# Uncertainty in Qualitative Risk Analysis and Rating Systems:

# Modeling Decision Making Determinants

by

Ogaga Jonathan Tebehaevu

July, 2015

Director of Thesis: Dr. Michael Behm

Major Department: Technology Systems

As workplace risk assessment is pivotal to ensure the safety and health of workers, adopting a reliable technique in performing this assessment cannot be overemphasized. The qualitative risk analysis is considered the most common technique of performing risk assessment, yet has received strong criticism as being influenced by subjectivity and lack of systematic process. The utility of risk matrices in scoring and obtaining risk rating has further complicated this technique and made it quite challenging for management to establish confidence in decision-making based on qualitative analysis. This study identified those subjective factors impairing the credibility of qualitative techniques and actually measured their impacts. By means of a simulated worksite scenario with identified hazards, Certified Safety Professionals, Engineers and Students were made to analyze, rate and make an overall decision on the scenario with a view to understanding the influence of those subjective predictors in the decision outcome. The goal was to determine what factors influence the decision making process and if Certified Safety professionals would be most influenced by these factors to produce a distinct outcome from the other groups. A comprehensive decision model was also used as a holistic approach to model the decision outcome of these predictors. The predictor factors were statistically significant though, but the results presented further systematic characteristics in the risk analysis and ratings among the three groups.

# **Uncertainty in Qualitative Risk Analysis and Rating Systems:**

# **Modeling Decision Making Determinants**

# A Thesis

Presented To the Faculty of the Department of Technology Systems

East Carolina University

In Partial Fulfillment of the Requirements for the Degree

Masters of Science in Occupational Safety

by

Ogaga Jonathan Tebehaevu

July, 2015

© Ogaga Jonathan Tebehaevu, 2015

Uncertainty in Qualitative Risk Analysis and Rating Systems:

# Modeling Decision Making Determinants

by

Ogaga Jonathan Tebehaevu

APPROVED BY:	
DIRECTOR OF THESIS:	
COMMITTEE MEMBER:	(Name, Degree Here)
COMMITTEE MEMBER:	(Name, Degree Here)
CHAIR OF THE DEPARTMENT OF	(Name, Degree Here)
DEAN OF THE GRADUATE SCHOOL	(Name, Degree Here) Paul J. Gemperline, PhD

# Dedication

This research work is dedicated to the Almighty God, Jehovah, and His Beloved Son Jesus Christ, for their grace, mercies and faithfulness upon me and my wife in successfully completing this program.

# Acknowledgements

Firstly, I give thanks to Jehovah and Jesus Christ for their protection upon me and my wife all through my studies and the help to successfully complete and defend this thesis. I would like to thank the department of Technology Systems for the opportunity given me to fulfill my dream in pursuing a graduate degree in Occupational Safety. Special thanks to my committee, Dr. Michael Behm, Dr. Hamid Fonooni, Dr. Kevin O' Brien for the invaluable support, encouragement, advice, and for painstakingly reviewing this thesis to ensure each and every piece stands out. To my beloved wife, Edirin, I want to sincerely express my indebtedness for the priceless support accorded me, even at your expense sometimes, in achieving my dream. I love you so much and thank you for being there! To the department Chair, Dr. Tijjani Mohammed and the staff of Technology Systems department, thank you for your support and encouragement in seeing to the completion of this thesis and indeed my study. To all MSOS/ASSE students, as well as others too numerous to mention, who in one way or the other contributed in making this work a success, I say a big thank you to you all!

Special thanks also goes to my parents and siblings for their understanding and not leaving me alone at any time. I deeply appreciate your prayers and consideration. Again, I am fully indebted to Dr. Hamid Fonooni, MSOS program coordinator, for your inestimable support provided me all through my being in the program. Also, for believing in me and directing me professionally to get the best out of my career. It is my prayers to Jehovah to bless and reward you all accordingly by His grace

TITLE PAGE	i
COPYRIGHT PAGE	ii
SIGNATURE PAGE	iii
DEDICATION	iv
ACKNOWLEDGEMENTS	v
TABLE OF CONTENTS	vi
LIST OF TABLES	viii
LIST OF FIGURES	ix
CHAPTER 1: BACKGROUND	1
CHAPTER 2: REVIEW OF THE LITERATURE	5
Risk Analysis	5
Qualitative Risk Analysis	7
Study Variation with Qualitative Analysis Technique	8
Basis of Inconsistency	
Risk Analysis Uncertainty	10
Risk Matrix and Scoring System	12
Procedures for Risk Quantification	14
The Comprehensive Decision-Making Model	15
Individual Level Indicator	17
Hazard Event	17
Risk Factors	17
Decision Outcome	
CHAPTER 3: RESEARCH DESIGN AND METHODOLOGY	19
Identifying the Research Questions and Hypotheses	19
Research Procedures	
Scenario Justification	21
Participant Selection	
Survey Administration	24
Statistical Methods	25
CHAPTER 4: RESULTS	26
Data Analysis	26

Probability of Hzard 1	26
Severity of Hazard 1	
Probability of Hazard 2	
Severity of Hazard 2	
Overall Risk Rating	
Research Hypotheses	
CHAPTER 5: DISCUSSION AND CONCLUSIONS	
REFERENCES	45
APPENDIX A	49
APPENDIX B	54
APPENDIX C	55
APPENDIX D	56

# List of Tables

1.	ANSI/ASSE Z590.3 Risk Matrix Scoring System	6
2.	ANSI Z10 Risk Matrix Scoring System	6
3.	Recommended Principles for Uncertainty and Variability Analysis by NRC	11
4.	ANSI B.11.0 Risk Scoring Matrix System	13
5.	Limitation of Risk Matrices	13
6.	Participant Demographics in Percentages	24
7.	Hazard Probability Description	26
8.	Hazard Severity Description	26
9.	Chi Square Cross tabulation of Overall Risk Level	33
10.	Chi Square Statistical Results of Significance	33
11.	Kendall's W T-Statistics	34
12.	Kendall's W T- Statistic for each Study Group	34
13.	Ordinal Logistic Regression Statistical Summary	36
14.	Ordinal Logistic Regression Results for Comprehensive Decision Model	37
15.	Ordinal Logistic Proportional Odds Results	37

# List of Figures

1.	Black Box View of Risk Scoring	14
2.	The Comprehensive Decision-Making Model	16
3.	Survey Case Study Scenario	21
4.	Bar graph of Probability Rating of Hazard 1	27
5.	Biplot analysis of Probability Rating of Hazard 1	27
6.	Bar graph of Severity Rating of Hazard 1	28
7.	Biplot analysis of Severity Rating of Hazard 1	28
8.	Bar graph of Probability Rating of Hazard 2	29
9.	Biplot analysis of Probability Rating of Hazard 2	29
10.	Bar graph of Severity Rating of Hazard 2	30
11.	Biplot analysis of Severity Rating of Hazard 2	30
12.	Bar graph of Overall Risk Rating of Scenario	31
13.	Biplot analysis of Overall Risk Rating of Scenario	31
14.	Bar graph of Cumulative Distribution of Professions and Ranking Patterns	38

## **CHAPTER 1: BACKGROUND**

Risk, uncertainty and decision making are evidently a combined problem of interest that has become recurrent in some contemporary fields of study. Peer reviewed articles and continuous research have been a major effort to resolving this complexities and clarify its distinctions. Still, no acceptable approach or standard best describes these terms or operationalizes its application in practice. What is more worrisome is the fact that it is a necessary part of every business, industry and enterprise and without clearly defining and harmonizing its discrepancy, a reliable and dependable risk management system will not be realized.

Historically, the roots of risk analysis have been traced to the era preceding the Greek and Roman times, a concept that history's greatest mathematicians and scientists had struggled to simplify. In the sixteenth century when the concept started developing, the interest was primarily the impact of chemical risks on human health; it then evolved through the Society of Risk Analysis (SRA) to areas of environmental health concerns. Since then, there has been numerous and expanding broad areas of interest relating to risk, such that has gradually found its way into virtually all organizations ( Covello & Mumpower, 1985; Bernstein, 1998; Thompson et al., 2005; Aven, 2012 ). Due to demanding attention caused by different concerns and challenges, risk analysis has become a critical issue that risk experts deal with. The aim of which is to address the existing challenges and develop reliable and scientifically-supported techniques tailored to specific organizations as a model for risk analysis. In occupational safety, which is the focus of this research, risk analysis has been an integral part of the profession for as long as it exists. Besides, this process has considerably developed recently that it has now taken occupational safety to a higher level of formalizing a more structured analytical method, aimed at making intelligent management decisions (Manuele, 2001).

Indisputably, no workplace is absolutely risk free. Lowrence (1976) had long ago established that nothing is risk free and nothing can be absolutely safe. Zwikael and Ahn (2011) confirmed that the global

business environment involves risk and complexity as it is a necessary condition for future growth and development. Managers will therefore have to deal with various types of risk such as technological, financial, insurance, chemical, software, regulatory, health, environment and safety etc. and would also be faced with the challenge of making good decisions in this process. One of the effects of inadequate risk analysis resulting in uncontrolled or poorly controlled risk is that it will impact on profitability and business continuity. With occupational risk however, this impact is paramount as it does not only affect business sustainability but workers' lives. Consequently, management is constrained with the responsibility of reducing operational risk to a level As Low as Reasonably Practicable (ALARP) for the health and safety of its workforce. To achieve this, a reliable risk analysis technique must be applied for the purpose of making the right decision due to constrain of limited resources. Indeed, Manuele (2010) confirmed that management would have to set priorities, based on risk analysis decision, on what risk worth reducing or not due to its limited resources.

Due to this consideration then, the need for a reliable and verifiable decision making process cannot be overemphasized; as this must ensure a satisfactory justification of all components used in assigning risk rating and levels in the risk assessment process. The need for this accuracy underpins the concept of this research –qualitative analysis– known as a widely used technique of risk assessment (Roughton and Crutchfield 2014). This technique, together with the quantitative and semi-quantitative has become the three known risk analysis techniques. But only the former is covered within the scope of this research.

Qualitative risk analysis has been described as inexpensive, flexible and easy to apply which is why it is preferred to other techniques (Bowers and Khorakian, 2014). Although widely used, it is also criticized for being unreliable since it is not data-driven but based mostly on subjective or judgmental influence. Edwards and Bowen (2005) identified bias, experience and preference as affecting its reliability. Similarly, sparse and imprecise information from the nature of risk, limited knowledge, variety of scenario description and the domino effect have also been identified (Emblemsvag and Kjølstad, 2006;

Pasman et al., 2009; Anuraj et al., 2013). These diverse views have set up an argument for risk experts resulting in a drive to justify all components used in assigning risk rating and qualitative analysis for effective decision making (Sims, 2012).

According to Stephans (2004), accuracy of decisions based on qualitative analysis is an important concern as the lack of it can frustrate the risk management practice. Hence, the occasional reliance on incorrect decision (due to uncertainty and subjectivity) could lead to insignificant risk source and unacceptable safety level. This is of much concern as it is now the most used technique in decision making process and in the control of identified undesired occupational safety events (Arunraj et al., 2013).

Although, the uncertainty of qualitative analysis and its rating system is further appraised at the literature review section, only a few researchers have discussed, using defined methodology, the factors that actually influence decision making process in risk assessment using the qualitative analysis technique. The aforementioned factors of experience, bias, preference, lack of knowledge, etc. were preconceived thoughts of authors, and not research-based. For example, in the study by Backlund and Hannu (2002), where three independent analyst teams conducted risk analysis and came up with broadly different results, the authors identified vague requirement specification, lack of systematic analysis process and incomplete documentation as affecting the consistency of the results. These factors were what the authors thought as being responsible for the variance, and not what was proven to cause the variance in the decisions made.

Wintle and Nicholson (2014) stressed that there has to be a deliberate approach to recognize the sources of error and conflicting judgment in the techniques of risk assessment which would transformed into a structured technique for adequate decision making. This is the focus of this research and a point of departure from previous research. This research proposes factors such as professional background, knowledge of hazards, experience, knowledge of risk assessment and risk perception, and uses a

Comprehensive Decision Making model (a proposed model discussed in chapter 2) to validate these factors as influencing the decision making outcome during qualitative risk analysis. This is achieved by a systematic application discussed under the method section in Chapter 3.

