DEVELOPING FACTOR-BASED MODELS FOR MEASURING AND PREDICTING HAZARD RECOGNITION CAPABILITY OF CONSTRUCTIONWORKERS

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May, 2019

Declaration

I declare that the work in this thesis entitled 'DEVELOPING FACTOR-BASED MODELS FOR MEASURING AND PREDICTING HAZARD RECOGNITION CAPABILITY OF CONSTRUCTION WORKERS' has been performed by me in the Department of Building. The information derived from the literature has been duly acknowledged in the text and a list of reference provided. No part of this thesis was previously presented for another degree or diploma at this or any other institution.

Abubakar Mu'awiya	_____	_____
Name of Student	Signature	Date

Certification

This thesis entitled 'DEVELOPING FACTOR-BASED MODELS FOR MEASURING AND PREDICTING HAZARD RECOGNITION CAPABILITY OF CONSTRUCTION WORKERS' by Mu'awiya Abubakar meets the regulations governing the award of the degree of Doctor of Philosophy of the Ahmadu Bello University, and is approved for its' contribution to knowledge and literary presentation.

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Professor K. Bala Member Supervisory Committee	_____ Signature	_____ Date
Professor A. D. Ibrahim Member Supervisory Committee	_____ Signature	_____ Date
Dr. D. Dahiru Head of Department	_____ Signature	_____ Date
Professor S. Z. Abubakar Dean, School of Postgraduate Studies	_____ Signature	_____ Date

Dedication

This work is dedicated to all those who, despite hard work and commitment, were not able to achieve this much in life, and to those who help and stand for the course of truth no matter the difficulties.

Acknowledgement

Every successful endeavor have been blessed with numerous contributors, and this research is no exception. Therefore, it is charitable to acknowledge a few, while I continue to pray for all that in one way or the other supported me in this all important PhD journey. First and foremost, to Allah Ta'ala belongs all praises, thanks and adorations for His immeasurable blessings upon me, one of which is the timely and successful completion of this work. I pray that He grant me the wisdom and tenacity to live a life of utmost appreciation and service to
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Abstract

The construction industry has been characterised with alarming rate of accidents and fatalities. This problem has been largely attributed to the inability of construction workers to recognise and manage hazards in complex and dynamic construction environments. Several studies have been conducted on improving hazard recognition of construction workers. However, existing studies have not made efforts in determining the hazard recognition competence of construction workers based on the different attributes of hazard recognition related to the workers and their environment. In addition, the existing hazard recognition techniques do not take into account the factors that influence workers' hazard recognition capabilities based on the nature of jobs and trades they engage in, and on which the hazards are being managed. This study has developed factor-based models for measuring and evaluating hazard recognition capability of construction workers. The factors were identified from literature review and experts interview. Through the use ofa structured questionnaire,distributed purposively to construction professionals and workers in excavation, roof works and steel construction works, the extent of influence of the factors on hazard recognition capability of construction workers was determined. Five Hundred and Sixty-One questionnaires were analysed using descriptive and inferential statistical tools. Factor analysis and reliability analysis were used to establish a structure of the key determinants of hazard recognition capability of workers, forming a self-assessment tool. Logistic regression analysis was then used to determine the relationship among the categories of factors and develop a model for predicting hazard recognition capability of construction workers. A total of 53 factors were identified in four categories as personal, organisational, social and project factors. The four categories of factors and

their sub factors have been found to have significant influence on hazard recognition capability of construction worker. However, the organizational factors have the highest influence with a group mean value of 3.57, followed by project factors with a mean value of 3.56, then social factors, recording an overall mean of 3.50 and lastly, personal factors with an overall mean score of 3.49. Generally, there is no significant difference between the responses of the different groups of respondents on the extent of influence of the factors on hazard recognition of workers. For the determinants of hazard recognition among the groups of factors, factor analysis revealed a structure of four categories of determinants of hazard recognition capability of construction workers as organizational factors, inherent human factors, conditional human factors and project factors. Moreover, logistic regression analysis revealed that all the four of factors have direct positive relationship to hazard recognition of workers and have proved to be significant predictors of the recognition capability of construction workers. The results implied that any increase in the categories of determinants would yield an increase in workers' hazard recognition capability. Based on the coefficients of logistic regression (B), the organisational category has the highest level of predictive power for hazard recognition capability (B=4.024), followed by the inherent human factors category (B=3.088), then the conditional human factors (B=2.967) and lastly the project factors (B=2.195). The predictive model developed has been able to correctly classify up to 93.2% of the HRC cases with a significant chi-square value, (538.864, df=4, p<.000*).* The model validation revealed its ability to correctly predict up to 76% of the cases, which is good enough for prediction purposes.

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CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Construction has been severally referred to as the most dangerous industry globally due to its alarming rate of accidents and fatality, with specific reference to its small scale of accidents of high frequency and diverse hazards sources (Zhou, Goh, & Li, 2015). According to Sunindijo & Zou, (2012), the construction industry employs only about 7% of the global work force, but it accounts for 30–40% of fatalities. Lingard (2013) reported that more than 60,000 fatalities are reported from construction projects around the world. This equates to approximately one fatal construction accident in every 10 minutes. In the U.S., the construction sector employs 7% of the work force, but it was reported to be responsible for 20% of fatal work injuries; the highest in 2013. It was also found that the sector recorded 908 fatal injuries and more than 200,000 non-fatal injuries in 2014 (U S Bureau of Labour Statistics, 2013; Marks & Teizer, 2013). In the U.K, the construction sector employs 5% of the workforce, but accounts for 31% of fatal work injuries (HSE, 2014), while in Hong Kong, the construction industry was ranked as the most dangerous in 2012, accounting for 24% of the total fatalities in 2011 (Li, Chan, & Skitmore, 2013). These are examples of the developed countries, with more proactive safety measures and technological advancements.

The situation is uglier in developing countries, where there is poor enabling environment, inadequate resources and low usage of technology to address construction safety issues. In India, the construction sector has been is the second most hazardous industry, recording the

average fatal accident frequency rate (FAFR; incidents/1,000 employees/year) of between 0.22 to 15.8 between 2008 to 2012 (Patel & Jha, 2014). Kheni, Dainty, & Gibb (2008); Kheni, Gibb, & Dainty (2006) reported that Ghana's construction industry employs 1.4% of the country's workforce but contributed up to 14% of occupational fatalities in the year 2000. In Nigeria, there is dearth of reliable statistics on the occupational accidents and injury of the construction sector (Okeola, 2009). Notwithstanding, hundreds of construction workers are being killed while several others are rendered permanently disabled on construction sites each year (Smallwood & Haupt, 2005; Kheni et al., 2008; Okeola, 2009). These alarming and disproportionate statistics indicate the dangers associated with working in the construction sector.

To address this problem, a plethora of research efforts in different perspectives have been made to improve safety performance of the construction industry. These efforts range from the safety management point of view, (with focus on accident cause analyses, safety climate, safety culture, workers' safety perception and competency, behaviour-based safety, hazard management, etc) to the technological applications (such as the application of Building Information Modelling (BIM), Data Mining, Geographic Information System (GIS), Radio Frequency Identification (RFID), robotics, sensing technology, wireless networks and virtual reality among others). These strides have been reported to bring about significant improvements in the safety performance of the construction industry in recent times (Chan et al., 2008; Hallowell, 2012; Huang & Hinze, 2006; Mitropoulos, Howell, & Abdelhamid, 2005; Shishlov, Schoenfisch, Myers, & Lipscomb, 2011). However, despite the reported improvement in the accident profile of the construction industry, unacceptable

injury and fatality rates in construction continue to be a source of great concern globally (Goh & Binte Sa'adon, 2015; Namian, Zuluaga, & Albert, 2016). This is more so, considering the amount of emotional and physical distress and the annual cost of the injuries, which was reported to exceed 48 billion dollars in the United States (Jeelani et al., 2017; Namian, Albert, & Feng, 2018b). It also adversely affects profit margins and overall success of construction projects. The efforts have therefore proved to be inadequate for addressing the safety incidence of the industry and reversing the ugly trend of construction accidents towards the globally acclaimed vision of zero accidents/injuries espoused by several construction stakeholders. This inadequacy has been attributed to poor hazard recognition of workers.

Hazard recognition has been identified as a fundamental requirement for addressing the health and safety challenges encountered on construction sites (Namian, Albert, Zuluaga, & Behm, 2016; Namian, Albert, Zuluaga, & Jaselskis, 2016). It is the ability of managers and workers to sense, analyse, and extract physical or mental stimuli that indicates the existence of a hazardous situation in a complex and dynamic scenario of construction environments (Albert, Hallowell, Kleiner, Chen, & Golparvar-Fard, 2014; Namian, Zuluaga, et al., 2016). Every safety management initiative rely on managing the identified hazards, which occur in multitude of ways (Namian,et al., 2016), because of the specific nature of the construction that often presents highly complex and dynamic scenarios of workers, equipment and materials interacting in close proximity to potentially hazardous conditions (Teizer & Cheng, 2015). These hazardous situations often when not recognized and managed lead to unsavory safety incidences and fatalities in construction. Furthermore,

considering the nature of construction workforce, the high proportion of which are unskilled and unlettered, coupled with the high labour turnover in the sector, hazard recognition must be given proper attention if the safety profile of the industry is to be improved.

Unfortunately, poor hazard recognition of workers have consistently been reported to lead to several accidents in the construction industry. (Carter & Smith, 2006; Perlman, Sacks, & Barak, 2014; Haslam et al., 2005; Bahn, 2013; Albert, Hallowell, & Kleiner, 2014). It therefore, becomes imperative to address the problem of hazard recognition performance of construction workers in order to improve safety management practices of the industry.

1.2 Statement of the Research Problem

The construction industry suffers from poor safety records that include a high accident rate and a large number of fatalities (Mohamed, 1999). To address this problem, workers' hazard recognition capabilities have become the core issue in safety management. This is because risks cannot be assessed, and control measures cannot be developed and implemented, if those involved (workers) are not aware of the hazards in the first place (Carter & Smith, 2006).

Despite the importance of hazard recognition to safety management, many studies have reported the poor ability of construction workers to identify hazards in dynamic and unpredictable environments as a result of the diversity and fragmentation of the industry

(Carter & Smith, 2006; Perlman, Sacks, & Barak, 2014). Haslam et al., (2005) observed that

42% of accidents involve inadequate hazard identification and appraisal skills of workers. This notion was corroborated by Bahn, (2013) who reported that novice workers failed to recognise an average of 57% of hazards in occupational environments in Australia. More recently, in a study of several projects across the United States of America, Albert, Hallowell, Kleiner, et al., (2014), discovered that more than 40% of hazards were not recognized at the time of pre-job safety meetings. As a result of these shortcomings, workers that are unable to recognise the active, emerging or latent hazards, in the work environment may not behave safely, and may, then, be exposed to uncontrolled safety risks, leading to catastrophic accidents and injuries. This, therefore, shows the need to improve hazard recognition performance of workers on construction sites, which would give rise to improvement in safety management practices in the industry.

Generally, safety managers conduct hazard identification inspections on a construction site using a process often called job hazard analysis (Albert, Hallowell, & Kleiner, 2013; Patel & Jha, 2017). Albeit these efforts, many studies (Albert, Hallowell,and Kleiner, 2014; Carter & Smith, 2006; Mitropoulos et al., 2005) have indicated that a number of hazards remain unidentified or not well assessed in a construction project. Consequently, a large portion of construction accidents occur as a result of the inability of construction workers to predict, identify, and respond to hazardous situations in dynamic construction environments.

Regrettably, there has not been any effort made towards determining the hazard recognition competence of construction workers based on the different attributes of hazard recognition related to the workers and their environment, and the existing hazard recognition techniques do not take into account the factors that influence workers' hazard recognition capabilities based on the nature of jobs and trades they engage in, and on which the hazards are being managed. This is important because different construction trades, present different safety risks, and thus different hazards (Patel & Jha, 2017). Such techniques only consider the hazards that have been incorporated in the risk assessment process (Albert & Hallowell, 2012). This may lead to underestimation of potential hazards, which can cause poor control measures, and workers developing false sense of safety in the face of great danger. Therefore, no effective hazard management strategy can be developed without improving the hazard recognition performance of workers.

1.3 Aim and Objectives

1.3.1 Aim of the study

The aim of this research is to develop model for measuring and predicting hazard recognition capability of construction workers with view to improving safety performance.

1.3.2 Objectives

1. To identify the factors affecting hazard recognition capability of construction workers
2. To assess the extent to which the factors influence hazard recognition capability of construction workers
3. To establish the determinants of hazard recognition capability of workers

4. To determine the relationships among the determinants of hazard recognition capability

5. To develop factor-based models for predicting hazard recognition capability of workers based on their trades

1.4 Justification

Recognition of hazards by construction workers leads to better safety performance of projects. The evaluation of the hazard recognition capability of workers in advance will identify the areas of weaknesses which will be useful in the adoption of improvement measures prior to the occurrence of any accident. This will also lead to an effective management of safety issues and a continuous improvement of safety management practices at construction sites. Similarly, identifying hazard recognition capabilities of construction workers will enable construction managers and safety supervisors to channel safety training initiatives to specific areas of weaknesses in order to improve recognition capacities of workforce.

Most importantly, safety hazards in construction vary with different construction trades that workers engage in, therefore, linking hazard recognition to the nature of construction jobs performed by workers will provide an opportunity for the construction industry to be more effective in hazard identification and safety management in general. Hazard recognition improvement initiatives will be directed to areas of needs, in order to reduce accidents and fatality rates in construction.

1.5 Scope

This research has focused on factors influencing the ability of construction workers to recognise hazards in selected construction trades comprising excavation, roof and other works at height, and steel construction; that have already been identified among the most hazardous in construction. This formed the basis for developing the hazard recognition evaluation tool and the subsequent models.

Data for the research were collected on reasonably complex construction projects, involving a minimum of three storey buildings where all the construction trades interact in the same environment. Moreover, the models developed in this research are meant for evaluation of hazard recognition capability of construction workers in the specific trades considered for the data collection. These models yield the result of hazard recognition capability of the workers as a score approximated to either 'yes' or 'no'. No specific grades are given. The result is therefore serving as an important guide to users in taking job assignment decisions to workers on the basis of their hazard recognition capability.

1.6 Limitations

The fact that the research variables were tested by the use of questionnaire, the validity of the data collected might have been influenced by the possible difficulty in the respondents' understanding of those questions, especially in the case of the workers/tradesmen whose level of knowledge might impede clear understanding in some cases. The researcher had to interpret the questions to most of them, however, the accuracy is only limited to their level of understanding of the interpretations. Similarly, their willingness to respond to those questions honestly might also affect the quality of the conclusions reached.

CHAPTER TWO

LITERATURE REVIEW

2.1 Preamble

The most important construct in this study is hazard recognition. This chapter uses a general overview of related literature on construction safety to articulate the concept and its associated constructs. It began by drawing on the literature pertaining to the general safety management in construction and narrow down to the key issues of hazard recognition of construction workers and related variables. Empirical studies on hazard recognition performance of construction workers were then reviewed, with emphasis on factors affecting hazard recognition capability of workers and interplay between them before the research gap was clearly established. This was followed by a summary of previous conceptual and empirical studies related to hazard recognition in construction; before the chapter was concluded with a conceptual framework for the study forming the basis for the research as a prelude to the research methodology used in the study. The literature-based conceptualisation of the construct as presented in this chapter lays the basis for operationalising the major variables of the research in the questionnaires and interviews used.

2.2 Conceptualising Safety Hazard Recognition and Risk Perception

The term ‘hazard’ in the context of safety is defined as anything that presents a potential to cause harm or accident Howarth and Watson (2009). A safety hazard in a work place is a pre-existing condition with negative safety potential such as any sharp object, falling object, and so on. Construction sites are known to be associated with numerous hazardous

situations that must be managed in order to have safe outcomes. Therefore, Hinze (1993) and Howarth and Watson (2009) emphasise the importance of clearly understanding the concept of hazard as something different from, though closely associated with risk. Risk refers to the chance or likelihood of being harmed by a hazard or hazardous situation Howarth and Watson (2009). It is associated with a probability or frequency of occurrence of a hazard and the magnitude of the consequence of occurrence. To keep any construction work environment safe, it is essential to identify and manage inherent hazards and risks in the environment.

Hazards are usually removed systematically by designers at the conception and design development stage of a construction project Howarth and Watson (2009). They make efforts to ensure that the design and specification does not pose any danger to the health and safety of workers and professionals on the construction site. However, not all the hazards can be eliminated at this stage. There can still be residual hazards which may have to be identified using other standard techniques prior to, or during the course of construction. These hazards may be associated with different aspects of the project such as the project characteristics, environmental features, design and construction methods, and the workers that perform the operations on site Howarth and Watson (2009).

The systematic and identification and management of construction hazards is at the heart of any safety management initiative Howarth and Watson (2009). The unsafe behavior of construction workers has been attributed to poor understanding of hazards and associated with the tasks they perform and poor perception of the risks inherent in the work hazards

Tixier et al. (2014). This has made it imperative for any construction environment to put measures in place to ensure that people working in the environment recognise the inherent work hazards. Hazard recognition, has been defined as the ability of construction workers or managers to sense, analyse, and extract physical or mental stimuli that indicates the existence of a hazardous situation in a complex and dynamic scenario of construction environments (Namian et al. 2016). Risk perception on the other hand has been defined as the accurate prediction or estimation of the likelihood and nature of negative outcomes associated with a hazard or hazardous environment (Namian et al. 2016b).

To buttress the significance of hazard recognition and risk perception to any safety management initiative, Namian, Albert, Zuluaga, & Behm, (2016) developed a conceptual safety management model to illustrate the centrality of hazard recognition or identification to any safety management process as shown in figure 1. The model shows that hazard recognition is the first step in managing safety, followed by the assessment of safety risks, and the adoption of effective controls to prevent the occurrence of accidents. In the absence of these, no safety management initiative will be successful in preventing injuries and fatalities on sites. Therefore, construction stakeholders use different methods and techniques to identify hazards on construction sites and improve safety awareness of workers and managers.

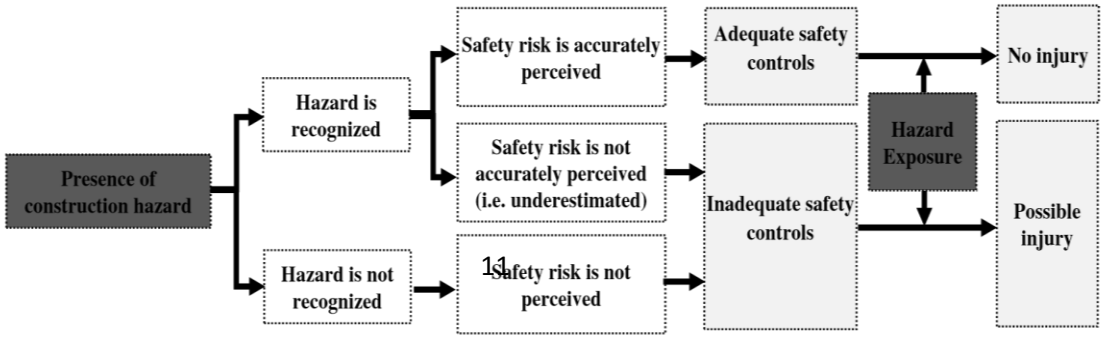

Figure I: Conceptual Safety Management Process
(Source: Namian et al, 2016)

2.2.1 Hazard recognition methods

A number of hazard recognition techniques used in the construction and other industries have been documented in the literature. According to Albert & Hallowell, (2012), some of these techniques are predictive in nature, while others are retrospective. The predictive methods try to visualise the scenario of a future construction activity and extrapolate the potential hazards that may be encountered, then put in place measures of addressing them. Examples of these methods include job hazard analysis (JHA), which studies subtasks in identifying hazards (Albert & Hallowell, 2012; Kim et al., 2015), task demand assessments, which focus on the likelihood of errors by workers based on the difficulty of tasks (Mitropoulos & Guillama, 2010). Others, are what-if analyses, job safety assessments, and energy based methods among others (Albert & Hallowell, 2012).

On the other hand, retrospective methods of hazard recognition are based on the knowledge and experience of workers gathered from past projects. Based on these, the managers device measures of dealing with the types of hazards experienced in previous projects with the hope that such can be avoided in a current job. Example of these include checklists, which make use of certain templates prepared to assist workers in identifying hazards; others include safety alert systems, audits, methods statement, etc (Albert & Hallowell, 2012, 2014) have described the different techniques applied in various industries to directly or indirectly enhance hazard recognition, which may be applied to the construction industry as follows:

2.2.1.1 Predictive Hazard recognition methods

1. Job safety analysis (JSA) or job hazard analysis (JHA) is a formal hazard identification technique where planned activities are identified, divided into subactivities or work packages, and then risks identified on the basis of a number of accident scenarios. Thereafter, safety strategies are laid out in order to control dangerous outcomes and to prevent accidents. According to (Zhang, et al., 2015), job hazard analysis (JHA) technique centers on the job tasks in relation to the worker, the tools, and the work environment to identify potential hazards prior to their occurrence, and then suggest preventive measures. The process for conducting the analysis includes:
    a. establishing all the stages of a given activity;
    b. identifying potential hazards associated with the different job stages; and
    c. Suggesting preventive actions or precautions to eliminate, reduce, or control the hazards.

Albert & Hallowell, (2012) observed that despite the wide use of JSAs in construction for hazard identification, they are not often used to their maximum potentials. However, the application of the procedure varies significantly one organisation to another.

2. **Task demand assessment:** This method, is built on the belief that workers prospect of making mistakes depends on the difficulty of the tasks they perform

and on their capacity in terms of training, fatigue etc that impact their capability to deal with with the task demands. Like in JHAs, the each operation is broken down into individual tasks needed to complete it, and the task factors that increase the task demand are identified (Albert & Hallowell, 2012). It was observed that task demand assessment technique has a high potential to evaluate work activities and identify potential errors that may result due to the increase in task difficulty.

3. **The energy method:** This is a unique hazard recognition technique which proposed that safety incidents occur due to ten energy sources in the work environment. That means, energy is directed in an undesired path, resulting in unwanted outcomes. The various energy categories, as reported by (Albert & Hallowell, 2012), include:

i. gravity (e.g. falling objects),
ii. motion (e.g. vehicle),
iii. mechanical (e.g. conveyors),
iv. electrical (e.g. power lines),
v. pressure (e.g. compressed cylinders),
vi. temperature (e.g. steam),
vii. chemical (e.g. toxic compounds),
viii. biological (e.g. pathogens),
ix. radiation (e.g. welding arcs) and
x. sound.

Workers are given trainings to use the energy sources in recognising hazards in their jobsites. For instance, slips consists of three energy categories - gravity (pull towards earth), motion (walking motion) and pressure (impact on the floor). Once the hazards are identified, measures are put in place to either eliminate or control the energy in some cases by providing a protective barrier against it.

4. **What-if analyses:** This is another structured method of hazard identification which is relatively simple. It brings together a group of experienced persons to use a logical, but loosely structured form of brainstorming. The objective is to identify hazards, hazardous conditions or events that may likely cause an unwanted outcome. They make the assessment is based on the possible combinations of events that have occurred in the past.

5. **Simulation:** This technique involves exposing workers to virtual models of real site conditions that allow them to experience different forms of hazards and hazardous situations that novice employees may not have encountered before. These virtual environments have the advantages of revealing to the workers all areas of danger expected in the work process at no risk and with minimal cost, unlike other active learning techniques (Albert & Hallowell, 2012). It also provides feedback to the workers on their level of performance and areas of improvement in hazard recognition. Though this technique is not widely used in construction, it has the potentials for improving hazard recognition capability of employees, considering the high complexity of construction operations.

6. **Action plan critique:** This method of hazard identification is a feedback mechanism involving a critique of the traditional techniques. It is meant to critically review any of the methods by a group of experts to identify highly hazardous work practices and develop a continuous improvement cycles.

7. **Employee-led reviews:** This methodentails involving workers in safety reviews as an informal means of hazard identification in order to enhance their hazard recognition improve the level of employee engagement in safety management (Albert & Hallowell, 2012). Workers on the field may have their personal experiences dealing with a number of hazards at work. Involving them can help to identify and resolve many different safety issues based on their knowledge and previous experience, which the employer may lack. This strategy may be complemented by perception surveys that quantify the workforce's acceptable risk levels and other areas of interest.

