.2	0.5	1	0.1	0.6	0.1	0	0.5	0.4	0.9	1
Sum	13.4	13.6	12.5	0.9	1.1	3.5	4.6		8.3	9.7	7.0	1.3	2.7	7.0	9.7	

Hit Rate = 0.93 FA Rate = 0.24 Hit Rate = 0.84 FA Rate = 0.28

	Worker 27								Worker 28							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.5	0.6	0.5	0	0.1	0.4	0.5	1	0.2	0.4	0.2	0	0.2	0.6	0.8	1
2	0.1	0.9	0.1	0	0.8	0.1	0.9	1	0.3	0.7	0.3	0	0.4	0.3	0.7	1
3	1	1	1	0	0	0	0	1	0.7	1	0.7	0	0.3	0	0.3	1
4	0.8	0.9	0.8	0	0.1	0.1	0.2	1	0.5	0.9	0.5	0	0.4	0.1	0.5	1
5	1	1	1	0	0	0	0	1	0.4	0.5	0.4	0	0.1	0.5	0.6	1
6	0.3	0.7	0.3	0	0.4	0.3	0.7	1	0.7	0.3	0.3	0.4	0	0.3	0.3	1
7	0.8	0.8	0.8	0	0	0.2	0.2	1	0.8	0.6	0.6	0.2	0	0.2	0.2	1
8	1	1	1	0	0	0	0	1	0.7	1	0.7	0	0.3	0	0.3	1
v	0.7	0.5	0.5	0.2	0	0.3	0.3	1	0.3	0.7	0.3	0	0.4	0.3	0.7	1
10	0.2	0.6	0.2	0	0.4	0.4	0.8	1	0	1	0	0	1	0	1	1
11	1	0.7	0.7	0.3	0	0	0	1	0	1	0	0	1	0	1	1
12	0.3	0.7	0.3	0	0.4	0.3	0.7	1	1	1	1	0	0	0	0	1
13	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	1
14	0.8	0.6	0.6	0.2	0	0.2	0.2	1	0.9	1	0.9	0	0.1	0	0.1	1
15	0.2	0.8	0.2	0	0.6	0.2	0.8	1	0.3	0.8	0.3	0	0.5	0.2	0.7	1
16	1	1	1	0	0	0	0	1	0.4	0.9	0.4	0	0.5	0.1	0.6	1
17	0.2	0.9	0.2	0	0.7	0.1	0.8	1	0.1	0.8	0.1	0	0.7	0.2	0.9	1
18	0.9	0.8	0.8	0.1	0	0.1	0.1	1	0.1	1	0.1	0	0.9	0	0.9	1
Sum	11.8	14.5	11.0	0.8	3.5	2.7	6.2		8.4	14.6	7.8	0.6	6.8	2.8	9.6	

Hit Rate = 0.93 FA Rate = 0.56 Hit Rate = 0.93 FA Rate = 0.71

Table B.1...contd.

	Worker 29								Worker 30							
Q.No.	s	r	H	M	FA	CR	1-s	sum	s	r	H	M	FA	CR	1-s	sum
1	0.3	0.8	0.3	0	0.5	0.2	0.7	1	0.2	0.8	0.2	0	0.6	0.2	0.8	1
2	0	1	0	0	1	0	1	1	0.1	0.8	0.1	0	0.7	0.2	0.9	1
3	0.8	0.8	0.8	0	0	0.2	0.2	1	0.5	0.8	0.5	0	0.3	0.2	0.5	1
4	0.5	0.5	0.5	0	0	0.5	0.5	1	0.2	0.8	0.2	0	0.6	0.2	0.8	1
5	0.6	0.8	0.6	0	0.2	0.2	0.4	1	0.5	0.8	0.5	0	0.3	0.2	0.5	1
6	0	0.7	0	0	0.7	0.3	1	1	0.3	0.8	0.3	0	0.5	0.2	0.7	1
7	0.6	0.7	0.6	0	0.1	0.3	0.4	1	0.3	0.8	0.3	0	0.5	0.2	0.7	1
8	0.8	1	0.8	0	0.2	0	0.2	1	0.3	0.8	0.3	0	0.5	0.2	0.7	1
9	0.3	1	0.3	0	0.7	0	0.7	1	0.5	0.8	0.5	0	0.3	0.2	0.5	1
10	0.4	0.8	0.4	0	0.4	0.2	0.6	1	0.3	0.8	0.3	0	0.5	0.2	0.7	1
11	0.5	1	0.5	0	0.5	0	0.5	1	0.2	0.8	0.2	0	0.6	0.2	0.8	1
12	1	1	1	0	0	0	0	1	0.3	0.8	0.3	0	0.5	0.2	0.7	1
13	1	1	1	0	0	0	0	1	0.6	0.8	0.6	0	0.2	0.2	0.4	1
14	0.2	0.8	0.2	0	0.6	0.2	0.8	1	0.2	0.8	0.2	0	0.6	0.2	0.8	1
15	0.2	0.8	0.2	0	0.6	0.2	0.8	1	0.5	0.8	0.5	0	0.3	0.2	0.5	1
16	0.5	0.5	0.5	0	0	0.5	0.5	1	0.4	0.8	0.4	0	0.4	0.2	0.6	1
17	0.1	1	0.1	0	0.9	0	0.9	1	0.2	0.9	0.2	0	0.7	0.1	0.8	1
18	0	1	0	0	1	0	1	1	0.2	0.8	0.2	0	0.6	0.2	0.8	1
Sum	7.8	15.2	7.8	0.0	7.4	2.8	10.2		5.8	14.5	5.8	0.0	8.7	3.5	12.2	

Hit Rate = 1.00 FA Rate = 0.73 Hit Rate = 1.00 FA Rate = 0.71

Table B.1...contd.

APPENDIX C

RASMUSSENS MODEL OF
COGNITIVE SYSTEMS ENGINNERING

Jens Rasmussen's Theory of Cognitive System Engineering

Figure 3.1 illustrates the three zones of risk, and shows how work migrates from one boundary to the other. Zone 1 - IN THE SAFE ZONE: Enlarge the safe zone through planning the operation. Identifying hazards in an operation assumes that the operation has been designed.

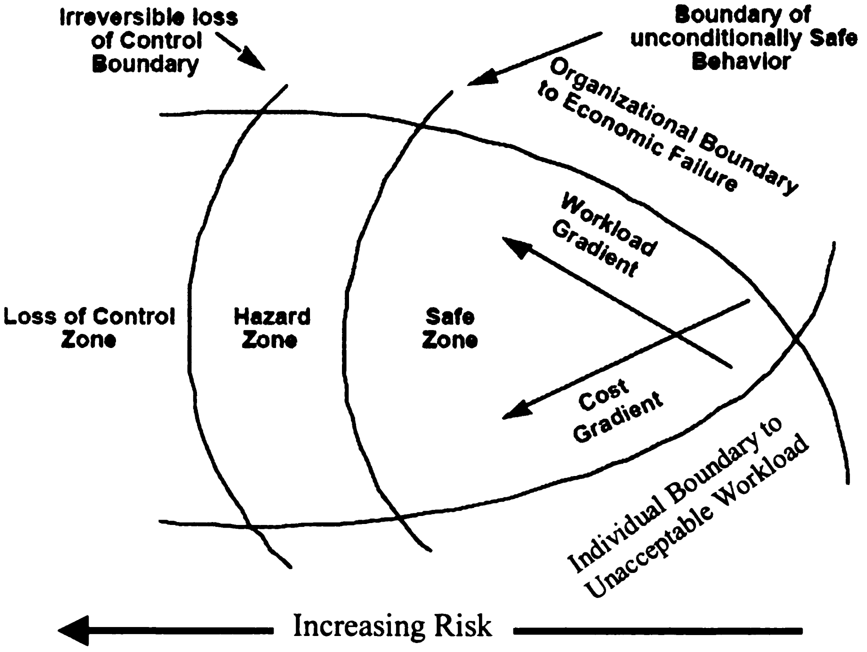


Figure C.1: Three zones of risk

Zone 2 - AT THE EDGE: a) Make visible the boundary beyond which work is no longer safe (a hazard can be released) and teach people how to recognize the boundary. b) Teach people how to detect and recover from errors at the edge of control.