There are five chapters in this document. Following this Introduction, Chapter 2 reviews previous literature on the concept of risk, risk analysis, performance, challenges, quantification and modeling. Chapter 3 clarifies the methods of the study and discusses the applied model- Comprehensive Decision Making Model- and its relevance in decision making during risk assessment. Chapter 4 presents the results of data and analysis to address the research hypotheses. Chapter 5 presents a discussion of results and conclusions.

## **CHAPTER 2: REVIEW OF THE LITERATURE**

#### **Risk Analysis**

In spite of the maturity of risk management, a broad consensus has still not been established on its fundamental principles, including definitions of some basic concepts (Aven, 2012). The effort to define and adopt a generalized meaning for risk analysis has been an issue of controversy for over thirty years ago. A special committee set up by the Society of Risk Analysis (SRA) in 1980 found it impossible to reach a consensus on terms such as "risk analysis and risk assessment" (Thompson et al., 2005). For the purpose of this review, risk analysis "is the science of evaluating health, environmental, and engineering risks resulting from past, current, or anticipated future activities" (Lee et al., 2013 p 1). This definition was adopted as it covers a broad range of risk activities involved in occupational safety, and is by no means the standard definition.

As diverse as its definition, so are the variations in its analytical techniques. Some authors have listed different approaches for risk analysis. For example, it was described as involving eight sequential steps (Main, 2012); nine ordered steps (Manuele, 2001); and four summarized steps (Brauer, 2006) and so on. In any case, the evaluation of identified risk is one of the essential steps that must be performed, and two most common techniques involved are quantitative and qualitative analysis techniques. The remaining part of this literature will review the qualitative techniques being the center of this research and discuss its applicability in risk rating and decision making in the risk assessment practice.

Qualitative risk analysis is a risk assessment technique that uses word form or descriptive scale to describe the magnitude of potential consequences and likelihood that those consequences will occur (Main 2012). It is considered a common analytical technique that describes the likelihood of an event occurring in terms of probability and severity. Samples of risk matrix scoring are shown in Tables one and two below. Table 1 appears in the ANSI/ASSE Z590.3 *Prevention through Design* standard. The system is semi quantitative and achieves a risk level by multiplying the two risk factors values. Table 2 is

the ANSI Z10 Safety Management System standard, a system that correlates the resulting risk level to the permissibility of operations (Main, 2012).

Severity Levels and Values	Unlikely (1)	Seldom (2)	Occasional (3)	Likely (4)	Frequent (5)
Catastrophic (5)	5	10	15	20	25
Critical (4)	4	8	12	16	20
Marginal (3)	3	6	9	12	15
Negligible (2)	2	4	6	8	10
Insignificant (1)	1	2	3	4	5
Very high risk: 1	5 or greater	High risk:10-14	Moderate risk:	6-9 <b>Low</b>	risk: Under 1 to 5

 Table 1– ANSI/ASSE Z590.3 Risk Matrix Scoring System

Source: Main, B (2012) Risk Assessment challenges and Opportunities

Table 2– ANSI Z10 Risk Matrix Scoring System

	Severity of Injury or Illness Consequence and Remedial Action			
Likelihood of	Catastrophic	Critical	Marginal	Negligible
Occurrence or	Death or	Disability in	Minor injury, lost	First Aid or Minor
Exposure	permanent total	excess of 3 months	workday accident	Medical Treatment
For selected Unit of	disability			
Time or Activity				
Frequent	HIGH	HIGH	SERIOUS	MEDIUM
Likely to Occur	Operation not	Operation not	High Priority	Take Remedial
Repeatedly	permissible	permissible	Remedial action	action at
				appropriate time
Probable	HIGH	HIGH	SERIOUS	MEDIUM
Likely to occur several	Operation not	Operation not	High Priority	Take Remedial
times	permissible	permissible	Remedial action	action at
				appropriate time
Occasional	HIGH	SERIOUS	MEDIUM	LOW
Likely to occur	Operation not	High Priority	Take Remedial	Risk Acceptable
sometime	permissible	Remedial action	action at	Remedial Action
			appropriate time	Discretionary
Remote	SERIOUS	MEDIUM	MEDIUM	LOW
Not likely to occur	High Priority	Take Remedial	Take Remedial	Risk Acceptable
	Remedial action	action at	action at	Remedial Action
		appropriate time	appropriate time	Discretionary
Improbable	MEDIUM	LOW	LOW	LOW
Very unlikely-may	Take Remedial	Risk Acceptable	Risk Acceptable	Risk Acceptable
assume exposure will	action at	Remedial Action	Remedial Action	Remedial Action
not happen	appropriate time	Discretionary	Discretionary	Discretionary

Source: Main, B (2012) Risk Assessment challenges and Opportunities

Nilsen and Aven (2002) said that for an adequate risk analysis to be meaningful and dependable, the process is expected to take both certain and uncertain quantities into account and calculate to what extent specific events or scenarios can be expected to occur in the future. This "uncertain quantities" leading to predicting the "occurrence of events in the future" has become the source of leading debate on the accuracy and reliability of qualitative analysis.

Jean-Paul (2004) queried that it is difficult and almost impossible in reality to measure what is not known. This impossibilities or gap was described as disconnect that hinder the use of risk assessment as a decision making tool (Abt et al., 2010). Thus, the National Research Council (NRC) proposed the need to improve the risk assessment process to ensure that it makes use of best available science, is technically accurate and is most relevant for decision making (NRC, 2009). With regards to science, Cumming (1981), disagreed with the risk assessment process as being scientific. He argued that risk assessment is only a scientific activity in terms of its process, but that it is not like the intense traditional scientific method or discipline which is one that involves systematic study through observation, experiment and the testing of hypothesis. According to Aven (2012), with considerable research, risk assessment can be considered scientific to a varying degree though, not like the traditional science. This is because of its effect in describing uncertainty.

#### **Qualitative Risk Analysis**

Regardless of type and approach, the main objective of performing risk analysis is to support decision making processes. Despites its weakness, qualitative risk analysis is still a technique utilized in analyzing risk and decision making in safety health and environmental (SH&E) profession. In comparison with quantitative approach each has its own advantage and disadvantage and none is adjudged to be the best method in risk assessment. A major reason in applying this technique is that it provides a rough, imprecise, but useful knowledge available in practice than do overly numerical inputs required by the quantitative process (Cox et al., 2005).

In any case both techniques cannot be used in the assessment of the same situation as both are assumed to lead to different results and decisions (Backlund and Hannu, 2002). Nonetheless, the Ontario Ministry of Agriculture and Food (OMAF) has recommended that quantitative techniques should preferably be used when sufficient data are available, while qualitative should be used with insufficient data (McNab and Alvas, 2003). However, Cox et al. (2005) argued that since the value of information (VOI) that qualitative analysis and its ratings provide are not worthwhile for management decisions, a simple quantitative risk models should be used than adopting a qualitative approach. In exemplifying the ineffectiveness of qualitative analysis with respect to its rating system, the author noted that the system is best useful only with joint distribution of the elements being rated. He stated further that when the distribution does not align, qualitative analysis rating becomes a poor decision making method. He posited that:

"...if cases can be clearly separated into three clusters, with the risks in cluster A all being larger than those in cluster B, which are all larger than those in cluster C, then qualitative ratings of H, M and L can discriminate perfectly among these clusters. However, qualitative ratings may perform extremely poorly for problems that do not naturally cluster in a way that justifies qualitative ratings." (Cox et al., 2005 p 659).

#### **Study Variation with Qualitative Analysis Technique**

The concern about the accuracy of qualitative analysis as a decision making technique at work places has attracted serious attention in many research. Authors have questioned if credible decisions can really be made using this technique or if the source of discrepancy is dependent on the human factor imperfection and not the process. In one study for example, three physical hazardous scenarios were given to a group of 50 students majoring in occupational safety to risk-analyzed qualitatively using a 5x5 risk matrix tool, with no information on the scenarios. Obviously, different results were obtained! The broad difference in results was not only what drew the authors' attention; even when 21 subset of same group of students were given similar scenarios with much explained information of the process,

completely different results were again produced (Ball and Watt, 2013). Even in non-occupational hazard settings, this discrepancy has also been experienced. For example, in what was considered to be an objective carcinogenic risk assessment of Alachlor performed by three independent stakeholders using similar starting data and objective approach (qualitatively), completely different results were obtained (Hatfield and Hipel, 2002). Both comparative studies utilized different analysis techniques that produced different results. The implication of this is that analysis performed on the same case with different techniques is likely to produce different result. In contrast, the design of this research will utilize similar technique (qualitative analysis) performed by different groups on the same case to measure the outcome. In addition, it will statically test factors identified from these studies as sources of variation to establish its significance.

Even though qualitative analysis technique is described to produce inconsistent results, it could not have solely been responsible for the variability of these studies. This is evident from the study Backlund and Hannu (2002). In this study, three analyst teams performed risk analysis using quantitative, qualitative and simple qualitative techniques on a hydropower plant. At the end the results were completely different. The authors based on this study could not conclude if it were the different methods that produced the different outcome or if it was the approach used. They however claimed that to perform a satisfactory risk analysis, there has to be careful preparation, clear aims and goals couple with a systematic approach.

In tracing the sources of variance, lack of adequate knowledge and uncertainty were identified as major factors. In fact, Hatfield and Hipel (2002) concluded that lack of sufficient and detailed system identification, lack of understanding or information and high level of uncertainty were the most factors affecting the process. They added that regardless of how clear a risk assessment mandate and objective is, the process itself gives rise to new questions that lead to assumptions on the part of the analysts. Brunk et al. (1991) supported this that the discrepancy was not tied to bad science and incompetence, but on underlying deep-seated fundamental values of the stakeholders (the risk assessors).

#### **Basis of Inconsistency**

From the above, a summarized factors leading to vast inconsistency in qualitative risk analysis techniques are: uncertainty in the process, lack of sufficient knowledge or information leading to subjective judgment and the methods or tools of performing the qualitative analysis which in itself is subjective (Emblemsvag and Kjølstad, 2006; Pasman et al., 2009; Anuraj et al., 2013). These factors are reviewed accordingly.

#### **Risk Analysis Uncertainty**

Uncertainly is defined as something that is doubtful or unknown (Merriam-Webster, 2003). In discussing uncertainty, it is necessary to distinguish between aleatory (stochastic) and epistemic uncertainty. Epistemic uncertainty is what is encountered in occupational risk assessment as it is characterized by lack of knowledge about events or activity. Regardless of what technique deployed, uncertainty is one of the obstacles that affects reliable and consistent decision-making outcome. Uncertainty is attributed to poor knowledge on the high consequence risk problem for which the information available does not provide a strong basis for a specific probability assignment (Nelson and Aven, 2002). Jean-Paul (2004) claimed it was a difficult achievement that relies on human judgment rather than perfect information. He identified complexities of the uncertainty which in turn affects good decision-making.

Due to this much debate, it was recommended that a quantitative evaluation of uncertainties should be presented as an addendum to outcome of qualitative risk analysis. The National Research Council (NRC) in its recommendation to Environmental Protection Agency on the need for quantifying uncertainty supported this position. It recommended that EPA should characterize and communicate uncertainty and variability in all key computational steps of risk assessment. Its recommended principles are summarized in Table 3. Effective characterization of uncertainty and variability is very crucial to all

approaches of risk assessment. This is because inconsistent treatment of uncertainty can sometimes be

misleading and makes the overall communication outcome difficult (Abt et al., 2010).

# Table 3– Recommended Principles for Uncertainty and Variability Analysis by NRC

- <sup>1</sup> Risk assessments should provide a quantitative, or at least qualitative, description of uncertainty and variability consistent with the available data. The information required to conduct detailed uncertainty analyses may not be available in many situations.
- <sup>2</sup> In addition to characterizing the full population at risk, attention should be directed to vulnerable individuals and subpopulations that may be particularly susceptible or more highly exposed.
- <sup>3</sup> The depth, extent, and detail of the uncertainty and variability analyses should be commensurate with the importance and nature of the decision to be informed by the risk assessment and with what is valued in a decision. This may best be achieved by early engagement of assessors, managers, and stakeholders in the nature and objectives of the risk assessment and terms of reference (which must be clearly defined).
- <sup>4</sup> The risk assessment should compile or otherwise characterize the types, sources, extent, and magnitude of variability and substantial uncertainties associated with the assessment. To the extent feasible, there should be homologous treatment of uncertainties among the different components of a risk assessment and among different policy options being compared.
- <sup>5</sup> To maximize public understanding of and participation in risk-related decision making, a risk assessment should explain the basis and results of the uncertainty analysis with sufficient clarity to be understood by the public and decision makers. The uncertainty assessment should not be a significant source of delay in the release of an assessment.