2.2.1.2 Retrospective Hazard Recognition Methods

1. Recordkeeping and accident analyses: this is a hazard recognition method in which safety incidents including near misses are documented and a root causes analysed in order to ascertain the source of failure. The database established from this process is used to guide management and employees of the latent hazards that are not effectively recognised on sites. Based on that, corrective measures are

taken to prevent accident occurrences for a particular work scenario building from past records. It is an effective technique for learning from past experience.

2. Checklists: Checklist analysis uses a collection of items that verify the safety status on a project site with respect to standard practices. In conducting the analysis, the person makes use of a list of statements to identify familiar hazard types, faults, deficiencies, and other accident prone scenarios. Checklists are often prepared by the company management using domain experts. This technique helps novice workers to recognise hazardous situations and follow safety procedures. Checklists are criticised for lack of robustness and are rarely comprehensive in terms of their coverage of hazards (Albert & Hallowell, 2012).

3. Methods statement analysis: This is a hazard identification technique in which information is provided on the means and methods of constructing or operating a facility. The information presents the sequence of activities, nature of resources to be used, hazard evaluations, and environmental conditions of the site. These information are reviewed by the management and experts making comparisons with construction industry publications and information held by the management with a view to ensuring that hazards are well identified and evaluated before the onset of the project. The management thereafter gives a written permit to begin the work based on the outcome. The method statement analysis/work permitting methodology is a technique to ensure that hazards are not overlooked. Unlike a JHA which is a predictive technique, methods statement analysis relies on a comprehensive hazard database developed on the basis of past experience.

The method can also be used to evaluate the effectiveness of a JHA by calculating the ratio of hazards identified and assessed

4. **Audits:** This technique involves observation and review of the application and operation of safety management within a project and organisational context in the process of performing the tasks. The purpose of such inspections is to identify active hazardous conditions, unsafe behavior, and safety violations in the job-site. Walkthrough safety and health audits are usually conducted by the safety professional to identify injuries that may occur, for example due to improper storage of material or cluttered work spaces and proffer solutions.

5. **Worker-to-worker observation program:** This hazard identification technique makes use of worker-to-worker observations and feedback methodology to detect and mitigate unsafe behavior of workers. The behaviors of workers capable of yielding hazardous conditions are identified by a peer observers to form the basis for discussion on proper safety practices. The method requires cooperation of the workers and it has to be conducted on a no-blame bases. The program is capable of yielding a significant improvement in safety culture as it fosters a collaborative approach to managing safety (Albert & Hallowell, 2012).

6. **Safety alert systems:** These are proactive hazard identification systems that incorporate detection technologies into equipment that give an alarm when workers are exposed to hazardous conditions. Such a real-time feedback systems

allow workers to take corrective measures as soon as the loss of control event is detected.

These method that sense hazardous situations before resulting in injuries.

7. **Pre-use planning:** Pre-use analysis and studies are usually conducted any time a new modification is introduced in the work process. For example, when a new equipment or chemical is introduced into a project site, a test is conducted before using in order to identify hazards and correct them. Same applies to the use of new personal protective equipment in a project environment.

2.3 Empirical Studies on Safety in the Construction Industry

Safety in the construction industry has been a major issue that consistently attracts the attention of stakeholders in the sector. This resulted from the poor safety records of the industry globally. In devising solutions to the alarming rates of accidents and fatalities in the construction sector, the academia and other stakeholders have tried addressing the construction safety challenges using different approaches. A good number of the issues being studied are directly or indirectly related to the identification or recognition and management of hazards in the construction environment. Some of the studies are directed towards the process of construction while others are focused towards the people and machines that are used.

According to Zhou, Irizarry, & Li, (2013) and Zhou et al., (2015) there are two broad types of approach used by researchers and practitioners to address issues in construction health and safety. These include the management driven approaches and the technology driven

approaches. In the management perspective, stakeholders believe that in order to effectively guarantee construction safety and avoid injuries or fatalities on construction sites, it is imperative to ensure improvement in safety management processes and practices. Therefore, studies in this perspective are usually centered on managerial issues such accident cause analysis (Gyi, Gibb, & Haslam, 2016), safety climate (Alruqi, Hallowell, & Techera, 2018), safety culture (Tam & Fung, 2012), workers' safety perception and competency (Dainty, Cheng, & Moore, 2004; Tam & Fung, 2012), behavior-based safety (Li, Lu, Hsu, Gray, & Huang, 2015; M. Zhang & Fang, 2013), hazard management (Abbas, Mneymneh, & Khoury, 2018; Bernardes, Trzesniak, Trbovich, & Mello, 2018; Clark & Goldberg, 2002; Jaselskis, 2013; Jeelani, Albert, Han, & Azevedo, 2019; Kim, Lee, Park, Chung, & Hwang, 2015), and so on.

On the other hand, technology driven approaches are based on the premise that safety performance on construction sites can be improved through the application of different types of technologies. In this dimension, researches have been focused on, among others, process automation, use of building information modelling (BIM) technologies (Riaz, Arslan, Kiani, & Azhar, 2014; Sijie Zhang, Boukamp, & Teizer, 2015; Sijie Zhang, Sulankivi, et al., 2015; Sijie Zhang, Teizer, Lee, Eastman, & Venugopal, 2013), data mining, geographic information system (GIS) (Zhou et al., 2013), radio frequency identification (RFID) systems (Arslan, Riaz, Kiani, & Azhar, 2014; Cheng, Venugopal, Teizer, & Vela, 2011; Su, Li, Yuan, Cai, & Kamat, 2011), robotics, sensing technologies (Choe, Leite, Seedah, & Caldas, 2014; Park, Marks, Cho, & Suryanto, 2016a; Teizer, 2015) wireless networks and virtual reality systems (Albert, Hallowell, Kleiner, et al., 2014; J.

Park, Marks, Cho, & Suryanto, 2016b; Sacks, Perlman, & Barak, 2013). These two approaches have been found to complement one another in preventing construction accidents and improving the safety profile of the construction industry.

In another dimension, Zhou et al., (2015) have further classified researches in construction safety into three different standpoints. These include the dimensions of utilising accident/incident records in improving safety performance, safety management process, and investigating the influence of individual and group characteristics on safety performance. Further, Jin et al., (2019) in a different approach have further broken down these approaches into five different themes or topics under which safety related issues in the construction industry are studied. These include safety climate and safety culture, application of ICT tools in construction safety, workers' safety perception and behavior, safety management systems and hazard identification, accident causation and risk perception. While the first two classifications of approaches are broad and clear about the issues, the subsequent one comprises five interwoven themes with no clear demarcation between the topics considered. In any case, some of the approaches consider the process of safety management, others pay attention to the entities that are involved in managing the safety, such as the individuals, the organisations and the projects.

Any initiative meant to improve safety on construction must give regards to the construction practitioners whether as managers or most importantly as workers, who are the primary targets in any construction accidents. The following sections therefore review studies that have been conducted in the area of safety management with specific focus to hazard recognition and management.

2.3.1 Safety climate, culture and behaviour

Some studies on safety management approaches are centered towards the groups or organisations in which the workers conduct their activities. The characteristics of a group or organisation in which a person works usually have a lot of influence on the workers' safety performance. This comes under the umbrella of safety culture, and safety climate, which have impact on safety behavior and hazard recognition of construction workers. Safety culture encompasses beliefs, values, and attitudes that are shared by a group or members of an organisation. Safety climate on the other hand refers to the organisational members' shared perceptions about their work environments and organisational safety policies. These two interrelated terms have been reported to significantly impact safety performance of construction workers and their organisations, and thus studied in different dimensions. Safety climate has been mostly studied in projects or organisations. For instance, Choudhry, Fang, & Lingard, (2009) measured safety climate in a leading construction company in Hong Kong, Lingard, Cooke, & Blismas, (2010) carried out a survey on safety climate in a large hospital construction project in Australia, and Zhou, Fang, & Mohamed, (2011) studied the safety climate of a Chinese construction company.

Most of the areas studied in safety climate relate to safety behavior (Zhang, Li, Fang, & Wu, 2017), co-workers caring and communication (Gao, Chan, Utama, & Zahoor, 2017), management commitment (Zahoor, Chan, Utama, Gao, & Memon, 2017), and a host of others. Much of the researchers' attention in safety climate studies have been paid on

workers, such as worker behavior (H. Jiang, Wang, Han, & Yin, 2018)**,** safety compliance (Xia, Griffin, Wang, Liu, & Wang, 2018), and perceptions (Stiehl & Forst, 2018)**.** On the other hand, Studies on safety culture have made comparisons of culture among three levels of construction management: top management, supervisory level and frontline operatives**.**

Studies have proposed measures to further improve safety culture on sites (Chinda & Mohamed, 2008; Gilkey et al., 2012; Molenaar, Park, & Washington, 2009)**.** Other studies (Guldenmund, 2000; Marquardt, Gades, & Robelski, 2012)show that safety culture encapsulates safety climate. Safety culture studies have been taken on the organisational level both for contractors and other stakeholders (Goncalves Filho & Waterson, 2018; Karakhan, Rajendran, Gambatese, & Nnaji, 2018; C. Wu, Song, Wang, & Fang, 2015). Ai, Teo, Yean, & Ling, (2009)reported that safety climate influenced safety culture in terms of psychological, situational/environmental and behavioral aspects, and safety climate could be used to predict safety culture, which might further affect safety performance (Choudhry et al., 2009)**.** All these are issues to do with either the individuals, groups or organisations in which they work.

2.3.2 ICT in construction safety management

Despite the seeming resistance of the construction industry to accept innovative technologies

(Zhou et al., 2013), the advancement in information and communications technology (ICT) has presented a great opportunity for improvement of construction safety management (Skibniewski, 2014, 2015). As a result, researchers and practitioners have realised the

importance of technology in addressing safety management issues in construction (Zhou, Irizarry, & Li, 2013). Different solutions were developed to proactively address safety issues in construction. These include sensors and sensor-based systems, robotics information analysis, management and reporting systems among others (Skibniewski, 2014).

For example, (Marks & Teizer, 2013) took advantage of developments in sensing and computing technologies developed a solution for improving safety performance by providing rich information about location and worker safety with respect to use of equipment on construction sites. In the same vein Marks & Teizer, (2013); Shen, Marks, Pradhananga, &

Cheng, (2016); Teizer & Cheng, (2015); Wang, Zhang, Du, Pan, & Xue, (2016); and Wang & Razavi, (2016) have worked to improve on the existing systems by developing an unsafe proximity detection model aiming at decreasing the false alarms generated by the systems. Radio Frequency Identification (RFID) sensors have also been used to develop safety early warning systems that were able to inform workers of the existence of potential safety risks on construction site. Using real-time visible and traceable information, accidents involving collision with equipment can be averted if workers-on-foot and equipment operators informed or alerted when a person comes too close to the equipment (Ding et al., 2013; Teizer, Cheng, & Fang, 2013). RFID and wireless sensor networks have also been applied to improve construction site safety management as reported by Costin, Pradhananga, & Teizer, (2012) and Teizer, (2015).

Similarly,wireless remote sensing technologies provide great potentials to advance the management of construction safety by providing real-time access to the locations of workers, on sites (Skibniewski, 2014). Tracking technologies such as RFID, Global Positioning System (GPS), Wireless Local Area Networks (WLAN), and Indoor GPS have been used due to their ability to cover a wide areas of land with significant accuracy (Pradhananga & Teizer, 2013; Su et al., 2011; Teizer et al., 2013). In robotics, Seo, Lee, Kim, & Kim, (2011) developed and autonomous excavation system to make an optimal excavation plan based on

3D models of the structure being constructed in a work environment and of the excavator. The system integrated the intelligence of a construction planner and a skilful operator in coming up with the plans. Jung, Chu, Park, & Hong, (2013) developed a robotic beam assembly (RBA) system for use in executing a beam assembly operation. In the area of information analysis, management and reporting, BIM and allied technologies have shown enormous potentials for being applied to improving construction safety.

Studies on laser scan status capture and early warning systems have been published in increasing numbers, especially in the recent times. (Sijie Zhang et al., 2013) applied automated safety rule checking to Building Information Models (BIM) with algorithms that automatically analyse a building model to detect safety hazards and suggest preventive measures to users. In the system, a safety checking platform was used to report to construction engineers and managers why, where, when, and what safety measures are required for preventing fall-related accidents in a project before construction work starts.

Riaz et al., (2014) developed an integrated solution based on BIM and wireless sensor technology for use to reduce hazards on construction sites.

Similarly, Zhang, Teizer, Lee, Eastman, & Venugopal, (2013) developed a safety rule checking platform for fall hazard detection and prevention in building information models. In the system, potential fall hazards that are mistakenly built into construction schedules can be recognised and excluded early in the planning phase of a construction project. Ding & Zhou, (2013) developed a web-based system for safety risk early warning in urban metro construction. They used a hybrid data fusion model based on information from monitoring measurements, calculated predictions, and visual inspections, to mimic human experts in giving safety risk assessment and early warnings automatically. The system was reported to significantly improved information collection, sharing and communication in safety management. Several other studies in this area have been reported (Ding et al., 2013, Wu, Yang, Li, & Chew, 2013, Hu & Qu, 2015, Teizer, Allread, Fullerton, & Hinze, 2010, and Wang et al., 2018).

2.3.3 Workers' Safety perception and behavior

Several works were therefore directed towards the construction workers in order to explore the effects of individual and or group characteristics on construction safety management. Studies in this area include those that consider the workers based on the trades they engage in. These were on the basis that different construction trades present different safety scenarios. For instance, Baradan & Usmen, (2006) analysed the occupational injury and fatality risks on 16 building construction trades and found that ironworkers and roofers had

the highest occupational risk. Fung, Lo, & Tung, (2012) established a risk evaluation model for different construction trades.

Others consider them based on their origin (Chan, Javed, Lyu, Hon, & Wong, 2016; Suo & Zhang, 2016; Chan et al., 2016; Lyu, Hon, Chan, Wong, & Javed, 2018; Suo & Zhang, 2016) while others study the workers based on some conditions that affect them in the process of doing their works. Han, Feng, Zhang, Jin, & Aboagye-nimo, (2019) studied the perception of safety hazards by construction workers based on feature of the hazards and the workers' subgroup demographic factors such as job position and experience level. They established a significant variation among employees' opinions in perceiving hazard based on its degree of severity. Further, the workers perceive differently based on their experience levels. In a similar dimension, Chen & Jin, (2015) investigated subgroup workers' perceptions of a safety program between general contractors' and subcontractors' workers. More positive perceptions of the safety program was noticed among the general contractors' workers.

Other studies directed their attention to the site conditions/characteristics that affect workers safety perception (Yi & Chan, 2017). All these were studies that centered on workers' characteristics.

Another trend was based on belief that unsafe behavior is intrinsically linked to workplace accidents (H. Lingard & Rowlinson, 1998) and the need for proactive management of worker behavior. In this regard, Fang, Zhao, & Zhang, (2016) developed a cognitive model

of construction workers' unsafe behaviors with a view to ensure prevention of safety incidence. Andersen et al., (2015) and Choudhry, (2014) revealed that social and psychological dynamics of workers may have a strong influence on their safety behaviour on construction sites. Similarly, Lingard & Turner, (2017) found that embracing of healthy behaviours by workers is influenced by factors playing around the individual, family, workplace and industry levels. Other studies such as Leung, Chan, & Yuen, (2010) showed that safety cases and risky behaviors can be affected by the safety attitudes of construction workers. Patel &Jha, (2015) developed a model to predict safe work behavior of construction employees using certain climate determinants. Different other studies were carried out to improve the attitude of workers towards safety in their workplaces. In this light, Tam, Fung, & Chan, (2001) used an attitude-changing model based on reinforcement theory to provide and improvement in safety attitude of construction practitioners. Conchie, Taylor, & Charlton, (2011) investigated the relationship between trust or distrust and safety leadership of construction workers.

2.3.4 Safety management system

A system for management of personnel's safety involving the planning, organising and implementing a policy and measuring, auditing and performance evaluation of the functions is referred to as safety management system (Yiu, Sze, & Chan, 2018). Any of such must pay attention to safety planning, education, training, and inspection to proactively reduce accidents on construction site. An effective safety management system is essential for accident prevention and reduction. Many studies revealed the significance of safety management to safety performance of construction organisations. For instance,

(Yiu et al., 2018) found that senior management commitment in form of resource allocation, safety managers' competency, are the major drivers of safety management system implementation. They also reported that safety management system yields reduction in the rate and costs of accidents, improved organisations framework and improved audit rating. Similarly,(Bavafa, Mahdiyar, & Kadir, 2018) discovered the critical factors that ensure improvement is safety programs as commitment and responsibilities towards safety in any organisation, subcontractors and personnel's selection, safety supervisor and professionals, plan for safety, and "employee involvement and safety evaluation. Many other studies have related the influence

2.4 Hazard Recognition in Construction

Over time, studies on construction safety management have focused on, among others, hazard identification, accident investigation, and risk assessment. Researchers have documented factors responsible for poor safety performance which manifests in several accidents and fatalities in the construction industry (Mitropoulos et al., 2005; Ale et al., 2008; Han et al., 2019; Haslam et al., 2005; Mitropoulos & Guillama, 2010; Tixier, Hallowell, Albert, Boven, & Kleiner, 2014; Zhao, Liu, Zhang, & Zhou, 2018). The root causes of workplace accidents comprise the failure of workers to identify a hazardous condition that occurs before starting an activity or that developed after starting an activity; resolving to continue with a work after the worker detects an existing dangerous condition; or deciding to act in an unsafe manner irrespective of initial conditions of the work environment. Ding & Zhou, (2013) observed that workers found themselves in a position of risk either due to their ignorance or inability to behave safely. Although their ignorance

may be linked to limited knowledge and experience, their attitude towards safety may inform their unsafe behavior. Other researchers that worked on accident causation in the construction industry include (Haslam et al., 2005; Kadiri, Avre, et al., 2014; Manu, Ankrah, Proverbs, & Suresh, 2010; Mitropoulos & Guillama, 2010; L. Wong, Wang, Law, & Lo, 2016).

Among the antecedent factors responsible for the poor safety performance, hazard recognition of construction workers has recently received significant attention of researchers (Albert et al., 2013; Carter & Smith, 2006; Namian, Zuluaga, et al., 2016; Pereira, Ahn, Han, & Abourizk, 2018; Goh & Chua, 2009). Hazard has been defined as the potential for harm, or an aspect of technology or activity that leads to risks (Bahn, 2013). Hazard recognition is the ability of managers and workers to sense, analyse and extract physical or mental stimuli that indicate the existence of a hazardous situation in a complex and dynamic scenario of construction environments (Albert, Hallowell, & Kleiner, 2014; Namian, Zuluaga, et al., 2016). The stimuli may arise from unsafe equipment or installation; unsafe environment; or unsafe work practices" engaged in by the workers.

Hazard recognition is central to any effort made in addressing the health and safety challenges encountered on construction sites (Albert & Hallowell, 2014; Albert, Hallowell, Skaggs, & Kleiner, 2017; Namian, Albert, & Feng, 2018). Safety management efforts are always designed to manage the identified hazards, which occur in multitude of ways. When hazards are not recognised and managed, the likelihood of calamitous and sudden injuries will increase. Studies have reported that more than 42% of injuries in construction occur

because of inadequate hazard recognition and evaluation (Carter & Smith, 2006; Haslam et al., 2005; Perlman, Sacks, & Barak, 2014). Another finding by Bahn, (2013), was that workers failed to recognise an average of 57% of hazards in occupational environments in Australia. More recently, in a study of several projects across the United States of America, Albert, Hallowell, & Kleiner, (2014), discovered that more than 40% of hazards were not recognized at the time of pre-job safety meetings. These problems have been aggravated by the inherent characteristics of the industry such as frequent rotation and interaction of teams, constantly changing weather and environmental conditions, higher proportion of unskilled laborers, high labor turnover, and so on.

Similarly, hazard recognition capabilities of construction workers are hampered by the poor knowledge transfer between construction projects, resource limitations on small projects (which are usually more in the industry), lack of standardization of construction methods and the dependence on the tacit knowledge of workers, which is acquired through practice over time (Carter & Smith, 2006). In this light, Haslam et al., (2005) referred to the unrecognised hazards as the principal causes of the disproportionate number of accidents, injuries, and fatalities in the construction industry. This is because when workers fail to recognise hazards, they tend to underestimate the risks associated with the tasks they are performing and they will not be able to behave safely because of the inability to recognize the situations with the potential to cause injury. Similarly, when workers repetitively perform related activities, they may be accustomed to working in an unsafe manner due to their previous records of success. Hence hazard identification skills are necessities for all construction workers, since no meaningful improvement in safety management can be

achieved, if hazards are not properly identified and managed. For these and many other factors, several hazard recognition techniques have been developed and used in the construction and other sectors, with many improvements.

2.4.1 Hazard recognition methods

A number of hazard recognition techniques used in the construction and other industries have been documented in the literature. According to Albert & Hallowell, (2012), some of these techniques are predictive in nature, while others are retrospective. The predictive methods try to visualise the scenario of a future construction activity and extrapolate the potential hazards that may be encountered, then put in place measures of addressing them. Examples of these methods include job hazard analysis (JHA), which studies subtasks in identifying hazards (Albert & Hallowell, 2012; Kim et al., 2015), task demand assessments, which focus on the likelihood of errors by workers based on the difficulty of tasks (Mitropoulos & Guillama, 2010). Others, are what-if analyses, job safety assessments, and energy based methods among others (Albert & Hallowell, 2012).

On the other hand, retrospective methods of hazard recognition are based on the knowledge and experience of workers gathered from past projects. Based on these, the managers device measures of dealing with the types of hazards experienced in previous projects with the hope that such can be avoided in a current job. Example of these include checklists, which make use of certain templates prepared to assist workers in identifying hazards; others include safety alert systems, audits, methods statement, etc (Albert & Hallowell, 2012, 2014) have described the different techniques applied in various industries to directly

or indirectly enhance hazard recognition, which may be applied to the construction industry.

2.4.2 Limitations of the existing hazard recognition methods

Despite reported successes in the use of the existing hazard recognition strategies, it has been observed that a large number of hazards remain unrecognised, partly as a result of their several limitations (Albert et al., 2013; Bahn, 2013; Carter & Smith, 2006; Jeelani, Albert, & Gambatese, 2016). For example, the predictive strategies are based on a wrong notion that workers inherently possess adequate skills of predicting future hazardous work conditions. Contrarily, studies have shown that the dynamic nature of construction projects makes it extremely difficult for workers to visualise and predict construction processes (Mitropoulos et al., 2005). This is further aggravated by the distinctive nature of the construction jobs which often involves rotation and interactions of work groups and teams, constantly dynamic environmental and weather conditions. These make the kinds of hazards encountered in different projects vary significantly. Further, construction projects are generally characterised with large number of unskilled laborers and high labor turnover. This also exacerbates the difficulty of hazard recognition improvement measures taken by employers in the industry.

Moreover, the methods are not robust enough to accommodate sudden alterations in project scope and conditions of work, which are common characteristics of construction projects. They are also not cognisant of hazards posed by adjacent construction crews, which are not related to the workers' primary tasks (Albert, Hallowell, & Kleiner, 2014). Therefore

predictive hazard recognition techniques cannot be effectively relied on for controlling workers safety behavior on every construction projects.

Similarly, the limitations of the retrospective hazards recognition techniques have been identified in the literature (Goh & Chua, 2009; Behm & Schneller, 2012). The techniques are based on the knowledge acquired from previous safety incidents and injuries which are applied to new situations and projects. The assumption of the techniques that this knowledge captured from previous projects can be easily applicable to other projects has been faulted. It was also observed that most accident reports hardly capture adequate information that will enhance future experiences. The techniques neglect the uniqueness of each construction project. Furthermore, unreported injuries and near misses limit the usefulness of knowledge gained past projects (Namian, Albert, Zuluaga, & Jaselskis, 2016; Shen & Marks, 2016) Based on the foregoing, these methods have not been effective in addressing hazard recognition problems faced in the construction industry.

2.4.3 Improving hazard recognition in construction

In order to overcome the limitations of the traditional hazard recognition methods and ensure effective development of workers' capacity to recognise work hazards and behave safely, a number of innovative approaches for improving hazard recognition of construction workers have been developed.

One of the most effective interventions adopted by construction companies to ameliorate the poor safety performance of the construction industry is safety training. Construction

organizations globally have invested millions of dollars in the development and deployment of numerous safety and hazard recognition training programs for their workers. These training programs are meant to provide the workers with the requisite skills needed for them to recognise and manage hazards in complex and dynamic construction environments (Huang & Hinze, 2006). Albert & Hallowell, (2012) observed that new and experienced workers are made to undergo different forms of hazard recognition training programs in order to boost their perception of latent hazards and improve their situational awareness. Through the training schemes, workers are taught to use observations of their environments together with the knowledge and experience gained over time to project possible consequences of hazardous situations. This then make them informed on possible ways of avoiding the consequences and behaving safely in performing their duties.

