QUANTIFYING WORKERS' HAZARD IDENTIFICATION ABILITY USING FUZZY SIGNAL DETECTION THEORY

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ABSTRACT

Safeguarding construction workers from occupational hazards, whether arising from traumatic, ergonomic, and/or exposure accidents, is part and parcel of the lean construction ideal of waste elimination. Howell et al. (2002) proposed a new approach to understand construction accidents based on Rasmussen's theory of cognitive systems engineering. One aspect of the model focused on worker training to recognize hazards (unsafe conditions). The primary goal of this paper is to develop a method to quantify workers' ability to identify these hazards. Abdelhamid et al. (2003) explored the need for an assessment of the process of identification and applied Signal Detection Theory (SDT) to assess workers' ability to detect unsafe conditions. This research applies Fuzzy SDT, proposed by Parasuraman et al. (2000), to increase the applicability of conventional SDT analysis to construction settings where the definition of a signal event and its associated response do not follow a binary or dichotomous structure. Application of the methodology is demonstrated using a pilot study involving structural steel workers. Results from the sample of 10 ironworkers indicated the average sensitivity in identifying hazards was above average and that workers generally adopted a conservative strategy. Data analysis using conventional SDT model showed a marginally increased sensitivity, but with a very high variation. This result illustrated that fuzzy SDT model was more reflective of the ability of construction workers to identify construction hazards.

KEYWORDS

Occupational Safety, Construction Safety, Signal Detection Theory, Construction Accidents, Hazard Identification.

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INTRODUCTION

Occupational accidents are unquestionably wasteful and non-value adding events in any system of production. Similar to other wasteful and non-value adding events that result in unreliable workflow such as late delivery of material and equipment, design errors, change orders, equipment breakdowns, and environmental effects, occupational accidents also result in the same. It follows then that safeguarding construction workers from occupational hazards, whether arising from traumatic, ergonomic, and/or exposure accidents, is part and parcel of the lean construction ideal of waste elimination.

While safety is clearly important to Lean Construction, a question is frequently raised regarding whether Lean Construction is important to safety[3]. The influence of Lean Construction on safety becomes apparent when one considers the procedures and tools devised based on lean concepts and principles that force the explicit consideration of occupational safety issues. For example, in the Lean Design phase, wherein the product and process are designed simultaneously, occupational safety issues are considered during Constructability reviews. Underscoring the importance of "Design for Safety", in 1997, the Construction Industry Institute (CII), compiled and disseminated detailed guidelines for designers to help reduce safety issues during construction. Examples of such guidelines include avoiding roof edges and skylights as locations for rooftop mechanical equipment, scheduling night work sparingly, and designing slabs on grade and mat foundations with closely spaced reinforcement, which allows a continuous walking surface (Gambatese 2000). In addition, under a lean production paradigm, Lean Assembly refers to simplifying the process of assembly through industrialization, modularizations, standardization, and continuous flow processes. To aid in this simplification process, the assembly or production operations are placed under scrutiny (e.g., using Kaizen events) and improvements are suggested (e.g., using the 5S process) to reduce waste that manifests itself as overproduction, rework, and long cycle times. It is typical for such reviews to identify opportunities for reducing the number of operations/steps required for production, thus leading to the reduction of waste and increase in quality. A welcome outcome of these efforts is the improvement of occupational safety and ergonomics related issues in the production process. The mere reduction of operations required for a production process means that there are less chances for traumatic, ergonomics, and exposure injuries to occur. This follows from the same logic that the fewer the number of operations, the higher the quality of the product because there are less chances of making errors.

With increased attention on safety, construction companies have focused on the implementation of safety training programs and the appointment of a safety officer or an entire department in some cases. These efforts typically aim to assure legal requirements are met and hazards and incidents are reduced. These industry wide guidelines and programs are constantly evolving and form the foundation for all safety training. While these programs have resulted in improvements, the industry remains one of the most dangerous. Further improvement is needed, but improvement has reached a plateau and construction still kills or injures more than eight percent of its workers each year.

Improving the situation must focus on understanding the dynamics behind occupational accidents. This inevitably means that we have to start with the worker, who is performing his/her job and often needs to make decisions that would result in the release or containment of resident hazards on site. Consequently, hazard identification, or the lack thereof, by workers is probably the most critical aspect in successfully implementing safety regulations and guidelines.

[3] In fact, one of the reviewers of this paper has raised this very important question.

This topic receives fewer attention compared to other factors such as personal protective equipment and mandatory guidelines and directives that are employed in the form of written instructions and formal training. This paper, however deals with the other less popular side of analyzing construction workers' ability to identify hazards. Assessment of the hazard identification ability of workers is imperative in understanding the dynamics of construction accidents under different situations.