Zone 3 - OVER THE EDGE: Design ways to limit the effect of the hazard once control is lost.

APPENDIX D

CRISP SDT V/S FUZZY SDT - MATRIX

Model type	**Crisp SDT**	**Fuzzy SDT**
	Stimuli Presented (s value)	
Signal Present	1	Value of 's' ranges from 0 to 1 (Degree to which an event is a signal)
Signal Absent (Noise)	0	
	Response Generated (r value)	
Yes	1	Value of 'r' ranges from 0 to 1 (Degree to which a YES response was made)
No	0	

Various combinations of stimuli & response give a value that falls only under one of the four outcomes i.e. H, M, FA and CR. Each event is mapped exclusively to only one of the outcome four categories.

Each event represented by a stimuli – response pair belongs, with some degree, to more than one of the four categories used in SDT. So there will be events that claim nonzero membership in more than one outcome category.

s	**r**	**H**	**FA**	**M**	**CR**
0	0	0	0	0	1
0	1	0	0	1	0
1	0	0	1	0	0
1	1	1	0	0	0

s	**r**	**H**	**FA**	**M**	**CR**
.8	.9	.8	.1	0	.1
.2	.2	.2	0	0	.8
.5	.2	.2	0	.3	.5
.1	.9	.1	.8	0	.1

Crisp SDT
v/s
Fuzzy SDT
Matrix

Figure D.1

APPENDIX E

REGRESSION ANALYSIS: MINITAB RESULTS

```
Regression Analysis: Sensitivity versus Exp

The regression equation is
Sensitivity = 1.74 - 0.0226 Exp


Predictor        Coef   SE Coef      T      P
Constant       1.7446    0.2168   8.05  0.000
Exp          -0.02257   0.01826  -1.24  0.227


S = 0.662967   R-Sq = 5.2%   R-Sq(adj) = 1.8%


Analysis of Variance

Source           DF       SS      MS     F      P
Regression        1   0.6714  0.6714  1.53  0.227
Residual Error   28  12.3067  0.4395
Total            29  12.9781
```

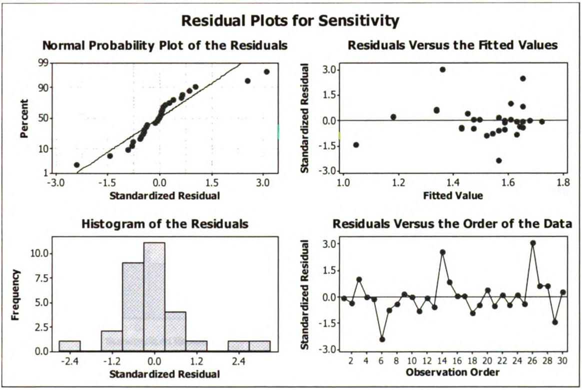


Figure E.1

Regression analysis: Sensitivity and Industry Experience of Ironworker

```
Regression Analysis: Bias versus Age

The regression equation is
Bias = 0.406 - 0.00010 Age


Predictor         Coef   SE Coef      T      P
Constant        0.4063    0.2299   1.77  0.088
Age          -0.000098  0.006783  -0.01  0.989


S = 0.254068   R-Sq = 0.0%   R-Sq(adj) = 0.0%


Analysis of Variance

Source          DF       SS       MS     F      P
Regression       1  0.00001  0.00001  0.00  0.989
Residual Error  28  1.80742  0.06455
Total           29  1.80743
```

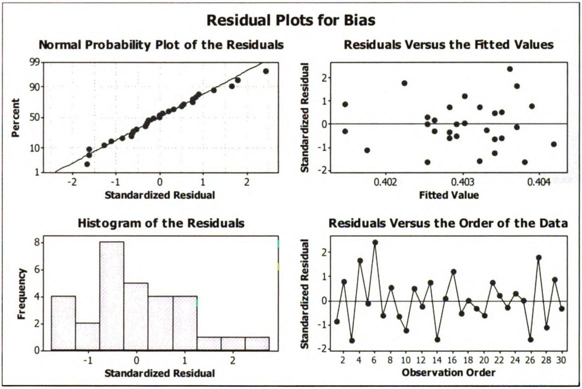


Figure E.2

Regression analysis: Bias and Age of Ironworker

Regression Analysis: Bias versus Exp

```
The regression equation is
Bias = 0.392 + 0.00112 Exp


Predictor       Coef   SE Coef     T      P
Constant     0.39199   0.08304  4.72  0.000
Exp         0.001117  0.006994  0.16  0.874


S = 0.253953   R-Sq = 0.1%   R-Sq(adj) = 0.0%


Analysis of Variance

Source          DF        SS        MS     F      P
Regression       1   0.00165   0.00165  0.03  0.874
Residual Error  28   1.80578   0.06449
Total           29   1.80743
```