Considering its importance, several studies have established a causal relationship between training and safety performance in the construction industry (Albert & Hallowell, 2017; Bosché, Abdel-wahab, & Carozza, 2008; Cunningham et al., 2018; Kadiri, Nden, et al., 2014; Lingard, Pink, Harley, & Edirisinghe, 2015; Zuluaga, Namian, & Albert, 2016). Others have underscored the significance of safety training in empowering workers to make decisions that will help them to remain safe in their work place (Bahn, 2013; Demirkesen & Arditi, 2015). For instance, training has been identified as the only distinguishing variable that separates individuals with high and those with low levels of safety risk perception (Namian et al., 2018a; Perlman et al., 2014). There is, therefore, a consensus among researchers and other industry stakeholders on the role of safety training in improving hazard recognition performance and general safety management.

The trainings come in variety of forms ranging from the promotion of the use of Personal Protective Equipment (PPE), to the implementation of effective hazard identification and management and other injury prevention approaches. Further, there are different approaches that have been used in the design and implementation of safety training programs.

2.2.4.1 Traditional Safety Training Methods

Construction safety education and training has mostly been conducted in the traditional teaching approach. In this method, health and safety related information is presented to trainees in order to enhance their knowledge and awareness of health and safety issues (Burke et al., 2006). They are usually conducted in a classroom format with emphasis made by the trainer or instructor, while the trainees are listening. It sometimes involves the use of materials like visual aids, textbooks, pamphlets or other types of written materials to communicate safety information. In some cases, safety information are presented in a video for workers to see the examples of safety scenarios being shared (Goldenhar, Kohler, & Colligan, 2001; Lingard et al., 2015). Demonstration is also used in other cases as a training method in some construction companies (Dzeng, Fang, & Chen, 2014; Lehtola et al., 2008; Pereira, Han, AbouRizk, & Hermann, 2017). These one-way transmission of knowledge from instructors to trainees has been referred to as passive methods. This is because concentration is on the instructor who delivers the training without necessarily obtaining any feedback from the trainees. However, despite the unanimous agreement among researchers on the significance of training to achieving safety improvement, the

persistence of negative safety outcomes put the efficacy of the traditional training approaches to question.

2.2.4.2 Shortcomings of the traditional training approaches

Past researchers have reported several shortcomings of the traditional training methods. According to Demirkesen & Arditi, (2015), the traditional training efforts failed as a result of the use of ineffective instructional approach, incompetent instructors, and defective training materials. It was concluded that, no matter the good intention of construction organisations in providing training to their workers, no significant improvement will be achieved if proper teaching approaches and effective resources are not employed.

Another factor that has been reported to enhance the effectiveness of training is the level of engagement. The traditional passive classroom training approaches have been reported to have minimal level of engagement (Bosché et al., 2008; Dawood, Miller, Patacas, & Kassem, 2014). Studies like Burke et al., (2006) and Namian, Albert, Zuluaga, & Behm, (2016) reported that these unengaging methods are not effective in transferring qualitative safety knowledge. Haslam et al., (2005) observed that the conventional training techniques have limited value and, instead of enhancing safety consciousness, can instigate negative attitudes among workers.

To buttress theses points, in a survey that assessed workers' satisfaction with traditional trainings they received, Wilkins (2011) found that 32% of workers were unsatisfied with the training materials and resources. More so, 41% of the workers believed that their

trainers were ineffective. Furthermore, in the study of training methods' effectiveness. Sacks et al., (2013) reported that workers who received low-engaging training were more prone to distractions during training; while those that received high-engaging training were attentive for longer periods of time. In addition, Namian, Albert, Zuluaga, & Jaselskis, (2016) found that only less than 40% of projects in the United States adopted high-engagement training methods. (Zuluaga et al., 2016) reported that construction workers who were given safety training using high-engaging methods were able to recognise a larger amount of hazards, and perceived risk levels higher than those trained using the low engaging methods. Similarly, in an assessment of the different training approaches, Burke et al. (2006) established a statistical evidence linking the active and high-engaging training methods with achieving desirable outcomes in terms of safe conduct of workers.

2.2.4.3 Barriers to Effective Training

However, despite the huge investment in providing workers with training, using different approaches, researchers have observed that not significant improvement has been achieved in workers ability to recognize and manage work hazards. This translates to the failure of the training efforts, since no positive correlation exists between the training efforts and workers safety performance (Albert et al., 2013; Carter & Smith, 2006). For instance, it was estimated that only 10–15% of investments in safety training yield tangible benefits (Baldwin & Ford,

1988). (Haslam et al., 2005) also reported that deficit in workers' safety knowledge is a major contributing factor to the high rate (more than 70%) of accident in construction. This is in congruence with the constant recommendation for more training to prevent accident

recurrence at the end of most injury investigations. Therefore the expected return on investment is yet to be achieved.

In order to address the issues of failure in training methods, attempts have been made by researchers to identify factors that hinder the effectiveness of training. These factors have been summarized in Table 1.

Table 2.1: Barriers to Effective Training

S/N	Barriers	Sources
1	Poor design of the training programs	(Wilkins 2011)
2	Use of ineffective training delivery approaches	(Demirkesen & Arditi, 2015)
3	Use of inferior training materials	(Wilkins 2011). (Demirkesen and Arditi 2015)
4	Language barriers	Haslam et al. (2005); Wang et al. (2008) Demirkesen and Arditi (2015)
5	Incompetent trainers	Haslam et al. (2005); Wang et al. (2008) Demirkesen and Arditi (2015)

6	Negative attitude of the trainees	Haslam et al. (2005); Wang et al. (2008)
7	Poor training transfer by workers	Namian et al. (2016)
8	Poor training practices	Jeelani et al. 2017
9	Transient nature of construction workforce	Goldenhar et al. (2001)
10	Temporal basis of projects	Goldenhar et al. (2001)
11	Schedule constraints in time-sensitive projects	Wang et al. (2008)
12	Lack of funds and other resources	Wang et al. (2008)
13	Lack of interest among workers	Wang et al. (2008)
14	Uncertainty and difficulty of quantifying training benefits	Wang et al. (2008)
15	Conflicts in projects,	Wang et al. (2008)
16	Workers learning style	Wilkins (2011)
17	Workers literacy level	

Critical look at these factors infers that the traditional training approaches (such as the class room teaching/lecture method) have not been able to effectively address them in the design and delivery of training programs. For example, the training programs have been consistently designed and delivered in a lecture format, using demonstrations, visual aids and in some cases group discussions. In these approaches, only group discussions have been shown to have the ability to enhance learning. Others have been criticized of as lacking engagement and realism. They therefore failed to impart knowledge to the trainees in such a way that they can retain and transfer it in their future works. In the same vein, the lecture method has also been accused of being too passive, and therefore lacking in

interaction. Therefore, they may not maximize knowledge acquisition and retention. The materials used to deliver the training; textbooks, videos and pamphlets have also been criticized as ineffective in knowledge transfer.

Moreover, the traditional training approaches have not been able to capture the learning styles of construction workers, who are all adults. Andragogy has been identified as the best way of transferring knowledge to adult learners. This is because it engages the learners physically and psychologically. The traditional training methods have severally been delivered in a pedagogic manner. In order to improve safety training effectiveness, Wilkins (2011) recommends replacing traditional classroom-type training with andragogical approaches that are more effective in engaging adult learners. Similarly, Burke et al. (2011) and Namian et al. (2016) posit that more engaging training methods can improve knowledge gain. In addition, it has been argued that learning construction safety is best taking place in real construction sites. Therefore, the traditional training approaches do not have the capabilities of transferring safety knowledge on site without endangering the workers. In order to address these and several other concerns, the need for improved training approaches became imperative. A good number of these improved training techniques have been reported in construction safety literature, with different tools and technologies.

2.2.4.4 Innovative Safety Training Methods in Construction

As a result of the failure of the traditional training approaches to enhance significant hazard recognition improvement in construction workers, modern training approaches have been

developed with different capabilities. These new solutions have been developed to address the critical need of trainee engagement, interaction, and realism, which have not been offered by the traditional training approaches. The innovative methods employed the use of computer based technologies such as the gaming technologies and real-time technologies such as the virtual environment training systems.

Gaming technology has been applied in the training of construction workers to improve hazard recognition capabilities. Serious games or serious gaming has been defined by Dawood et al. (2014) as the use of computer games technology to create tools to solve real world problems. These technologies offer the possibility of simulating processes that are not possible with field-based training, such as high risk construction activities, providing workers with knowledge of what occurs on the actual construction site beforehand. This have been due to a number of advantages offered by the technology. For example, serious games have the ability to simulate different site conditions, while avoiding potentially hazardous and expensive on the job training. The technology also increases the realism of the virtual training environment (Nashwan Dawood & Mallasi, 2006). Serious games present virtual computerbased tools to produce interactive simulations that can impart knowledge and skills to the user, which includes the consideration of the consequences of workers' actions. This can help a great deal in lessening human-error based accidents in construction sites.

Previous studies have reported the suitability of serious games for hands-on training purposes, which are most appropriate for construction workers (Chen, Golparvar-Fard, &

Kleiner, 2013; Chi, Kang, & Wang, 2013; Cunningham et al., 2018; Wall et al., 2007). For example, the visual capabilities of serious games, together with 4D modelling, have been used to raise the awareness of safety experts and designers, and provide more effective training of workers (H. Chi et al., 2013). Moreover, studies like (Dawood,
Patacas, & Kassem, 2014; Esmaeili, Hallowell, & Rajagopalan, 2015; Guo, Li, & Li, 2013) have designed and developed different serious games solutions for improving the realism and long term retention of training learning outcomes. These studies have been reported to achieve different levels of improvement in workers' hazard recognition and safety performance.

In order to increase the immersive experience opportunities and realism of training and to enable real-time practice of future operations in construction safety training, a new trend of modeling and visualization has been developed in form of virtual environments. Wang et al. (2005) referred to the training programs incorporating these virtual technologies as virtual training systems (VTS). A VTS, according to Bowman et al. (2005) is a 3-dimensional background seen from a first-person point of view that is under real-time control of the user. These systems focus on augmenting virtual reality (VR) environments with real construction site images and videos (Chen et al., 2013) to create augmented reality (AR) or augmented virtuality (AV) environments.

In particular, AV environments in which the underlying VR is augmented with real-world photos and videos can significantly minimize the time required for modeling details beyond the typical underlying 3D model of a construction project. The environments also minimize

the gap between game design and user perception, which has been reported by (Teo & Feng, 2011) as one of the game modeling concerns for construction safety education.

Previous studies have reported the advantages of virtual training systems (VTS) for construction safety training. For instance, VTSs are often used in place of on-the-job training or full size simulation because the technology allows for safe simulation of real-life events in a digital environment that might otherwise be too dangerous or expensive to create (Hilfert, Teizer, & König, 2016a; Kassem, Benomran, & Teizer, 2017). According to Ergun, (2015); Hilfert, Teizer, & König, (2016), virtual training systems can be used to create a problembased learning exercise in an environment that imitates the trainee's actual working environment. Moreover, a training program that uses a VTS offers an interactive, active, and cognitive learning experience for trainees (Guo et al., 2013; Hilfert et al., 2016a; Park & Kim, 2013). This provides an opportunity for the trainees to learn by active participation, which increase their motivation, and flexibility in terms of time and location. Moreover, any desired level of engagement and realism can be achieved with virtual environments.

To demonstrate the real benefits of AV for improving hazard recognition, particularly for construction workers. Albert, Hallowell, Kleiner, et al., (2014) argued that it is essential to perform field experimentations with construction teams and systematically observe how the introduction of AV game environments can improve their ability to recognise hazard. This approach has been found to record significant improvement in hazard recognition skills of construction workers and has the potential to reduce construction injuries. With the

increasing research efforts to enhance hazard recognition capability of construction workers using virtual training systems, greater potentials for achieving significant improvement has been established. Also, as a result of these achievements, researchers have continued to devise more measures of improving the systems for sustained improvement in overall safety performance of the construction industry.

In a similar effort, Chen, Golparvar-Fard, & Kleiner, (2014) developed a 3D environment for the training of workers on hazard recognition. The system consisted an augmented virtuality environment that integrates BIM with photographs of energy sources on a jobsite, in which workers are trained to walk around different hazardous scenarios and gain improved hazard recognition skills. Similarly, Zhang, et al., (2015) developed a BIM-based system for the recognition and prevention of fall hazard in construction safety planning. The system dynamically visualises potential fall hazards in a simulated construction process and use the information to improve workers' safety awareness and plan for preventive measures.

To further improve performance of the innovative approaches, Jeelani et al., (2017) and Jeelani, Han, & Albert, (2018) argued for determination of workers' specific hazard recognition skills deficiency. This, they believe will facilitate the development of personalized improvement strategies targeting the specific deficiencies identified. The knowledge gaps and training needs of individual construction workers were then used to develop and test the first personalized training intervention which tackle specific deficiencies in worker performance. This strategy was meant to enhance systematic hazard-

recognition through the use of visual cues and the use of eye-tracking technology to facilitate the process of hazard searching feedback. It also employed the use of metacognitive prompts for self-introspection and diagnosis in order to facilitate the adoption of remedial measures (Jeelani et al. 2017).

Empirical evaluation of the effectiveness of the training strategy was conducted using the experimental non concurrent multiple-baseline studies with construction workers. The findings indicated an improved level of hazard recognition from 42% prior to receiving the intervention to 77% of hazards in the intervention phase. Although this intervention was reported to record significant improvement in the workers' hazard recognition levels, the training methods had significant shortcomings in the areas of determining the training needs of workers. To determine the hazard recognition level of workers, there are various categories of factors that play significant roles, which include personal, organizational, social and so on. The study considered only a few personal factors in establishing the training needs of the workers. Notwithstanding their significance in hazard recognition, those factors cannot sufficiently explore the real deficiencies in the hazard recognition competencies of workers in a dynamic construction environment. It is therefore expected that this research will address such an important knowledge gap.

2.2.4.5 Research Gaps on Training

The research in the area of training for enhanced hazard recognition and general safety performance has advanced from the use of traditional safety training methods to the application of technological solutions to improve workers hazard recognition capabilities. This was the result of unanimous agreement among stakeholders on the failure of the

traditional training approaches to bring about improved hazard recognition of construction workers. Various advanced technologies were utilized to assist in the process. Some technologies are responsible for gaining real-time safety hazard recognition skills such as gaming technologies and the use of virtual training systems such as BIM, virtual reality, augmented reality and augmented virtuality, which have recently been developed and tested. However, some gaps in knowledge will severely limit the adoption of any of these training approaches for training of workers to increase their hazard recognition levels.

Fundamentally, the major arguments leading the development of the innovative approaches include the issues of

a. level of engagement of trainees,
b. enhancing realism of the training,
c. immersive experience and
d. interaction in training.

Most of the innovative methods have not addressed these important issues that can help greatly in achieving the effectiveness of the training. There are categories of factors such as personal characteristics, organizational, social and project characteristics that have been found to influence hazard recognition capabilities of construction workers. These training approaches have not adequately taken care of those factors in their design and deployment. This would have provided an avenue for the establishment of a baseline skills required and the different training levels necessary for workers to recognise hazards in construction environments. It can also be used to categorise workers based on their training needs with respect to the trades they work on, and their deficiency levels in hazard recognition.

For example, the studies on these different technologies used to enhance training for hazard recognition were limited to academic research exercises. Limited implementation had been carried out in the training of construction workers. Researchers and practitioners should focus more on technology transition from research into practice. This will help in evaluating and choosing the most effective of these approaches.

Similarly, though the findings from the validation of these innovative training approaches have been found to be encouraging in improving hazard recognition levels of workers, the end users (construction safety officers and construction managers) have not been engaged to use these technologies in order to establish empirical evidence on the ease and suitability of using the approaches by construction organisations.

On the other hand, application of innovative technologies will certainly result in an unavoidable increase in cost or investment Zhou, et al. (2013). Presently, the challenges in using such approaches remain in measuring the long term impact, and costs associated with developing and delivering the interactive content to the trainees and subsequently finding ways to reduce those costs and maximise the positive benefits attained using such technology. The cost-effectiveness analysis of these innovative training approaches will therefore be significant for construction companies. This has to be addressed in order to guide selection of the appropriate training system for improving hazard recognition of workers.

2.5 Factors Influencing Hazard Recognition Capability of Construction Workers

Several literature on construction safety have reported the importance of hazard recognition to any safety management initiative. The persistence of poor safety records of the construction industry has been linked to the inability of workers to recognise and manage work hazards (Albert & Hallowell, 2014). This is certainly among the major reasons for the growing research interests on the improvement of hazard recognition performance of construction workers. However, in order to avert the negative consequences of poor hazard recognition of workers, it is inevitable to understand the factors that influence their hazard recognition capabilities. This will enable the development of appropriate strategies to improve the level of hazards recognised and managed by the workers, thereby achieving the desired improvement on the general safety performance of the construction industry.

Previous studies have documented the contributing factors to the inability of workers in construction and allied sectors to recognize hazards at work places. Notable among them is the work of Namian, et al., (2016) in which they established 36 factors that influence hazard recognition performance of construction workers. The factors were identified through literature review and interview of construction managers and safety professionals.

Table 2.2: Critical Factors That Impact Construction Workers' Hazard Recognition Performance

S/N	Factors
	Personal
1	Safety Attitude / Culture
2	Safety Complacency
3	Cognitive and Visual Ability
4	Knowledge and Experience (Competence)
5	Fatigue/Depletion
6	Emotional State

7	Physical Worker Characteristics
	Organizational
8	Worker / Crew Involvement
9	Supervisor / Leadership Involvement
10	Project-level Safety Climate / Culture
11	Safety Training Programs
12	Participant Empowerment, Accountability, and Organizational Structure
13	Communication Channels
14	Work Pressure
15	Project-level Policies, Procedures, and Methods
16	Regulations / Regulatory Policy Implementation
17	Crew Size
	Social Factors
18	Hazard Recognition Ability and Motivation Levels of Peers
19	Social Conformance
20	Owner / Societal Influences
	Situational and industry-related factors
21	Worker Distraction
22	Hazard Visibility
23	Orientation / Position / Location
24	Weather / Local Conditions
25	Housekeeping / Tidy Practices
26	Use of Temporary Employee
27	Project Characteristics and Task Type
28	Site Characteristics / Configuration
29	Scope and Schedule Changes
	Miscellaneous Factors
30	Hazard Predictability and Perceivability
31	Cause - Effect Clarity
32	Equipment / Tool Characteristics
33	Frequency and Duration of Hazard Exposure
34	Hazard Recognition Method / Tool Adopted
35	Hazard Plurality
36	Hazard Presence and Outcome Onset Lag

Source: Namian et al. (2016)

They assembled the factors into five categories as personal, organisational, social, and situational, industry related and miscellaneous factors. Table 2.2 presents the list of factors established by Namian et al. (2016).

The first category comprised of the personal factors, which refer to the human characteristics that play a role in the way a worker recognise job hazards, assess their risk level and manage them in order to remain safe at work. Namian et al. (2016) have listed seven sub factors under the personal factors that impact on workers hazard recognition capability (Table 1). These factors are inherent in the worker such as the cognitive ability which deal with the psychological processes that drive the person's behaviour and actions. Others include the safety culture or attitude of the worker, knowledge, experience, and other habitual characteristics that influence behaviour. Aside the personal factors, they identified another category that relates to the organizational characteristics.

Organizational factors are those related to the organisational environment, culture, and practices. Namian et al. (2016) have identified 10 factors related to the organizational environment and practices which have potential impact on the hazard recognition performance of workers. These include among others, training programs available in the organization, communication channels, organizational structure, safety and hazard recognition policies, procedures and methods and the regulatory environment within which the organisation operates. Further, they also reported another category of factors referred to as social factors. These are factors whose impacts are based on the social interaction with people of the community and fellow workers. Three sub factors have been identified as the hazard recognition ability and motivation levels of peers in a work place, social conformance, and the owner / societal influences. These, according to Namian et al. (2016) are the social factors that have impacts on the level of hazards recognised by construction workers.

Furthermore, another set of factors categorized by Namian et al. (2016) are what they called Situational and industry-related factors. They described this category as those factors representing the contextual or industry specific factors which can influence the hazard recognition capability of construction workers at a job site. Nine factors were identified in this category such as worker distraction, hazard visibility, orientation/position/location of hazard, weather/local conditions, housekeeping/tidy practices among others. The fifth category is what they termed miscellaneous factors. These were described as factors that were found to be unrelated to any of the previous four categories: personal, organizational, social, situational, and industry related categories that have impact on hazard recognition performance of workers. They include, among others, hazard predictability andperceivability, cause - effect clarity of hazards, characteristics of the equipment/tool used to perform a certain work, then frequency and duration of hazard exposure. These factors have not been given a specific category, but were referred to as miscellaneous factors. This has been the first work on this subject meant to contribute in addressing the poor hazard recognition performance of workers in the construction industry. Namian et al. (2016) referred to the list as comprehensive as compiled based on the judgment of construction experts and the review of related literature.

However, despite being the first attempt to identify a large number of these factors and categorise them into different groups, it can be observed that the list of factors is not comprehensive enough. This is because there are other important factors that have not been covered. Consequently, more factors need to be identified to make the list as exhaustive as

possible. This will be useful to the attempts being made by researchers to understand the different dimensions of the factors affecting workers hazard recognition performance. It will also help in the development of strategies for improving the number of hazard recognised in workplace, towards ensuring better health and safety performance of the construction industry.

Similarly, there has not been any clear and systematic criteria used in categorising the different factors into the clusters suggested put forward by Namian et al. (2016). No effort has been reported to establish and validate the different categorisations of the factors with construction experts. One of the limitations of this is, for example, the miscellaneous factors, which have not been attributed to any aspect of construction such as either the project, the organization or even the specific hazard types. It will therefore be difficult to provide a specific approach towards addressing them. The term miscellaneous can be confusing since the construction processes can be categorized into issues to do with workers, projects, site characteristics, and so on. For this reason, it will be important to have a scientific basis for the categorisations to be validated with construction experts based on identified characteristics of the factors. This is important because it will guide future research to be focused in aligning different hazard recognition improvement strategies to the specific areas of hazard recognition. This research has made an attempt to address these loopholes by systematically identifying and categorising the critical factors impacting construction workers' hazard recognition capabilities.

It is pertinent to note that most other studies on the factors impacting hazard recognition performance of construction workers have tried to explore how human characteristics play a role in the way a worker recognise job hazards, assess their risk level and manage them. In addition to the factors identified by Namian et al. (2016), so many other studies have established similar and other factors, and in some cases went further to examine their influence on hazard recognition performance of workers.

For example, Tam, Fung, Yeung, & Tung, (2003) investigated the relationship between the personal characteristics of construction workers and their recognition of safety signs and symbols on site. Among the personal characteristics they studied are the workers' smoking and drinking habits, job positions, age, risk perception level, and their cultural and linguistic backgrounds. A strong correlation was established between these personal characteristics of the construction personnel and their level of safety signs recognition, which signifies their ability to recognise and manage job hazards.

Another study by Ai et al., (2009) aimed at enhancing the safety performance of construction sites also established that personnel characteristics have significant impact on the construction site safety performance. These impact have been linked to, among other things, the way the workers detect work hazards on site. Moreover, Tixier et al., (2014) undertook a study in which they measured the impact of emotions on risk perception in a work place context. In their study, they found that workers' emotional states influence their risk-taking behaviour and by implication, the extent of hazard recognition. It can therefore be implied from their findings that workers in positive and neutral emotional states can be

more prone to engage in risk-taking behaviors. This will therefore affect their situational awareness and hazard recognition by reducing their level of risk perception. On the other hand, individuals in a mild negative emotional state may have a better risk perception level which may enhance their level of hazard recognition. In a similar study, Bhandari, Hallowell, Boven, Gruber, &

Welker, (2016); examined the relationship between construction workers' emotional states and their level of hazard recognition. It was found that workers registered a decrease in hazard identification skills on being induced with positive emotions. These two studies have revealed interesting results that hazard recognition skills can be greatly influenced by psychological factors.