6 Uncertainty and variability should be kept conceptually separate in the risk characterization. Source: Abt et al. (2010). Science and Decisions: Advancing Risk Assessment

As reducing uncertainty becomes more and more important, risk experts have adopted different measures to model uncertainty in performing risk assessment. So far there is no generally acceptable model that is best applied in defining uncertainty, but different representations have been proposed by authors, all supporting it as beneficial to the process. Chang et al. (1985) described it on the basis of probability density functions; Boncivini et al. (1998) and Davidson et al. (2006) used the fuzzy theory; Arunraj et al. (2013) used the 2D FMEA and so on. This diversity is based on three major components namely: (i) identifying the source and group of failure event sequence which could lead to the credible worst (case accidents); (ii) predicting and estimating consequences of the undesired situation, and (iii) modeling the risk incorporating both variability and uncertainty in probability of failure and its consequence.

Although one collective agreement lies in the fact that modeling uncertainty during risk assessment is a very important component for effective decision-making (Arunraj et al., 2013). Case studies have been reported by researchers on the application of proposed uncertainty models for risk assessment in practical workplace settings that produced positive results. A study once performed showed the application of a proposed uncertainty model to a benzene extraction unit (BEU) of a chemical plant which provided a better measure of uncertainty (Arunraj et al., 2013). Nonetheless, Apeland et al. (2001) argued that there is no obvious procedure for quantifying uncertainty in terms of probability, and described approaches such as heuristics and biases, application of historical data, dependency and updating of probabilities as "so-called" methods.

#### **Risk Matrix and Scoring System**

Another contributory source of uncertainty in qualitative analysis is the use of risk matrices and the matrix scoring systems. A risk matrix table is a common tool for estimation of risk or rating of hazards in risk management. It does specifically, based on the assessor's competency, assign risk levels to the hazard analyzed. A typical 4 x 4 risk matrix table is shown in Table 4. There are several variations of this tool and literature supports that no template is a one fits all as long as its use is consistent and relevant to the required purpose. Cox (2008) wrote extensively on the risk matrix and scoring system, and the techno-mathematical problems associated with its design and utility. This matrix table has been depicted as an ineffective tool and guide for predicting risk level.

Ball and Watt (2013) claimed that risk matrices are not that simple as they may appear to be, and that the perception of its simplicity should attract concern and deep reasoning. Cox (2008) described it as a rough approximate tool for risk analysis, useful particularly for distinguishing qualitatively between the most urgent and least urgent risks in many settings, and certainly much better than nothing. With respect to its scoring system, he further argued that it does not record the risk attitude of its users. That is to say people could order risk differently based on their perception.

Woodruff (2005) critiqued it from a different perspective claiming that it is best at only ranking risk in relative to each other e.g. medium or high risk. He stated further that it does not provide information or any indication whether the calculated risk is acceptable, tolerable or unacceptable, such that an assessor would not have to make any further decision based on common sense and judgment. Supporting this position Cox (2008) listed four major drawbacks, represented in Table 5, and how each impacts on the utility of the matrix. He claimed that the best results produced using the matrix can only be obtained when probability and severity are strongly positively correlated.

*Table 4*–ANSI B.11.0 Risk Scoring Matrix System (4 x 4 risk matrix)

Probability of Occurrence	Severity of Harm				
of Harm	Catastrophic	Serious	Moderate	Minor	
Very Likely	High	High	High	Medium	
Likely	High	High	Medium	Low	
Unlikely	Medium	Medium	Low	Negligible	
Remote	Low	Low	Negligible	Negligible	

Source: Main, B (2012) Risk Assessment challenges and Opportunities

Poor Resolution	Typical risk matrices can correctly and unambiguously compare only small fraction (e.g., less than 10%) of randomly selected pairs of	
	hazards. They can assign identical ratings to quantitatively very	
	different risks ("range compression").	
	Risk matrices can mistakenly assign higher qualitative ratings to	
Errors	quantitatively smaller risks. For risks with negatively correlated	
	frequencies and severities, they can be "worse than useless," leading to	
	worse-than-random decisions	
	Effective allocation of resources to risk-reducing countermeasures	
Suboptimal Resource Allocation	cannot be based on the categories provided by risk matrices	
	Inputs to risk matrices (e.g., frequency and severity categorizations) and	
Ambiguous Inputs and	resulting output (risk ratings) require subjective interpretation, and	
Outputs	different users may obtain opposite ratings of the same quantitative risks	

Table 5 – Limitation of risk matrices by Cox

Source: Cox, L. (2008) What's Wrong with Risk Matrices?

Due to this challenge of risk matrix scoring system, some experts have concluded that rather than dealing with the overwhelming difficulty of building a "perfect" risk matrix system, focus should be on methods that fit well into any design process (Main, 2012). Illustrating this concept, Main (2012) used the Black Box View shown in Figure 1 to explain that what matters in risk scoring system are the output and not the input source. What this means is that if a selected scoring system works well for a process it should be utilized instead of investigating the consistency, genuineness and reliability of its content. The black color of the box is an indication of being passive or blind to the input source, but to focus more on the output. Manuele (2001) agreed that since hazard analysis and risk assessment are altogether subjective, risk ranking system would also be subjective. This much debate has led to on-going effort to develop models aimed at enhancing the quality of the content of risk matrices.

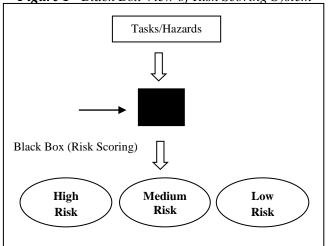


Figure 1-Black Box View of Risk Scoring System

Source: Main, B (2012) Risk Assessment challenges and Opportunities

### **Procedures for Risk Quantification**

These discrepancies described in the literature so far, has led to the development of models and measures for reducing uncertainty, subjectivity and improving the reliability of qualitative risk analysis. In practice, these approaches interrelate as the basic elements of risk quantification. Apeland et al. (2002) identified these elements as expert judgment, use of historical data and application of models. It claimed that since risk analysis deals with rare events, it makes the availability of relevant data scarce, thus

leading to the reliance on expert judgment for risk quantification. Even if it has been proved that expert judgment is a good source of information at the scarcity of available data, its credibility has also been questioned. Hanea et al. (2010) argued that the choice of selection of experts' team, the choice of expert judgment experiment and the chosen expert judgment method are all potential bias on the quantified data. Cognitive psychology experts have also acknowledged the imperfection of human and expert judgment especially with the estimation of probabilistic and uncertainty interpretation (Slovic, 2000; Pidgeon et al., 2003). Zwikael and Ahn (2011) stated however that popular expert judgment and other current listed tools may seem to present some drawbacks in the risk assessment practices.

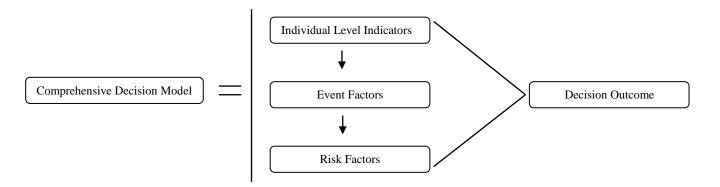
Despite these various risk quantification tools which have produced some level of credibility in qualitative analysis of risk, there are still numerous questions on the basis of these approaches and their applicability in risk, uncertainty and decision-making. Aven (2012) stated that many experts are not even convinced on the use of the existing quantification approaches for the treatment of uncertainty and decision making, and that others have expressed strong criticism against these approaches.

Resolving the issues of qualitative analysis in particular and risk assessment processes is not the focus of this study. It suffices however to state that more research in this topic is still being conducted as a conscious effort to improve the present satiation. This is because achieving improvement can only occur when there is harmony of well thought-out strategies for risk analysis (Roughton and Crutchfield, 2014).

#### The Comprehensive Decision-Making Model

As noted in the introductory chapter, the comprehensive decision-making model is a proposed model that will be utilized in this study to validate the influence of knowledge, experience, risk assessment knowledge, risk perception and other factors such as gender, education, hunch as decision making factors during risk assessment. The comprehensive decision model in Figure 2 is an analytical model that conceptualizes the framework behind decision making in individuals. Designed by Nicole

(2002), it was first used to model decision making outcome by individuals in the face of impending hurricane disaster.



*Figure 2*– *The Comprehensive Decision Making Model* 

The model identifies three predetermining factors as influencing the outcome of decisions that individuals make in the face of anticipated risks. These are: "Individual level indicators" "Hazard event" and "Risk factors or perception" and the uniqueness of the model is that it attempts to capture and integrate the broad range of all factors than focusing on one.

In the original research titled "decision making under extreme uncertainty: rethinking hazard relation perceptions and action" the author developed certain variables under each indicator to measure how they interact to determine decision outcome. Since the original research involves environmental risk variables such as socio-economic, race, level of income, evacuation plan, safety variables etc. constitute the independent variables. While the dependent or outcome variable was a Yes or No decision to escape prior to impending hurricane warning. However, these independent variables were modified for this research to suit its objective which is occupational risk. In addition, the independent variables were based on identified factors from literature that impact on decision making during workplace risk assessment. Nonetheless, it is based on the same underlying principles. "This specificity is necessary because each hazard has its own specific conditions as well as unique type of knowledge that is needed to make decisions in that setting" (Nicole, 2002 p 25). The subset of each element-individual level indicators,

hazard event and risk factors-becomes the independent variables that were analyzed to measure its influence in the dependent variable-decision made.

**Individual Level Indicator:** Independent variables of gender, education, years of experience considered through professional certifications altogether constitute the individual level indicator. These variables are supported by literature as influencing the judgment of risk assessor in performing qualitative analysis (Backlund and Hannu, 2002).

**Hazard Event:** These are the Events Factors in Figure 3. The variable refers to the specific knowledge of the hazard being assessed as well as knowledge of the analysis approach. The confidence by which a satisfactory risk rating and assessment is performed is dependent on the extent of knowledge of the hazard and analysis technique. Deck and Verdel (2012) confirmed that a risky situation is that where there is sufficient knowledge by the risk assessor to make a decision, whether the knowledge is probabilistic or not. Similarly, a reliable decision is a product of "understanding the analysis approach (qualitative or quantitative) through testing and use of prototype of experiment to achieve a high level of confidence (Johnson, 2008).

**Risk Factors**: The third variable of the decision model is risk factors or perception. This variable is considered broad and rather complicated to measure experimentally as various factors such as technical and social are known to influence it (Nicole, 2002). Slovic (1987) stated that individuals employ mental strategies in their attempt to understand an uncertain world. A study on risk perception once showed that in a similar risk event, the perception of one study group was amplified compared to the other (Kasperson et al., 1988). Factors such as way of life, world view, society, norms, values, institutions, social group influence etc. have been identified as affecting individual risk perception (Perko, 2012). Turner (1979) in variation stated that it is influenced by "individual bias or false assumption" "inability to understand information" and "feeling of invulnerability". Consequently, this variable was measured using the probability and severity ranking of the case scenario utilized for this study.

**Decision Outcome:** This variable, which is the dependent variable, is the eventual decision made by the integration of all other independent variables. This was measured using the overall ranking of the study scenario in terms of low, medium and high.

## **CHAPTER 3: RESEARCH DESIGN AND METHODOLOGY**

The purpose of this study is to present non experimental research and analysis on decision making in risk assessment using qualitative technique, and to measure factors that influence the process. As noted in the literature review, these factors are knowledge of hazard, knowledge of risk assessment, professional background and risk perception (Emblemsvag and Kjølstad, 2006; Pasman et al., 2009; Anuraj et al., 2013). There are different techniques for performing risk analysis. Of these, none has a reference to the context from which they have been developed (Pinto, 2002). In this study, a virtual scenario design simulating a practical setting will be used. Furthermore, the Comprehensive Decision-Making model will be tested statistically as a good fit or not in predicting consistency of outcome during qualitative analysis. The Pearson Chi-Square, Kendall W, and Ordinal Logistic Regression are a list of statistical analysis with which all variables (dependent and independent) will be analyzed.