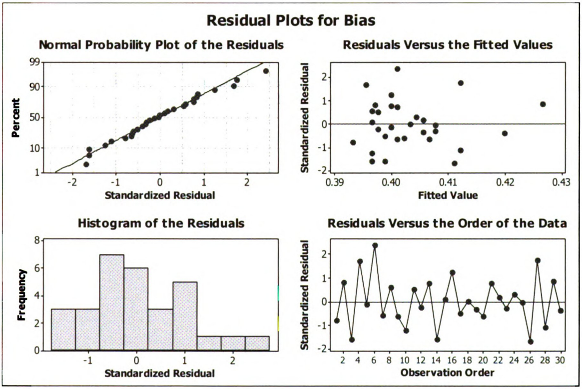


Figure E.3

Regression analysis: Bias and Industry Experience of Ironworker

APPENDIX F

CUMULATIVE STANDARD NORMAL DISTRIBUTION TABLE

z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
0.0	0.5000	0.5040	0.5080	0.5120	0.5160	0.5199	0.5239	0.5279	0.5319	0.5359
0.1	0.5398	0.5438	0.5478	0.5517	0.5557	0.5596	0.5636	0.5675	0.5714	0.5753
0.2	0.5793	0.5832	0.5871	0.5910	0.5948	0.5987	0.6026	0.6064	0.6103	0.6141
0.3	0.6179	0.6217	0.6255	0.6293	0.6331	0.6368	0.6406	0.6443	0.6480	0.6517
0.4	0.6554	0.6591	0.6628	0.6664	0.6700	0.6736	0.6772	0.6808	0.6844	0.6879
0.5	0.6915	0.6950	0.6985	0.7019	0.7054	0.7088	0.7123	0.7157	0.7190	0.7224
0.6	0.7257	0.7291	0.7324	0.7357	0.7389	0.7422	0.7454	0.7486	0.7517	0.7549
0.7	0.7580	0.7611	0.7642	0.7673	0.7704	0.7734	0.7764	0.7794	0.7823	0.7852
0.8	0.7881	0.7910	0.7939	0.7967	0.7995	0.8023	0.8051	0.8078	0.8106	0.8133
0.9	0.8159	0.8186	0.8212	0.8238	0.8264	0.8289	0.8315	0.8340	0.8365	0.8389
1.0	0.8413	0.8438	0.8461	0.8485	0.8508	0.8531	0.8554	0.8577	0.8599	0.8621
1.1	0.8643	0.8665	0.8686	0.8708	0.8729	0.8749	0.8770	0.8790	0.8810	0.8830
1.2	0.8849	0.8869	0.8888	0.8907	0.8925	0.8944	0.8962	0.8980	0.8997	0.9015
1.3	0.9032	0.9049	0.9066	0.9082	0.9099	0.9115	0.9131	0.9147	0.9162	0.9177
1.4	0.9192	0.9207	0.9222	0.9236	0.9251	0.9265	0.9279	0.9292	0.9306	0.9319
1.5	0.9332	0.9345	0.9357	0.9370	0.9382	0.9394	0.9406	0.9418	0.9429	0.9441
1.6	0.9452	0.9463	0.9474	0.9484	0.9495	0.9505	0.9515	0.9525	0.9535	0.9545
1.7	0.9554	0.9564	0.9573	0.9582	0.9591	0.9599	0.9608	0.9616	0.9625	0.9633
1.8	0.9641	0.9649	0.9656	0.9664	0.9671	0.9678	0.9686	0.9693	0.9699	0.9706
1.9	0.9713	0.9719	0.9726	0.9732	0.9738	0.9744	0.9750	0.9756	0.9761	0.9767
2.0	0.9772	0.9778	0.9783	0.9788	0.9793	0.9798	0.9803	0.9808	0.9812	0.9817
2.1	0.9821	0.9826	0.9830	0.9834	0.9838	0.9842	0.9846	0.9850	0.9854	0.9857
2.2	0.9861	0.9864	0.9868	0.9871	0.9875	0.9878	0.9881	0.9884	0.9887	0.9890
2.3	0.9893	0.9896	0.9898	0.9901	0.9904	0.9906	0.9909	0.9911	0.9913	0.9916
2.4	0.9918	0.9920	0.9922	0.9925	0.9927	0.9929	0.9931	0.9932	0.9934	0.9936
2.5	0.9938	0.9940	0.9941	0.9943	0.9945	0.9946	0.9948	0.9949	0.9951	0.9952
2.6	0.9953	0.9955	0.9956	0.9957	0.9959	0.9960	0.9961	0.9962	0.9963	0.9964
2.7	0.9965	0.9966	0.9967	0.9968	0.9969	0.9970	0.9971	0.9972	0.9973	0.9974
2.8	0.9974	0.9975	0.9976	0.9977	0.9977	0.9978	0.9979	0.9979	0.9980	0.9981
2.9	0.9981	0.9982	0.9982	0.9983	0.9984	0.9984	0.9985	0.9985	0.9986	0.9986
3.0	0.9987	0.9987	0.9987	0.9988	0.9988	0.9989	0.9989	0.9989	0.9990	0.9990

Table F.1 Cumulative Standard Normal Distribution Table

APPENDIX G

DATA ANALYSIS: CONVENTIONAL (CRISP) SDT

		Worker 1							Worker 2						
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	0.3		0	1	0	0	1	0.4		0	1	0	0	1
safe	2	0		0	0	0	1	1	0.3		0	0	0	1	1
unsafe	3	1		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	4	0.5		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	5	0.6		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	6	0		0	1	0	0	1	0.7		1	0	0	0	1
unsafe	7	0.3		0	1	0	0	1	0.4		1	0	0	0	1
unsafe	8	1		1	0	0	0	1	0.9		1	0	0	0	1
safe	9	0.5		0	0	1	0	1	0.3		0	0	0	1	1
safe	10	0.9		0	0	1	0	1	0.2		0	0	0	1	1
safe	11	0.1		0	0	0	1	1	0.3		0	0	0	1	1
unsafe	12	0.1		0	1	0	0	1	0.8		1	0	0	0	1
unsafe	13	0.3		0	1	0	0	1	1		1	0	0	0	1
unsafe	14	0.2		0	1	0	0	1	0.6		1	0	0	0	1
safe	15	0.2		0	0	0	1	1	0.4		0	0	1	0	1
unsafe	16	0.2		0	1	0	0	1	0.5		1	0	0	0	1
safe	17	0		0	0	0	1	1	0.2		0	0	0	1	1
safe	18	0.3		0	0	0	1	1	0.4		0	0	1	0	1
	Sum	6.5		4.0	7.0	2.0	5.0		9.4	0.0	10.0	1.0	2.0	5.0	
		Hit Rate =		0.36		FA Rate =		0.29	Hit Rate =		0.91		FA Rate =		0.29
		Worker 3							Worker 4						
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	0.6		1	0	0	0	1	0.8		1	0	0	0	1
safe	2	0.3		0	0	0	1	1	0.2		0	0	0	1	1
unsafe	3	0.7		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	4	0.5		1	0	0	0	1	0.9		1	0	0	0	1
unsafe	5	0.5		1	0	0	0	1	0.5		1	0	0	0	1
unsafe	6	0.7		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	7	0.8		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	8	0.8		1	0	0	0	1	0.9		1	0	0	0	1
safe	9	0.3		0	0	0	1	1	0.3		0	0	0	1	1
safe	10	0.1		0	0	0	1	1	0		0	0	0	1	1
safe	11	0.1		0	0	0	1	1	0		0	0	0	1	1
unsafe	12	0.8		1	0	0	0	1	0.9		1	0	0	0	1
unsafe	13	0.8		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	14	0.8		1	0	0	0	1	0.9		1	0	0	0	1
safe	15	0.2		0	0	0	1	1	0.5		0	0	1	0	1
unsafe	16	0.1		0	1	0	0	1	0.1		0	1	0	0	1
safe	17	0.1		0	0	0	1	1	0.1		0	0	0	1	1
safe	18	0.2		0	0	0	1	1	0.1	0.9	0	0	0	1	1
	Sum	8.4	0.0	10.0	1.0	0.0	7.0		9.1	0.9	10.0	1.0	1.0	6.0	
		Hit Rate =		0.91		FA Rate =		0.00	Hit Rate =		0.91		FA Rate =		0.14

Table G.1

		Worker 5							**Worker 6**						
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	0.3		0	1	0	0	1	0.6		1	0	0	0	1
safe	2	0.4		0	0	1	0	1	0.3		0	0	0	1	1
unsafe	3	0.4		1	0	0	0	1	0.4		1	0	0	0	1
unsafe	4	0.5		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	5	0.5		1	0	0	0	1	0.5		1	0	0	0	1
unsafe	6	0.6		1	0	0	0	1	0.3		0	1	0	0	1
unsafe	7	0.7		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	8	1		1	0	0	0	1	0.8		1	0	0	0	1
safe	9	0.4		0	0	1	0	1	0.2		0	0	0	1	1
safe	10	0.1		0	0	0	1	1	0.1		0	0	0	1	1
safe	11	0.4		0	0	1	0	1	0.2		0	0	0	1	1
unsafe	12	0.7		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	13	0.9		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	14	0.9		1	0	0	0	1	0.7		1	0	0	0	1
safe	15	0.4		0	0	1	0	1	0.4		0	0	1	0	1
unsafe	16	0.3		0	1	0	0	1	0.7		1	0	0	0	1
safe	17	0.3		0	0	0	1	1	0.3		0	0	0	1	1
safe	18	0.2		0	0	0	1	1	0.2		0	0	0	1	1
	Sum	9.0	0.0	9.0	2.0	4.0	3.0		8.5	0.0	10.0	1.0	1.0	6.0	
		Hit Rate =		0.82		FA Rate =		0.57	Hit Rate =		0.91		FA Rate =		0.14