Furthermore, other studies on personal cognitive factors that influence the behaviour of construction workers include the works of (Goh & Binte Saadon, 2015; Hasanzadeh, Smaeili, & Dodd, 2016; Mohammadpour, Asadi, & Karan, 2016). All these studies have wholly or partly focused on cognitive factors inherent in workers that influence the behavior and ability of workers to recognize and manage work hazards on construction sites. Goh & Binte Saadon, (2015) explored the extent to which cognitive factors such as workers' attitude, subjective norms, perceived behavioral control, and intention significantly determine the safety behavior of scaffolders in Singapore. Another study by (Mohammadpour, Asadi, & Karan, 2016) investigated the extent to which concentration and attentional control impact on the number of safety hazards recognized by construction workers. The research concluded that that safety knowledge have significant direct influence on the level of hazard recognized by workers.

Another important category of factors influencing hazard recognition of workers, as established above, is the social factors. It is known that construction activities are carried out in groups, teams and work crews. These collection of different workers tend to develop some culture, norms and values as a result of the interactions between members. These values and norms have been reported in the literature to significantly affect the manner in which workers recognize and deal with a number of work related hazards. Studies on these factors include the work of Albert and Hallowel (2014) in which they made use the concept of social network analysis (SNA) on construction crews to explore the relationship that exist between patterns of worker interactions and situational hazard awareness on active construction projects in the United States. Key factors considered in the study were the patterns of social interaction and role of supervisors. The results of the research revealed strong evidence signifying that well connected crews with higher network density surpassed the poorly-connected crews in recognizing and communicating hazards in a work environment. In another study, (Jiang, Fang, Zhang, & Ph, 2015) considered having participative supervisors among the factors that influence hazard recognition and safety behaviours of construction workers.

Similarly, Choi and Lee (2016) examined the social norms and social identification in safety behavior of construction workers. In this study, they reported a significant relationship between social norms (such as perceived workgroup norms) and safety behavior of workers in different cultural backgrounds and organizational structures. Therefore, the interaction between different personalities in a construction environment

context have significant influence on the hazard recognition and management capabilities of construction workers.

In another dimension, construction works are undertaken in organizational settings in any form of contractual arrangements. For this reason, the structure, policy and culture of the organization in which workers operate are known to have certain influence on the workers hazard recognition competencies. In this regard, Slates, (2008) reviewed literature on safety and hazard recognition with a view to identifying the factors that determine the effectiveness of any safety programme. He argued that only leadership and organizational commitment are important in ensuring employee involvement, training, hazard identification and management, if organisations must achieve safety improvement in the hazardous construction scenarios. Working conditions in an organization and the behaviour of workers were also seen to impact hazard recognition and the extent of accident and injury causation (Chi, Han, & Kim, 2013). Moreover, the safety management system of a company and the level employee and supervisors involvement have been reported to impact on workers hazard recognition capability(Namian, et al., 2016; Patel & Jha, 2015; Slates, 2008; Tam et al., 2003).

In another perspective, studies have established that there are factors related to the construction projects or the different activities in projects that impact the capability of workers to recognize hazards. Based on the premise that different construction trades present different sets of hazards, Choe & Leite, (2017); Namian, Zuluaga, et al., (2016) and Patel & Jha, (2017), argued that the nature and attributes of the job or tasks performed by

workers have significant influence on the hazard recognition levels of the workers. It was on this note that Patel and Jha (2017) developed a framework to evaluate a construction project hazard index (PHI), which represents the hazard level of a construction project. They used the attributes of different construction trades to evaluate the hazardous nature of the trades and ranked them. The ranks were then used in the process of determining the hazard level of every kind of construction projects. In this regard, it will therefore be convenient to introduce another category of factors impacting hazard recognition performance of workers to be referred to as project factors. This idea will help in refining the work of Namian et al. (2016) to put the factors in proper perspective and ensure a more specific focus in the efforts being made to address the hazard recognition performance of workers.

Other factors include the project level safety and hazard recognition training, which greatly enhances hazard recognition (Namian et al., 2016). Further, Namian, Zuluaga, et al., (2016); Sawacha, Naoum, & Fong, (1999); and Shang & Shen, (2016) identified Site layout configuration and level of traffic on the site to have significant influence on the ability of workers to recognize hazards. Delivery and productivity pressure on the workers and workers' distractions can also greatly influence hazard recognition (Bernardes et al., 2018;

Debnath, Blackman, & Haworth, 2015; Namian et al., 2018b, 2018a; Patel, Kikani, & Jha, 2006). Others include operational unfamiliarity of construction tools (Jeelani et al., 2017), project scope and schedule changes (Namian, Albert, Zuluaga, & Behm, 2016), and so on. To further substantiate some of these factors, Jeelani et al., (2016) undertook a study to

identify specific reasons why construction hazards remain unrecognized at work interfaces. The study revealed among other reasons, the multiplicity of hazards in a particular place, low prevalence of certain hazards, the time taken between hazard exposure and manifestation of effects, task unfamiliarity and so on. All these project based characteristics play significant role in determining the extent to which construction workers recognise and manage work hazards.

To put all these different categories into context, (Jiang et al., 2015) posit that construction safety management is a system that has so many components. Therefore, they used the concept of system dynamics to explore the causation of construction accidents and poor hazard recognition. Hence, all the different segments of the system such as the organisation, the workers and managers, and the project environments interact with one another to influence the level of hazard recognition and general safety management in every setting.

Based on the foregoing, Table 2.3 presents a more comprehensive list of the factors impacting hazard recognition performance of construction workers. These include the factors compiled by Namian et al. (2016) and others identified from literature sources. In the table also, the factors are reorganized to capture the other categorisations not specifically considered by Namian et al. (2016) and put some of the factors in more encompassing contexts to reflect the different perspectives of the construction industry.

Table 2.3: Comprehensive list of factors impacting hazard recognition performance of construction workers

S/N	Factors	Sources
	Personal	Tam, et al. (2003) Ling (2009)
1	Safety attitude / culture	Teo and Ling (2009); Namian et al. (2016)
2	Safety complacency	Namian et al. (2016)
3	Cognitive and visual ability	Namian et al. (2016) Goh and Sa'adon (2015)
4	Knowledge and experience (competence)	Namian et al. 2016; Rodríguez-Garz´on, et al 2016; Patel and Jha(2014); Teo and Ling (2009)
5	Fatigue/depletion	Namian et al. 2016; Seo et al; 2016
6	Emotional state	Namian et al. 2016, Bhandari, et al. 2016 Tixier, et al. (2014)
7	Physical worker characteristics	Namian et al. 2016, Teo and Ling (2009)
8	Concentration and attentional control	Mohammadpour et al. (2016)
9	Smoking and drinking habits/substance use	Tam, et al. (2003) Wang, et al; 2016, Gambatese, et al 2016
10	age	Tam, et al. (2003)
11	job positions,	Tam, et al. (2003)
12	cultural and linguistic backgrounds	Tam, et al. (2003)
13	Race and ethnicity	Dong et al 2009
14	Belief system	Nordlöf et al. (2015), Gao et al. (2017)
15	Value system	Kheni, Dainty, and Gibb, 2007
16	Superstition	*Kheni, Dainty, and Gibb, 2007*
	Orgabisational	
17	Worker / crew involvement	Namian et al. 2016; Patel and Jha(2014)
18	Supervisor / leadership involvement	Namian et al. 2016, Albert and Hallowel (2014) Jiang et al. (2015)
19	Safety training programs	Namian et al. 2016; Haslam et al. (2005); Teo and Ling (2009); Patel and Jha(2014)
20	Participant empowerment, accountability	Namian et al. 2016; Teo and Ling (2009)
21	organizational structure	Namian et al. 2016; Teo and Ling (2009)
22	Communication channels	Namian et al. 2016
23	Regulations / regulatory policy implementation	Namian et al. 2016; Mohamed 2002; Fang et al. 2006).
24	Unethical/corrupt practices	Chan and Owusu (2017)
25	Working conditions	Chi, Han and Kim 2013).

	Social Factors	
26	Hazard recognition ability and motivation levels of peers	Namian et al. 2016
27	Social conformance	Namian et al. 2016; Andersen et al. (2015)
28	Owner / societal influences	Namian et al. 2016
29	Work group subculture	Namian et al. 2016; Andersen et al. (2015)
30	Social norms	Choi and Lee (2016)
31	Social identity	Namian et al. 2016 Choi and Lee (2016) Andersen et al. (2015)
32	Supportive environment	Zohar (1980); Mohamed (2002) Glendon and Litherland 2001; Fang et al. 2006
	Project factors	
33	Project-level safety climate / culture	Namian et al. 2016 Patel and Jha(2014)
34	Work pressure	Namian et al. 2016, Teo and Fang 2006; Feng et al. 2012, Patel and Jha2014 Goh et al. (2012) and Han, Saba, Lee, Mohamed, and Pena-Mora (2014), Guo et al. (2016),
35	Project-level policies, procedures, and methods	Namian et al. 2016, Mohamed 2002; Fang et al. 2006).
36	Crew size	Namian et al. 2016
37	Worker distraction	Namian et al. 2016
38	Hazard visibility	Namian et al. 2016
39	Orientation / position / location	Namian et al. 2016
40	Local site conditions	Namian et al. 2016
41	Housekeeping / tidy practices	Namian et al. 2016
42	Use of temporary employee	Namian et al. 2016
43	Project characteristics	Namian et al. 2016
44	Nature of task/job/ task type/trade	Namian et al. 2016, Choe and Leite, 2017,
45	Site characteristics / layout configuration	Sawacha et al. (1999), Namian et al. 2016 Haslam et al. (2005)
46	Scope and schedule changes	Namian et al. 2016 Haslam et al. (2005)
47	Hazard predictability and perceivability	Namian et al. 2016
48	Cause - effect clarity	Namian et al. 2016
49	Equipment / tool characteristics	Namian et al. 2016
50	Frequency and duration of hazard exposure	Namian et al. 2016
51	Hazard multiplicity	Namian et al. 2016
52	Hazard presence and outcome onset lag	Namian et al. 2016
53	Site traffic	Teizer & Cheng 2015
54	Hazard recognition method / tool adopted	Namian et al. 2016

The resulting list of factors presented in Table 2.3 have been put clustered into four categories with the total number of 54 factors. The factors have been defined and described to provide proper perspective on how they affect hazard recognition performance of construction workers.

2.5.1 Personal factors

Those factors related to individual workers characteristics that can impact their hazard recognition performance. A total of nine factors were found in this category as follows:

1. **Safety Attitude / Culture:** the product of individuals' competencies and patterns of behaviour that determine their commitment to safety.

2. **Safety Complacency:** This is the false immunity developed by workers when they become used to unsafe behaviour repeatedly without facing its negative consequences, which then reduce their situational awareness and make them unmindful of dangerous outcomes over time.

3. **Cognitive and Visual Ability:** This refers to the mental and analytical reasoning capability of individuals which allows them to visualise the construction process and predict the likely hazards to be encountered in the process.

4. **Knowledge and Experience (competence):** this the general awareness and understanding of construction processes and associated hazards either through formal training or practical experience gained over time.

5. **Fatigue/Depletion:** loss of maximal force-generating capacity that develops during physical activities that are repetitive and energy demanding.

6. **Emotional State:** refers to the mental state that expresses how a person feels at a particular time. It may include feelings such as depression, fear, dread, worry, and anxiety, frustration, joy, and satisfaction, which can affect decision making. They also the way individuals respond in threatening/dangerous situations.

7. **Physical Worker Characteristics:** these are the bodily features of the individual such as visual and auditory abilities that directly impact how the individual receives messages from the external environment.

8. Concentration and attentional control:

9. **Smoking and drinking habits/substance use**: is a where workers engage in the use of drugs, alcohol, or other psychoactive substances, believing that taking such substances enhances their performance at work. However, the substances may usually have harmful consequences, among which is reducing their hazard recognition performance.

10. **Age:** the age of a worker has been linked to his/her ability to recognise hazards. While young people tend to be careless with hazards that can lead to accidents, aged people have the tendencies of being more careful and meticulous in the attention they pay when working in a hazardous environment.

11. Job positions: the position of a worker in a group or an organisation either as a leader, such as a mason or just a labourer can affect his/her hazard recognition level.

12. Race and ethnicity: Race and ethnicity of workers has been associated with their level of safety practices and hazard recognition performance (Moore & Wagner, 2014; Chan et al., 2016; Lyu et al., 2018).

13. Belief, culture, Value system Superstition: a situation where workers uphold certain beliefs, due to religion or culture, rightly or wrongly that make them act unsafely as a result of religion or culture. Some workers may believe in the intervention of certain superstitious practices on whether or not they get hurt by their conducts at work or when dealing with others. These will definitely influence the way such people will approach hazardous situations and recognise hazards at work.

2.5.2 Organizational Factors

These are factors related to the organizational environment, culture, and practices.

1. **Worker / Crew Involvement:** This refers to the extent to which workers are proactively involved in the projects hazard recognition and management processes of an organization.

2. **Supervisor / Leadership Involvement:** the extent to which supervisors/managers get fully involved in safety planning/management practices and serve as role models that reinforce safety values and hazard recognition practices.

3. **Safety Training Programs:** this means the effectiveness of training practices adopted by the organization to equip workers to properly recognize and manage both obvious and less-obvious hazards.

4. **Participant Empowerment/ motivation & accountability:** this refers to the incentive/disincentive system and empowerment programs available in the organisation for enhancing hazards recognition and management practices.

5. **Organizational Structure:** This means the hierarchical structure put in place by the organisation with responsibilities for hazards recognition and management. It can be restricted or distributed.

6. **Communication Channels:** this is the communication system in place for managing hazards information in the organisation. It can be workers to fellow workers or to the managers and supervisors.

7. **Regulations / Regulatory Policy Implementation:** This refers to the extent of safety regulations in place and whether or not they are properly implemented.

2.5.3 Social factors

These are a factors resulting from social interaction with people of the community and fellow workers.

1. **Hazard Recognition Ability and Motivation Levels of Peers**: This is the level of motivation and capabilities for hazard recognition of fellow workers

interacting in the same work environment, which influence the hazard recognition performance of individual workers.

2. **Social Conformance:** This is the extent of peer influence among co-workers which makes individuals adjust their behaviour to align with the norms of their work groups.

3. **Owner / Societal Influences:** This means the level of influence exerted by the project owners or communities where the projects are located on the workers in relation to safety and hazard recognition.

4. **Social norms:** This means a socially accepted and enhanced benchmark of behaviour which defines or limits the way a person or group interprets the world.

5. **Supportive environment**: the kind of environment provided by the organisation or a project may hinder or aid hazard recognition of workers (Tymvios & Gambatese, 2016; Zhang, Lingard, & Nevin, 2015).

2.5.4 Project factors

These are factors specific to the circumstances or the industry that can impact the hazard recognition performance at a worksite.

1. **Project-level Safety Climate / Culture:** this refers to the relative importance given by project participants to safety objectives and safety related issues in the organisation.

2. **Work Pressure:** this refers to the productivity and other delivery pressures put on workers by the organisation or supervisors which may increase mental stress and or reduce emphasis on safety hazard recognition performance of workers.

3. **Project-level Policies, Procedures, and Methods**: this refers to the project level safety policies and practices adopted such as pre-task safety planning, job hazard analysis, and safety inspection which may be integrated as part of standard work practices and may impact hazard recognition.

4. **Crew Size/composition**: this refers to the number of workers with different backgrounds and experiences that are put to work together and identify hazards collaboratively.

5. **Worker Distraction:** This refers to the disturbances resulting from the dynamic nature and the different activities of the construction site which can interfere with the attention of workers from their primary tasks.

6. **Hazard sensibility:** this refers to the way of detecting the hazard using any of the human sense organs. It can be visual sensing or through any other impulse.

7. **Orientation:** This is the physical and mental orientation of workers and their position or direction with respect to the hazard.

8. **Local site condition:** this entails the external factors specific to the area of work such as the elements of weather like temperature, humidity and so on which affect the workers physically and psychologically.

9. **Poor site management/Housekeeping Practices:** this is the extent of orderliness and tidiness maintained in a project site.

10. **Use of Temporary Employees:** this means the irregular and temporal nature of the most construction workers, which affect workers' familiarity with the safety policy and practices of the construction site.

11. **Project Characteristics:** this refers to the specific features of the project such as size, scope, materials, height and so on that dictate the kinds of hazards associated with it.

12. **Nature of the Task/job**: this entails the kind of trade engaged by the worker which defines the nature of hazards to be encountered. It has been found that each construction trade or occupation presents a unique pattern of safety data structure in terms of hazards encountered and sources of injuries (Choe & Leite, 2017)..

13. **Site Configuration/characteristics:** The physical characteristics of work environments such as site topography, soil condition, and constraints encountered like difficult access to site subareas, inadequate space and the likes.

14. **Scope and Schedule Changes:** the alterations in the scope of work or project schedule such as crashing, which may expose the workers to hazards that were never anticipated in the initial work plans.

15. **Hazard Predictability and Perceivability**: This entails the extent to which a hazard can be expected in a particular work scenario which often changes due to the highly dynamic and unpredictable nature of construction activities.

16. **Cause - Effect Clarity:** the familiarity of workers with the possible consequences or undesirable outcomes related to a specific hazard.

17. **Tool / Equipment Characteristics:** this is the nature and tendencies of the equipment used on site to expose a person to hazards at different work scenarios.

18. **Frequency of Hazard Exposure:** the rate of occurrence of a particular hazard, whether common or rare, which influence the kind of attention given towards its detection by workers.

19. **Duration of Hazard Exposure**: this is the length of the period of exposure to the hazards.

20. **Hazard Recognition Method / Tool Adopted**: the mode of tool of hazard recognition adopted, either such as automated systems and so on.

21. **Hazard Multiplicity:** This refers to the varieties of hazards present in a project site which may obscure the capacity of workers to recognise all of them.

22. **Hazard Presence and Outcome Onset Lag**: the period of time between the encounter of a hazard and occurrence of the consequence.

23. **Site traffic:** This refers to the number of different work teams and crews that move around the different areas or routes while performing their jobs in a construction site.

These factors have been reported to have impact on workers hazard recognition capability. However, this review revealed that the existing hazard recognition techniques both the

traditional and the modern systems do not consider these factors in a holistic manner. However, there are a few of them that considered one or more of the factors. This is believed to be among the reasons why the several studies reported the poor ability of workers to recognise most construction hazards in workplaces. No system exist for a holistic evaluation of workers hazard recognition capability based on these factors that have been fully established to impact workers hazard recognition capability. All the existing systems have been found to be scenario based, using simulation, virtual reality systems and other technological solutions. This work therefore bridges the gap by using the established factors in an effort to create solutions to poor hazard recognition capability of construction workers.

2.6 CONCEPTUAL FRAMEWORK

A study's conceptual framework shows the researcher's synthesis of the literature review on concepts or themes used to explain a particular phenomenon. It shows the researcher's understanding of the concept and interrelationships of the constructs and variables in a study and the order of researches that lead to the knowledge gap being filled by the researcher. It can be made in a narrative of graphical form.

This research developed models for evaluating hazard recognition capability of construction workers in different construction trades using the factors affecting hazard recognition capability of construction workers as the determinants. It has been established that hazard recognition is at the center of every safety management initiative (Carter and Smith 2006, Namian et al.; 2016).

Literature on construction safety and hazard recognition have considered hazard from different perspectives. Most of the works have their focus on one or more factors affecting hazard recognition. Namian et al.; (2016) made an attempt to present a comprehensive list of factors responsible for hazard recognition capability of construction workers. Since then, studies have been conducted on the influence of one or more of the factors on hazard recognition performance and to develop systems, mostly experimental, for improving hazard recognition capability of workers.Unfortunately, despite these solutions, poor hazard recognition remains a major cause of construction accidents on sites.

Jiang et al., (2015) suggest that construction safety management is a system that has so many components. They used the concept of system dynamics to explore the causation of construction accidents and poor hazard recognition in construction. Based on their work, safety has been considered according to the different segments of the system such as the organisation, the workers and managers, and the project environment. These components interact with one another to influence the level of hazard recognition and general safety management in every setting. This has therefore provided a premise to consider all the factors affecting hazard recognition capability of construction workers in a single framework, and relate them to the individual trades in which workers engage, to come up with a measurement and prediction instruments for determining hazard recognition capability of construction workers.

CHAPTER THREE

RESEARCH METHODOLOGY

3.0 Introduction

This chapter, opens with a discussion on philosophy and how it characterises construction management research, before describing the philosophical viewpoint of the current study as a background towards selecting the appropriate research methodology. Further, the chapter explains the various research approaches and designs before finally discussing and justifying the appropriate research methods that fit the objectives of this study.

3.1 Philosophical Considerations

Research methodology in social research encompasses not just the methods adopted in undertaking the inquiry, but also the rationale and the philosophical assumptions that supports a particular investigation. These, then, determine the particular research methods that are adopted to study a problem and to collect, analyses and interpret them. This implies that, research methods cannot be considered in isolation from the philosophical paradigms adopted by the researcher, as these directly affect the ways in which data is collected and analysed and the nature of the contributions to knowledge that are arrived at. The diagram/table below summarises the relationship between the aspects of a research paradigm:

Table 3.1: Research Paradigms

Paradigm	**Ontology** What is reality?	**Epistemology** What and how can I know reality or knowledge?	**Methodology** What procedure can we use to acquire knowledge?	**Methods** What tools can we use to acquire knowledge?
Positivism	there is a single reality	Reality can be measured and hence the focus is on reliable and valid tools to obtain that	Experimental research Survey research	Usually quantitative, could include sampling Measurement and scaling Statistical analyses Questionnaire Focus group interviews
Constructivism	there is no single reality or truth, and therefore reality needs to be created by individuals or groups,	therefore reality needs to be interpreted, it is used to discover the underlying meaning of events and activities	Ethnography Grounded theory Phenomenological research Heuristic inquiry Action research Discourse Analysis Feminist standpoint research, etc	Ususally qualitative, could include qualitative interview, observations, Participant, non-participant, case study Life history Narrative theme identification etc

Adapted from http://salmapatel.co.uk/academia/the-research-paradigm-methodologyepistemology-and-ontology-explained-in-simple-language/

It is therefore fundamental for any researcher in the management and social sciences to construct a philosophical position and orientation towards their investigation. Construction management knowledge area is relatively new and lies between the natural and social sciences, unlike many domains that have established practices emanating from a deeply

entrenched knowledge base (Dainty, 2008). As a result, construction management researchers are faced with conflicts of choice of methodologies among different theories of knowledge that compete for supremacy. Based on the theoretical and philosophical foundations of their inquiries, construction management researchers draw from both traditions in designing their studies. However, there are arguments suggesting the shift from strict positivism to either interpretivism or, in recent times, pluralism (Dainty 2008).

3.1.1 Ontological considerations

Ontology relates to the assumptions or belief regarding conceptual reality and the question of existence apart from specific subjects and events (Fellows & Liu, 2015). It has been defined by Scotland, (2012)) as the study of being. Ontological philosophy is concerned with the nature of reality. Researchers are required to take a position on how they think the world operates, how society is constructed and how this influences everything around us. Ontology talks about the difference between reality, our perception of reality and how this influences people's behaviour. In other words, it helps us to answer questions such as "what is the nature of what we know?" or "what is the nature of being?" According to Don-Solomon & Eke, (2018), ontological philosophy comprises of positivism and subjectivism as the two important school of thoughts upon which the science of being or reality on the nature of a societal phenomenon under study can be considered.

Positivism, otherwise known as objectivism is an ontological position that stresses that social phenomena and their meanings have an existence that is independent of social actors. This school of thought believes that the world is external and that there is a single objective

reality to any research phenomenon or situation regardless of the researcher's perspective or belief (Don-Solomon & Eke, 2018). The positivist philosophical viewpoint sees the positivist researcher as an objective analyst and interpreter of a tangible social reality (Fellows & Liu 2015). In other words, it assumes that the researcher is independent of, and neither affect nor is affected by the subject of the research. Researchers with this philosophy take a controlled and structural approach in conducting their investigations by identifying clear research topics, constructing appropriate hypotheses and by adopting a suitable research methodologies (Don-Solomon & Eke, 2018).

Objectivists hold the belief that as in natural science, theory is used in generating hypothesis, which is simply tested using direct observation with a view to finding universal laws and causal accounts on social phenomena. This entails the possibility of objectivity. Positivist researchers usually use quantitative methods of research to study relationships between entities because they are objective and yield generalisable and replicable results.