Based on the work of Howell et al. (2002), which proposed that workers must be trained to recognize hazards and how to respond to them in a 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. The application of Signal Detection Theory (SDT) was proposed for 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 response criterion of the observer, and these help quantify the signal (hazard, in the case of construction) identification process.

Although the application of SDT provided a very good initial understanding of the hazard identification process in construction, the SDT model fails to capture all the information because of its intrinsic binary structure. In particular, SDT works on a yes/no dichotomy, forcing a respondent in to a black or white response. This inevitably results in the loss of critical information related to the respondent's selection. To provide an accurate assessment of a worker's ability to identify hazardous situations, there is a need to improve the model that is used for this assessment.

It is proposed in this research to use fuzzy SDT as a means to expand the applicability of conventional SDT analysis to real world construction settings where the definition of a signal event is non-dichotomous. Basically, in fuzzy SDT the binary definition of a signal is fuzzified by allowing an observer to assign non-binary membership degrees to a particular signal. 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.

A brief description of fuzzy SDT follows. Application of the methodology is demonstrated using a pilot study involving structural steel workers. Results from the pilot study are presented. A comparison between conventional and fuzzy SDT concludes the paper. More details on the study are available in Narang (2005).

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)» 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)» 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 1 (left) explains this difference between binary and non-binary classification. Assuming that there are two defined stimuli classes, the responses generated in a 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.

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 1 (right), 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.

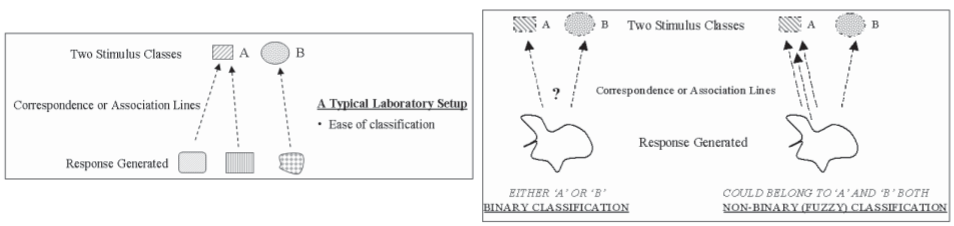

Figure 1. Detection process in a laboratory setup (left). Real world setting – Blurred definitions of stimuli and response (right).

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 of detection abilities.

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.

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). 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.

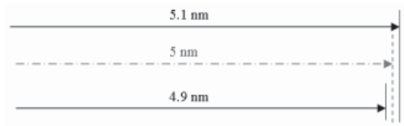

Figure 2. ATC horizontal separation regulations for aircrafts in flight

If we represent the framework as shown in Figure 2, i.e., abandon the 5 nm separation definition; the 4.9nm and 5.1nm 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. For example, 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 conventional SDT by Parasuraman et al. (2000). This allows the response to be somewhere in between the black and white classes. In other words, in fuzzy SDT binary categorization is not forced, which allows the preservation of useful /information and a more sensitive analysis.

MECHANICS OF FUZZY SIGNAL DETECTION

The construction worker is inevitably faced with situations where he or she has to make a call and decide whether to go on working in the same manner as he/she has been before that instance. This decision point is preceded by a detection phase, wherein the worker either succeeds in identifying a hazard or not. 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 "no-signal" or "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 2003 and Abdelhamid et al. 2003).

This framework follows the conventional SDT model, wherein 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. The aforementioned two states of the world, namely, noise and signal, do not present themselves as crisp, defined sets from which the worker can easily pick one. Even if the worker is uncertain, there is always a binary response generated. 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.

Fuzzy SDT specifically recognizes that a worker's response is subject to an overlapping membership in the two sets of 'yes' and 'no'. 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 is made (i.e., when the worker says "yes this is an unsafe condition"), and a smaller degree to which the same response would be "no, signal is absent."

In the fuzzy SDT framework, the concepts of Hit, Miss, False Alarm and Correct Rejection are still valid. However, 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 conventional (or crisp) SDT. Consequently, it is possible that events would claim nonzero membership in more than one outcome category, as shown below in Table 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).

To illustrate the difference between conventional and fzzy SDT, Table 2 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. It should be noted that both the signal ('s') and the response ('r') only take binary values. This clearly ignores that in most scenarios there is a distinct overlap where the stimuli does not fall into one category, but rather has some degree of membership in the other.