		Worker 7							**Worker 8**						
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	0.6		1	0	0	0	1	0.6		1	0	0	0	1
safe	2	0.2		0	0	0	1	1	0.3		0	0	0	0	0
unsafe	3	0.7		1	0	0	0	1	0.5		1	0	0	0	1
unsafe	4	0.8		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	5	0.5		1	0	0	0	1	0.4		1	0	0	0	1
unsafe	6	0.5		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	7	0.9		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	8	0.8		1	0	0	0	1	1		1	0	0	0	1
safe	9	0.4		0	0	1	0	1	0.4		0	0	1	0	1
safe	10	0.2		0	0	0	1	1	0.3		0	0	0	0	0
safe	11	0.1		0	0	0	1	1	0.2		0	0	0	0	0
unsafe	12	0.8		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	13	0.8		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	14	0.6		1	0	0	0	1	0.7		1	0	0	0	1
safe	15	0.6		0	0	1	0	1	0.5		0	0	1	0	1
unsafe	16	0.2		0	1	0	0	1	0.5		1	0	0	0	1
safe	17	0.1		0	0	0	1	1	0.4		0	0	1	0	1
safe	18	0.3		0	0	0	1	1	0.1		0	0	0	0	0
	Sum	9.1	0.0	10.0	1.0	2.0	5.0		9.4	0.0	11.0	0.0	3.0	0.0	
		Hit Rate =		0.91		FA Rate =		0.29	Hit Rate =		1.00		FA Rate =		0.43

Table G.1...contd.

		Worker 9							**Worker 10**						
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	0.4		1	0	0	0	1	0.6		1	0	0	0	1
safe	2	0.2		0	0	0	1	1	0.1		0	0	0	1	1
unsafe	3	0.7		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	4	0.8		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	5	0.6		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	6	0.6		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	7	0.7		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	8	0.8		1	0	0	0	1	0.8		1	0	0	0	1
safe	9	0.4		0	0	1	0	1	0.4		0	0	1	0	1
safe	10	0.1		0	0	0	1	1	0.1		0	0	0	1	1
safe	11	0.2		0	0	0	1	1	0.2		0	0	0	1	1
unsafe	12	0.8		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	13	0.7		1	0	0	0	1	0.9		1	0	0	0	1
unsafe	14	0.7		1	0	0	0	1	0.9		1	0	0	0	1
safe	15	0.3		0	0	1	0	1	0.4		0	0	1	0	1
unsafe	16	0.2		0	1	0	0	1	0.1		0	1	0	0	1
safe	17	0.2		0	0	0	1	1	0		0	0	0	1	1
safe	18	0.3		0	0	0	1	1	0.3		0	0	0	1	1
	Sum	8.7	0.0	10.0	1.0	2.0	5.0		9.0	0.0	10.0	1.0	2.0	5.0	
		Hit Rate =		0.91		FA Rate =		0.29	Hit Rate =		0.91		FA Rate =		0.29

		Worker 11							**Worker 12**						
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	0.8		1	0	0	0	1	0.5		1	0	0	0	1
safe	2	0.2		0	0	0	1	1	0.5		0	0	1	0	1
unsafe	3	0.6		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	4	0.4		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	5	0.5		1	0	0	0	1	0.5		1	0	0	0	1
unsafe	6	0.4		1	0	0	0	1	0.3		0	1	0	0	1
unsafe	7	0.6		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	8	0.8		1	0	0	0	1	0.2		0	1	0	0	1
safe	9	0.3		0	0	0	1	1	0.3		0	0	0	1	1
safe	10	0.4		0	0	1	0	1	0.5		0	0	1	0	1
safe	11	0.6		0	0	1	0	1	0.4		0	0	1	0	1
unsafe	12	0.6		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	13	1		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	14	0.8		1	0	0	0	1	0.5		1	0	0	0	1
safe	15	0.4		0	0	1	0	1	0.5		0	0	1	0	1
unsafe	16	0.5		1	0	0	0	1	0.3		0	1	0	0	1
safe	17	0.4		0	0	1	0	1	0.1		0	0	0	1	1
safe	18	0.3		0	0	0	1	1	0.3		0	0	0	1	1
	Sum	9.6	0.0	11.0	0.0	4.0	3.0			0.0	8.0	3.0	4.0	3.0	
		Hit Rate =		1.00		FA Rate =		0.57	HR =		0.73		FA Rate =		0.57

Table G.1...contd.

		Worker 13						Worker 14						
state	Q.No.	s		H	M	FA	CR	s		H	M	FA	CR	sum
unsafe	1	0.6		1	0	0	0	0.4		1	0	0	0	1
safe	2	0.2		0	0	0	1	0		0	0	0	1	1
unsafe	3	0.7		1	0	0	0	0.5		1	0	0	0	1
unsafe	4	0.9		1	0	0	0	0.4		1	0	0	0	1
unsafe	5	0.3		0	1	0	0	0.2		0	1	0	0	1
unsafe	6	0.3		0	1	0	0	0.2		0	1	0	0	1
unsafe	7	0.5		1	0	0	0	0.5		1	0	0	0	1
unsafe	8	0.3		0	0	0	0	0.5		1	0	0	0	1
safe	9	0.4		0	0	1	0	0.5		0	0	1	0	1
safe	10	0.2		0	0	1	0	0.8		0	0	1	0	1
safe	11	0.4		0	0	0	1	0.2		0	0	0	1	1
unsafe	12	0.9		1	0	0	0	1		1	0	0	0	1
unsafe	13	0.9		1	0	0	0	1		1	0	0	0	1
unsafe	14	0.8		1	1	0	0	0.2		0	1	0	0	1
safe	15	0.8		0	0	0	1	0.3		0	0	0	1	1
unsafe	16	0.4		1	0	0	0	0.5		1	0	0	0	1
safe	17	0.9		0	0	0	1	0.2		0	0	0	1	1
safe	18	0.5		0	0	0	1	0.3		0	0	0	1	1
	Sum	10.0	0.0	8.0	3.0	2.0	5.0	7.7	0.0	8.0	3.0	2.0	5.0	
		Hit Rate =		0.73			FA Rate =	Hit Rate =		0.73			FA Rate =	0.29

		Worker 15						Worker 16						
state	Q.No.	s		H	M	FA	CR	s		H	M	FA	CR	sum
unsafe	1	0.6		1	0	0	0	0.5		1	0	0	0	1
safe	2	0.3		0	0	0	1	0.2		0	0	0	1	1
unsafe	3	0.8		1	0	0	0	0.9		1	0	0	0	1
unsafe	4	0.7		1	0	0	0	0.7		1	0	0	0	1
unsafe	5	0.5		1	0	0	0	0.3		0	1	0	0	1
unsafe	6	0.8		1	0	0	0	0.5		1	0	0	0	1
unsafe	7	0.9		1	0	0	0	0.7		1	0	0	0	1
unsafe	8	0.9		1	0	0	0	0.9		1	0	0	0	1
safe	9	0.3		0	0	0	1	0.4		0	0	1	0	1
safe	10	0.2		0	0	0	1	0.2		0	0	0	1	1
safe	11	0.3		0	0	0	1	0.2		0	0	0	1	1
unsafe	12	0.9		1	0	0	0	0.9		1	0	0	0	1
unsafe	13	0.9		1	0	0	0	0.7		1	0	0	0	1
unsafe	14	0.7		1	0	0	0	0.9		1	0	0	0	1
safe	15	0.5		0	0	1	0	0.4		0	0	1	0	1
unsafe	16	0.3		0	1	0	0	0.2		0	1	0	0	1
safe	17	0.4		0	0	1	0	0.4		0	0	1	0	1
safe	18	0.2		0	0	0	1	0.4		0	0	1	0	1
	Sum		0.0	10.0	1.0	2.0	5.0	9.4	0.0	9.0	2.0	4.0	3.0	
		HR =		0.91			FA Rate =	Hit Rate =		0.82			FA Rate =	0.57

Table G.1…contd.