# Identifying the Research Questions and Hypotheses

Unlike previous studies that suggest factors that were responsible for analysis variation by experts and non-experts, this study tested the validity of those factors. In doing this some research questions were developed as listed:

- i. Do individuals with similar professional background analyze risk same way?
- ii. Is consistency in risk analyses influenced by hazard knowledge, professional experience, knowledge of risk assessment, or by hunch?
- iii. Does the comprehensive decision-making model sufficiently incorporate decision making variables, such that can reliably predict decisions for qualitative analysis?

To answer these research questions, the following hypotheses were proposed:

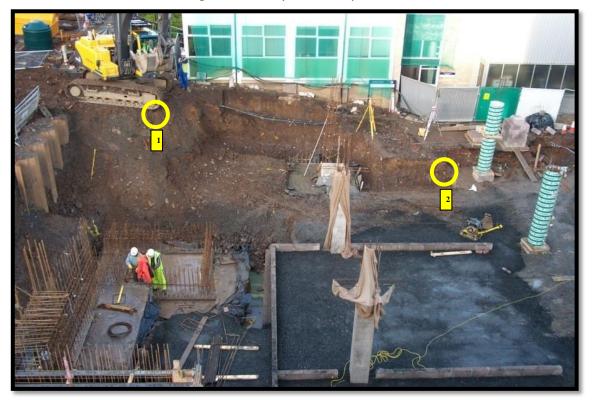
- i. There is a relationship among Certified Safety Professionals, engineers and students in determination of probability and severity of hazard and in assigning risk levels to occupational hazards.
- ii. Hazard knowledge, professional experience, and knowledge of risk assessment are agreed factors that drive decision making outcome in qualitative risk analysis than hunch.
- The comprehensive decision model is a good fit for predicting decision outcomes in qualitative risk analysis.

### **Research Procedures**

Considering the study objective and research hypotheses, a distinct research design was developed to measure risk analysis decision-making process and factors of influence. A graphic scenario, (Figure 3) of a typical construction work site environment with already identified hazards was given to participants to analyze and rate qualitatively. Leading questions with a 4-point Likert scale response was used to satisfy the rating process. The scenario contained a number of hazards but two major hazards were carefully selected with sufficient information provided to guide the judgment of study participants. The survey (Appendix A) was distributed to participants with responses adequately recorded. The questions were designed to reflect the research questions and also to satisfy the research hypotheses.

While this design does not expect all participants to analyze the risk the same way, it is to measure and compare the analysis results among groups of the same professional background to those of different background. Being able to successfully model this process will add to the body of knowledge that qualitative risk analysis is or is not a random process, such that is based on guess estimate, but on clearly defined methods. The results of this research will add evidence to support or counter the arguments that decisions made by assessors are mostly based on uncertainty, timing and lack of information (Thompson and Bloom, 2000; Hassenzal and Johnson, 2004).

Figure 3– Survey Case Study Scenario



## **Scenario Justification**

The construction industry has been reportedly recording a high number of fatalities among the "Fatal Four" leading causes of worker deaths. The Occupational Safety and Health Administration (OSHA) states that in the calendar year 2013, 796 or 20.3% of worker fatalities were from this industry (osha.gov). It was thus considered a better tool to adopt in measuring the perception of professionals and non-professionals that work in this environment to understand how their judgment is transferred into practice. The hazard labeled 1 shows an excavator machine that appears too close to the edge of the excavation at the work site which has the potential of falling off the edge to the excavation. The other hazard labeled 2 shows no obvious access to the excavation by workers or supervisor. The lack of designated entrance could lead to fall hazard even at a low height.

The scenario graphic was obtained from the Open Resources for Built Environment Education (orbee.org), an independent educational resources organization in the United Kingdom. This same scenario had been used as a training material on risk assessment for various study groups. The identified hazards and risk analysis have been validated by expert team in the United Kingdom. Originally, four hazards were identified, but for ease of participation, these were reduced to two. Besides, the two hazards removed were those with similar descriptions, this is to prevent duplicity and enhance variety. A confirmation of the scenario validation was provided by Dr. Smith Simon (Appendix B), and a revalidation was considered unnecessary as none can be considered a gold standard for qualitative analysis (Emblemsvag, 2010).

### **Participant Selection**

Three different groups were selected to participate in this study: Engineers, Certified Safety Professionals and undergraduate students. The rationale for participant selection was such that Certified Safety Professionals have as a primary responsibility: the identification, evaluation, and control of workplace risk (Manuele, 2010). These persons perform at least 50% of professional level safety duties which essentially includes worksite assessment to determine risks, evaluating risks and hazard control measures etc. To be eligible for this certification, individuals must have a minimum of a Bachelor's degree or an Associate in safety, health or environment and at least four years of safety experience (www.bcsp.org/csp). Individuals under this category were therefore expected to have met these minimum requirements that qualify them to participate for this purpose.

Engineers, regardless of specialty, are by training responsible for the manufacturing and design of machines, equipment, tools, vehicles, electro-mechanical processes and systems that worker are exposed to at work places. The selected engineers for this study were those licensed as professional engineers as defined by National Society of Professional Engineers (NSPE), while the few nonprofessional engineers, most of which were academia, have had their credentials verified by Accreditation Board for Engineering and Technology (ABET) or belong to recognized engineering professional bodies. The third group was undergraduate students that major in art history and appreciation, art education, studio art with different concentrations including painting, photography, textile design, illustration, ceramics etc. The group was exclusively freshmen to seniors recruited from the School of Art and Design in the College of Fine Arts and Communication at East Carolina University, North Carolina. This group was used as a control group as it represents a class with little or no experience of risk assessment, safety or qualitative risk analysis. The relevance of this group is to satisfy the study objective and research question in comparing results due to the effect of knowledge, experience, professional background, and training between professional and non-professionals.

A sample size of 131 was drawn from all three groups of participants with a percentage demographic summary shown in Table 6 below. The Certified Safety Professionals had 51 sample size with 39 male participants and 12 female. This group was recruited through LinkedIn by posting the survey link on the Board of Certified Safety Professional (BCSP) page with follow up reminder. Their education level shows that 35% of respondents had a bachelor's degree as the highest attained education, 63% a master degree and 2% a doctoral.

The Engineering group of 28 sample size had all 27 males and 1 female. There were 17 professional engineering designees, while the others were non-professional engineers. This group was recruited from diverse engineering groups such as academia, engineering associations, and working engineering practitioners. This was to get a diverse specialty of engineers than restricting it to a single specialty. The education level was 71% bachelor's degree, 26% master degree and 3% doctoral.

The 52 undergraduate students sample size had 22 males and 30 females. This group had no professional work experience, with a high school degree as being the highest level of education. This group was recruited exclusively from the College of Arts and Design at East Carolina University. The survey link was sent out by professors in the college to the pool of students- all undergraduate.

Demographics	Certified Safety Professionals	Engineers	Students
	(CSPs)		
Number of Participants	39%	21%	40%
Male	76%	96%	42%
Female	24%	4%	58%
Certified Safety Professionals	100%	0%	0%
Professional Engineers	0%	55%	0%
Doctorate Degree	2%	3%	0%
Bachelor's Degree	35%	71%	0%
Master's Degree	63%	26%	0%
High School Diploma	0	0	100%
Sample size (N) = 131;	CSPs: 51; En	gineers: 28; Si	tudents: 52

*Table 6*– *Summary of Participant Demographics in Percentages* 

#### **Survey Administration**

To protect the rights and welfare of human subjects engaged in the research, an Institutional Review Board (IRB) approval was obtained from the University and Medical Center Institutional Review Board at East Carolina University (Appendix C). Survey was voluntary and anonymous with participants giving the option to opt out if they choose to. Key terms and other vocabularies used in designing the survey questions and its content were clearly explained to ensure that participants, especially the student group, understood what was required even though they had no experience.

Data was collected within six weeks with 2% drop out rate recorded. Final survey outcome however showed that some participants other than the three required groups (safety professionals, engineers and students) also took the survey. These included lawyers, accountant, data analyst, banker and insurance specialist etc. However, these were excluded to avoid possible invalidation of results within the student group. Only full-time students were included in the final analysis.

## **Statistical Methods**

As listed in the beginning of this chapter, three different statistical methods will be used to analyze and discuss the hypotheses. These are Chi Square statistic, Kendall W test and the Ordinal Logistic Regression. Since most of the variables are categorical, the chi square statistic will be used to test if relationship exists or not for variables in the first research hypothesis. This chi-square is considered useful as it will help to simultaneously evaluate tests of independence between the variables of profession and overall risk rating.

Since the study requires participants to rank priorities of categorical variables of knowledge, experience, training and personal hunch as influencing their decision, the Kendall W test will be used. This test is considered useful as the result comes from different groups or judges. Its coefficient would help measure and describe reliability strength of each of these categorical variables as judged by the groups: that is how strongly the members of each group agree.

The ordinal logistic regression will be used to analyze the Comprehensive Decision Model. Norusis (2008) stated that the ordinal logistic regression is a suitable statistical method to determine factors that influence certain behavior, either in decision making, choice of selection or specific outcome. The more than two categorical response variables of *high*, *medium* and *low* as will be determined by various predictor variables also make this method most relevant. These ordered categorical variables (of *high*, *medium* and *low*) will be recoded and treated as numerical count of *1*, *2* and *3* respectively for ease of analysis. In all statistical analyses used, a p-value of 0.05 or less will be considered a statistical significance.

### **CHAPTER 4: RESULTS**

#### **Data Analysis**

The analysis presents data collected from a sample size of 131 respondents, representing 51 CSPs, 28 engineers and 52 students. There were 23 missing data and these were omitted from the analysis as not to alter the result. Discussing this section, an overview of participants responses are first analyzed before focusing on the research hypotheses. Reponses are discussed separately for each group of hazard presented in the scenario to compare relationship across groups and the ranking patterns.

### **Probability of Hazard 1**

Probability is the likelihood of occurrence of hazards indicated in the scenario. This is expressed in an ordered scale of *Very Likely, Likely, Unlikely and Remote*; while severity is the gravity of harm in the event of occurrence expressed in scale of *Catastrophic, Serious, Moderate* and *Minor*. The probability and severity descriptions were adopted from the United States Military risk matrix standard (MIL-STD-882D) as shown in Tables 7 & 8 below. This was provided for purpose of understanding and consistency.

Probability Description			
Very Likely	Likely to occur repeatedly		
Likely	Likely to occur several time		
Unlikely	Likely to occur sometime		
Remote	So unlikely, can assume occurrence will not be experienced		

#### Table 8– Hazard severity description.

Severity Description			
Catastrophic	Death or permanent total disability, system loss, major property damage		
Serious	Permanent, partial, or temporary disability in excess of 3 months, major system damage, significant property damage		
Moderate	Minor injury, lost work-day accident, minor system damage, minor property damage		
Minor	First aid or minor medical treatment, minor system impairment		

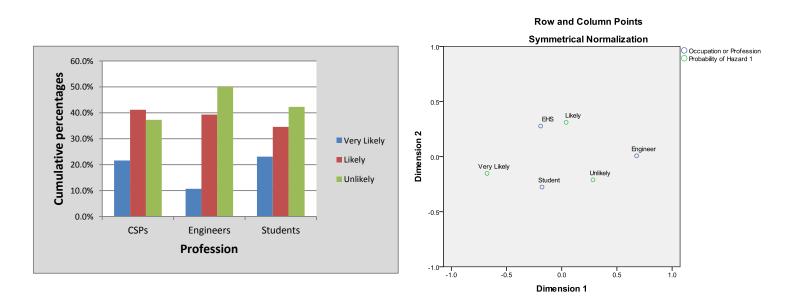
The bar graph in Figure 4 below shows a weighted percentage scale of all three groups: CSPs,

engineers and students, which explain a pattern of responses. For the CSP group, the highest rating was

likely which had 41.2%; the highest rating for engineers was unlikely with 50% while the students'

highest rating was *unlikely* with 39%. A breakdown of the observed and expected values of various risk probability ranking (*Very Likely, Likely, Unlikely and Remote*), group percentages and statistical summary is presented in Appendix D. In rating the probability of this first hazard, there was no association between the groups and rating systems. The value of p= 0.639 indicates that the variables are independent without a statistical relationship between the categorical variables. The implication of this rating was to see if the groups viewed the hazard probability differently. The collective result does not align. While the engineers and students aligned with the choice of *unlikely*, the CSPs seem closely aligned with the choice of *likely*, but this was not statistically significant.