On the other hand, constructivism ontology, also known as interpretivism or subjectivism is the belief that there is no single reality or truth, and therefore reality needs to be constructed or interpreted. It is an important philosophical thought which holds that the researcher and the societal phenomenon under study are mutually interrelated and dependent (Don-Solomon & Eke, 2018). The goal of interpretivist research is to understand and interpret the meanings in human behaviour rather than to generalise and predict causes and effects. This researcher goes to the field with prior knowledge of the research context

but remains open to new knowledge throughout the study and let it develop with the help of informants. These researchers are therefore more likely to use qualitative methods to get insights on the presupposed multiple realities that exist in the particular contexts.

Given the nature of the research problem portrays the need to establish knowledge on the nature of influence of factors affecting hazard recognition on the capability of construction workers to recognise hazards in a work context. It also seeks to establish the determinants of hazard recognition and their relationship to hazard recognition capability of workers. This suggest that there is a single reality, which can be measured and known, the positivist approach therefore suffices in achieving the objectives of the study. According to Dainty (2008), most construction management researches also appear to be firmly rooted within the positivist tradition albeit some criticisms of the approach.

3.1.2 Epistemological consideration

Epistemology is the branch of philosophy involves the origins, nature, methods and limits of human knowledge (Fellows & Liu, 2015). It is concerned with addressing the facts by asking what the acceptable knowledge is. It helps one to define what acceptable knowledge about one's field of research is and what information is known to be true and is treated as fact due to rigorous testing (Don-Solomon & Eke, 2018). Epistemological philosophy according to Scotland, (2012) is concerned with the nature and forms of knowledge. In other words, epistemological assumptions are concerned with how knowledge can be created, acquired and communicated. This philosophy is most commonly used in scientific

research as it searches for facts and information that can be proved without doubt rather than changeable situations and opinions. There are four epistemological perspectives identified between social sciences and management research – positivism, realism, interpretivism and pragmatism.

3.2 Research Approaches

This involves the method of collection and analysis of data, which is generally classified into two – quantitative approach and qualitative approach (Cooper & Schindler, 2014; Kothari, 2004; Fellows and Liu 2015). Quantitative research approach involves the use of scientific methods, where the study of theory and literature yields precise aim and objectives with propositions and hypotheses to be tested Fellows and Liu (2015). This kind of research approach provides objective measures, therefore, they are used to answer questions such as what, how much, how many? Accordingly, the data and results are instantaneous or cross-sectional. According to Kothari, (2004), quantitative approach involves the generation of data in quantitative form which can be rigorously analysed quantitatively in a formal and rigid fashion. It can be further sub-classified into inferential, experimental and simulation approaches.

Inferential research approach is meant to form a data base from which to deduce characteristics or relationships of a given population. This usually involves survey research where a sample of a population is studied (questioned or observed) to determine its characteristics, and inference is then made that the population possesses the same features.

Experimental approach is considered to have much greater control over the research environment and in this case some variables are manipulated to observe their influence on other variables. Simulation approach on the other hand entails the creation of an artificial environment within which relevant information and data can be generated. This permits an observation of the dynamic behaviour of a system (or its sub-system) under controlled conditions (Cooper & Schindler, 2014; Kothari, 2004). Quantitative research works well in identifying general patterns and making predictions and is appropriate for mature knowledge domains.

On the other hand, Qualitative approach to research involves an exploration of a subject matter, sometimes without even a prior formulation with the objective of collecting data and information, understanding it such that a theory will emerge (Cooper & Schindler, 2014) (Fellows and Liu 2015). It is mostly exploratory in nature. It works best in developing new theoretical ideas and interpreting a theory. Qualitative research approach is majorly concerned with subjective assessment of attitudes, opinions and behaviour. Research in such a situation is a function of the researcher's insights and impressions. Such an approach to research generates results either in non-quantitative form or in the form which are not subjected to rigorous quantitative analysis. Generally, the techniques of focus group interviews, projective techniques and depth interviews are used (Kothari, 2004). Classifying any research as quantitative or qualitative or a combination of the two-mixed method depends on the nature of the research questions, objectives as well as the techniques of data collection and analyses.

3.3 Methodological Considerations of Current Study

3.3.1 Approach considerations

Kothari, (2004) described research methods as all the methods/techniques used in performing research operations. In other words, all those methods which are used by the researcher during the course of studying his research problem are termed as research methods. All the objectives of this research including the establishment of the factors affecting hazard recognition capability of construction workers, assessing their impact on same, establishment of key determinants of hazard recognition among the factors require quantitative and qualitative responses using facts and figures.

Therefore, both qualitative and quantitative data collection methods (field surveys with structured questionnaires and follow up interviews) and statistical analyses were employed to achieve all the objectives, including the development of a predictive model for evaluating hazard recognition capability of construction workers. This is because the nature of the problem that seeks to address 'how much' and 'what' questions regarding the phenomenon investigated. The data collection and analyses were both done using both qualitative and quantitative methods, which emphasises objective and some level of subjective measurements and statistical, mathematical, or numerical analysis of data. These include the determinants of hazard recognition capability of workers, weight of the factors, and developing the model for predicting hazard recognition capacity of workers in the different construction trades.

3.3.2 Research Design

In broad terms, 'research design' means the process of situating the researcher in the empirical world and connecting research questions to data (Dainty 2008). According to Kothari, (2004), research design refers to the organisation of conditions for collection and analysis of research data in a manner that aims to combine relevance to the research purpose with economy in procedure. It entails the conceptual structure within which a study is conducted; and constitutes the framework for the collection, measurement and analysis of data. Therefore, the design includes an outline of what the researcher will do from writing the propositions and their operational implications to the final analysis of data. In summary, every research design must, at least, contain a clear statement of the research problem; procedures and techniques to be used for gathering information; the population to be studied; and methods to be used in processing and analysing data.

Making decisions about research design is fundamental to both the philosophy underpinning the research and the ultimate contributions that the research is likely to make. A well thought out research design therefore is a necessity for any study to be systematic and successful.

This study has chosen a reductionist approach to examining a social phenomenon at hand (using a questionnaire survey). This is based on the research problem that seeks to answer the question what or how much?

3.4 Research Methods Adopted in the Study

3.4.1 Literature review

Every research is built on existing concepts emanating from the theories and literature established from previous studies. Theories are statements of principles and laws which have been found to hold. In this context, literature concerns the findings of previous studies on particular applications of theories. The first stage of this research involved the exploration of theories and review of conceptual and empirical literature in order to provide a theoretical background to the research, identify and articulate the research variables such as the concept of hazard recognition in relation to the health and safety management in the construction industry. This lays the foundation for achieving the first objective of the study, which centers on the identification of factors affecting hazard recognition capability of construction workers. The literature review also helped in arriving at a decision on the philosophical and methodological considerations for achieving the remaining objectives of the research.

In conducting this work, relevant literary materials were sourced from different bases such as the libraries of different institutions (both physical and electronic). Types of materials sourced include textbooks, research papers from peer reviewed journals and conference proceedings obtained from different databases such as science direct, the American Society of Civil Engineers online database, emerald, elsevier and many others. Similar works from research reports, technical notes, and government publications stored in either physical or electronic forms were also consulted for the search and review of related works that provide sound theoretical underpinnings of the research.

3.4.2 Field Survey

The second stage involved a field survey; using structured questionnaires, to collect data for achieving the objectives of the research. Surveys are conducted to collect information about a large population (Fellows and Liu 2015). Survey research has other advantages which include collecting a great deal of data about an individual respondent at a particular time at low cost. The method is versatile enough to be used in virtually any setting (Cooper & Schindler, 2014). Survey research involves the use of structured or systematic set of data collected on certain research variables. Information in surveys are collected from respondents using the personal interviews, questionnaires (mail, telephone or online) survey. According to (Kothari, 2004), survey researches possess the following features:

i. Survey research is a quantitative method, requiring standardised information from and/or about the subjects being studied.

ii. The main data collection method is by asking people structured and predefined questions. Their answers, which might refer to themselves or to some other unit of analysis, constitute the data to be analysed.

iii. Information is generally collected about a portion of the studied population, but it is collected in such a way as to be able to generalise the findings to the population. The sample should be large enough to allow extensive statistical analysis.

3.4.3 Research population

A research population is a distinct collection of individuals or objects characterised by at least a common feature, which forms the focus of a scientific investigation. The issue under investigation focuses on hazard recognition capability of construction workers, who are spread across different trades. Therefore, the population considered in this study is composed of the construction workers in different trades and the experienced construction managers, safety managers and site supervisors, who have direct contact with construction workers on site and have experience on the way these workers encounter, recognise and respond to various hazardous situations at work. However, these individuals comprising the population is far too wide for a full survey to be possible, it is necessary to take a portion of the whole that reflects the structure and characteristics of the entire population in order to undertake the study and draw meaningful and generalizable conclusions.

3.4.4 Sampling and sample size

In a research that involves a mall population size, the researcher usually considers the entire items in the population to carry out the inquiry. This procedure is referred to as census inquiry (Kothari, 2004). However, when the study involves a large number of items in the population, thus the population size is large, in that it is not possible to examine every item, and then the researcher is compelled to select a sizable number to concentrate on. Sampling is referred to as the process of selecting a representative proportion of a particular population for use in conducting a research. Often, it is possible to obtain sufficiently accurate results by studying only a part of a total population. Considerations of time and cost invariably lead to sampling a population for research. Kothari (2014) stated that it is important to ensure that the respondents selected should be as representative of the total population as possible in order to produce a miniature cross-section.

In developing a sampling design, it is imperative to pay attention to the following, among other requirements:

i. Type of population: the type of population may be of a known size (finite) or of unknown size (infinite).

ii. Sampling frame: this is the total number of items in a particular population when the population size is finite. For an infinite population, it is virtually impossible to have a sampling frame.

iii. Size of sample: this refers to the number of items to be selected from the population to form a sample. The size of sample should be optimum, neither be excessively large, nor too small. An optimum sample is one which fulfills the requirements of efficiency, representativeness, reliability and flexibility

iv. Sampling procedure: the researcher must decide the type of sample he will use

i.e., he must decide about the technique to be used in selecting the items for the sample. This is dictated by the nature of research and the type of population. In selecting a sampling procedure, researcher must ensure that the procedure does not cause a large sampling error and helps to control any form of bias.

Broadly, there are two categories of sampling design, viz., non-probability sampling and probability sampling. The former does not afford any basis for estimating the probability that each item in the population has a chance of being included in the sample (Kothari 2014). It is also known as deliberate, purposive or judgmental sampling. The researcher purposively choose the particular units of the population for constituting a sample such that they will be typical or representative of the whole. Examples of non-probability sampling include quota sampling.

On the other hand, probability sampling, also known as ‘random sampling’ or ‘chance sampling’ is the one in which every item of the population has an equal chance of inclusion

in the sample. It is considered as the best technique of selecting a representative sample. Examples of probability sampling include simple random sampling, stratified random sampling, multi-stage sampling, etc.

For this research, the population comprises construction workers in different trades and the construction managers or site supervisors and safety managers. Thus the size of the population is infinite because there is no any database that specifies their number. Therefore, to determine the appropriate sample size for this study, the following equation developed by Cochran (1963) for determining a representative sample for proportions was used.

$$n_o = \frac{Z^2 pq}{e^2}$$

Where n_o is the desired sample

Z^2 is the abscissa of the normal curve that cuts off an area α at the tails (1 - α equals the desired confidence level, e.g., 95%), e is the desired level of precision, p is the estimated proportion of an attribute that is present in the population, and q is 1-p. The value for Z is found in statistical tables which contain the area under the normal curve.

For this research, p = 0.5 (maximum variability), at 95% confidence level and ±5% precision. The resulting sample size is determined to be 385. This figure was proportionately distributed among the four groups of respondents in the research.

3.5 Data Collection Instrument

Primary research data are collected either through experimental set ups or in descriptive researches through surveys. In surveys, primary data can be collected through observation, interview, questionnaires, and so on (Kothari 2014, Fellows and Liu 2015). This data collection is a communication process between the researcher (collector) and the respondent

(provider), with the aim of maximising the amount and accuracy of the data being collected.

The use of questionnaires for data collection is quite popular, among researchers, especially in case of large investigations. . A questionnaire consists of a number of questions printed or typed in a definite order on a form or set of forms. It is sent to the target respondents with a request to answer the questions and other information regarding the subject of inquiry (Kothari, 2014). Questionnaires come in two forms- open and closed ended. Open ended questionnaires are designed to collect information in full, not minding the form, content and extent to which the respondent may wish to provide. Such questions are easy to ask but the answers very difficult to analyse. Closed ended (structured) questionnaires on the other hand, are designed with a set of answers determined by the researcher in which a respondents select options that match their answers. Some allowances are provided to accommodate flexibility of responses and avoiding bias by providing an option where the respondents state answers they feel are not provided for by the researcher. This kind of questionnaires are easy to analyse (Fellows and Liu 2015).

Questionnaires may be administered by post, mail/web or even physically to respondents by the researcher or his agents. Questions in the questionnaire must be unambiguous and easy for the respondents to understand and answer. They must also strictly address the objectives of the research they are meant to cover. Questionnaires have advantages of being the lowest cost option in survey research, reaching expanded geographic coverage without increase in costs, allowing respondents time to think about questions and so on. Based on the foregoing, two sets of structured questionnaires were used to collect information and address the objectives of this research.

The first objective of the research was to identify the factors influencing hazard recognition capability of construction workers. To achieve this, the list of factors influencing hazard recognition capability of construction workers as identified from literature was used to prepare the questionnaire. This was meant to ascertain the relevance of the factors to hazard recognition capability of workers from the experts' perspective, to confirm the categorisations of the factors. They were also requested to suggest additional ones that were not covered by the literature review.

The questionnaire (see Appendix A) comprised of two sections, 1 and 2. Section 1 contains preliminary questions related to attributes respondents. These question were on the size of the organization, nature of work handled, and years of experience, and their educational qualification. The questions and were categorised into four sections, in accordance with the categorisation of the factors impacting hazard recognition performance of construction workers. The categories are:

A. Personal factors

B. Social factors

C. Organisational factors

D. Project factors

Section A of the table had 23 factors, section B had 12, section C had 16 and section D comprised of 9 factors. All these were drawn from the factors established from literature. The experts were requested to assess the factors on the basis of their level of relevance to hazard recognition of construction workers using a scale of 0 to 4, (where 0 – Irrelevant, 1 – Unsure, 2 – Fairly Relevant, 3 – Relevant, and 4 - Most Relevant). Another option was presented as 'Recast', for the experts to choose if they feel the wording is not appropriate. They were also expected to suggest the recast version of the factors as the case may be. Moreover, an evaluation sheet was presented at the end of the tool for them to respond to certain open ended and closed ended questions regarding the comprehensiveness of the list.

To achieve the subsequent objectives of the research, another structured questionnaire was designed. In this case, the questionnaire was meant to evaluate the extent to which the factors established from literature and the confirmed/validated through the first experts' survey affect hazard recognition capability of construction workers. The second questionnaire (Appendices B and C) was also in two parts, A and B. Part A comprised of questions regarding the characteristics of respondents, while part B was focused on the evaluation of the extent to which the factors affecting hazard recognition capability of workers. The questionnaire was designed for two sets of respondents, the tradesmen

(workers) and the professionals (construction managers, safety managers and site supervisors). For each questionnaire type, the information requested by the section A differ a little bit to capture the relevant demographics for each class of respondents. For the workers, issues such as the trade engaged by a worker, years of experience, educational qualification (where the respondents attended any form of school), and the nature of jobs being handle by their organisations were enquired. In the case of the professional respondents, the demographic information requested were the nature of the projects they work on, their designations, years of professional experience and educational qualifications. The section B of the questionnaires were both containing the same information-requesting the respondents to indicate the extent to which the factors affect hazard recognition of construction workers. While the ones answered by the professionals were meant to elicit responses on the influence of the factors on hazard recognition capability of construction workers generally, the ones answered by the workers were meant to elicit responses from the perspective of the respective trades engaged by the workers. Both the questionnaires used a 5-point Likert scale, ranging from 1=very low,

2=low, 3=average, 4=high, 5=very high.

3.5.1 Validation of the data collection tools

In both cases, the questionnaires were pilot tested to ensure validity. In the first exercise, a panel of five experienced researchers were selected for a pilot evaluation of the questionnaire. The researchers were selected based on their level of experience in research and supervision, including construction safety researches. Their years of experience ranged

between 10 to 25 years. The objective of the pilot validation was to test the clarity of the wordings and the entire structure of the tool. This was achieved in a meeting that lasted for about three hours. The views and suggestions arising from the interaction with the panel were used to standardise and improve the tool. For example, some questions and statements were recast while others were merged to avoid repetition. Expressions were improved for clear understanding of the expected respondents. Similarly, some questions were introduced to ensure adequate coverage of all the relevant issues in the evaluation of hazard recognition capability of workers. The categorisation of factors considered in developing the questions were also validated from academic point of view.

On the second questionnaire, which was developed to assess the extent to which the factors affect hazard recognition capability of construction workers, postgraduate students in the M. Sc. Construction Management class were used for the validation. Ten students were given the questionnaires to fill and were asked to suggest improvement in terms of the structure of questions, understanding of the issues covered and the timing for filling the questionnaire. All suggestions were used in finalising and improving the questionnaire prior to the distribution to respondents.

3.5.2 Psychometric properties of the measurement scales

The psychometric properties of a measurement scale refer to certain parameters that indicate the extent of soundness of a measurement tool. Three criteria are used to evaluate any measurement scale. They are: validity, reliability and practicality (Cooper and Schindler, 2014, Kothari, 2014).

3.5.2.1 Validity Measures

Validity is the most critical criterion indicating the soundness of a research instrument. There are two major forms of validity discussed in many research literature: external and internal validity. The external validity concerns the manner in which data used in a research makes generalization of research findings possible across persons, settings, and times (Cooper and Schindler 2014). On the other hand, internal validity entails the extent to which a test instrument measures what it is actually supposed to measure. In other words, internal validity is the degree to which variances found with a measuring instrument reflect true variances among those being tested. Research literature widely accept the classification of internal validity into three classes: Content validity; Criterion-related validity and Construct validity. This section only describes content validity, which was employed in the process of carrying out the work.

Content Validity refers to the extent to which a measuring instrument provides adequate coverage of the investigative questions guiding the subject matter under study. If the instrument contains a representative sample of the research population, the content validity is said to be good (Cooper and Schindler, 2014, Kothari, 2014). The determination of content validity is mostly judgmental and intuitive. In order to evaluate content validity, it is essential that the researcher agrees on what elements constitute adequate coverage of the subject matter first. Secondly, items to be scaled, and the scales to be used must all be decided upon. This logical process often relies on the intuition of the researcher and is unique to each research designer (Cooper and Schindler, 2014).

Cooper and Schindler, (2014) and Kothari, (2014) opined that content validity can be achieved through careful examination of the measuring instrument by a panel of persons who shall judge how well the instrument meets the standards, however, there is no numerical way of expressing it. The panel independently assesses the test items for an instrument to determine those that are essential, useful and necessary for achieving the stated objectives of the instrument. In any case, content validity is primarily concerned with inferences about test construction rather than inferences about test scores

3.5.2.2 Reliability

Reliability is another important test of sound measurement. A measuring instrument is believed to be reliable to the extent that it provides consistent results (Cooper and Schindler, 2014 and Kothari, 2014). Reliable measuring instrument does contribute to validity, but a reliable instrument does not necessarily possesses validity. According to Kothari (2014), a reliability measure is not as valuable as validity, but it is easier to assess reliability in comparison to validity. If the quality of reliability is satisfied by an instrument, then while using it we can be confident that the transient and situational factors are not interfering. Reliability is concerned with estimates of the degree to which a measurement is free of random or unstable error. Reliable instruments are robust; they work well at different times under different conditions.

Reliability measure is considered in terms of stability and equivalence. Stability entails securing consistent results in repetitive measurements of the same entity using the same

instrument. Equivalence, on the other hand is concerned with the extent of error that may be introduced by different samples of the population being studied. In this study, reliability of the instrument was evaluated using the Cronbach alpha test.

3.5.3 Data Collection Procedure

This section describes the data collection procedure at different levels of the research as follows:

3.5.3.1 Expert validation of the factors

After the pilot validation with the panel of researchers, the revised questionnaire for the validation of the factors affecting hazard recognition of construction workers were then subjected to the validation by industry experts. The essence of doing this was to arrive at a standardised list of factors with input from both researchers and industry practitioners. It was also meant to ensure wide coverage of all the issues relevant to the evaluation. The expert validation was also aimed at providing more empirical evidence supporting the categorisation of factors considered in the evaluation of hazard recognition competencies of construction workers.

Construction managers and safety managers with minimum of 5 years of professional working experience were selected to do the validation exercise. This is because they are the professionals that deal with construction workers directly in managing safety and hazard recognition on construction sites.

To ensure high quality and integrity of the data, only professionals with experience from 10 years in construction management or construction safety management were contacted to perform the validation exercise. They were requested to assess the questionnaire on the basis of the following:

i. Relevance of the questions/statements

ii. Adequacy of the issues considered

iii. Clarity of wording of the questions/statements

Based on the criteria for selecting the interviewees, 25 experts were purposively selected and invited to take part in the evaluation exercise. The experts were contacted via emails and phone calls to seek their consent and to explain the purpose of the validation exercise. The exercise involves filling the evaluation questionnaire, and a follow up interview. The purpose of the interview was to probe the responses of the experts and provide more clarification on issues that were not fully understood, in order to ensure reliability of the data. The experts were meant to understand that participation in the evaluation process was entirely voluntary. 14 experts indicated interest to participate in the study. Subsequently, the tool was sent to them and appointments were made to conduct the interviews. The interviews lasted for between 45 minutes to 1 hour with most of the respondents.

The introductory section of the questionnaire explained the purpose of the validation and provided clear instructions on the validation process. Some preliminary questions were also asked for the experts to provide information regarding nature of construction works they handled, their professional affiliations, years of experience, positions in their organisations

and level of educational attainments. These were asked to provide some bases for analysing the quality of responses of the validation.

During the follow up interview, the objective of the exercise, the factors used as well as the methodology of developing the evaluation tool were further explained to the participants to establish a common understanding prior to the interview. They were also specifically made to understand the significance of ensuring consistency in their responses.

3.5.3.2 Main data collection

In the second segment of the data collection exercise, copies of the questionnaires were self-administered by the researcher to the respondents. Other copies were given to some research assistants and friends from personal contacts across the country to ensure optimum coverage of a reasonable number of respondents with different backgrounds and geographical locations. Moreover, some questionnaires were sent to the respondents via emails for ease of administration. The use of different methods in distributing the questionnaires was meant to ensure adequate coverage of the respondents and to achieve reasonable response rate within a short period of time.

3.6 Methods of Data Analysis

Analysis here denotes the scrutiny and computation of certain indices or measures and searching for patterns of relationship that exist among the groups of data. Analysis may be categorised as descriptive analysis or inferential analysis (Inferential analysis is often known as statistical analysis). Descriptive data analysis largely involves the study of

distributions and summarising the data. It describes items in the data based on the different characteristics (Kothari, 2014). The tools of analysis in this context include frequency distribution, measures of central tendency (mean, median and mode) and measures of dispersion (range, mean deviation, standard deviation, quartile deviation and variance).

Inferential statistics are techniques that allow researchers to draw inferences from numerical/mathematical data. They allow generalisations to be made about the population by examining a particular sample. Some of these techniques include correlations, regressions, and comparison of means tests (such as ANOVA or t-tests). Others include multiple regression, factor analysis, multidimensional scaling, logistic regression and so on. In this research, a combination of both descriptive and inferential statistical techniques were used to achieve the different objectives. These include frequency distribution, percentages, mean value analyses and standard deviation, ANOVA, Factor analysis and logistic regression analysis.

The responses were collated, sorted and then analysed using descriptive statistical tools such as frequency, means and standard deviation. The analyses were conducted using the Statistical Package for Social Sciences (SPSS) for windows version 23. The follow up interview data were analysed through qualitative content analysis.

3.6.1 Respondents' characteristics

The characteristics or demographic variables of the respondents are all presented in a single table. The characteristics covered by the questionnaire include the nature of job handled by

the respondents' organisations, highest educational qualification obtained, years of experience and the type of trade engaged in the case of the workers. All these characteristics are tabulated into a single table and presented in chapter 4.

Objective 1: identification of the factors affecting hazard recognition capability of construction workers: Analysis of the experts' responses.

This objective was addressed using literature review and experts validation exercise using a questionnaire. Descriptive statistical tools were used to analyse the information provided by the respondents in this exercise. These include the mean, standard deviation and percentages. These were used for the purpose of summarizing the data for the subsequent exercises in the study.