		Worker 17							Worker 18						
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	0.3		0	1	0	0	1	0.5		1	0	0	0	1
safe	2	0.3		0	0	0	1	1	0.4		0	0	1	0	1
unsafe	3	0.4		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	4	0.4		1	0	0	0	1	0.9		1	0	0	0	1
unsafe	5	0.3		0	1	0	0	1	0.3		0	1	0	0	1
unsafe	6	0.7		1	0	0	0	1	0.3		0	1	0	0	1
unsafe	7	0.8		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	8	0.9		1	0	0	0	1	0.5		1	0	0	0	1
safe	9	0.2		0	0	0	1	1	0.5		0	0	1	0	1
safe	10	0.1		0	0	0	1	1	0		0	0	0	1	1
safe	11	0.2		0	0	0	1	1	0.2		0	0	0	1	1
unsafe	12	0.9		1	0	0	0	1	0.9		1	0	0	0	1
unsafe	13	0.9		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	14	0.7		1	0	0	0	1	0.9		1	0	0	0	1
safe	15	0.4		0	0	1	0	1	0.4		0	0	1	0	1
unsafe	16	0.3		0	1	0	0	1	0.1		0	1	0	0	1
safe	17	0.3		0	0	0	1	1	0.1		0	0	0	1	1
safe	18	0.3		0	0	0	1	1	0.3		0	0	0	1	1
	Sum	8.4	0.0	8.0	3.0	1.0	6.0		8.5	0.0	8.0	3.0	3.0	4.0	
		Hit Rate =		0.73		FA Rate =		0.14	Hit Rate =		0.73		FA Rate =		0.43
		Worker 19							**Worker 20**			27		8	
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	0.6		1	0	0	0	1	0		0	1	0	0	1
safe	2	0.3		0	0	0	1	1	0		0	0	0	1	1
unsafe	3	0.5		1	0	0	0	1	1		1	0	0	0	1
unsafe	4	0.6		1	0	0	0	1	0.5		1	0	0	0	1
unsafe	5	0.3		0	1	0	0	1	0.7		1	0	0	0	1
unsafe	6	0.4		1	0	0	0	1	0		0	1	0	0	1
unsafe	7	0.5		1	0	0	0	1	0		0	1	0	0	1
unsafe	8	0.5		1	0	0	0	1	1		1	0	0	0	1
safe	9	0.3		0	0	0	1	1	0.5		0	0	1	0	1
safe	10	0.2		0	0	0	1	1	1		0	0	1	0	1
safe	11	0.1		0	0	0	1	1	0		0	0	0	1	1
unsafe	12	0.8		1	0	0	0	1	0		0	1	0	0	1
unsafe	13	0.7		1	0	0	0	1	0		0	1	0	0	1
unsafe	14	0.7		1	0	0	0	1	1		1	0	0	0	1
safe	15	0.3		0	0	0	1	1	0		0	0	0	1	1
unsafe	16	0.5		1	0	0	0	1	0		0	1	0	0	1
safe	17	0.3		0	0	0	1	1	0		0	0	0	1	1
safe	18	0.1		0	0	0	1	1	0		0	0	0	1	1
	Sum	7.7	0.0	10.0	1.0	0.0	7.0		5.7	0.0	5.0	6.0	2.0	5.0	
		Hit Rate =		0.91		FA Rate =		0.00	Hit Rate =		0.45		FA Rate =		0.29

Table G.1…contd.

		Worker 21							**Worker 22**						
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	0.7		1	0	0	0	1	1		1	0	0	0	1
safe	2	0.3		0	0	0	1	1	0.2		0	0	0	1	1
unsafe	3	0.5		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	4	0.7		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	5	0.4		1	0	0	0	1	0.4		1	0	0	0	1
unsafe	6	0.4		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	7	0.8		1	0	0	0	1	0.9		1	0	0	0	1
unsafe	8	0.9		1	0	0	0	1	1		1	0	0	0	1
safe	9	0.2		0	0	0	1	1	0.4		0	0	1	0	1
safe	10	0.21		0	0	0	1	1	0.2		0	0	0	1	1
safe	11	0.2		0	0	0	1	1	0.7		0	0	1	0	1
unsafe	12	0.7		1	0	0	0	1	1		1	0	0	0	1
unsafe	13	0.9		1	0	0	0	1	1		1	0	0	0	1
unsafe	14	0.7		1	0	0	0	1	1		1	0	0	0	1
safe	15	0.9		0	0	1	0	1	0.8		0	0	1	0	1
unsafe	16	0.6		1	0	0	0	1	1		1	0	0	0	1
safe	17	0.3		0	0	0	1	1	0.5		0	0	1	0	1
safe	18	0		0	0	0	1	1	0.5	0.8	0	0	1	0	1
	Sum	9.4	0.0	11.0	0.0	1.0	6.0		12.5	0.8	11.0	0.0	5.0	2.0	
		Hit Rate =		1.00		FA Rate =		0.14	Hit Rate =		1.00		FA Rate =		0.71

		Worker 23							**Worker 24**						
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	0.8		1	0	0	0	1	0.8		1	0	0	0	1
safe	2	0.3		0	0	0	1	1	0.2		0	0	0	1	1
unsafe	3	0.6		1	0	0	0	1	0.5		1	0	0	0	1
unsafe	4	0.5		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	5	0.3		0	1	0	0	1	0.4		1	0	0	0	1
unsafe	6	0.6		1	0	0	0	1	0.5		1	0	0	0	1
unsafe	7	0.9		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	8	1		1	0	0	0	1	0.9		1	0	0	0	1
safe	9	0.4		0	0	1	0	1	0.2		0	0	0	1	1
safe	10	0.4		0	0	1	0	1	0.1		0	0	0	1	1
safe	11	0.2		0	0	0	1	1	0.3		0	0	0	1	1
unsafe	12	1		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	13	1		1	0	0	0	1	0.9		1	0	0	0	1
unsafe	14	0.6		1	0	0	0	1	0.6		1	0	0	0	1
safe	15	0.5		0	0	1	0	1	0.4		0	0	1	0	1
unsafe	16	0.4		1	0	0	0	1	0.6		1	0	0	0	1
safe	17	0.4		0	0	1	0	1	0.3		0	0	0	1	1
safe	18	0.3		0	0	0	1	1	0.1		0	0	0	1	1
	Sum	10.2	0.0	10.0	1.0	4.0	3.0		9.0	0.0	11	0.0	1.0	6.0	
		Hit Rate =		0.91		FA Rate =		0.57	Hit Rate =		1.00		FA Rate =		0.14

Table G.1…contd.