To further analyze how each of the probability variables applies to the study groups, the biplot from a correspondence analysis was developed and shown in Figure 5. The approach shows the proximal relationships between the variables of probability of hazard 1 and profession. It allows one to spatially visualize the association between categories on dimensional axes (Agresti, 2002).

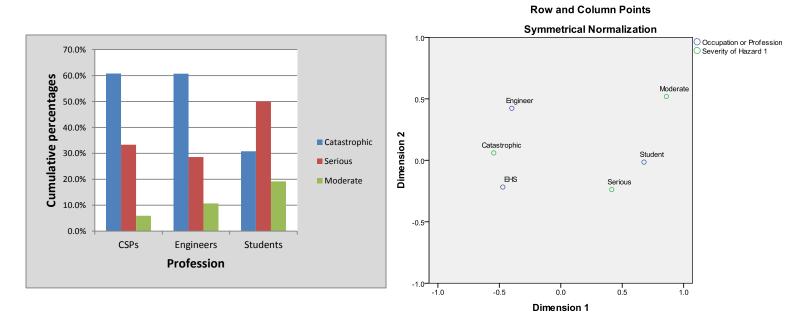


*Figure 4* – Bar graph showing pattern probability rating of hazard 1 by study groups. *Figure 5* – *Biplot from a correspondence analysis of hazard 1 probability among study groups.* 

### Severity of Hazard 1

On the severity rating of the first hazard scenario, the CSPs and engineers showed a major similarity that is different from the students. As shown in Figure 6, both CSPs and engineers predominantly rated the severity of the hazard as *catastrophic*. This *catastrophic* rating was 60.8% for the CSPs and 60.7% for engineers. However, the student group mostly rated the severity as *moderate* with 50% response. There was a statistically significant association between the groups and the rating of this hazard severity as indicated by the small value of p= 0.015. This statistical significance indicates that the variables of profession and hazard severity are dependent in the population. The table summary is also contained in Appendix D.

From the biplot correspondence analysis in Figure 7, the CSPs and engineers were closely associated with *catastrophic* severity. The students however were between *serious* and *moderate* levels of severity.

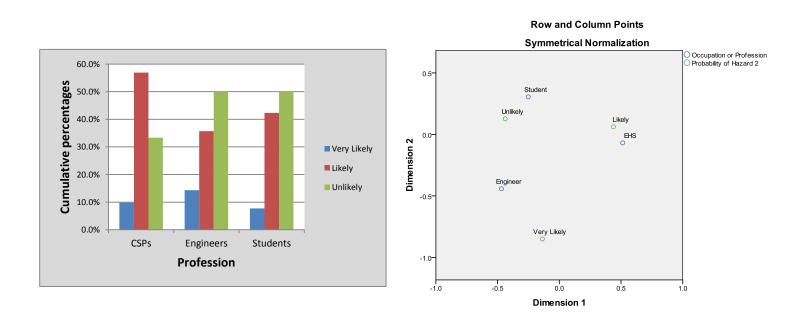


*Figure 6* – Bar graph showing pattern severity rating of hazard 1 by study groups. *Figure 7* – Biplot from a correspondence analysis of hazard 1 severity among study groups.

### **Probability of Hazard 2**

Figure 8 shows that the probability rating for this hazard was similar to that of hazard 1. The engineers and student groups mostly rated the probability as *unlikely*, with a 50% rating each. In contrast, 56.9% of the CSP group selected as *likely* the highest probability of hazard 2. As with the probability of the first hazard, there was no association between the groups and rating trend. The value of p= 0.302 indicates that the variables are independent without a statistical relationship. The chi-square cross tabulation table in appendix D shows the distributions of various probabilities across the groups. On this probability, it can be inferred that the groups were consistent in pattern across all three likelihood.

The biplot correspondence analysis in Figure 9 shows the CSP group was strongly aligned to the *likely* hazard probability, while the student group was *unlikely*. The engineers nonetheless seem split between *unlikely* and *very likely*.

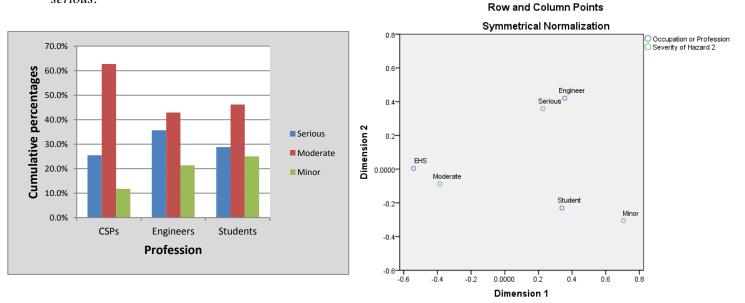


*Figure 8* – Bar graph showing pattern probability rating of hazard 2 by study groups. *Figure 9* – Biplot from a correspondence analysis of hazard 2 probability among study groups.

### Severity of Hazard 2

None of the groups saw this severity as *catastrophic* as choices were from *serious* to *minor*. Figure 10 shows that all three groups rated the hazard severity similarly with *moderate* being the highest and *minor* least. The CSP category had 62.7% of *moderate* as the highest rating, the engineers 42.9% of *moderate* as the highest rating and the students 46.2% of *moderate* still as its highest rating. The three groups aligned for this severity rating with *moderate* as the highest followed by *minor* and *serious*. Unlike the first hazard severity, there was no significant association between the groups and their rating of this hazard severity as indicated by the large value of p= 0.283.

Using the symmetric normality biplot from a correspondence analysis, there is a relationship between the categories of the variables. The CSPs overall tend to interpret the scenario as *moderate;* the engineers were quite close to *serious* than *moderate* while the students were aligned to *minor* than *serious*.

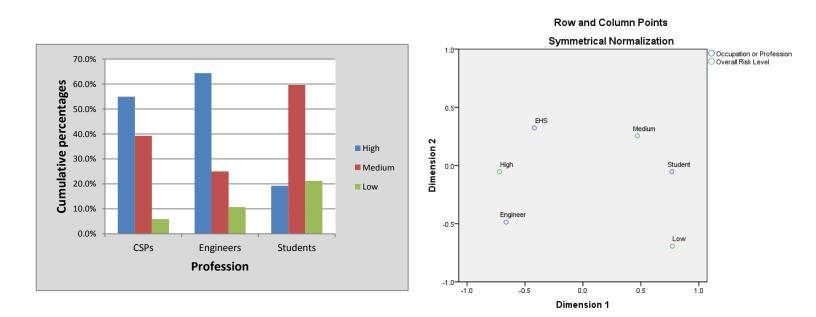


*Figure 10* – Bar graph showing pattern severity rating of hazard 2 by study groups. *Figure 11* – Biplot from a correspondence analysis of hazard 2 severity among study groups.

### **Overall Risk Rating**

This task for the participants was to assess the overall risk perception in order to understand the odds of evaluating practical decision in real work situation. As indicated in Figure 12, 64.3% of engineers thought the risk scenario was *high* with only 10.7% judging it as *low*. 54.9% of CSPs judged the overall risk as *high* as well, while 39.2% considered the risk to be *medium* with only 5.9% *low*. For the student group, 19.2% rated the overall risk as *high*, 59.6% as *medium*, and 21.2% *low*. There was an association between the groups and the overall risk rating as indicated by the small value of p< 0.001 in Table 10. This statistical significance shows that the variables of profession and overall risk rating are dependent in the population.

The overall risk ranking in Figure 13 using the symmetric normalization biplot shows clearly that the CSPs and engineers shared a much similar view on the overall risk scenario. The position of *high* risk is closed to both groups. The students however were between *low* and *medium*.



*Figure 12* – Bar graph showing pattern overall risk rating of scenario by study groups. *Figure 13* – Biplot from a correspondence analysis of overall risk rating of scenario among study groups.

#### **Research Hypotheses**

**Hypothesis 1** ( $\mathbf{H}_1$ ): There is a relationship among Certified Safety Professionals, engineers and students in determination of probability and severity of hazard and in assigning risk levels to occupational hazards.

The result provided by the overall scenario was used in testing this research hypothesis. The overall rating of *high*, *medium* and *low* was the dependent variable which represented the final decision made by the study groups on the scenario provided. As shown in Table 10, the chi square statistic of 21.7 and probability value of p< 0.001 was strong evidence against the null hypothesis that among the group of CSPs, engineers and students, the variables of analyzing occupational risk and eventual outcome are independent or not associated in the population from which the sample was drawn. At 5% significance level the null hypothesis was strongly rejected as there was strong evidence of a relationship in outcome of performance of risk analysis among professionals and non-professionals that conducted the analysis.

However, when the separate variables of probabilities and severities for both hazards were statistically tested as discussed earlier, not all results were significant. It was only the severity of hazard 1 that was statistically significant. The first and second hazard probabilities and the second hazard severity were not significant. As such, we failed to reject the null hypothesis in these cases as there was insufficient evidence against it. The non-significant statistical outcome variables support the study of probability prediction by Ball and Watt (2013). Predicting probabilities concurrently have been identified a major challenge in risk assessment. Murphy (2011) stated that even with the availability of a predictor model in quantifying probabilities, there is a concern that these models do not sometimes reflect an absolute degree of confidence. Assessing severity equally is influenced by a number of factors one of which is the depth of knowledge about the concept being studied which influences the position of the decision maker (Flage, et al., 2014).

32

		0	verall Risk L	evel	
			Т	1	Total
Profession	Summary	Low	Medium	High	
CSPs	Count	3	20	28	51
	Expected Count	6.5	22.2	22.2	51.0
	% within profession	5.9%	39.2%	54.9%	100.0%
ENGINEERS	Count	3	7	18	28
	Expected Count	3.8	13.1	11.1	28.0
	% within profession	10.7%	25.0%	64.3%	100.0%
STUDENTS	Count	11	31	10	52
	Expected Count	6.6	22.7	22.7	52.0
	% within profession	21.2%	59.6%	19.2%	100.0%
Total	Count	17	58	56	131
	Expected Count	17.0	58.0	56.0	131
	% within profession	13.0%	44.3%	42.7%	100.0%

Table 9-Chi Square Crosstabs Analysis Results of Study Groups Responses on Overall Risk Level

Table 10– Chi Square Statistical Results of Significance

	Value	df	Asymp.Sig (2-sided)
Pearson Chi-Square	21.704	4	.000
Likelihood Ratio	23.167	4	.000
Linear-by-Linear	14.219	1	.000
Association			
N of Valid Cases	131		

**Hypothesis 2** ( $H_1$ ): Hazard knowledge, professional experience, and knowledge of risk assessment are agreed factors that drive decision making outcome in qualitative risk analysis than hunch.

These variables were tested using the priority ranking of factors that most influence the choice of decision made by study groups. The categorical variables of hazard knowledge, training in risk assessment, experience and personal hunch were analyzed using the Kendall's W test.

The test statistics in Table 11 shows that the strength of relationship index as computed by the Kendall's coefficient of concordance for the dependent variables was 0.18 (less than 1). This implies that

there is a weaker relationship in how these factors were ranked collectively by all three groups. However, the result was statistically significant as the chi square test statistic value of 73.7 and a value of p < 0.001 was strong evidence against the null hypothesis that among the study groups there was no agreement. The null hypothesis was therefore rejected at 5% significance level that there was no agreement or relationship among the groups that hazard knowledge, experience, and training in risk assessment increase the strength of risk assessment.

In Table 12, a separate analysis was tested for each study group according to the priority selected. Of these, the CSPs showed a stronger level of agreement in the priority ranking as evident from the .377 Kendall's coefficient of concordance. In addition, there was an association in ranking priority among this group indicated by the small p-value. The engineers were also statistically significant, but the level of agreement of .270 was less in comparison to the CSP group. The 0.05 coefficient of students which is much more less than 1 shows that there was a rather random priority among this group. Besides, it was not also statistically significant as the p-value was greater than the significance level of 5%.

Test Statistics			
N	133		
Kendall's W	.185		
Chi Square	73.746		
d <sub>f</sub>	3		
Asymp. Sig.	.000		

Table 11–Kendall's WT-Statistics

Table 12– Kendall's WT-Statistic for each Study Group

<b>Statistical Parameters</b>	CSPs	Engineers	Students
Ν	51	30	52
Kendall's W	.377	.270	.050
Chi Square	57.612	24.280	7.846
df	3	3	3
Asymp. Sig.	.000	.000	.49

#### **Comprehensive Decision Model Analysis**

**Hypothesis 3** ( $\mathbf{H}_1$ ): the comprehensive decision model is a good fit for predicting decision outcomes in qualitative risk analysis.