Objective 2: To assess the extent to which the factors influence hazard recognition capability of construction workers.

Univariate descriptive statistics such as mean the standard deviation were used for analysing the extent to which the factors affect hazard recognition capability of construction workers.

Group means for each of the categories of factors were compared across the different groups of respondents in order to identify any numerical variability among them in assessing the factors.

3.6.2 Analysis of variance

To establish statistically the significance of difference between the ratings of the group of respondents, one-way analysis of variance (ANOVA) was employed. ANOVA is a useful technique concerning researches in the fields of social sciences. This technique enables the researcher to perform a simultaneous test of differences among the means of all the groups of respondents in the study. According to Kothari (2004), ANOVA is a procedure for testing the difference among different groups of data for homogeneity. There may be variation between samples and also within sample items. ANOVA involves splitting the variances for analytical purposes. Hence, it is a method of analysing the variance to which a response is subject into its various components corresponding to various sources of variation.

Objective 3: To establish the determinants of hazard recognition capability of workers:

Since there is no existing self-assessment instrument for evaluating hazard recognition capability based on these factors, there is the need to establish that empirically by identifying the key determinants of a worker's hazard recognition capability. To achieve this, factor analysis was undertaken to establish the structure of the key determinants, which would be used to form the assessment tool.

3.6.3 Factor Analysis

Factor analysis is an interdependence multivariate statistical technique. By interdependence, it means all variables are considered simultaneously without any distinction between the dependent and independent variables (Hair, Black, Babin, & Rolphe, 2010). It is primarily used to establish the interrelationships among a large number of variables for the purpose of reducing or defining the underlying structure among them (Hair et al., 2010; Kothari, 2004). Data reduction refers to the removal of redundant (highly correlated) variables from a set of data, resulting in a smaller number of uncorrelated dimensions. On the other hand, structure detection means examining the underlying (or latent) relationships between the variables that help in explaining the pattern of correlations among them. The key objective of factor analysis is to condense the information contained in a number of variables into a smaller set, with minimal loss of information. It is a powerful basis for establishing summated scales by providing an empirical estimate of the structure of the variables.

Factor analysis can be achieved using either an exploratory or a confirmatory approach. According to Hair et al, (2010), there is a debate among researchers as to the most appropriate role of factor analysis. While many researchers consider it as only exploratory, others see it as confirmatory. In the exploratory perspective, the technique becomes handy only in establishing structures among a set of variables, or serves a data reduction purpose, where the researcher takes what the data gives. In a confirmatory approach, the researcher may have a prior thought on the actual structure of the data based on a theoretical or empirical evidence, and the factor analysis technique is used to test the extent to which the

data meets the expected structure. However there are circumstances where some elements of the two perspectives may feature in one another based on the peculiarities of the problems at hand.

The choice of factor analysis in this research is meant for the purpose of establishing the underlying structure among the array of factors influencing hazard recognition capability of construction workers. This is to enable an accurate prediction by removing redundancy among the set of variables at any level of the analysis.

3.6.3.1 Suitability of Data for Factor Analysis

To use factor analysis in any research, the data must be suitable and adequate. The following were considered to determine the suitability of the data.

(a) inter-item correlation matrix;

(b) off-diagonal of the anti-image covariance matrix;

(c) Bartlett's test of sphericity; and

(d) Kaiser-Meyer-Olkin measure of sampling adequacy.

In the first place, the inter-item correlation matrix should reveal positive relationships among each of the items; however, items with correlations that exceed .90 and above must be analysed to ensure that they are not measuring the same thing. Secondly, the values on the off-diagonal of the anti-image covariance matrix are expected to be small, indicating that the appropriateness of the data for factor analysis. Third, Bartlett's test of sphericity was also used to determine whether the correlation matrix is an identity matrix; that is, all diagonal terms are 1 and off-diagonal terms are 0. It measures the multivariate normality of

the variables and the measure of sample activities (SMA). A large Bartlett's test statistic is an indicator that the off-diagonal terms are near zero and the data are suitable for factor analysis.

Another test for the suitability of factor analysis is the Kaiser-Meyer- Olkin (KMO). This test measures the adequacy of the sampling and the distribution of values among factors. It tells whether the partial correlations among variables are small. The procedure compares the magnitude of sum of the squared partial correlation coefficients of all variables to the sum of their squared correlation coefficients. If the magnitude is small, the KMO measure is close to 1. A suitability index ranging from 0 to 1 has been provided with the following breakdown by Keiser (1987).

Table 3.2: KMO Suitability Index

KMO Value	Interpretation
0.9 and above	Marvellous
0.8 - 0.9	Meritorious
0.7 - 0.8	Middling
0.6 - 0.7	Mediocre
0.5 - 0.6	Miserable
under 0.5	Unacceptable

However, Burns & Burns (2008), Hair et al (2010) and (Chan 2012) suggest that KMO values greater than 0.5 indicate dataset suitability for factor analysis.

3.6.3.2 Factor Extraction

There are two similar yet unique methods of extracting or defining the factors that will represent the structure of the variables in factor analysis. Component factor analysis, otherwise referred to as principal component (PC) which is used when the objective is to

summarise most of the original information in a minimum number of factors for prediction purposes. (Hair et al., 2010). Usually, a few components will account for most of the variation, and these components can be used to replace the original variables. In contrast, common factor analysis is used to identify the underlying dimensions or factors that reflect what a set of variables share in common. This extraction method goes a step further by adding the assumption that some of the variability in the data cannot be explained by the components (usually called **factors** in other extraction methods). This makes the study of relationship among the variables more ideal.

There is considerable debate about which of the factor analysis methods is more appropriate (Gorsuch, 1990). Some of them argue that common factor analysis is more appropriate when the objective is to identify latent dimension represented in the original variables and when the researcher does not have much idea regarding the specific and error variance and therefore wish to eliminate them. Component analysis is said to be more appropriate when data reduction is the main concern and the researcher has some knowledge about the specific and error variance representing a small proportion of the total variance (Hair et al 2010). Component analysis is said to have more theoretical basis but it has some shortcomings of factor indeterminacy, meaning that it can compute different scores in one model for a particular respondent, with no single solution as in component analysis, although the differences are not always substantial. It also has the tendency of calculating invalid communalities which may lead to deletion of some variables in the analysis (Hair et al, 2010).

However, it was observed that the choice of extraction method does not necessarily affect the results of factor analysis in most cases, since the difference is not significant in most applications. Empirical research has often shown similar results (Gorsuch, 1990; Velicer & Jackson, 1990). Both common factor analysis and component analysis arrive at essentially identical results if the nature of variables exceed 30 (Hair et al 2010). For this reason, principal component analysis was used for this study with a view to achieve higher percentage variance explained in the established structure of the factors affecting hazard recognition capability of construction workers. This is also to retain as more factors a possible that would be useful in the subsequent analyses.

3.6.4.3 Factor Rotation

In order to ensure interpretability of factors, factor rotation must be necessarily considered. Rotation removes ambiguities in understanding the results. According to Kothari (2004), a different factor rotation always reveals a different structure in the data. Therefore, to make sense of the results of any factor analysis, it is necessary to select the right rotation method. The major aim of any rotation is to arrive at some theoretically meaningful factors and where possible the simplest factor structure (Hair et al 2010). There are basically two methods of rotation; orthogonal, in which the axes of factor matrix rotation are maintained at 90 degrees and oblique rotations, when the angle of rotation is not constrained to be at 90 degrees between the reference axes. When factors are assumed to be uncorrelated or independent, orthogonal rotation, which is the simplest form of rotation, is deemed appropriate.

Oblique rotation is however used, when the factors are considered to be correlated. Oblique rotation more accurately represents the complexity of the variables. However, in practice, the objective of any rotation method is to simplify the rows and columns of the factor matrix to facilitate interpretation. Orthogonal rotation is more widely used because its methods are more developed and more available in most packages. According to Hair et al (2010), there is no compelling analytical evidence suggesting the use of one rotational method or another.

The varimax method of orthogonal rotation was chosen for this research because it gives clearer association between variables and factors than others and it is more widely used in similar studies.

3.6.4.4 Number of Factors to Extract

Both factor extraction methods are concerned with finding the best linear combination of variables that account for more variance in the data than any other. In any case, the researcher is guided by conceptual foundation and empirical evidence in making such a crucial decision Hair et al (2010). Various criteria such as latent root, scree test, percentage variance and a priori criteria are used in this regard. Based on the suggestion of Hair et al (2010), several trials were performed in order to get the best structure of the variables. This is to avoid using too many or too few factors and to determine the structure that is in line with the theoretical underpinnings in the research area.

3.6.4.5 Factor loadings

A factor loading represents the correlation between an original variable and its factor. In making a decision regarding the factor loading acceptable in a structure, consideration is made on either the practical significance of factor loadings or on their statistical significance.

Using practical significance, the squared loading is the amount of variable's total variance explained by the factor. Thus 0.3 loading approximates to 10% explanation and 0.5 translates to approximately 25% of the variance explained by the factor and so on. On this basis, for a sample of 100 or larger when practical significance is preferred to statistical significance, according to Hair et al (2010):

- Factor loadings in the range of $\pm$0.3 to $\pm$0.4 areconsidered to meet the minimal level for interpreting a factor structure
- Loadings $\pm$ 0.50 or greater are considered practically significant
- Loadings exceeding 0.7 are indicate a well-defined structure

In assessing statistical significance of factor loadings, the loadings should be evaluated in a stricter level due to the large standard errors associated with factor loadings. For example a loading of 0.55 and above should be considered significant for a sample of 100 respondents,

0.75 is required for a sample of 50 respondents and so on.

Other considerations include adjustment of acceptable factor loadings based on the number of variables being considered. As the number increases, the acceptable level of factor loading decreases. Based on the foregoing, this study considered a factor loading of 0.5 and above to be acceptable in the results and all decisions are made based on that. This is considering the large enough sample size in the research and taking cognizance of both the practical and statistical significance of the loadings. Other researchers also adopt a bit lower than 0.5 with different justifications.

To interpret the results of factor analysis, one has to consider the factor matrix, the following five steps are followed to arrive at the final results from the rotated factor matrix:
Step 1: examine the factor matrix of loadings. An optimal structure can only be achieved when the variables have significant loadings on a factor.

Step 2: identify the significant loadings for each variable. When a variable loads significantly on more than one factor, it is considered cross loaded and this makes interpretation difficult. This can be significantly reduced by changing the rotation methods, after which any factor that persist in cross loading at >0.35 was deleted.

Step 3: assess the communalities of the variables. Only variables having communalities greater than 0.5 were retained in the analysis.

Step 4: re-specify the factor model if needed by deleting problematic variables, changing rotation methods or decreasing or increasing the number of factors as the case may be.

Step 5: label the factors: when acceptable facto solution has been obtained, the variables with the most significant loadings can then be used in naming or labelling the factors to have a meaning based on the theoretical underpinnings of the research.

3.6.4 Reliability analysis of the factors in the structure

After conducting the factor analysis to establish the structure among the factors affecting hazard recognition capability of workers, the internal consistency of the factor structure needs to be established. Reliability analysis is used to measure the internal consistency between multiple measurements of a variable. According to Hair et al (2010) and Cooper & Schindler (2014), internal consistency determines the degree to which the items in a survey instrument are homogenous and reflect the same underlying constructs. A common tool used for measuring internal consistency and reliability is the Cronbach alpha coefficient. Generally, the agreed level of internal consistency measure using Cronbach's alpha is 0.7, although it may decrease to 0.6 in exploratory research (Hair et al 2010). However, Cronbach alpha value has been reported to have direct relationship with the number of items being measured. The more the number of items the more the reliability value and vice versa (Hair et al 2010).

Objectives 4 and 5: To determine the relationships among the determinants of hazard recognition capability and to develop a factor-based model for predicting hazard recognition capability of workers based on their trades

Binary logistic regression (LR) analysis was used to explore the relationship among the factors influencing hazard recognition capability of workers and to develop a predictive model.

3.6.5 Logistic Regression

Logistic regression is a mathematical modeling technique which is useful in situations where the presence or absence of a categorical characteristic or outcome (a binary dependent variable) is to be predicted based on values of a set of predictor (independent) variables (Pallant, 2010). It is similar to linear regression except that it is suited to models in which the dependent variable is dichotomous. LR helps in assessing the extent to which a set of categorical or continuous predictor variables predicts or explains a categorical dependent variable. It provides an indication of the adequacy of the model (set of predictor variables) by assessing 'goodness of fit'. It gives an indication of the relative importance of each predictor variable or the interaction among a number of predictor variables. It models the logit-transformed probability as a linear relationship with the predictor variables.

More formally, let y be the binary outcome variable indicating /success with 0/1 and p be the probability of y to be 1, p = prob(y=1).

Let X1,….., Xk be a set of predictor variables. Then the logistic regression of y on X1, …, Xk estimates parameter values for$\beta 0, \beta 1, \ldots, \beta k$ via maximum likelihood method of the following equation.

$$\text{Logit}(p) = \log(p/(1-p)) = \beta 0 + \beta 1 x1 + \beta 2 X2 + \ldots.. + \beta k Xk \quad (1)$$

In terms of probabilities, the equation above is translated into

$$p = \exp(\beta 0 + \beta 1 X1 + \ldots + \beta k Xk)/(1+\exp(\beta 0 + \beta 1 X1 + \ldots + \beta k Xk)). \quad (2)$$

Logistic regression coefficients can be used to estimate odds ratios for each of the independent variables in the model.

Alternatively, other models such as the probit model could have been used instead, since the factors will be treated as binary variables. Differences between logit and probit models are generally marginal. The logistic model has marginally flatter tails, that is, the probit curve approaches the 0 and 1 Y-axis probability values slightly more quickly (Aznar, Pellicer, Davis, & Ballesteros-pérez, 2017). In this study, logistic has been preferred over probit as the former allows for an easier interpretation (logistic regression, unlike probit, can be interpreted as modeling log odds).

This technique has been used in social science, psychology, and organizational behavior. In construction management research, a logistic model was used to predict the likelihood of disputes in construction contracts. Wong, (2004) has used it to develop contractor performance prediction model. Russell, Jaselskis, & Members, (1993) used it to predict contractors' failure. Ye et al., (2018) have used it to analyse firms' willingness to

participate in PPP projects. LR was also used by Yiu, Cheung, & Mok, (2007) for predicting the likely mediation outcomes in conflicts. Other researchers have used LR to predict bid or no-bid decisions (Lowe & Parvar, 2010), labour productivity (Gurmu & Aibinu, 2017) workplace stress among construction professionals (Bowen, Edwards, Lingard, & Cattell, 2014) and work life balance (Malone & Issa, 2014) among others. Notwithstanding, LR application in construction safety is relatively less popular compared to other statistical analysis techniques.

Logistic regression does not make assumptions regarding the distribution of scores for the predictor variables; however, it is sensitive to high correlations among the predictor variables (multicollinearity). Outliers can also impact the results of logistic regression.

All of the independent variables were incorporated into the analysis using the Forced Entry Method, in which all predictor variables are tested in one block to assess their predictive ability while controlling for the effects of other predictors in the model was used. Other techniques—for example, the stepwise procedures (e.g. forward and backward) which allow for the specification of a large group of potential predictors from which the software picks a subset that provides the best predictive power. These stepwise procedures have been criticised because they can be influenced by random variation in the data, with variables being included or removed from the model on purely statistical grounds (Pallant, 2011).

3.6.5.1 Data Manipulation for Logistic Regression Analysis

In order to perform logistic regression analysis, it is necessary to transform the data to create the categorical dependent variable. From the data set, the mean and median response values were established for all variables. For each variable or factor, a median-split method (Bowen et al., 2014; Lingard, 2013) was used to position the responses for each variable into one of two (categorical) groups, including values falling below the median and values equal to or exceeding the median. The median value for the level of workers' hazard recognition capability was 3.0 (on a scale of 1–5). Therefore, the responses were grouped into those <3.0 and those ≥3.0, which created a dichotomous (dependent) variable (HRC). As suggested by

Pallant (2010), the value of '0' was assigned to the response grouping that revealed a lack or absence of the characteristic of interest. In this case, '0' indicated lack of hazard recognition capability and '1' was used to represent having hazard recognition capability. The independent variables were aggregated into their four categories with their mean values used in the analysis. This exercise of data manipulation gave rise to the logistic regression modeling which made possible the testing of models to predict categorical outcomes (Pallant 2010).

3.6.5.2 Logistic Regression Model Development

In this study, LRs were performed using the IBM SPSS 23 software for windows. LR prediction model was developed based on the 541 responses determined for developing the model, while 20 responses were reserved for validation purposes. Logistic regression analysis was performed to assess the relationship between the factors influencing hazard

recognition capability of construction workers as well as developing the model for predicting

HRC of workers. The results of these analyses are presented in the following sections.

CHAPTER FOUR

DATA PRESENTATION, ANALYSIS AND DISCUSSION OF RESULTS

4.1 Introduction

In this chapter, the results of the research are presented and discussed, with inferences drawn where necessary. The chapter is presented in the order of the objectives of the research. Each objective is used as a heading before presenting results that show the achievement of the objective.

4.2 Identification of Factors Affecting Hazard Recognition Capability of Construction Workers

The main objective of the expert validation exercise was to determine the relevant questions or factors that will make up the tool for the evaluation of the construction workers' hazard recognition capability. In other words, the emphasis was on determining

the final standardized evaluation tool that captures questions and statements that are relevant to, and adequate enough for the evaluation of workers' hazard recognition capabilities.

In order to standardise the evaluation tool, the experts were presented with the tool to assess the relevance, adequacy and ease of understanding of all the questions and statements prepared for the evaluation of workers hazard recognition capabilities. In the first place, the experts were given the questionnaires to answer based on the above criteria. Afterwards, follow up interviews were conducted with the experts in order to probe some of their responses and to further understand the results. Probing the responses was important because it provided an opportunity to examine the respondents' level of understanding of the issues and clarification on some questions. Reasons for their responses were further explored from their perspectives.

Apart from the questions on the background of the experts, a table was presented with questions seeking the experts to indicate the degree of relevance of the questions/statements based on a five point Likert scale, from 0, which denotes "irrelevant", 1, representing "unsure", 2, "fairly relevant", 3, "relevant", and 4, denoting "most relevant". In order to select the question/statement that would finally make it into the evaluation tool, any statement or question that has a mean of 2 and above was selected. This is because, the essence of this exercise was to establish consensus among the experts on the factors and relevant questions to be used in the evaluation tool. Therefore, ranking is

not the most important, but establishing the fact that a certain factor under consideration is relevant for the evaluation.

Therefore, only factors that the experts rated as 'irrelevant', or those they are 'unsure' about their relevance were not included. The findings and discussions are presented in the following sections:

Table 4.1 presents the results of respondents' characteristics for the experts that participated in the evaluation exercise.

Table 4.1: Characteristics of the Experts

Characteristics of the Experts				
Years of Experience of the Experts				
Year Range	Frequency	Percent	Average	Cumulative
6-10	2	14.3	**17.4**	**244**
11-15	4	28.6		
16-20	3	21.4		
21-25	3	21.4		
26-30	2	14.3		
Total	**14**	**100**		
Discipline of the Experts				
Disciplines	Frequency	Percent		
Safety Manager	6	42.9		
Construction Manager	8	57.1		
Total	**14**	**100.0**		

Source: Survey 2017

From the Table 4.1, it can be seen that all the experts have acquired professional experience from 10 years and above. Professional experience in this context refers to the experience of an expert in dealing with construction workers of different trades directly while performing their duties, encountering and managing construction safety hazards. About 14% of the experts have exactly 10 years of experience, 28% have recorded between 11 to 15 years of experience in managing construction safety. Further, about 21% of the experts have acquired between 16 to 20 years of professional experience, while another 21% garnered between 21 to 25 years of experience. The last 14% of the experts have acquired between 26 to 30 years of professional experience. Overall, the experts have an average of over 17 years and a cumulative of 244 years of professional experience. These high amount of experience of the experts signifies the extent of quality and dependability of information obtained from the questionnaire and interview and therefore adds to the validity of the results.

On the discipline of the respondents, it can be seen that about 43% of them are safety managers, who are mainly concerned with managing the safe conduct of the construction workers prior to, and during the construction operations. Further, 57% of them are construction managers, who manage the entire construction production process including the safety of workers and that of every construction activity or operation carried out on the site.

These profiles have therefore, made the results of the exercise very valuable as they were obtained from professionals with the requisite training to know how construction workers recognise and manage construction safety hazards in different work scenarios. They are also in position to authoritatively give a well-informed guidance on all the relevant factors that influence the hazard recognition capabilities of construction workers.

4.2.1 Relevance of the questions

The responses of the experts on the relevance of the questions and statements were analysed using SPSS. Means and standard deviations were computed for each of the questions.

Table 4.2: Relevance of the Personal Factors

Codes	Sub factors	Mean	S.D
A	**Overall group rating of the personal factors**	**3.09**	**1.05**
A1	I have the requisite competence (Knowledge and Experience) to safely do my work	3.93	0.27
A2	I have sound auditory ability	3.79	0.43
A3	I have undergone safety training to recognize hazards	3.71	0.61
A4	I have a positive attitude towards safety in general	3.71	0.47
A5	I always respond to recognized hazards	3.71	0.61

A6	I have a good visual ability	3.71	0.47
A7	I do not have safety complacency at work	3.57	0.65
A8	I don't use Substances (like drugs, alcohol and so on) at work	3.57	1.08
A9	I am experienced in using hazard recognition techniques	3.5	0.76
A10	I have a stable emotional disposition at work	3.43	0.85
A11	I have a good appreciation of the risks associated to my job	3.29	1.14
A12	I have a strong risk-taking ability	3.21	1.05
A13	Fatigue hampers my hazard recognition ability	2.93	1.27
A14	I have been involved in/witness a construction accident	2.86	1.61
A15	My belief system encourages hazard recognition	2.71	1.64
A16	Location of hazards affects my level of recognition	2.5	1.56
A17	Large number of construction tasks on site hampers my hazard recognition level	2.29	1.54
A18	I only recognize hazards whose risks (consequences) are known to me	2.29	1.6
A19	I believe luck can impact hazards recognition	1.71	1.64
A20	My race and ethnicity impacts my ability for hazard recognition at work	1.57	1.79

Source: Validation interview (2017)

A total of 20 sub-factors were used in preparing measurement statements to cover the personal characteristics of workers that influence their hazard recognition levels. Table 4.2 shows the result for the evaluation of the measurement statements based on the consensus of the experts. An overall group mean of 3.09 and group standard deviation of 1.05 were recorded for the entire sub factors in the personal factors category. This indicates that the experts rated all the sub factors closely around the scale of 3, which signifies that most of the factors are relevant for the evaluation of hazard recognition level of workers. The statements were presented in descending order of their mean value scores as depicted in Table 4.

It can be seen that, out the 20 statements, covering the different sub-factors under personal factors affecting workers' hazard recognition performance, 12 recorded mean values greater than 3.0, while about 9 of the factors recorded relatively very low standard deviations less than 1. This signifies that there is some consensus among the experts in rating the sub factors as being relevant for evaluating hazard recognition capabilities of workers.

The factor with the highest mean value score is the statement on competence. It recorded a mean score of 3.93 (SD 0.27), very close to the highest scale of relevance, which is 4. This signifies the level of importance knowledge and experience have in hazard recognition according to the experts. Aside the competence of workers, all other factors that followed it with mean values ranging from 3.79 to 3.21 are all sub factors that are either related to the level of knowledge gained through safety training, or related to the inherent worker characteristics that influence behaviour in different circumstances. For instance, A3, which measures whether or not a worker has undergone safety training to recognise hazards on site, is rated 'relevant' by the experts, with a mean score of 3.71 (SD 0.61), due to the importance of safety training to any construction activity. This issue of training has been found to significantly affect the actions and behaviour of construction workers in performing their duties safely. Several studies have been undertaken on safety training in different construction contexts. It has also been found to be a distinguishing factor between the safety behaviour of different groups of construction crews.

When probing their responses at the time of the interview, all the experts agreed on the importance of workers' competence and level of training on hazard recognition. It was unanimously agreed that any worker that has the knowledge gained through training or work experience in hazard recognition will have the tendency to recognise a good number of hazards and even manage them effectively to remain safe in the work place. One of the interviewees observed that, a construction worker that has good level of training will definitely act safely and even influence other coworkers in his team or crew to behave safely. Such a person will even choose use his knowledge to choose the company to work, based on the safety practices of the different construction companies at his disposal. Therefore, competence, and level of training are very relevant issues to consider when evaluating hazard recognition capability of construction workers.