Table 1. Possible outcomes of Fuzzy SDT

'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 2. Possible outcomes of crisp SDT

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

To apply FSDT to a construction jobsite setting, it is important to understand how the worker perceives the situation. This must then be transformed into quantifiable data. We know from SDT literature that when a worker is faced with a hazardous situation, the 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 a 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:

$$s\,(SW) = f\,(x) \tag{1}$$

In equation 1, the value of 's' is calculated as a function of the severity of unsafe state. Since the severity, or how critically unsafe a situation is does not depend upon any one single on-site variable, it is not possible to propose an overall function that includes all possible unsafe construction 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. A 'zero' would mean a condition with a very low likelihood of hazard release. It is worth noting here that labeling a condition with a zero-rating as a safe condition was avoided because it would be almost impossible to prove any condition absolutely harmless on a typical construction job-site. However, discussion with safety managers and workers indicated that it would be much easier to understand this condition with a zero rating if it is described as "absolutely safe". This does provide a worker with a range that has two clear extremes, and, hence, aids in generating a more realistic response to presented stimuli. 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 either responses, namely, 'yes – signal present' or 'no-signal not present'. The sole variable here is the level of conviction, and the equation is given as:

r (RV) = f (y) ...(2)

In equation 2, 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 the response to its r-membership is also 0.1.

The following example will illustrate how the values of "s" and "r" are determined. In this example, a worker is presented with the situation shown in Figure 3. The construction worker shown in Figure 3 is an ironworker engaged in typical work on a job-site. The condition is specifically explained above the image, indicating that the ironworker is connecting 4th floor primary beams, with an unprotected edge and no decking in place on the lower floors. The ironworker is also wearing fall protection (fall arrest) gear. The worker presented with this situation is asked the two questions shown in Figure 3, and is required to select one answer from the eleven possible values under each question.

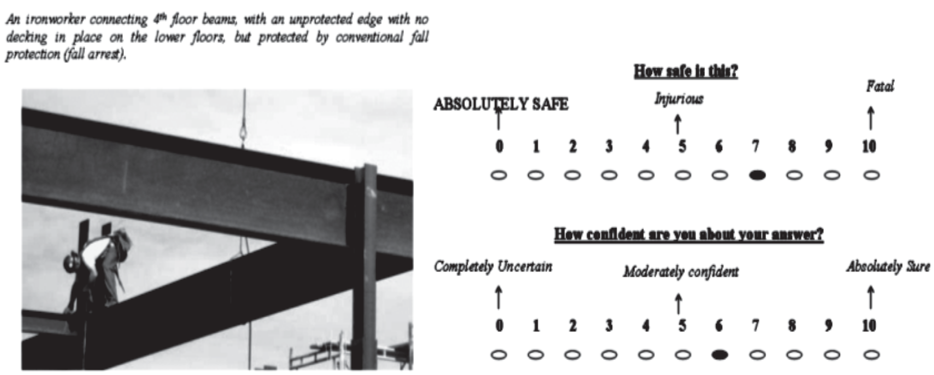

Figure 3. Example to illustrate proposed methodology: Ironworker making initial connections

The first question, namely, "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 for calculating the sensitivity or the discriminability with which he/she can identify a hazard.

The second question asks "How sure are you about your answer?". This question deals with the level of conviction the worker has in his/her answer. An integer value ranging from 0 to 10, where 10 reflects being absolutely sure and 0 being completely uncertain. The specific value selected will reflect the response criterion of the worker towards the situation, i.e., whether the worker is using a risky or conservative strategy in making the decision about the safety of the presented situation.

Assuming that a worker selects 7 for the first question and 6 for the second one. Using equations 1 and 2, 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 using: 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). The results are listed in Table 3.

Table 3 Example to illustrate proposed methodology

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

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 response criterion, d' and β, respectively. The parameter d' measures how well a person can discriminate between whether a signal is present or absent is represented by the difference between the means of the signal and noise distributions. The inclination of a person to say 'Signal Present' in response to a stimulus is captured by the parameter β. These two parameters, d' and β, are not connected to 's' or 'r, but are indirectly affected by their values.

Table 4 gives a sample list of a 12-question survey with one worker's responses, providing an 's-r' pair for each question. The calculations for arriving at the two parameters, d' and β, are also shown (the detailed equations are found in Narang (2005)).

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

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

STUDY DESIGN AND RESULTS

Assessing worker safety competencies using a survey design for fuzzy SDT is very different from that of crisp SDT. The difference lies in the structure of the questions. As explained earlier, the eleven options shown in Figure 5 provide a more continuous mapping. Worker sensitivity and response criterion 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 response criterion.

An 18-question survey was developed following that in Patel (2003). In addition, the original survey in Patel (2003) was enhanced with images such that the worker can visualize the condition described in the question. The survey was primarily intended as a pilot for implementing fuzzy SDT and, therefore, was neither comprehensive nor exhaustive. The survey can be found in Narang (2005).

To illustrate the use and analysis of the survey, 10 ironworkers (average age was 35 and average construction experience was 6 years) were selected at random to complete the survey. The results of the 10 workers using fuzzy SDT is shown in Table 5.

Table 5: Calculation for Sensitivity (d') and Response criterion (b) based on FSDT

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

Analysis of the survey data shown in Table 5, 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 10 subjects perceived the 18 conditions presented to them in the survey. Nonetheless the subjects were confident of their responses, which was confirmed by the higher mean for the responses to the second question – 'how sure are you about your answer?'.