As earlier explained in the methodology section, this hypothesis was to validate the fitness of the Comprehensive Decision model as a good predictor of risk analysis decision. To achieve a good fit, it ought to be the best explanatory model integrating components of the independent variables (factors) as impacting on the eventual decision made.

Table 13 shows a summary of statistical results of the ordinal logistic regression analysis of the dependent and independent variables. The measure of error in the model as explained by the model fitting information shows a statistical significance. With a -2 log likelihood of 262.4 and a significant chi square statistic, with p=0.001, of 33.8, the variables in the model significantly explain the overall risk ranking pattern. In addition, the Pseudo-R<sup>2</sup> as reflected from the Cox value of .225 is an indication that the model predicts 22.5% of the variation on the response variable.

In testing the goodness-of-fit measure, the null hypothesis, " $H_0$ : the model is exactly correct" was not rejected due to the probability value of p=0 .404 which probably suggests that the model somehow is a good fit in explaining how decisions were made across the three study groups. However, for an overall test of the null hypothesis that "the variable coefficient location in the model is zero", the chi square statistic was significant with p-value<0.001. Thus, the null hypothesis was rejected that the variable predictors are independent of the model. It was concluded statistically that the variables impact on the outcome of the model.

In Table 14, a separate analysis including all of the independent variables was performed to show the corresponding impact on the odds of the dependent variable (risk ranking decision).

For education predictor variable, the analysis suggests that it has an effect on the dependent variable of risk ranking by a ratio of 1.21. In other words, those that are educated are 1.21 times more

likely to rank occupational hazard as *high* than *medium* or *low*, compared to an uneducated population. This variable however was not statistically significant with a large probability value of p=0.726. Gender was also found not to have a statistically significant impact on the outcome. Although the analysis suggests that male gender are 0.64 times likely to rank occupational risk as *high* than *medium* or *low* as compared to female gender. In addition, knowledge, experience and risk assessment knowledge were not statistically associated with the outcome.

However, both CSPs and engineers were significantly different from students in their pattern of assessments. The result shows that CSPs have a 4.49 times likelihood of ranking occupational hazard as *high* than *medium* or *low* compared to how same would be ranked by student population without experience and knowledge of risk assessment. Similarly, engineers have 6.66 times likelihood of ranking occupational hazard as *high* than *medium* or *low* compared to how same would be ranked by student population without experience or knowledge of risk assessment. These two groups also were statistically significant with values of p<0.001 for both-CSPs and engineers.

<b>Model Fitting Inform</b>	nation			
Model	-2 Log Likelihood	Chi Square	df	Sig.
Intercept Only	262.481			
Final	228.579	33.884	13	.001
Goodness-of-Fit				
	Chi Square	df	Sig	
Pearson	107.684	111	.572	
Deviance	113.994	111	.404	
Pseudo R-Square				
Cox and Snell	.225			
Nagelkerke	.261			
-				
McFadden	.129			

 Table 13– Ordinal Logistic Regression Statistical Summary

	Parameter Estimates	Est. (B)	Std.	Wald	df	Sig.	Exp $(e^{B})$
			Error				
	Overall Ranking (Low)	-1.188	.304	15.271	1	.000	.305
Threshold	Overall Ranking (Medium)	1.295	.310	17.436	1	.000	3.651
	Education (High Sch.Deg.)	.190	.542	.123	1	.726	1.209
Location	Gender (Male)	453	.468	.938	1	.333	.636
	Profession (CSPs)	1.501	.404	13.811	1	.000	4.486
	Profession (Engineers)	1.896	.483	15.414	1	.000	6.659
	Knowledge	.965	1.059	.830	1	.362	2.625
	Experience	.899	1.065	.713	1	.398	2.457
	Risk Assessment Training	.442	1.080	1.68	1	.682	1.556

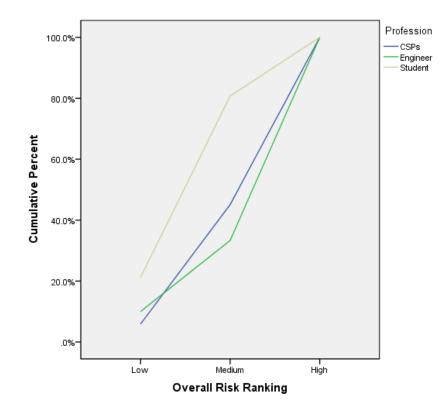
Table 14–Ordinal Logistic Regression Results for Comprehensive Decision Model

A test of proportional odds assumption was also carried out to test the null hypothesis that: "Ho: the slope coefficients are equal across the response variables". The implication of this test of assumption was to measure the level of coefficient consistency of the dependent or response variable from *low* to *medium*, *medium* to *high* and *high* to *low*. That is whether or not it is proportional by the same coefficient factor. From the value of p>0.05, the null hypothesis was not rejected. Thus, it was concluded that the proportional assumption holds. That is to say the odds of each of the explanatory variables of education, gender, experience, risk assessment knowledge and professions are fairly consistent across the different thresholds of the response variables of *low* to *medium*, *medium* to *high* and *high* to *low*.

Test of Parallel Lines					
Model	-2Log Likelihood	Chi Square	df	Sig.	
Null Hypothesis	155.268				
General	133.968	21.299	13	.067	

Table 15– Ordinal Logistic Proportional Odds Results

To further visualize the ordinal regression model as a result of the statistical significance of predictor variables of professions, in relation to the response variables, a cumulative distribution was produced as shown in Figure 14. Considering the *low* variable, a larger number of students selected this category. The students' cumulative percentage for the *low* scale was above 21% and increased within the *low-medium* range up to 80%. It thereafter drops through *medium-high* scale to the concurrent end point of 100% cumulative percentage. The cumulative distribution for the CSP group is higher at the *low* scale with 12% and progresses fairly consistently within the *low-medium* range up to 44%, with a consistent progression to the *high* scale. However, the engineers are *higher* in the lower scale up to 10%, with a small cumulative percentage increase from *low* to *medium* scale (from 10%-30%), followed by a steep and consistent progression between *medium* to *high* scale. The intercept at the *low* and *high* region between the CSPs and engineers shows a level of association at those points.



*Figure 13* – Bar graph showing cumulative distribution of professions and ranking patterns.

#### **CHAPTER 5: DISCUSSION AND CONCLUSIONS**

The perceived complexities of performing quantitative risk analysis have made qualitative risk analysis the most common technique in risk assessment. Risk evaluation, through assigning of probabilities and severities to obtain risk levels (high, medium, low or negligible), as much as it appears easy, is actually a quite challenging process. This is because most of the techniques, principles, and tools used during this activity are not based on historical data, proven techno-mathematical principles but contain arbitrary assumptions based on subjectivity. Various researchers have explained this weakness in techniques especially with qualitative and suggested factors that influence decision making. Some of these factors are experience, knowledge of the hazard, experience and training in risk assessment, nature or risk, bias, preference or personal hunch, lack of systematic analysis, domino effect etc. The quality and outcome of such decision is dependent on how much one or more of these factors influence the assessor's judgment. Consequently, many studies have focused on this concern, but a few have demonstrated the association of these factors as influencing decision outcome. Incorporating this curiosity into a structured research design in this study has produced certain characteristics of qualitative risk analysis from assessor's and procedural perspective.

This study reinforces the weakness of and uncertainty associated with risk matrices as a tool for qualitative risk scoring. Practically, in performing occupational risk analysis, risk matrices are often used as basis for establishing risk rating or level. As reviewed earlier, there are different samples of risk matrices with each describing probabilities and severities in some ways. The United States Military risk matrix standard (MIL-STD-882) used in this research generates some implications as far as risk rating is concerned. One of such implications is that the groups rated the scenarios based on their understanding and only used the matrix likelihood as a decision "solution". This inference is drawn from the fact the scenario hazards were explained, the probability and severity rating were defined, still there was a marked variation in outcome. This variation characterizes all three groups. It appears more that informed decisions were already thought-out with or without the risk matrix, and not the matrix itself that informed

the decision making process. It is best used then to express what was intended as can be seen from the patterns with which the students performed their ratings. In other words, the risk matrix was not sufficient reasonably or technically to best explain the opinion about the hazards severities and probabilities. Therefore its use in risk rating and making of conclusive decisions during occupational risk analysis requires further consideration.

Apart from decision making factors, focus was placed on how risk ratings were assigned by the groups. The inclusion of undergraduate students into the design brought a number of attentions. The overall ratings of probabilities and severities (for hazard 1 &2) shows that there is a relationship in how CSPs and engineers both rank severities compared to the student group. The results of severity of hazard 1 and 2 clearly shows this comparative relationship. This is not the case however with the overall probabilities ratings from both or all three groups. If the sample size is a reflection of the general population, arguably then, individuals are more challenged to estimate probabilities or uncertainties in the face of making a risky decision. This result shows that in order to improve the quality of occupational qualitative risk analysis, probability estimation solely based on experience, knowledge or professional background is likely to produce variance regardless of the expertise of the risk assessor. This emphasizes that it is by the use of mathematical analysis or simulation or empirical test sets or a combination of approaches that a consistent estimate of risk probabilities can be achieved (Cox, 2005).

Another characteristic displayed by the three groups in the analysis of probabilities, severities and overall rating is the standard deviation ratings for each of the groups. In ranking the probabilities and severities, there was variance across all groups for each of the probability and severity rank. It was only in severity two that CSPs and engineers have less variance. This shows that profession has an impact in the ranking pattern. This is supported from the results of the ordinal logistic regression which was found to be statistically significant. In terms of each group, the standard deviation was least with the CSPs followed by the engineers and quite large with the students. This was demonstrated by the response coherence (of up to 50%), with which this group rated the scenario and made similar inference. This result is also an

40

indication of the preference for qualitative technique by safety professionals (Bowers and Khorakian, 2014). This claim nonetheless cannot be made for the engineers and student groups in the overall scenario ratings. The engineers and students rated probabilities and severities randomly within each group with large variance across the various ranking: from *catastrophic* to *minor* for severity; and *very likely* to *remote* or probability.

However, it can be argued that the relative consistency of the CSPs does not altogether predict accuracy of the scenario in reality. That is, the ratings by engineers and students might just be the correct consequence if the scenario had actually happened in reality with measured probability and severity consequence. This argument is considered valid as a way to compare risk analysis decision and actual consequential occurrence. The scope of this study does not cover this though, but it is a topic for future research. Through this work a foundation has been established on the pattern and outcome of analysis for a given scenario. By utilizing a cause and effect scenario (that which results in a known consequence), and having this analyzed by different groups as with this study, decision precision can be well measured.

Decision predictors of hazard knowledge, experience and training in risk assessment which was tested using the Kendall W test were agreed upon as increasing the strength of risk analysis decision. This level of agreement was shown more by the CSPs and engineers compared to the students. The percentage spread for probability and severity of hazard one and two across the probability and severity ranking scale indicates a rather fairly organized judgment which was attributed to experience, knowledge or training of the CSP and engineering professionals. This was not the case with the students. This level of agreement though was much stronger for the CSPs than the engineer, interpreted as the reason behind the some level of consistency recorded for this group.

Evidently, individuals with sufficient knowledge, experience and training in risk assessment are likely to predict risk outcome quite different from those without these factors just like the students. This results as deduced from this study could explain the reliance on safety professionals as being qualified in performing workplace risk assessment. This rationality however also hinders the opportunity to look into other areas such as quantifying uncertainties and probabilities that are much more relevant to the reliability of the process. In other words, in performing workplace risk assessment a systematic method beyond inference from knowledge, training and experience should be of primary concern. From previous studies, analyses that were solely based on knowledge and experience of risk analyst or assessor rather than standard methods produced different results (Backlund and Hannu, 2002).

The influence of personal hunch in qualitative risk analysis has been stated by some authors as sometimes influencing the decision making process. In this study, this was statistically significant. 53.8%, 53.3% and 25.5% of students, engineers and CSPs ranked personal hunch as the second, third and fourth factor that influenced their decisions respectively. As discussed earlier, the engineers showed a proportional percentage for severity two and overall risk rating with CSPs. This outcome indicates the possibility of emerging with a similar decision outcome in risk analysis just by personal hunch. Although it is difficult to practically measure hunch as a person's hunch might still be based on past experience and knowledge. The Merriam Webster dictionary defines hunch "as a feeling or guess based on intuition rather than known facts" (Merriam-Webster, 2003). This factor is a limitation of this study as it is likely a confounding variable with knowledge and experience. Regardless of this however, 5.9% of CSPs and 6.7% engineers still ranked personal hunch as first of what influenced their overall decision making preference. This reinforces the position that even among professionals some decisions made are still based on hunch as against a standard method for performing risk analysis.