		Worker 25							**Worker 26**						
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	1		1	0	0	0	1	0.4		1	0	0	0	1
safe	2	0.4		0	0	1	0	1	0.3		0	0	0	1	1
unsafe	3	0.7		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	4	0.7		1	0	0	0	1	0.5		1	0	0	0	1
unsafe	5	0.8		1	0	0	0	1	0.3		0	1	0	0	1
unsafe	6	0.8		1	0	0	0	1	0.5		1	0	0	0	1
unsafe	7	1		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	8	1		1	0	0	0	1	0.7		1	0	0	0	1
safe	9	0.4		0	0	1	0	1	0.3		0	0	0	1	1
safe	10	0.4		0	0	1	0	1	0.3		0	0	0	1	1
safe	11	0.7		0	0	1	0	1	0.4		0	0	1	0	1
unsafe	12	1		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	13	1		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	14	0.9		1	0	0	0	1	0.6		1	0	0	0	1
safe	15	0.7		0	0	1	0	1	0.4		0	0	1	0	1
unsafe	16	0.9		1	0	0	0	1	0.5		1	0	0	0	1
safe	17	0.5		0	0	1	0	1	0.4		0	0	1	0	1
safe	18	0.5		0	0	1	0	1	0.1		0	0	0	1	1
	Sum	13.4	0.0	11.0	0.0	7.0	0.0		8.3	0.0	10.0	1.0	3.0	4.0	
		Hit Rate =		1.00		FA Rate =		1.00	Hit Rate =		0.91		FA Rate =		0.43

		Worker 27							**Worker 28**						
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	0.5		1	0	0	0	1	0.2		0	1	0	0	1
safe	2	0.1		0	0	0	1	1	0.3		0	0	0	1	1
unsafe	3	1		1	0	0	0	1	0.7		1	0	0	0	1
unsafe	4	0.8		1	0	0	0	1	0.5		1	0	0	0	1
unsafe	5	1		1	0	0	0	1	0.4		1	0	0	0	1
unsafe	6	0.3		0	1	0	0	1	0.7		1	0	0	0	1
unsafe	7	0.8		1	0	0	0	1	0.8		1	0	0	0	1
unsafe	8	1		1	0	0	0	1	0.7		1	0	0	0	1
safe	9	0.7		0	0	1	0	1	0.3		0	0	0	1	1
safe	10	0.2		0	0	0	1	1	0		0	0	0	1	1
safe	11	1		0	0	1	0	1	0		0	0	0	1	1
unsafe	12	0.3		0	1	0	0	1	1		1	0	0	0	1
unsafe	13	1		1	0	0	0	1	1		1	0	0	0	1
unsafe	14	0.8		1	0	0	0	1	0.9		1	0	0	0	1
safe	15	0.2		0	0	0	1	1	0.3		0	0	0	1	1
unsafe	16	1		1	0	0	0	1	0.4		1	0	0	0	1
safe	17	0.2		0	0	0	1	1	0.1		0	0	0	1	1
safe	18	0.9		0	0	1	0	1	0.1		0	0	0	1	1
	Sum	11.8	0.0	9.0	2.0	3.0	4.0		8.4	0.0	10.0	1.0	0.0	7.0	
		Hit Rate =		0.82		FA Rate =		0.43	Hit Rate =		0.91		FA Rate =		0.00

Table G.1...contd.

		Worker 29							Worker 30						
state	Q.No.	s		H	M	FA	CR	sum	s		H	M	FA	CR	sum
unsafe	1	0.3		0	1	0	0	1	0.2		0	1	0	0	1
safe	2	0		0	0	0	1	1	0.1		0	0	0	1	1
unsafe	3	0.8		1	0	0	0	1	0.5		1	0	0	0	1
unsafe	4	0.5		1	0	0	0	1	0.2		0	1	0	0	1
unsafe	5	0.6		1	0	0	0	1	0.5		1	0	0	0	1
unsafe	6	0		0	1	0	0	1	0.3		0	1	0	0	1
unsafe	7	0.6		1	0	0	0	1	0.3		0	1	0	0	1
unsafe	8	0.8		1	0	0	0	1	0.3		0	1	0	0	1
safe	9	0.3		0	0	0	1	1	0.5		0	0	1	0	1
safe	10	0.4		0	0	1	0	1	0.3		0	0	0	1	1
safe	11	0.5		0	0	1	0	1	0.2		0	0	0	1	1
unsafe	12	1		1	0	0	0	1	0.3		0	1	0	0	1
unsafe	13	1		1	0	0	0	1	0.6		1	0	0	0	1
unsafe	14	0.2		0	1	0	0	1	0.2		0	1	0	0	1
safe	15	0.2		0	0	0	1	1	0.5		0	0	1	0	1
unsafe	16	0.5		1	0	0	0	1	0.4		1	0	0	0	1
safe	17	0.1		0	0	0	1	1	0.2		0	0	0	1	1
safe	18	0		0	0	0	1	1	0.2		0	0	0	1	1
	Sum	7.8	0.0	8.0	3.0	2.0	5.0		5.8	0.0	4.0	7.0	2.0	5.0	
		Hit Rate =		0.73		FA Rate =		0.29	Hit Rate =		0.36		FA Rate =		0.29

Table G.1...contd.

Calculations for Crisp SDT with cut-off at 2, for the first question

Worker #	Hit Rate	FA Rate	z (HR)	z (FAR)	Sensitivity	Y (HR)	Y (FAR)	Bias
	HR	FAR			d'			β
1	0.64	0.43	0.35	-0.18	0.53	0.38	0.39	0.96
2	0.91	0.71	1.34	0.57	0.77	0.16	0.34	0.48
3	0.91	0.29	1.34	-0.57	1.90	0.16	0.34	0.48
4	0.91	0.22	1.34	-0.76	2.09	0.16	0.30	0.55
5	1.00	0.56	3.80	0.14	3.66	0.00	0.40	0.00
6	1.00	0.32	3.80	-0.48	4.28	0.00	0.36	0.00
7	0.91	0.34	1.34	-0.42	1.76	0.16	0.37	0.45
8	1.00	0.58	3.80	0.21	3.59	0.00	0.39	0.00
9	0.91	0.32	1.34	-0.46	1.80	0.16	0.36	0.46
10	0.91	0.33	1.34	-0.43	1.77	0.16	0.36	0.45
11	1.00	0.71	3.80	0.57	3.23	0.00	0.34	0.00
12	0.91	0.80	1.34	0.84	0.49	0.16	0.28	0.58
13	1.00	0.25	3.80	-0.67	4.47	0.00	0.32	0.00
14	0.73	0.39	0.60	-0.28	0.89	0.33	0.38	0.87
15	1.00	0.83	3.80	0.97	2.83	0.00	0.25	0.00
16	0.91	0.47	1.34	-0.09	1.42	0.16	0.40	0.41
17	1.00	0.42	3.80	-0.21	4.01	0.00	0.39	0.00
18	0.91	0.42	1.34	-0.20	1.53	0.16	0.39	0.42
19	1.09	0.29	3.80	-0.55	4.35	0.00	0.34	0.00
20	0.45	0.16	-0.11	-0.98	0.87	0.40	0.25	1.61
21	1.00	0.35	3.80	-0.39	4.19	0.00	0.37	0.00
22	1.00	0.71	3.80	0.57	3.23	0.00	0.34	0.00
23	1.00	0.77	3.80	0.74	3.06	0.00	0.30	0.00
24	1.00	0.43	3.80	-0.18	3.98	0.00	0.39	0.00
25	1.00	1.00	3.80	-3.80	7.60	0.00	0.00	1.00
26	1.00	0.62	3.80	0.30	3.50	0.00	0.38	0.00
27	1.00	0.48	3.80	-0.04	3.84	0.00	0.40	0.00
28	0.91	0.31	1.34	-0.49	1.82	0.16	0.35	0.46
29	0.82	0.29	0.91	-0.54	1.45	0.26	0.34	0.77
30	0.73	0.25	0.60	-0.69	1.29	0.33	0.31	1.05

Average	0.92	0.48			2.73			0.35
Min	0.45	0.16			0.49			0.00
Max	1.09	1.00			7.60			1.61
Std. Dev	0.132	0.213			1.588			0.423

Table G.2: Calculation for sensitivity and bias using Crisp SDT with cut-off at 2