The other sub factors rated closely are those related to cognitive characteristics that influence the behaviour of workers and influence their hazard recognition capacity. These include workers' attitude, with a mean value of 3.71 (SD 0.47). Workers' emotional disposition, with a mean of 3.43 (SD 0.85) and the risk-taking ability of a worker with a mean score of 3.21 and standard deviation of 1.05. These findings therefore indicate the level of agreement between the respondents on the relevance of these issues to hazard recognition evaluation.

Other sub factors with mean values of 3 and above include those that deal with habits of workers such as the use of substances like smoking and drinking habits, with a mean value

of 3.57 and standard deviation of 1.08. The result of the survey revealed that such a factor is also 'relevant' to the evaluation of workers hazard recognition capability. Others include the physical characteristics of workers such as the visual and auditory ability with respective means and standard deviation of 3.79 (SD 0.43) and 3.71 (SD 0.47).

In addition to the factors that got the rating of 3, meaning they are absolutely 'relevant' according to the experts, six other factors were able to scale through with ratings between 2.93 and 2.29. These factors, based on the rating scale are 'fairly relevant' to the hazard recognition evaluation. Top among them is the issue of measuring the extent to which fatigue hampers hazard recognition of a worker, with a mean score of 2.93, very close to the group mean and a standard deviation of 1.27. Following it, is the measure of the effect of witnessing or experiencing work accidents, (mean 2.86 and SD 1.61) and the effect of workers' belief system on hazard recognition performance with a mean value of 2.71 (SD 1.64). Despite the relatively low rating of the statement on the belief system of workers, some respondents strongly believe that it is relevant for evaluating hazard recognition of workers. During the interview, one of the experts gave an example of workers who refused to obey safety instructions because of their belief system. When he directed them to use safety devices in doing their work and was telling them the implications of not performing their works in a safe manner, they told him that whatever was meant to happen must happen, irrespective of the way they do the work. He then reported that only threat of losing their job could force them to behave safely in such circumstances. This is a typical example of how belief system of a worker would affect his level of hazard recognition and lead him to encountering avoidable safety incidents at work. Consequently, the respondent

concluded that knowing the influence of belief system on hazard recognition performance of worker will go a long way in shaping the decision regarding hazard recognition capability of such a worker.

The sub factors with the least rating among the relevant ones are those to do with location of hazard and hazard multiplicity and those hazards whose risks are known to the workers. Based on the established criteria for choosing the factors, all these 18 factors were rated to be either fully or fairly relevant to the evaluation of the level of hazard recognition of construction workers. Therefore, all of them would be included in the final evaluation tool.

Based on the foregoing, not all the sub factors under the personal factors category would be able to make it to the final evaluation tool. This is because, two items recorded a very low rating of less than 2, which indicates that the interviewees were 'unsure' of the level of relevance of such factors to the evaluation tool. These include the impact of luck on hazard recognition of workers, with a mean value of 1.71 (SD 1.64) and the effect of workers' race and ethnicity on their ability to recognise work hazards. Although these factors were envisaged to be relevant in assessing workers capacity to recognise hazards, the experts indicated their lack of confidence in the fact that these factors can influence the level of recognition of workers. Nevertheless, the fact that these factors were not rated 'irrelevant', signifies that they can still have some level of influence, which may require further investigation to ascertain their degree of relevance or irrelevance. However, when asked for reasons why these factors received a very low rating, 9 out of the 14 respondents were of the opinion that this issue of luck has no relevance to hazard recognition. One of the

interviewees said that the idea of luck has no scientific relationship to hazard recognition performance of a person.

On the issue of race and ethnicity of the workers most of the respondents were of the view that such a question would not yield any meaningful result. This is because it may lead to a feeling of stereotype among workers and managers. Another respondent observed that such a question will make the workers feel low about themselves. Thus, it may not be able to generate any objective response that can highlight the hazard recognition level of the worker.

Therefore, these two factors may require further inquiries to establish their actual degree of relevance or otherwise to the evaluation of hazard recognition of workers.

Table 4.3: Relevance of the Social Factors

Codes	Sub factors under the social factors	Mean	S.D
B	**Overall group rating of the social factors**	**2.66**	**1.28**
B1	My coworkers and superiors offer support on hazard recognition at work	2.93	1.07
B2	I adjust my behaviors to align with the norms of my work group/team members	2.86	1.03
B3	I am influenced by my co-workers on hazard recognition and safety practices	2.86	1.41
B4	I can be influenced by the hazard recognition ability of my peers at work	2.64	1.28
B5	The size and composition of work crew influence my hazard recognition level	2.00	1.62

Source: Validation interview (2017)

Table 4.3 presents the result of evaluating the relevance of the social factors in the evaluation of the hazard recognition levels of workers in a construction context. Unlike the personal factors, it can be seen that the sub factors under this category recorded an overall group mean of 2.66 and a standard deviation of 1.28. All other sub factors in this category recorded mean values between 2.00 to 2.93. This indicates the level of consensus between the experts on the level of relevance of all the sub factors under this category.

Among the sub factors, B1, which is based on the influence of supportive environment recorded a mean score of 2.93 (SD 1.07). This is the most relevant sub factor, as it tends toward the value of 3, which signifies absolute relevance. All other sub factors in the category remain within the scale of 'fairly relevant'. However, the experts were of the opinion that interaction between workers have a tendency to influence the behaviour and conduct of individual workers in a group or team. One of the interviewees observed that if a worker is a drunkard, there are tendencies that he may be able to adjust his behaviour to blend with the other members of the work group or team he finds himself with. On the

other hand, another interviewee opined that these sub factors are not important to hazard recognition evaluation. He believed that the level of education and training of a worker is the major driver of his conduct in hazard recognition and general safety management at work place.

It can therefore be concluded that while all the sub factors in the social factors category were rated in such a way that they can form part of the final evaluation tool, their level of relevance is not very high. The overall group mean value also shows that this group of factors recorded the least mean value among the four factors examined. This may be due to the fact that most of the important issues that affect the recognition capability of a worker with respect to human interactions can be taken care of by the personal factors. Further research will also be able to establish the extent of influence the social factors will have on hazard recognition capability of workers.

Table 4.4: Relevance of the Organisational factors

Codes	Sub factors under the Organisational factors	Mean	S D
C	**Overall group rating**	**3.51**	**0.72**
C1	Our organizational safety policy supports hazard recognition and management	3.86	0.54
C2	We have Safety Training Programs that enhance workers hazard recognition skills	3.64	0.50
C3	We have an organizational structure with responsibilities for hazard recognition and management	3.57	0.65
C4	We have incentive programs to motivate and empower employees for hazard recognition and management	3.57	0.51
C5	We appraise the hazardous tendencies of all equipment used in our projects	3.50	1.09
C6	We have a communication system for managing hazard information at work	3.50	0.52
C7	We have a healthy Supervisory environment that supports hazard recognition and safety management	3.50	0.52
C8	Employees are involved in hazard recognition and safety planning	3.50	0.86
C9	Our organization undertakes campaigns to promote hazard recognition	3.43	0.65
C10	We employ various hazard identification (both manual and automated) tools in our projects	3.29	0.73
C11	We strongly discourage the use of psychoactive substances by our workers	3.21	1.42

Source: Validation interview (2017)

The results of the experts' evaluation of the organizational factors are presented in Table 4.4.

All the 11 sub factors were rated as 'relevant', with an overall group mean score of 3.51 and a standard deviation of 0.72. It can be observed from the table that almost all the factors recorded a mean value very closed to the overall group mean. This goes to show the extent of agreement among the experts on the relevance of all the sub factors under the

organizational characteristics to the evaluation of the hazard recognition capability of workers.

The factor with the highest mean value of 3.86 is the one on organizational safety policy that supports hazard recognition and management. This result is emphasizing the important role played by the organizational safety policy in the achievement of high level of hazard recognition by workers. Another sub factor that came close to the policy issue is the issue of training programs in the organisation. The mean score of 3.6 and standard deviation of 0.5 (the lowest in the list) shows that the experts rated this factor with very high level of agreement to show the importance of training in ensuring good hazard recognition level of workers.

It is instructive to note that a good number of these organizational sub factors recorded mean values very close to each other. Similarly, almost all the standard deviations were much less than 1. This further confirms the consensus among the experts. The sub factors with the least mean values were C10, which represents hazard identification tools employed by the organisation. This recorded a mean score of 3.29 and standard deviation of 0.73. The sub factor that followed this one was the organizational program on the discouragement of the use of psychoactive substances by workers. It recorded the mean value of 3.21, and a standard deviation of 1.42, which further confirms that the rating is relatively far away from the overall group mean, signifying the extent of difference in opinion of the experts regarding its level of relevance. Nonetheless, this and all other sub factors in the organizational category have been rated to be absolutely relevant to the evaluation of the construction workers' hazard recognition capabilities.

Aside the rating of the organizational factors, all the interviewees agreed that the organizational factors are all very relevant and useful to the evaluation of hazard recognition level of construction workers. Some of the experts have underscored the importance of organizational policy in driving the success of hazard recognition and general safety management of workers in an organizational setting. Similarly, the experts have unanimously advocated the importance of incentives and appreciation of employees that recognise the highest number of hazards in an organisation. Two of the experts revealed that they usually encourage their workers to report hazards recognised in the process of undertaking site construction activities. They said at the end of every week or every month, the workers that recognise the highest number of hazards are given special incentives in form of physical recognition in a special meeting, and in some cases given some rewards. This, they said, has been very useful in encouraging the workers to recognise and report hazards on site. Another respondent believed that such initiatives will encourage workers to willingly devote more attention to hazard recognition and thereby increase their chances of remaining safe at work. It is therefore emphasized that incentive and motivation is very important in the improvement of hazard recognition performance of workers in a construction organisation.

In addition to the factors listed in the questionnaire, some of the experts suggested a number of additional issues that were not considered under the organizational factors. About 6 sub factors were suggested, however, only 2 of them were found to be relevant and got included into the hazard recognition evaluation tool. These are the top management

commitment to hazard recognition and management, and the use of 'lessons learned' programs which records and share knowledge on new hazard types encountered by workers on site. They argued that management commitment will go a long way in boosting the morale of workers to recognise and manage hazards on site. Therefore, if an organisation has this feature, it is expected that the workers will perform better in hazard recognition. Also, the lessons learned program will ensure that an organisation transfers knowledge on hazards recognised in one projects to future ones and increase the chances of their workers recognizing similar hazards in work interfaces. These two factors are therefore added to the list of sub factors under the organizational category.

Furthermore, the general consensus among the experts suggest that organizational factors are the most important factors to be considered in the evaluation of hazard recognition capacity of workers. This is depicted by the highest overall group mean scored by the organizational factors, compared to the other three components.

Table 4.5 presents the results of the experts' rating of the sub factors under the project factors category. The overall group mean recorded here is 3.27 with a standard deviation of 0.89. It can be seen here also that 12 out of the total of 15 sub factors have recorded mean values greater than 3, which means they are mostly 'relevant'. However, a close look at the spread of the individual means and standard deviations recorded by the sub factors shows some level of dispersion in agreement among the experts in rating the relevance of these sub factors. Sub factors coded D1 and D2, talking about the support of project owners and the nature of mechanical equipment used in the project both recorded similar mean value

and standard deviation of 3.79 and 0.43 respectively. These were followed by sub factors D3 to D6, all of which recorded the same mean value of 3.64 each and standard deviation of 0.50, expect D6, which has a standard deviation of 0.63, away from the rest. This signifies some level of agreement among the experts in rating the relevance of the sub factors.

Table 4.5: Relevance of the Project factors

Codes	Sub factors under the Project factors	Mean	S.D
D	**Overall group rating**	**3.27**	**0.89**
D1	The project owner and community support hazard recognition and management	3.79	0.43
D2	The project involves the use of mechanical plants and equipment	3.79	0.43
D3	Hazard recognition practices are employed in the project	3.64	0.50
D4	Job specific safety training is provided for workers in the project	3.64	0.50
D5	The project site is maintained in an orderly and tidy manner	3.64	0.50
D6	The project has a high safety climate that supports hazard recognition	3.64	0.63
D7	No excessive traffic is envisaged on the project site	3.29	0.83
D8	The layout plan of the construction site is made with the aim of improving workers' hazard recognition	3.21	1.12
D9	The productivity and delivery pressure of the project is not likely to hamper hazard recognition	3.14	1.23
D10	The project characteristics (e.g. size, scope, materials, height etc) will not hamper hazard recognition and management	3.14	1.10
D11	The site configuration (e.g. topography, soil condition, access, space, etc) will not hamper hazard recognition	3.07	1.14
D12	The site condition (e.g. elements of weather) are not inimical to hazard recognition (by having negative influence of the workers physically and psychologically)	3.07	1.07
D13	The project scope and schedule are not likely to change in the process	2.86	1.23
D14	No excessive noise is expected in the project site	2.86	0.95
D15	Advanced technological tools are used in hazard identification on the project	2.86	1.17

Source: Validation interview (2017)

It can be seen that from sub factors D8 to D12 have recorded different mean values, all within the range of 3.0. Notably, their standard deviations are relatively farther away at 1.0 and above. This confirms the extent of dispersion in the experts' rating on the relevance of these sub factors. Following them are factors D13 through D15, which, even though were tending towards the mean value of 3, but still featured under the scale of 'fairly relevant' with the same mean value of 2.86 for each of them. Overall, all the factors in this category have been rated by the expert interviewees to be relevant for the evaluation of construction workers' hazard recognition capabilities based on the characteristics of the construction project. Most of the experts also see the project factors as the second most important category of factors relevant to the evaluation of hazard recognition level of workers. Although, other interviewees differ on this, it can be safely concluded that project factors are very important in driving the extent of hazards recognised by a construction worker. One of the interviewees asserted that the project is the center of all the hazards, therefore, the nature of project determines the extent of hazard recognition of a worker irrespective of his training and the organization that performs the work.

4.2.2 Clarity and Adequacy of the factors covered

In the final evaluation sheet, there were two questions requiring the experts to rate the clarity and general ease of understanding of the factors as stated and the adequacy of the components in the factor structure. Five options were presented as strongly agree, agree,

neutral, disagree and strongly disagree. The percentages of the experts' responses are presented in Figure 1.

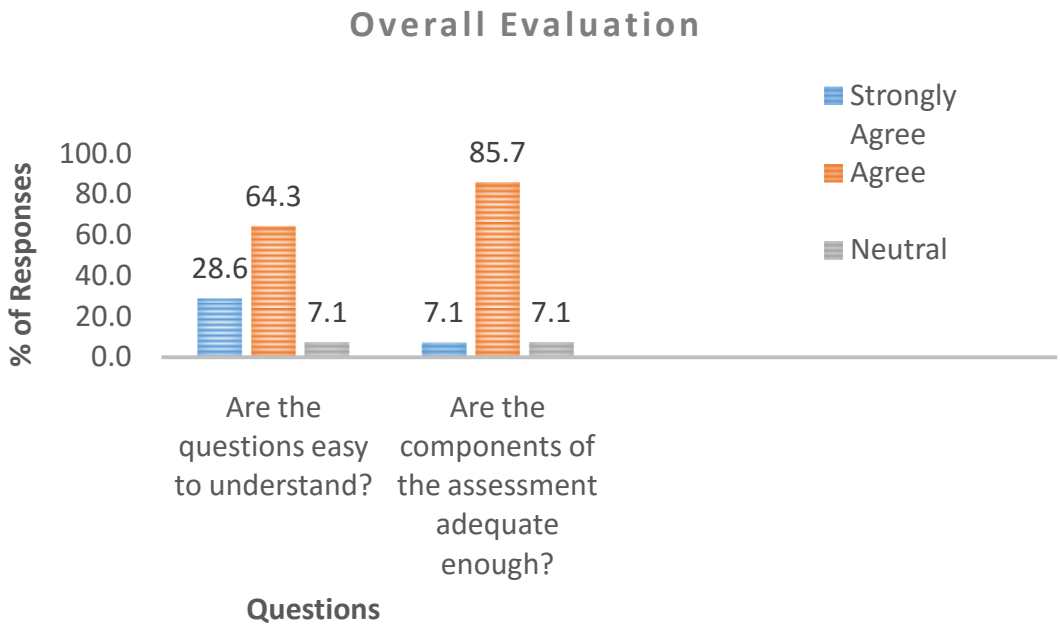

Figure II: Overall Evaluation Responses

It can be seen from figure 1 that 28% of the experts strongly agreed, while 64.3% agreed that the questions are easy to understand. 7.1% of the experts chose to remain neutral on the issue of ease of understanding of the questions.

On the adequacy of the components, majority (85%) of the evaluators agreed, while 7.1% strongly agreed that the components of the evaluation tool are adequate enough to serve the intended purpose. However, 7.1% still remained neutral on the issue. Further, on the adequacy of issues covered in each of the components, the experts also agreed almost unanimously that they are adequate. Nevertheless, some of them suggested a few more

questions which were further analysed on their merits in order to avoid repetitions. Finally, two of the suggestions were taken and included into the evaluation tool.

In the main table for the evaluation of the relevant of questions, the experts were given the option of 'recast', where they feel the wording of the questions are not appropriate. In that respect, they were encouraged to suggest the best way such questions should be put. Some suggestions were made to recast some of the questions for better understanding of their intent. Such suggestions were treated based on their merits and the tool was improved upon.

Additionally, the interviewees were asked to suggest any improvement to the evaluation tool if they see the need. Some of them suggested that open ended questions should be used. However, this suggestion was not taken because it negates the main objective of the work, which is to provide a quantitative measure of workers hazard recognition performance. Another interviewee also suggested that the questions in the evaluation tool should avoid making a worker feel inferior based on nationality, race or belief. This suggestion was in consonance with the result in Table 4.2, where the issue of race and ethnicity did not make it to the evaluation tool, based on its mean value that is less than 2. However, there is still the need to reconsider this issue in future research since there are literature sources that point to the influence of race and origin on hazard recognition of construction workers.

4.2.3 Ranking of the components of the evaluation

To further confirm the validity and consistency of the experts' evaluation of the tool, the interviewees were asked to rank the four components of the evaluation tool based on their level of importance and relevance. Table 4.6 presents a comparison between the group means of the component or group of factors in the initial questionnaire survey and the follow up interview.

Table 4.6: Overall Group Means Comparison between the Questionnaire and the Interview

Categories of Factors	Interview Assessment		Questionnaire Assessment	
	Overall Group Means	Ranks	Overall Group Means	Ranks
Personal factors	4.00	2	3.09	3
Social factors	2.57	4	2.66	4
Organisational factors	4.29	1	3.51	1
Project factors	3.40	3	3.27	2

Source: Survey, (2017)

As depicted in Table 4.6, the overall weighted mean values of the components show that organisational factors are the most relevant to the evaluation tool, with a mean value of 3.51.

This is followed by the project factors, with a mean score of 3.27, then personal factors, with mean value of 3.09. The least relevant factor is the social factor category, with a mean score of 2.66.

In the interview, it can be seen that the most relevant and important factor was the organizational factors category, with a weighted mean score of 4.29, followed by personal factors, with a mean score of 4.0, then project factors, which has a mean value of 3.40. The least relevant factors were the social factors, with a mean value of 2.57.

There are similarities between the rankings of the questionnaire survey and those of the follow up interview. In comparison, the mean values of the interview results were generally higher than those of the questionnaire evaluation, except for the social factors, in which the difference was not significant. Similarly, the ranking of the factors were mostly consistent, except in the case of the project and the personal factors. In the questionnaire assessment, the project factors were the second (mean value 3.27), and the personal factors came 3rd(mean value 3.09). In contrast, the follow up interview ranked the personal factor second (mean score 4.00), while the project factors came third (mean value 3.40).

Generally, it can be inferred that the follow up interview results, further confirmed and validated the results of the questionnaire survey. The higher mean values in the interview and the minor differences between the rankings may be due to the fact that the follow up interview was meant to probe the responses of the questionnaire and to give further clarifications to the experts on areas of the tool that were not clear to them. In such circumstances, some of the interviewees had to alter their choices on the level of relevance of some of the factors. They also expatiated on the reasons for some of their choices by giving examples to back up their choices. For instance, in making a case for ranking of the organizational factors as the most relevant in the evaluation, most of the interviewees argued that the policy of the organization drives every safety initiative. Once the organization set rules, every employee must be ready to abide by them. Therefore, if the organization has provisions on proactive safety management and hazard recognition, it is expected that employees working on any projects handled by the organization would be

likely to recognise more number of hazards and therefore act safely. Similarly, another interviewee observed that it is the organisaional policy that determines the extent of budgetary provisions and expenditure on safety and hazard recognition training for workers, the nature of relationship between workers and supervisors and the hazard identification and reporting system to be used. These are some of the measures that drive employees to recognise hazards. Based on the foregoing of the organizational factors have been chosen to be the most important and relevant component in the evaluation of workers hazard recognition levels.

In conclusion, the result of the follow up interview can be relied upon as the best representation of the experts' views on the entire evaluation tool. This because the interview explored the reasons behind the experts' choices and offered clarifications to them to ensure that everyone was at the same level of understanding on the nature and intent of every component on the evaluation exercise. This exercise has also achieved the validation of the categorization of the different factors into the components as personal, organizational, social and project. This has not been done clearly by previous studies. The importance of the categorization is to allow for specific efforts to be made towards addressing them in order to improve hazard recognition capability of workers.

4.3 Extent of Influence of the Factors on Hazard Recognition Capability of Construction Workers

4.3.1 Analysis of administered questionnaires

A total of 1200 questionnaires were distributed to the four groups of respondents. 605 (50.42%) were duly completed and returned, out of which 561 (46.75) were found fit for analysis. The remaining were discarded due to errors in the responses, improper responses and many blank spaces among other reasons.

Table 4.7: Analysis of Administered Questionnaires

Questionnaires	Number
Number Distributed	1200
Number filled and returned	605
Response rate (%)	50.42
Usable questionnaires	561
Percentage of usable responses (%)	46.75

Field Survey (2018)

From Table 4.7, it can be seen that a response rate of 561 (46.75) which is good enough for statistical analyses was used in the study.

4.3.2 Characteristics of respondents

Table 4.8 presents the characteristics of the respondents comprising information on the nature of trades they were involved in, designations, educational attainments, years of experience, and the nature of jobs engaged by their organisations. All these have been used

in one way or the other to guide the different sets of statistical analyses and explore the quality of data gathered from the respondents.

Table 4.8: Characteristics of Respondents

Characteristics	Classification	Frequency	%
Nature of their Trades	Roof Work	177	32
	Steel Work	62	11
	Excavation work	65	12
	Professionals	257	46
	Total	**561**	**100**
Designation	Safety Manager	32	6
	Construction Manager	226	40
	Workers	303	54
	Total	**561**	**100**
Educational Qualification	SSCE and below	130	23
	National Diploma	131	23
	Higher National Diploma	85	15
	Bachelors	164	29
	Masters	43	8
	Doctorate	8	1
	Total	**561**	**100**
Years of Experience	1-5	190	34
	6-10	194	35
	11-15	82	15

	16-20	54	10
	21-25	26	5
	26-30	10	2
	Above 30 years	5	1
	Total	**561**	**100**
Nature of Job Handled by their Firms			
	Building Construction	264	47
	Civil Engineering Construction	74	13
	Both Building and Civil Engineering	221	39
	Others	2	0
	Total	**561**	**100**

Considering the nature of jobs engaged in by the respondents, while 304 of the respondents were tradesmen engaged in different trades, 257 were professionals managing the workers on sites. Among the tradesmen, 177 were workers at height, 62 steel workers, and 65 were excavation workers. This gives a fair representation of responses across the groups. For the professionals, it can be seen that 32 of them are safety managers on site while 226 were construction managers. These professionals are directly managing the activities of construction workers in relation to the safety of the construction entire construction processes.

On educational qualifications, 190 (34%) of the respondents were holders of Secondary school certificates (SSCE) and below, 131 had National Diplomas, 85 had Higher National Diplomas, 164 had bachelors' degrees, 43 had up to a Masters degree while only 8 of the respondents hold a PhD in their fields. All the respondents without at least a diploma were workers, while the professionals had either a HND or Bachelors degree and above. This

spread of the educational qualification especially in the case of the professionals indicates the validity of their responses considering their knowledge of construction.

The table also shows the years of experience of the respondents. 34% (190) of them have between 1 to 5 years, 35% (194) have between 6 to 10 years of experience. 15% (82) have between 11 to 15 years of experience, while 10% (54) of the respondents have between 16 to 20 years of experience. 5% (26) have between 21 to 25 years of experience, 2% have between 26 to 30 years and 1% (5) of the respondents have over 30 years of experience. This spread in the experience of the respondents is an additional indication of the quality of the responses obtained from them on the influencing hazard recognition capability of construction workers.