In getting a holistic approach of various factors that influence decision making process, the Comprehensive Decision-Making Model was incorporated as decision making predictor in modeling risk assessment decision. The importance of modeling risk analysis decision was to capture collective predictors that influence conclusions made by those performing risk assessments. The ordinal logistic regression statistical method captures and analyzed the risk predictors which include: individual indicators, event factors and risk factors. The model appears to be a good fit for predicting decision outcome based on the regression analysis, but most of the factors were not statistically significant.

42

Although these variables were not significant, the model gives the odd ratios for the different risk predictors and how each impacts in the overall priority of risk rating (*high, medium* or *low*). Through the model, it was gathered that gender factor does not influence decision making in risk analysis due to the negative regression coefficient. While the small sample size could be attributed to the output of the model, incorporating it into this study gives a bit of understanding of how different variables manipulates risk analysis decision in relation to the likelihood of such factors.

In conclusion, this study has looked into qualitative analysis techniques of risk assessment with focus on occupational safety. It provides further understanding that while this technique might be considered subjective and a weaker tool for analyzing risk, its application in workplace assessment should be viewed more seriously. The study discussed a number of factors that hamper the strength of qualitative techniques but focus on measuring the factors that influence its ratings systems. As an improvement of previous works, hazard scenarios were systematically analyzed by professionals mostly involve in workplace risk assessment to find out how they perform assessment and what factors drive their decision.

The study has contributed to the body of knowledge in that, despite the subjectivity of qualitatively risk analysis, there is strong tendency that safety professionals view risk relatively from the same perspective as distinct from non-safety professionals. It also further evidenced that probabilities likelihood of risk is of much concerned than severity in the analysis process. As such, it requires further research through mathematical assessment supported by historical data

to enhance precision in probability assignment. This is not to deemphasize the relevance of severity as well, which seem likely to be interpreted through experience and hazard knowledge.

From the findings of this research, it was understood that experience, knowledge and training in risk assessment influence decision making than personal hunch. Furthermore, risk-based decisions were premeditated and the use of risk matrix was almost insignificant to how risk is rated. This study would enable managers and safety professionals in making adequate decisions of what methods, factors, expertise and areas of concerns to consider in workplace analysis using qualitative technique. It would

also help in evaluating risk rating decision reached from a qualitative assessment in order to apply adequate control measures.

### REFERENCES

- Abt, E., Rodricks, J., Levy, J., Zeise, L., & Burke, T. (2010). Science and Decisions: Advancing Risk Assessment. *Risk Analysis*, 30 (7), 1028-1036.
- Agresti, A. (2002). Categorical Data Analysis, Second Edition. Hoboken New Jersey: John Wiley & Sons, Inc.
- Apeland, S., Aven, T., & Nilsen, T (2002). Quantifying uncertainty under a predictive, epistemic approach to risk analysis, *Reliability Engineering and System Safety* 75, 93-102.
- Arunraj, N., Mandal, S., & Maiti, J (2013). Modeling uncertainty in risk assessment: An integrated approach with fuzzy set theory and Monte Carlo simulation. Accident Analysis and Prevention, 55, 242-255.
- Aven, T. (2012). Foundation Issues in Risk Assessment and Risk Management. *Risk Analysis* 32 (10), 1647-1656.
- Aven, T., & Nilsen, T. (2003). Models and Model Uncertainty in the context of risk analysis. *Reliability* Engineering and System Safety, 79, 309-317
- Backlund, F., & Hannu. J, (2002). Can we make maintenance decisions on risk analysis results? *Journal* of Quality in Maintenance Engineering, 8 (1), 77 91.
- Ball, D., & Watt, J. (2013). Further thoughts on the Utility of Risk Matrices. *Risk Analysis* 33(11), 2068-2078.
- Bernstein, L. (1998). Against the Gods: The Remarkable Story of Risk. New York: Wiley.
- Boncivini, S., Leonelli, P., & Spadoni, G. (1998). Risk analysis of hazardous materials transportation: evaluating uncertainty by means of fuzzy logic. *Journal of Hazardous Materials* 62, 59–74.
- Bonnie, C., & Nicholson, A. (2014). Exploring Risk Judgment in a Trade Dispute Using Bayesian Networks. *Risk Analysis* 34 (6), 1095-1111.
- Bower, J., & Khorakian, A. (2014). Integrating risk management in the innovation project. *European Journal of Innovation Management*, 17 (1), 25-40.
- Brunk, G., Haworth, L., & Lee, B. (1991). Value assumptions in risk assessment: A case study of the Alachlor controversy, Waterloo, Ontario: Wilfrid Laurier University Press.
- Chang, S., Park, J., & Kim, M. (1985). The Monte-Carlo method without sorting for uncertainty propagation analysis in PRA. *Reliability Engineering* 10, 233–243.
- Covello, T., & Mumpower, J. (1985). Risk Analysis and Risk Management: An Historical Perspective. *Risk Analysis*, 5 (2), 103-119.

- Cox, L. (2008). What's Wrong with Risk Matrices?" *Risk Analysis: An International Journal*, 28(2), 497-512.
- Cox, L., Babayev, D., & Huber, W. (2005). Some Limitations of Qualitative Risk Rating Systems, *Risk Analysis* 25 (3), 651-662.
- Cumming, R. (1981). Is Risk Assessment a Science? Risk Analysis 1 (1), 1-3.
- Davidson, V., Ryks, J., & Fazil, A. (2006). Fuzzy risk assessment tool for microbial hazards in food systems. *Fuzzy Sets and Systems* 157 (9), 1201–1210.
- Deck, O., &Verdel, T (2012). Uncertainties and Risk Analysis Related to Geohazards: From Practical Applications to Research Trends, Risk Management for the Future Theory and Cases, Dr Jan Emblemsvåg (Ed.), ISBN: 978-953-51-0571-8.
- Edwards, P., & Bowen, P. (2005). Risk Management in Project Organization. University of New South Wales Press Ltd. Australia.
- Emblemsvåg, J. (2010). The augmented subjective risk management process", *Management Decision*, 48 (2), 248 259.
- Emblemsvag, J. & Kjølstad, L. (2002). Strategic Risk Analysis--A Field Version. *Management Decision*, 40(9), 842-853.
- Emblemsvåg, J., & Kjølstad, L. (2006). Qualitative risk analysis: some problems and remedies, *Management Decision*, 44 (3), 395 – 408.
- Flage, R., Aven, T., Zio, E., & Baraldi, P.(2014). Concerns, Challenges, and Directions of Development for the Issue of Representing Uncertainty in Risk Assessment. *Society for Risk Analysis* 34 (7), 1196-1207.
- Hanea, D., Jagtman, H., Van Alphen, L., & Ale, B. (2010). Quantitative and Qualitative analysis of the expert and non-expert opinion in fire risk in buildings. *Reliability Engineering and System Safety* 95 (7), 729-741.
- Hassenzahl, D., Andrews, J., & Johnson, B. (2004). Accommodating Uncertainty in Comparative Risk. *Risk Analysis: An International Journal*, 24 (5), 1323-1335.

Hatfield, Adam., & Hipel, K. (2002). Risk and System Theory. Risk Analysis, 22 (6), 1043-1057.

http://www.bcsp.org/CSP accessed 05/05/2015.

http://www.orbee.org/

https://www.osha.gov/oshstats/commonstats.html assessed 04/22/2015

Jean-Paul, C. (2004). Risk Analysis is theory and practice. Elsevier Science and Technology.

Johnson, G. (2008). Defining Risk Assessment Confidence Levels for Use in Project Management Communications. PhD Dissertation, University of Central Florida. Kasperson, R., Renn, O., Slovic, P., Brown, H., Emel, J., Goble, R., Kasperson, J., & Ratick S. (1988). The Social Amplification of Risk A Conceptual Framework, *Risk Analysis* 8 (2), 177-187

- Lee, M., Bickel, P., Diggle, P., Fiienberg, S., Gather, U., Olkin, I., & Zeger, S.(2013). Risk Assessment and Evaluation of Predictions. Lecture Notes in Statistics Proceedings. ISSN: 1869-7240.
- Lowrance, F. (1976). Of acceptable risk: Science and the determination of safety. Los Altos, CA: William Kaufman Inc.
- Main, B. (2012). Risk Assessment Challenges and Opportunities. Ann Arbor, MI: Design Safety Engineering Inc.
- Manuele, F. (2001). Innovation in Safety Management, Addressing Career Needs. A John Wiley & Sons Inc., Publication.
- Manuele, F. (2010). Risk Assessment Acceptable Risk: Time for SH&E professionals to adopt the concept. Published at ASSE Professional Safety bulletin available at <u>www.asse.org</u>.
- Merriam-Webster, (2003). *Merriam-Webster's Collegiate Dictionary* (10th ed.).Springfield, MA: Merriam-Webster.
- McNab, B. & Alves, D (2003). Risk Assessment Frameworks—Food Safety Risk Assessment.
- Murphy, C., Gardoni, P., & Harris, C. (2011). Classification and moral evaluation of uncertainties in engineering modeling. *Science and Engineering Ethics*, 17 (3), 553–570.
- National Research Council. Science and Decisions: Advancing Risk Assessment. Washington, DC: National Academies Press, 2009.
- Nicole, D. (2002) Decision-Making Under Extreme Uncertainty: Rethinking Hazard Related Perceptions and Action. PhD Dissertation in Sociology, Florida International University, Miami, Florida.
- Norusis, M. (2008). SPSS Statistics 17.0: Statistical Procedures Companion. Prentice Hall, a division of Pearson Education, 1 Lake Street, Upper Saddle River, NJ 07458
- Pasman, J., Jung, S., Prem, K., Rogers, W., & Tang, X. (2009). Is risk analysis a useful tool for improving process safety? *Journal of Loss Prevention in the Process Industries* 22, 769–777.
- Perko, T. (2002). Modeling Risk Perception and Risk Communication in Nuclear Management: An interdisciplinary Approach
- Pidgeon, N., Kasperson, R., & Slovic, P. (2003). The Social Amplification of Risk. Cambridge: Cambridge University Press.
- Pinto, A. (2002). Desenvolvimento de Base de Conhecimento para Análise de Riscosem Estaleiros de Construção de Edifícios (Development of the Knowledge Base for Risk Analysis in Building Construction Sites). M/Sc Dissertation, Universidade Técnica de Lisboa/Faculdade de Motricidade Humana.

- Roughton, J., & Crutchfield, N. (2014). Safety Culture, An Innovative Leadership Approach. Elsevier Inc. ISBN 978-0-12-396496-0.
- Sims, S. (2012). Qualitative Vs Quantitative Risk Assessment, available at online source accessed 03/05/2015 <u>http://www.sans.edu/research/leadership-laboratory/article/risk-assessment</u>
- Slovic, P. (1987) Perception of Risk. Science, 236 280-285.
- Slovic, P. (2000). The Perception of Risk. London: Earthscan Publications.
- Stephans, R. (2004). System Safety for the 21<sup>st</sup> Century: The Updated and Revised Edition of System Safety 2000, USA: Wiley Interscience.
- Thompson, K., Deisler, P., & Schwing, R. (2005). Interdisciplinary Vision: The First 25 Years of the Society for Risk Analysis (SRA), 1980-2005, *Risk Analysis* 25 (6), 1333–1386
- Turner, B. (1979). The Social Aetiology of Disasters." Disasters 3(1), 51-59.
- Wintle, B., & Nicholson, A. (2014). Exploring Risk Judgments in a Trade Dispute Using Bayesian Networks. *Risk Analysis*, 34 (6), 1095-1111
- Woodruff, J. (2005). Consequence and likelihood in risk estimation: A matter of balance in UK health and Safety Risk Assessment Practice, *Safety Science* 43, 345–353.
- Zwikael, O., & Ahn, M. (2011). The Effectiveness of Risk Management: An Analysis of Project Risk Planning Across Industries and Countries.