The average d' (sensitivity) value for this group of ironworkers was found to be 1.6 (standard deviation = ±0.33), which based on SDT literature (Macmillan and Creelman 1991), shows an above average sensitivity to differentiate and detect an unsafe condition from a safe one. The average response criterion measure b for this group of 10 workers was 0.25 (standard deviation = ±0.15). This indicates that the group had a conservative strategy, which means they tended to have a high false alarm rate, i.e., consider some of the safe conditions as unsafe.

To facilitate the comparison of conventional and fuzzy SDT, the workers' responses were analyzed using conventional SDT. The results are shown in Table 6. Analysis of d' using conventional SDT resulted in a mean of 1.97 with standard deviation of ±1.10. This is higher than the sensitivity found using fuzzy SDT, and with a noticeably higher standard deviation as well. Similarly, the measure of response criterion using conventional SDT was 0.61 on average with a standard deviation of ±0.3.

The results listed in Tables 5 and 6 are graphically represented in Figure 4, which show a comparison of d' and the response criterion using FSDT with the same parameters when calculated with conventional SDT. The figures clearly show that the sensitivity and response criterion derived using conventional SDT shows a sharp increase in the spread for the 10 subjects compared to same parameters derived from fuzzy SDT.

The preceding analysis indicates that the data analysis using Fuzzy SDT differs significantly from that based on conventional SDT. The significance of the difference in values obtained for either parameters d' and response criterion lies in the final characterization of the worker's ability to identify hazards. For example, a worker may be regarded as having high sensitivity and conservative response criterion based on conventional SDT while fuzzy SDT could show him/her with a low sensitivity and risky response criterion. The wrong assessment may lead to an unnecessary course of action, such as more (less) training.

Table 6: Calculation for Sensitivity (d') and Response criterion (β) using conventional SDT

Worker #	Hit Rate HR	FA Rate FAR	z (HR)	z (FAR)	Sensitivity d'	Y (HR)	Y (FAR)	Bias 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

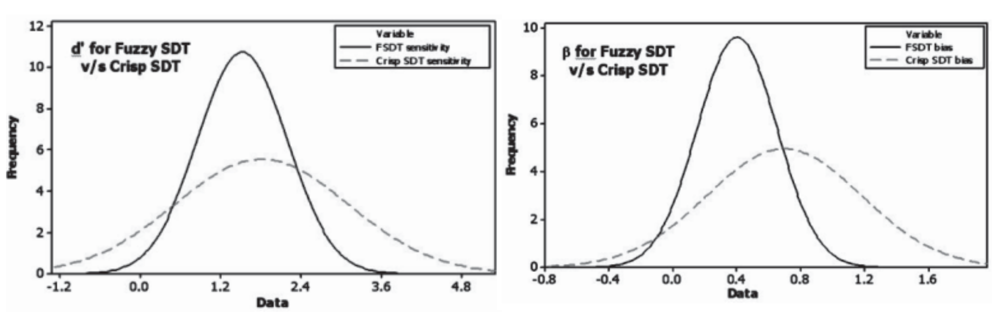

Figure 4. Sensitivity (d') distributions for Fuzzy SDT v/s Crisp SDT (left) ; Response criterion distributions for Fuzzy SDT v/s Crisp SDT (right)

While the sample size used is quite small, it is still possible to infer that, for the same subject, sensitivity and response criterion values are very different between the two methods. The FSDT model clearly captures the workers sensitivity and response criterion (in the form of s-r pairs). The s-r pair then leads to the HR and FAR which on further statistical treatment result in the d' and b 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.

CONCLUSION AND FUTURE RESEARCH

Safety training is only as good as the worker's ability to detect an unsafe condition when he/she is presented with one. Crisp SDT as implemented by Abdelhamid et al. (2003) and Patel (2003) provided a good tool for an assessment of this ability. However, the assumptions of the conventional SDT model may not be approairate for construction-specific situations. Preliminary results presented in this paper indicate that fuzzy SDT captures useful information that would have otherwise been lost with crisp SDT. It appears that fuzzy SDT provides a finer resolution of a worker's ability in identifying hazardous conditions on a construction jobsite. Overall the approach outlined in this research could be used in a variety of real world settings that involve assessment of hazardous construction conditions. Further research is needed to establish the reliability of the assessment framework presented. Additional research is also needed to develop surveys for other types of construction work and investigate the relation between age and work experience and hazard identification ability. Other researchers may choose to find other methods from other disciplines or industries. Regardless of the approach, efforts to develop new tools and ideas aimed at improving construction safety and health should be guided by the understanding that workers will inevitably choose to work or find themselves forced to work in hazard zones. Their ability to identify the zone they are working in will go a very long way in avoiding having them become another statistic.

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