Worker #	Hit Rate	FA Rate	z (HR)	z (FAR)	**Sensitivity**	Y (HR)	Y (FAR)	**Bias**
	HR	**FAR**			**d'**			β
1	0.82	0.57	0.91	0.18	0.73	0.26	0.39	0.67
2	0.91	1.00	1.34	3.80	-2.46	0.16	0.00	-3.52
3	0.91	0.57	1.34	0.18	1.16	0.16	0.39	0.42
4	0.91	0.34	1.34	-0.42	1.76	0.16	0.37	0.45
5	1.00	0.67	3.80	0.43	3.37	0.00	0.36	0.00
6	1.00	0.63	3.80	0.34	3.46	0.00	0.38	0.00
7	0.91	0.56	1.34	0.16	1.18	0.16	0.39	0.42
8	1.00	0.70	3.80	0.52	3.28	0.00	0.35	0.00
9	1.00	0.65	3.80	0.37	3.43	0.00	0.37	0.00
10	0.91	0.44	1.34	-0.14	1.47	0.16	0.40	0.41
11	1.00	0.83	3.80	0.97	2.83	0.00	0.25	0.00
12	1.00	0.80	3.80	0.84	2.96	0.00	0.28	0.00
13	1.00	0.38	3.80	-0.32	4.12	0.00	0.38	0.00
14	1.00	0.58	3.80	0.21	3.59	0.00	0.39	0.00
15	1.00	1.17	3.80	3.80	0.00	0.00	0.00	1.00
16	1.00	0.81	3.80	0.89	2.91	0.00	0.27	0.00
17	1.00	0.52	3.80	0.05	3.75	0.00	0.40	0.00
18	0.91	0.53	1.34	0.07	1.27	0.16	0.40	0.41
19	1.09	0.39	3.80	-0.28	4.08	0.00	0.38	0.00
20	0.45	0.16	-0.11	-0.98	0.87	0.40	0.25	1.61
21	1.00	0.70	3.80	0.52	3.28	0.00	0.35	0.00
22	1.00	1.00	3.80	3.80	0.00	0.00	0.00	1.00
23	1.00	0.90	3.80	1.27	2.53	0.00	0.18	0.00
24	1.00	0.71	3.80	0.57	3.23	0.00	0.34	0.00
25	1.00	1.00	3.80	3.80	0.00	0.00	0.00	1.00
26	1.00	0.62	3.80	0.30	3.50	0.00	0.38	0.00
27	1.00	0.97	3.80	1.85	1.95	0.00	0.07	0.00
28	1.00	0.31	3.80	-0.49	4.29	0.00	0.35	0.00
29	0.91	0.39	1.34	-0.27	1.61	0.16	0.38	0.43
30	1.00	0.49	3.80	-0.02	3.82	0.00	0.40	0.00
Average	0.95	0.66			2.11			0.16
Min	0.45	0.16			-2.46			-3.52
Max	1.09	1.17			4.29			1.61
Std. Dev	0.109	0.240			1.597			0.807

Table G.3: Calculation for sensitivity and bias using Crisp SDT with cut-off at 1

APPENDIX H

CORRELATION PLOTS INVESTIGATING FATIGUE FACTOR IN WORKERS' RESPONSES

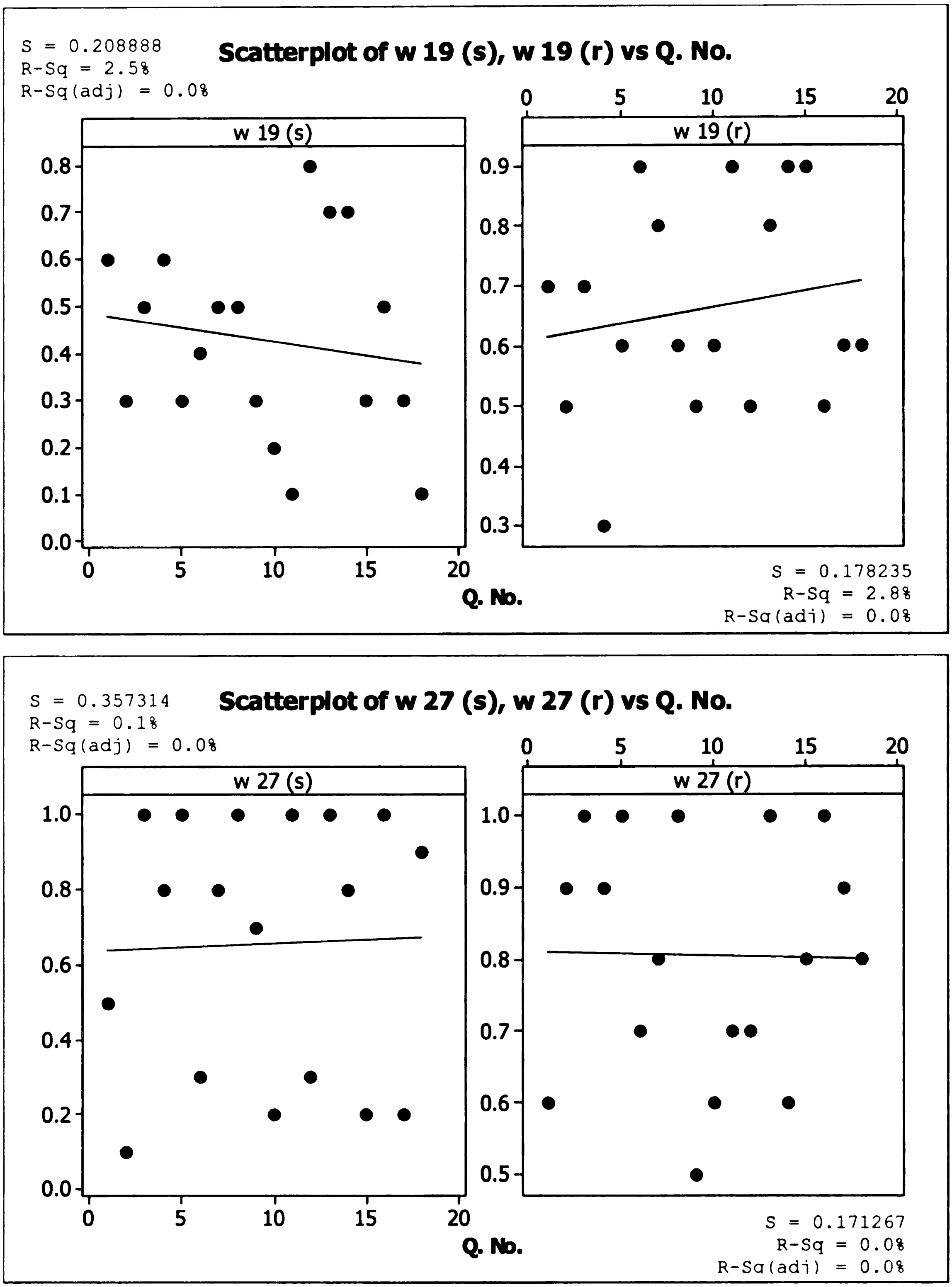
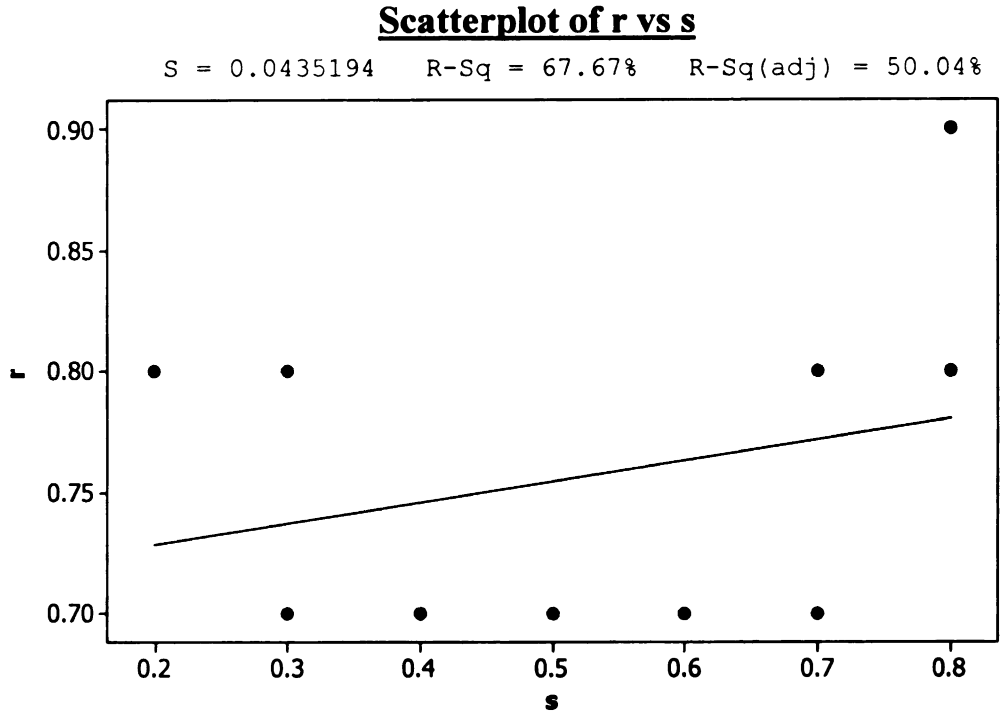