## APPENDIX A

Dear Survey Participant,

Thank you for taking the time to complete this feedback survey. I am Ogaga Tebehaevu, a master's student in Occupational Safety program at East Carolina University. My thesis research involves "measuring factors that influence decision-making" in risk assessment at work places, using qualitative analysis techniques. You have been selected as one of the relevant 200 participants whose contribution and response would greatly assist me to address my research hypothesis.

This survey is expected to take approximately 10 minutes and I would appreciate your participation and response within one week. Please note that your participation is completely voluntary as there are no foreseeable risks associated. If you have questions about this survey or its procedures, kindly contact Ogaga Tebehaevu at (252) 412-3492 or by email: tebehaevuo13@students.ecu.edu

Thank you in advance! Ogaga Tebehaevu East Carolina University

To protect the rights and welfare of human subjects engaged in research at East Carolina University, the University and Medical Center Institutional Review Board (IRB) has approved that this study meets acceptable research ethics. For questions and concerns about this research procedures, kindly direct all such to the East Carolina University Institution Review Board at 600 Moye Boulevard, Mail Stop 682, Greenville, NC 27834 or call (252) 744-2914.

What is your level of education?

- **O** High School Diploma (1)
- **O** Associate's Degree (2)
- O Bachelor's Degree (3)
- O Master's Degree (4)
- O Doctorate Degree (5)

What is your gender?

- **O** Male (1)
- O Female (2)

Which of the following best describes your profession?

- EH&S Professional (Safety Supervisor, Risk Manager, Safety related role) (1)
- O Engineer (2)
- O Student (3)
- O Other (4) \_\_\_\_\_

Please select your primary professional designation.

- **O** CSP (1)
- **O** CPE (2)
- **O** PE (3)
- **O** CIH (4)
- **O** ARM (5)
- **O** N/A (7)
- O Other (6) \_\_\_\_\_

**Instructions**: There is an illustrative scenario in this survey, which is a practical construction work-site situation. In this scenario, two hazards have been identified even though there may be more. These hazards are briefly described with six accompanying questions. Kindly respond to all questions using the scenario only. Please do not use any secondary means such as the Internet or textbooks as there is no right or wrong answer.

Below are some definitions of key terminologies as used in this survey. Besides, a descriptive Table of definitions is provided to guide you in responding to the questions.

Hazard- a source of potential damage, harm or adverse effect on someone or something

**Risk**- the chance or probability that a person will be harmed or experience an adverse health effect if exposed to a hazard.

Risk level means assigning a level (in terms of High, Medium, Low, Negligible) to risk.

Hazard 1- the excavator machine appears to be too close to the edge of the excavation (dig). There is potential hazard of the machine falling into the excavation.

Hazard 2- the excavation is not deep, yet there is no obvious access to it. Even at a low height, accessing it could result in a fall hazard.

## Case study Scenario



Question 1: How would you rank the PROBABILITY of occurrence for hazard 1 identified in the scenario above? Please use the Table of probability description below as a guide

Probability Description		
Very Likely	Likely to occur repeatedly	
Likely	Likely to occur several time	
Unlikely	Likely to occur sometime	
Remote	So unlikely, can assume occurrence will not be experienced	

Source: Incident Probability. Adapted from MIL-STD-882D and Sverrdrup Technology: Adopted from Manuele, F. (2001). Innovation in Safety Management, Addressing Career Needs. A John Wiley & Sons Inc., Publication pp104.

**O** Very Likely (1)

- O Likely (2)
- **O** Unlikely (3)
- O Remote (4)

Question 2: How would you rank the SEVERITY level for the occurrence of hazard 1 identified in the scenario above? Please use the severity description Table below as a guide.

Severity Description			
Catastrophic	Death or permanent total disability, system loss, major property damage		
Serious	Permanent, partial, or temporary disability in excess of 3 months, major system damage, significant property damage		
Moderate	Minor injury, lost work-day accident, minor system damage, minor property damage		
Minor	First aid or minor medical treatment, minor system impairment		

Source: Risk management Guide for the Aviation industry Severity Description from Aviation Ground Operation Safety Handbook: Innovation in Safety Management, Addressing Career Needs. A John Wiley & Sons Inc., Publication pp104.

- Catastrophic
- **O** Serious
- **O** Moderate
- O Minor

Question 3: How would you rank the PROBABILITY of occurrence for hazard 2 identified in the scenario above? Please use the Table of probability description Table.

- **O** Very Likely
- **O** Likely
- **O** Unlikely
- **O** Remote

Question 4: How would you rank the SEVERITY level for the occurrence of hazard 2 identified in the scenario above?

- **O** Catastrophic
- **O** Serious
- **O** Moderate
- O Minor

Question 5: How would you rank the overall risk level for the scenario?

- **O** Negligible
- O Low
- O Medium
- O High

Question 6: To complete this survey and help us understand your response to the scenario provided, please tell us which of these most influenced your decision-making? Kindly drag the options below in order of priority, with 1 being the most and 4 least.

- \_\_\_\_\_ Knowledge based on the scenario/settings and its hazards
- Knowledge and Experience based on my profession
- \_\_\_\_\_ Knowledge of Qualitative risk analysis approach
- Personal Hunch and Intelligent Judgment

## **APPENDIX B**

### Validation of Scenarios by Civil and Safety Engineering Professionals

From: Simon Smith <simon.smith@ed.ac.uk>
Sent: Tuesday, January 20, 2015 05:34 AM
To: Tebehaevu, Ogaga Jonathan
Subject: Re: Permission for the use of Resources

Dear Ogaga,

Thanks for your email. Yes, by all means please use these resources in any way you choose - that is what they are there for. The model answers are based on the experience from industry of both myself but also of a Safety Manager of a large UK construction company. I cannot say whether this constitutes a 'gold standard' and if act I would argue that there is never a single solution to any safety scenario.

Best wishes.

Simon

**Dr Simon Smith CEng FICE** 

Senior Lecturer in Construction & Project Management University of Edinburgh, School of Engineering, William Rankine Building, Edinburgh, EH9 3JL, UK

+44 131 650 7159

www.eng.ed.ac.uk

## **APPENDIX C**



EAST CAROLINA UNIVERSITY University& Medical Center Institutional Review Board Office 4N-70 Brody Medical Sciences Building· Mail Stop 682 600 Moye Boulevard · Greenville, NC 27834 Office 252-744-2914\_ · Fax 252-744-2284\_ · <u>www.ecu.edu/irb</u>

# Notification of Exempt Certification

From: Social/Behavioral IRB

- To: <u>Ogaga Tebehaevu</u>
- CC: <u>Michael Behm</u>
- Date: 2/23/2015
- Re: <u>UMCIRB 15-000216</u>

Uncertainty in Qualitative Risk Analysis and Rating Systems: Modeling Decision-Making Determinant

I am pleased to inform you that your research submission has been certified as exempt on 2/21/2015. This study is eligible for Exempt Certification under category #2.

It is your responsibility to ensure that this research is conducted in the manner reported in your application and/or protocol, as well as being consistent with the ethical principles of the Belmont Report and your profession.

This research study does not require any additional interaction with the UMCIRB unless there are proposed changes to this study. Any change, prior to implementing that change, must be submitted to the UMCIRB for review and approval. The UMCIRB will determine if the change impacts the eligibility of the research for exempt status. If more substantive review is required, you will be notified within five business days.

The UMCIRB office will hold your exemption application for a period of five years from the date of this letter. If you wish to continue this protocol beyond this period, you will need to su

The Chairperson (or designee) does not have a potential for conflict of interest on this study.bmit an Exemption Certification request at least 30 days before the end of the five year period.

IRB00000705 East Carolina U IRB #1 (Biomedical) IORG0000418 IRB00003781 East Carolina U IRB #2 (Behavioral/SS) IORG0000418

Study.PI Name: Study.Co-Investigators:

## **APPENDIX D**

			Probability of Hazard 1			
			Very Likely	Likely	Unlikely	Total
Occupation or Profession	CSPs	Count	11	21	19	51
		Expected Count	10.1	19.5	21.4	51.0
		% within Occupation or	21.6%	41.2%	37.3%	100.0%
		Profession				
	Engineer	Count	3	11	14	28
		Expected Count	5.6	10.7	11.8	28.0
		% within Occupation or	10.7%	39.3%	50.0%	100.0%
		Profession				
	Student	Count	12	18	22	52
		Expected Count	10.3	19.8	21.8	52.0
		% within Occupation or	23.1%	34.6%	42.3%	100.0%
		Profession				
Total		Count	26	50	55	131
		Expected Count	26.0	50.0	55.0	131.0
		% within Occupation or	19.8%	38.2%	42.0%	100.0%
		Profession				

Chi Square Cross-tabulation Results for Hazard 1 Probability

# Chi Square Tests of Significance

			Asymp. Sig. (2-
	Value	df	sided)
Pearson Chi-Square	2.530 <sup>a</sup>	4	.639
Likelihood Ratio	2.741	4	.602
Linear-by-Linear Association	.054	1	.817
N of Valid Cases	131		

			Severity of Hazard 1			
			Catastrophic	Serious	Moderate	Total
Occupation or Profession	CSPs	Count	31	17	3	51
		Expected Count	24.9	19.9	6.2	51.0
		% within Occupation or	60.8%	33.3%	5.9%	100.0%
		Profession				
	Engineer	Count	17	8	3	28
		Expected Count	13.7	10.9	3.4	28.0
		% within Occupation or	60.7%	28.6%	10.7%	100.0%
		Profession				
	Student	Count	16	26	10	52
		Expected Count	25.4	20.2	6.4	52.0
		% within Occupation or	30.8%	50.0%	19.2%	100.0%
		Profession				
Total		Count	64	51	16	131
		Expected Count	64.0	51.0	16.0	131.0
		% within Occupation or	48.9%	38.9%	12.2%	100.0%
		Profession				

Chi Square Cross-tabulation Results for Hazard 1 Severity

# Chi Square Tests of Significance

			Asymp. Sig. (2-
	Value	df	sided)
Pearson Chi-Square	12.414 <sup>a</sup>	4	.015
Likelihood Ratio	12.832	4	.012
Linear-by-Linear Association	10.117	1	.001
N of Valid Cases	131		

			Probability of Hazard 2			
			Very Likely	Likely	Unlikely	Total
Occupation or Profession	CSPs	Count	5	29	17	51
		Expected Count	5.1	23.7	22.2	51.0
		% within Occupation or	9.8%	56.9%	33.3%	100.0%
		Profession				
	Engineer	Count	4	10	14	28
		Expected Count	2.8	13.0	12.2	28.0
		% within Occupation or	14.3%	35.7%	50.0%	100.0%
		Profession				
	Student	Count	4	22	26	52
		Expected Count	5.2	24.2	22.6	52.0
		% within Occupation or	7.7%	42.3%	50.0%	100.0%
		Profession				
Total		Count	13	61	57	131
		Expected Count	13.0	61.0	57.0	131.0
		% within Occupation or	9.9%	46.6%	43.5%	100.0%
		Profession				

# Chi Square Cross-tabulation Results for Hazard 2 Probability

Chi Square Tests of Significance

			Asymp. Sig. (2-
	Value	df	sided)
Pearson Chi-Square	4.859 <sup>a</sup>	4	.302
Likelihood Ratio	4.879	4	.300
Linear-by-Linear Association	2.135	1	.144
N of Valid Cases	131		

			Severity of Hazard 2			
			Serious	Moderate	Minor	Total
Occupation or Profession	CSPs	Count	13	32	6	51
		Expected Count	14.8	26.5	9.7	51.0
		% within Occupation or	25.5%	62.7%	11.8%	100.0%
		Profession				
	Engineer	Count	10	12	6	28
		Expected Count	8.1	14.5	5.3	28.0
		% within Occupation or	35.7%	42.9%	21.4%	100.0%
		Profession				
	Student	Count	15	24	13	52
		Expected Count	15.1	27.0	9.9	52.0
		% within Occupation or	28.8%	46.2%	25.0%	100.0%
		Profession				
Total		Count	38	68	25	131
		Expected Count	38.0	68.0	25.0	131.0
		% within Occupation or	29.0%	51.9%	19.1%	100.0%
		Profession				

# Chi Square Cross-tabulation Results for Hazard 2 Severity

Chi Square Tests of Significance

	Value	df	Asymp. Sig. (2- sided)
Pearson Chi-Square	5.046 <sup>a</sup>	4	.283
Likelihood Ratio	5.134	4	.274
Linear-by-Linear Association	.532	1	.466
N of Valid Cases	131		