Figure H.1

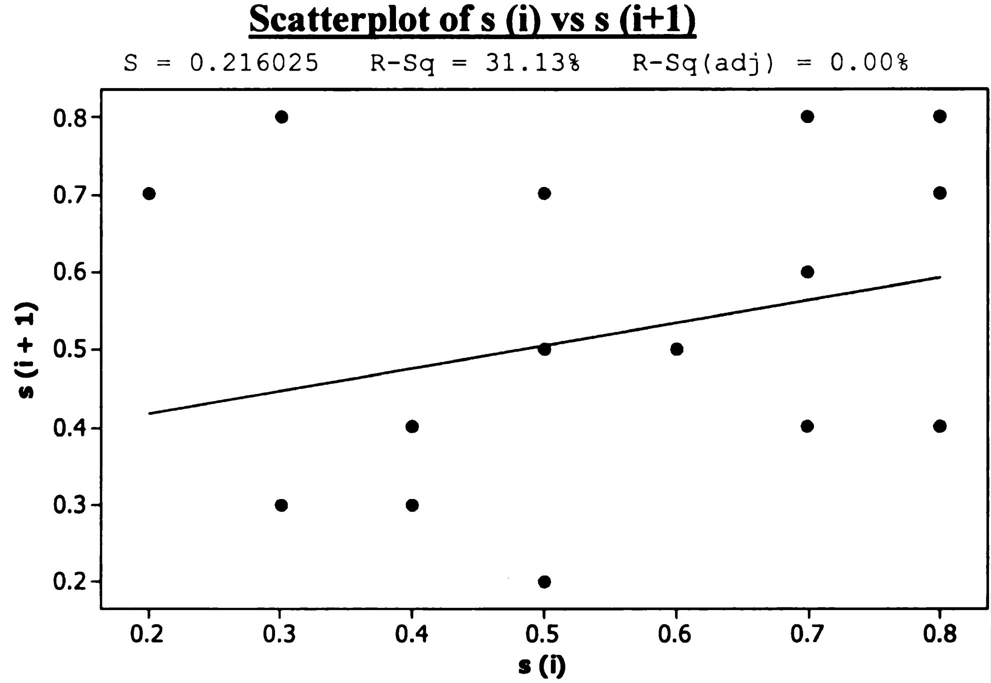
Scatter plot of s and r responses against survey conditions 1-18 for worker # 19 and 27



s	r
0.5	0.7
0.2	0.8
0.7	0.7
0.6	0.7
0.5	0.7
0.5	0.7
0.7	0.8
0.8	0.8
0.4	0.7
0.3	0.8
0.3	0.7
0.8	0.8
0.8	0.9
0.7	0.8
0.4	0.7
0.4	0.7
0.3	0.8
0.3	0.8

Figure H.2

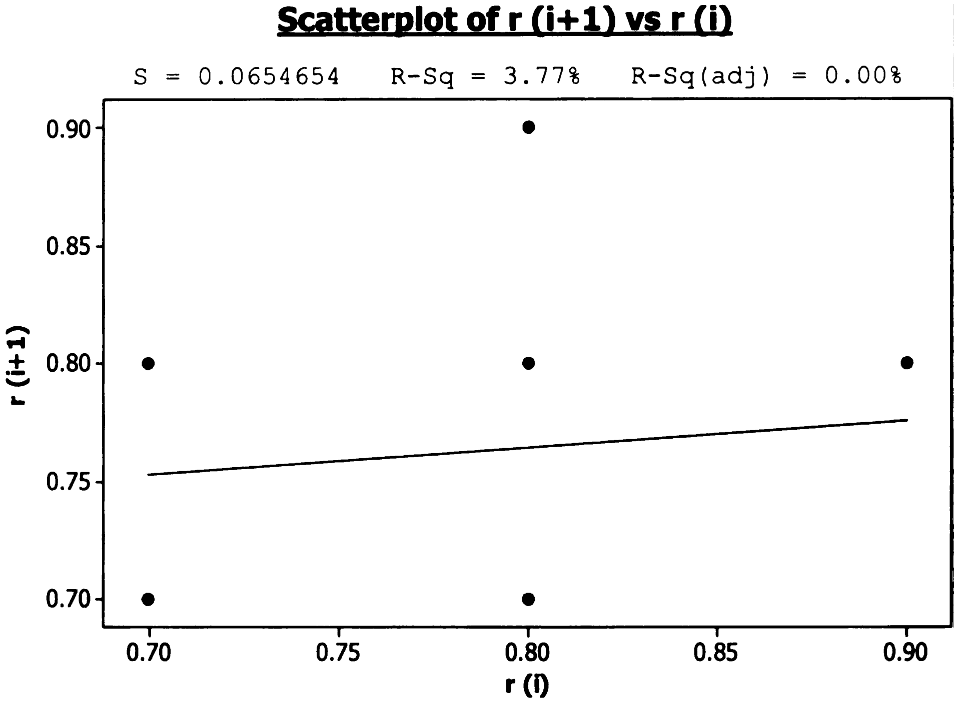
Scatter plot investigating correlation between workers average 's' and 'r' values for each of the 18 questions



s (i)	s (i + 1)
0.5	0.2
0.2	0.7
0.7	0.6
0.6	0.5
0.5	0.5
0.5	0.7
0.7	0.8
0.8	0.4
0.4	0.3
0.3	0.3
0.3	0.8
0.8	0.8
0.8	0.7
0.7	0.4
0.4	0.4
0.4	0.3
0.3	0.3
0.3	

Figure H.3

Scatter plot investigating auto correlation between workers responses using average 's' values for each of the 18 questions



r (i)	r (i+1)
0.7	0.8
0.8	0.7
0.7	0.7
0.7	0.7
0.7	0.7
0.7	0.8
0.8	0.8
0.8	0.7
0.7	0.8
0.8	0.7
0.7	0.8
0.8	0.9
0.9	0.8
0.8	0.7
0.7	0.7
0.7	0.8
0.8	0.8
0.8	

Figure H.4

Scatter plot investigating auto correlation between workers responses using average ‘r’ values for each of the 18 questions

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