On the nature of jobs handled by the respondents' organisations, 47% of them work in building construction firms only, while 13% work in firms handling only civil engineering construction works, and 39% works in companies that engage in both building and civil engineering construction firms. This blend of different types of construction works means that the responses capture safety hazards in most of the different types of construction works.

4.3.3 Influence of the factors on hazard recognition capability of construction workers

The influence of factors affecting hazard recognition capability of construction worker was measured using a 5-point Likert-type scale. Four categories of factors were presented to the both groups of workers and their managers. Given their experience in undertaking different

forms of construction activities, the respondents were asked to rate the extent to which the factors influence hazard recognition capability of construction workers. Table 4.9 shows the mean score and standard deviation for each of the fifty-three factors affecting hazard recognition capability of workers grouped into four categories.

Table 4.9: Descriptive Statistics

S/N	FACTORS	Mean	S D
A1	Knowledge of the job	3.90	1.04
A2	Level of experience in the job	3.92	0.96
A3	Sound auditory ability	3.68	1.02
A4	Safety training to recognize hazards	3.71	1.12
A5	Attitude towards safety	3.68	0.98
A6	Prior knowledge of the hazards	3.73	1.04
A7	Good visual ability	3.85	0.96
A8	Safety complacency	3.55	1.04
A9	Use of Substances (like drugs, alcohol and so on) at work	3.00	1.49
A10	Experience in using hazard recognition techniques	3.44	1.04
A11	Stable emotional disposition	3.44	1.00
A12	Appreciation of the risks associated with the job	3.46	1.02
A13	Risk-taking ability	3.39	1.06
A14	Fatigue and depletion	3.32	1.12
A15	Involvement in a previous construction accident	3.36	1.14
A16	Belief system	3.20	1.19
A17	Location of hazards	3.38	1.05
A18	Large number of construction tasks on site	3.55	1.01
A19	Knowledge of risks (consequences) associated with a hazard	3.45	1.06
A20	Race and ethnicity	2.86	1.23

		3.49	
B1	Coworkers' and superiors' support on hazard recognition at work	3.45	1.02
B2	Work group norms	3.48	0.98
B3	Co-workers' hazard recognition and safety practices	3.53	1.00
B4	Hazard recognition ability of peers at work	3.44	1.01
B5	The size and composition of work crew	3.55	0.93
B6	Supportive environment for hazard recognition and management	3.53	1.01
B7	Hazard recognition ability and motivation of peers	3.51	1.02
		3.50	
C1	Organizational safety policy	3.69	1.10
C2	Safety Training Programs in the organisation	3.63	1.10
C3	Organizational structure with responsibilities for HR and management	3.55	1.10
C4	Use of incentive programs to motivate employees for HR	3.47	1.10
C5	Hazardous nature/tendencies of equipment used in projects	3.65	1.04
C6	Organisational communication system for managing hazard info. at work	3.57	1.12
C7	Supervisory environment	3.65	1.01
C8	Employee involvement in hazard recognition and safety planning	3.59	1.03
C9	Organizational campaign to promote hazard recognition	3.59	1.06
C10	Use of hazard (both manual and automated) identification techniques	3.47	1.11
C11	Organisational policy on the use of psychoactive substances by workers	3.43	1.13
		3.57	
D1	The project owner and community support for HR and management	3.38	1.10
D2	The use of mechanical plants and equipment in the project	3.57	1.01
D3	Hazard recognition practices employed in the project	3.61	2.38
D4	Job specific safety training provided for workers in the project	3.61	1.09
D5	The project site house-keeping practices	3.55	1.01
D6	Project safety climate	3.52	1.02
D7	Traffic on project site	3.46	1.04
D8	The layout plan of the construction site	3.64	0.99
D9	The productivity and delivery pressure of the project	3.63	1.02
D10	Project characteristics (e.g. size, scope, materials, height etc)	3.68	0.99
D11	The site configuration (e.g. topography, soil condition, access, space, etc)	3.59	1.00
D12	The site condition (e.g. elements of weather)	3.60	1.02
D13	Project scope and schedule change	3.56	0.96
D14	Noise level in the project site	3.50	1.09
D15	Hazard recognition method / tool adopted	3.56	1.12
		3.56	

Table 4.9 shows that all the factors were rated by the respondents to have between moderate to high influences on hazard recognition capability of construction workers. On

the personal factors, all the 20 factors except the factor coded A20, race and ethnicity, recorded a mean value greater than 3. The overall group mean for the factors is also 3.49, which indicates that the respondents see all the factors as significantly affecting hazard recognition capability of workers. This is similar to the results obtained for the social factors, all of which also recorded a mean score greater than 3 and an overall mean of 3.50. The Organisational factors category had a total of 11 factors and all of them also recorded mean values greater than 3, with an overall group mean of 3.57. Similarly, the project factors category, having a total of 15 factors all rated above 3 and a group mean score of 3.56.

Comparing the group means the most influential group of factors is the organisational factors category, having an overall mean of 3.57, followed by project factors category, with a group mean value of 3.56. The next is the social factors category with a group mean of 3.50 and lastly the personal factors category with the least overall mean score of 3.49. This result is in line with the previous exercise where the experts established that the organisational and project factors are the most important groups of factors affecting hazard recognition capability of construction workers.

However, the standard deviations for all the factors are somewhat high, since most of them are up to 1. This indicates that there is no consensus among the respondents in rating the extent of influence of the factors. This may be due to the fact that there are different categories of construction workers, who might have different views on the level of

influence of each factor according to the nature of their works. On the other hand, there are also the professional construction managers and safety managers who are likely looking at the influence of these factors entirely differently from the workers, as a result of their training and experiences in managing construction safety and how hazards recognition of workers. This calls for further investigation to explore the respective mean scores of each factors based on the groupings of respondents considered in the study. Therefore, the mean value analysis was carried out for each of the categories of workers separately in order to ascertain their differences among groups. The results are presented in Table 4.10.

Table 4.10: Comparison of Mean Values across the Categories of Respondents

Codes	Factors Affecting HRC of Workers	Steel	Roofers	Excavatrs	All trades	Professnals	Combined
A	Personal Factors						
A1	Knowledge of the job	4.19	4.08	3.94	4.07	3.70	3.90
A2	Level of experience in the job	4.23	4.09	3.86	4.07	3.75	3.92
A3	Sound auditory ability	3.79	3.78	3.62	3.75	3.60	3.68
A4	Safety training to recognize hazards	3.73	3.68	3.75	3.70	3.72	3.71
A5	Attitude towards safety	3.89	3.67	3.68	3.72	3.63	3.68
A6	Prior knowledge of the hazards	3.92	3.81	3.63	3.80	3.64	3.73
A7	Good visual ability	4.24	3.93	3.75	3.96	3.73	3.85
A8	Safety complacency	3.82	3.56	3.71	3.65	3.44	3.55
A9	Use of Substances (like drugs, alcohol and so on) at work	2.69	2.61	3.19	2.75	3.30	3.00
A10	Experience in using hazard recognition techniques	3.39	3.42	3.24	3.38	3.52	3.44
A11	Stable emotional disposition	3.34	3.51	3.43	3.46	3.42	3.44
A12	Appreciation of the risks associated with the job	3.29	3.50	3.35	3.43	3.50	3.46
A13	Risk-taking ability	3.26	3.47	3.43	3.42	3.37	3.39
A14	Fatigue and depletion	3.13	3.27	3.86	3.36	3.27	3.32
A15	Involvement in a previous construction accident	3.26	3.18	3.92	3.35	3.37	3.36
A16	Belief system	3.31	3.20	3.30	3.24	3.14	3.20
A17	Location of hazards	3.18	3.39	3.27	3.32	3.45	3.38
A18	Large number of construction tasks on site	3.40	3.53	3.73	3.55	3.55	3.55
A19	Knowledge of risks (consequences) associated with a hazard	3.42	3.45	3.29	3.41	3.50	3.45
A20	Race and ethnicity	2.82	2.69	3.19	2.82	2.89	2.86
	Group Mean	**3.52**	**3.49**	**3.56**	**3.51**	**3.47**	**3.49**
B	Social Factors						

B1	Coworkers' and superiors' support on hazard recognition at work	3.23	3.59	3.17	3.43	3.49	3.45
B2	Work group norms	3.48	3.57	3.44	3.53	3.43	3.48
B3	Co-workers' hazard recognition and safety practices	3.65	3.58	3.63	3.60	3.44	3.53
B4	Hazard recognition ability of peers at work	3.65	3.44	3.38	3.47	3.40	3.44
B5	The size and composition of work crew	3.71	3.44	3.65	3.54	3.56	3.55
B6	Supportive environment for hazard recognition and management	3.63	3.49	3.49	3.52	3.53	3.53
B7	Hazard recognition ability and motivation of peers	3.56	3.45	3.33	3.45	3.58	3.51
	Group Mean	**3.56**	**3.51**	**3.44**	**3.51**	**3.49**	**3.50**
C	Organisational Factors						
C1	Organizational safety policy	3.71	3.41	4.10	3.61	3.77	3.69
C2	Safety Training Programs in the organisation	3.55	3.49	3.67	3.54	3.73	3.63
C3	Organizational structure with responsibilities for HR and mgt.	3.73	3.44	3.29	3.47	3.65	3.55
C4	Use of incentive programs to motivate employees for HR	3.48	3.22	3.54	3.34	3.63	3.47
C5	Hazardous nature/tendencies of equipment used in projects	3.61	3.41	4.11	3.60	3.72	3.65
C6	Organisational communication system for managing hazard at work	3.66	3.22	3.76	3.42	3.75	3.57
C7	Supervisory environment	3.85	3.64	3.51	3.66	3.64	3.65
C8	Employee involvement in hazard recognition and safety planning	3.68	3.49	3.75	3.58	3.60	3.59
C9	Organizational campaign to promote hazard recognition	3.84	3.37	4.13	3.62	3.55	3.59
C10	Use of hazard (both manual and automated) identification techniques	3.60	3.22	3.57	3.37	3.58	3.47
C11	Organisational policy on the use of psychoactive	3.50	3.21	3.21	3.27	3.63	3.43

	substances						
	Group mean	**3.66**	**3.37**	**3.69**	**3.50**	**3.66**	**3.57**
D	Project Factors						
D1	The project owner and community support for HR	3.37	3.15	3.71	3.31	3.46	3.38
D2	The use of mechanical plants and equipment in the project	3.89	3.45	3.62	3.57	3.56	3.57
D3	Hazard recognition practices employed in the project	3.60	3.40	3.46	3.46	3.79	3.61
D4	Job specific safety training provided for workers in the project	3.73	3.38	4.08	3.60	3.62	3.61
D5	The project site house-keeping practices	3.76	3.42	3.54	3.51	3.59	3.55
D6	Project safety climate	3.60	3.45	3.41	3.47	3.57	3.52
D7	Traffic on project site	3.61	3.30	3.57	3.42	3.50	3.46
D8	The layout plan of the construction site	3.73	3.63	3.33	3.58	3.70	3.64
D9	The productivity and delivery pressure of the project	3.56	3.54	3.83	3.60	3.67	3.63
D10	Project characteristics (size, scope, materials, height etc)	3.66	3.47	3.75	3.56	3.80	3.68
D11	Site configuration (topography, soil condition, access, space, etc)	3.47	3.36	3.68	3.45	3.74	3.59
D12	The site condition (e.g. elements of weather)	3.82	3.32	3.70	3.50	3.71	3.60
D13	Project scope and schedule change	3.60	3.45	3.90	3.57	3.55	3.56
D14	Noise level in the project site	3.55	3.42	3.95	3.56	3.42	3.50
D15	Hazard recognition method / tool adopted	3.50	3.52	3.46	3.40	3.49	3.56
	Group Mean	**3.63**	**3.42**	**3.67**	**3.50**	**3.61**	**3.56**

Table 4.10 shows the comparison of mean values across the different categories of respondents which is meant to show the variability in the views of the different groups on the extent to which the factors affect hazard recognition capability of construction workers.

In the first three columns, the mean values of the steel workers group, roofers and excavators were respectively presented, followed by their aggregated responses in the fourth column titled 'All trades'. The fifth column captures the mean values of the professionals' responses, after which all the generally combined mean values are shown in the last column. It can be observed that there is some similarities in the way the different groups of respondents view the influence of the factors on hazard recognition capability of construction workers. This is due to the fact that all the mean values are closely related for all the factors in the four categories. There is no any major variation in the mean values across the groups. Moreover, the group means for the four categories of factors were also not drastically different for all the groups' responses, even though they differ slightly in the overall mean values of the four categories of factors as shown in Table 4.11.

Table 4.11: Comparison of Means across the Categories of Factors

Codes	Factors Affecting HRC of Workers	Steel	Roofers	Excavatrs	All trades	Professnals	Combined
A	Personal factors	3.52	3.49	3.56	3.51	3.47	3.49
B	Social factors	3.56	3.51	3.44	3.51	3.49	3.50
C	Organisational factors	3.66	3.37	3.69	3.50	3.66	3.57
D	Project factors	3.63	3.42	3.67	3.50	3.61	3.56

Table 4.11 presents the comparison of overall group mean values for the different groups of respondents, showing the ranking of importance among the four categories of factors influencing hazard recognition capability of construction workers. For the steel workers, roof workers, professionals and the general combined mean values, organisational factors category is the most influential (mean values of 3.66 for steel workers, 3.69 for excavators, 3.66 for the professionals and 3.57 for the generally combined values). This is followed by the project factors, then social factors and lastly the personal factors category. However, little variation exists in the mean value analysis of the roofers, and the combined tradesmen responses where the highest mean scores were the social factors for the roofers group. This slight variation may be accounted for by the difference in training and experience, coupled with the nature of hazards presented by the roofing trade which may be distinctively different from the other trades.

In any case, to know whether or not the difference in the responses of these various groups of respondents is statistically significant, and to make scientific sense of the results, there is the need to use statistical tools meant for comparison of means among different groups of respondents in order to make meaningful conclusions and to guide further analyses on the data. Therefore, the following section presents the analysis of the means across the groups of respondents using ANOVA.

4.4 Determinants of Hazard Recognition Capability of Workers

To ascertain the factorability of the variables in this research Table 4.12 Presents the KMO and the Barlett's test of sphericity for each of the three data sets. All the datasets are suitable for factor analysis having KMO coefficients (> 0.50) ranging between 0.910 – 0.937 and Bartlett's significance < 0.05 as discussed previously. The communalities, variance explanations, eigenvalues and rotated sums loadings used in determining the principal components and rotations of each factor is shown in Appendix D. References are made to them in discussing the following sections.

Table 4.12: KMO and Bartlett's Tests Results

Data Set	KMO	Barlet's Test of Sphericity		
		Chi-Square	df	Sig.
Workers	0.9108	8970.741	1378	0
Professionals	0.9047	6772.574	1378	0
Combined	0.93733	13669.012	1378	0

Source: Survey (2018)

A total of 53 identified from literature and the expert assessment were used to run the analysis. In the first place, using the principal axis factoring and oblique rotation method, the results yielded 12 factors using the Keiser's criterion of eigen value, explaining a total variance of 49.945 (Appendix D). Several other trials were made using principal component analysis and in some cases changing the rotation methods in order to arrive at the best factor structure matrix that is suitable for interpretation based on the theoretical underpinnings of the research. Finally, principal component analysis with varimax rotation was used to analyse the variables with a four factor solution in line with the structure envisaged in the literature. Table 4.13 presents the rotated component matrix after all the cross loaded variables were removed. Among the 53 factors influencing hazard recognition capability of construction workers, only thirty made it to the factor structure derived from the factor analysis. Twenty-Two factors were either removed in the process for not loading significantly enough under any of the four factors realised, or were deleted as a result of cross loading.

Table 4.13: Rotated Component Matrix of Factors Affecting HRC of Workers

S/N	Factors	Components			
		1	2	3	4
1	Organisational Safety Policy	0.74			
2	Organisational communication system for managing hazard	0.70			
3	Use of incentives to motivate and empower employees for hazard recognition	0.69			
4	Safety Training Programs in the organisation	0.69			
5	Organizational structure with responsibilities for hazard recognition and management	0.69			
6	Employee involvement in hazard recognition and safety planning	0.68			
7	Organizational campaign to promote hazard recognition	0.67			
8	Use of hazard identification techniques	0.67			
9	Job specific safety training provided for workers	0.66			
10	The project owner and community support for hazard recognition	0.65			
11	Hazard recognition tool adopted	0.62			
12	Hazardous nature/tendencies of equipment used in projects	0.57			
13	Knowledge of the job		0.71		
14	Level of experience in the job		0.66		
15	Sound auditory ability		0.65		
16	Safety training to recognize hazards		0.62		
17	Prior knowledge of the hazards		0.58		
18	Attitude towards safety		0.56		
19	Good visual ability		0.52		
20	Risk taking ability			0.66	
21	Fatigue and depletion			0.62	
22	Belief System			0.59	
23	Appreciation of the risks associated with the job			0.54	
24	Noise Level on Site			0.50	
25	Site configuration				0.74
26	Productivity and delivery Pressure				0.71
27	Project characteristics				0.68
28	Site Condition				0.56
29	Traffic on site				0.55
30	Site layout Plan				0.54

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.a

a Rotation converged in 7 iterations.

Table 4.14: Summary of Factor Analysis Results

S/N	Components	Eigenvalues	% of Variance	Cumulative %
1	Organisational Factors	15.627	29.484	29.484
2	Inherent Human Factors	2.829	5.338	34.823
3	Conditional Human Factors	2.158	4.072	38.895
4	Project Factors	1.845	3.480	42.375

Component 1 explains 15.933 of the total variance and is composed of organisational factors affecting HRC of workers such as organisational safety policy, use of incentives, organisational structure and so on. Altogether, 12 factors loaded sufficiently from 0.5 and above. Based on the number of factors in this component which reflects the organisational policy and practices affecting HRC of workers, the component is made to retain its name as organisational factors affecting hazard recognition capability of workers.

Component 2 explains 10.907% of the total variance, among the 7 factors that loaded under this component, the most significant ones are the knowledge of the job 0.71, level of experience with 0.66 then sound auditory ability with 0.65 and so on. These factors reflect things that are inherent in any person and based on their characteristics, the component is named as ‘inherent human factors’ that affect hazard recognition capability of construction workers.

Component 3 has 5 factors that loaded under it, explaining 7.803% of the total variance. This component like the one before it also consist of factors having to do with humans but

in this situation the factors are mostly conditional, having no direct relationship with the make-up of an individual. They are therefore referred to as ‘conditional human factors’.

Component 4 has 6 factors with significant loadings under it and the percentage variance explained is 7.731%. All the factors are project related factors such as site condition, project characteristics and so on. Therefore based on this, the component is named ‘project factors’.

It can be observed that the factor analysis result eliminated most of the social factors and redistributed the remaining personal organisational and project factors among the four factor solution that is arrived at. This signifies that based on the opinion of the respondents, these are the most important factors.

Table 4.15: Structure of the Determinants of HRC for Use in the Self-Assessment Tool

S/N	Determinants of Hazard Recognition Capability of Construction Workers
A	**Organisational Factors**
1	Organisational Safety Policy
2	Organisational communication system for managing hazard
3	Use of incentives to motivate and empower employees for hazard recognition
4	Safety Training Programs in the organisation
5	Organizational structure with responsibilities for hazard recognition and management
6	Employee involvement in hazard recognition and safety planning
7	Organizational campaign to promote hazard recognition
8	Use of hazard identification techniques
9	Job specific safety training provided for workers
10	The project owner and community support for hazard recognition
11	Hazard recognition tool adopted
12	Hazardous nature/tendencies of equipment used in projects
B	**Inherent Human Factors**
13	Knowledge of the job
14	Level of experience in the job
15	Sound auditory ability
16	Safety training to recognize hazards
17	Prior knowledge of the hazards
18	Attitude towards safety
19	Good visual ability
C	**Conditional Human Factors**
20	Risk taking ability
21	Fatigue and depletion
22	Belief System
23	Appreciation of the risks associated with the job
24	Noise Level on Site
D	**Project Factors**
25	Site configuration
26	Productivity and delivery Pressure
27	Project characteristics
28	Site Condition
29	Traffic on site
30	Site layout Plan

4.4.1 Reliability of organisational factors variable

The original organisational factors construct was designed having eleven variables/factors. However, after the factor analysis was done, twelve factors were arrived at under the organizational factors (Table 4.16), with the inclusion of 'hazard recognition methods employed'. These factors are concerned with the policy and practices of a particular organisation that may aid or hinder an individual's capability to recognise hazards. All the items were tested for Reliability and the results are shown in Table 4.17.

Table 4.16: Organisational Factors

S/N	Organisational Factors
1	Organisational Safety Policy
2	Organisational communication system for managing hazard
3	Use of incentives to motivate and empower employees for hazard recognition
4	Safety Training Programs in the organisation
5	Organizational structure with responsibilities for hazard recognition and management
6	Employee involvement in hazard recognition and safety planning
7	Organizational campaign to promote hazard recognition
8	Use of hazard identification techniques
9	Job specific safety training provided for workers
10	The project owner and community support for hazard recognition
11	Hazard recognition tool adopted
12	Hazardous nature/tendencies of equipment used in projects

Table 4.17 shows a Cronbach alpha of 0.9271 which indicates that the combination of factors is much more than a 'very good' scale to measure the influence of organisational factors influencing hazard recognition of construction workers. It can be seen from the

table that deleting any of the items will not yield any improvement in the Cronbach alpha value. Therefore, all the items in the factor are considered internally consistent for measuring the capability of a construction worker to recognise hazards from the context of the organisational policy and practices.

Table4.17: Reliability and Item Total Statistics for Organisational Factors

Cronbach's Alpha	No. of Items			
0.927	12			
Organisational Factors	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Organisational Safety Policy	39.090	79.399	0.723	0.920
Organisational communication system for managing hazard	39.150	80.236	0.674	0.922
Use of incentives to motivate and empower employees for hazard recognition	39.220	79.519	0.720	0.920
Safety Training Programs in the organisation	39.300	79.583	0.711	0.920
Organizational structure with responsibilities for hazard recognition and management	39.200	79.212	0.717	0.920
Employee involvement in hazard recognition and safety planning	39.180	80.378	0.727	0.920
Organizational campaign to promote hazard recognition	39.190	80.933	0.670	0.922
Use of hazard identification techniques	39.300	80.159	0.676	0.921
Job specific safety training provided for workers	39.390	80.325	0.671	0.922
The project owner and community support for hazard recognition	39.170	80.043	0.698	0.921
Hazard recognition tool adopted	39.210	80.928	0.624	0.924
Hazardous nature/tendencies of equipment used in projects	39.120	81.482	0.655	0.922

4.4.2 Reliability of inherent human factors variables

Table 4.19 shows the seven items that resulted from the factor analysis under the inherent human factors influencing hazard recognition capability of workers. These factors were

termed inherent human factors affecting hazard recognition capability of workers. These items were also analysed to ascertain their reliability, and the result is presented in Table 4.20.

Table 4.19: Inherent Human Factors

S/N	Inherent Human Factors
1	Knowledge of the job
2	Level of experience in the job
3	Sound auditory ability
4	Safety training to recognize hazards
5	Prior knowledge of the hazards
6	Attitude towards safety
7	Good visual ability

The results of reliability analysis of the inherent human factors are presented in Table 4.20. It can be seen that the construct recorded a Cronbach alpha value of 0.833 indicating a very good measure of internal consistency among the factors. This shows that the items are a good measure of the hazard recognition capability of construction workers based on their inherent characteristics.

Table 4.20 Reliability and Item Total Statistics for Inherent Human Factors

Cronbach's Alpha	No. of Items			
0.8332	7			
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Knowledge of the job	22.570	18.489	0.655	0.798
Level of experience in the job	22.550	19.102	0.643	0.801
Sound auditory ability	22.790	19.215	0.579	0.811
Safety training to recognize hazards	22.760	18.520	0.587	0.810
Prior knowledge of the hazards	22.790	19.300	0.600	0.808
Attitude towards safety	22.740	19.063	0.586	0.810
Good visual ability	22.610	20.777	0.427	0.833

4.4.3 Reliability of conditional human factors variables

Table 4.21: Shows the five items under the conditional human factors affecting hazard recognition capability. These include the risk taking ability, fatigue and depletion, belief system, appreciation of job risks and noise level on construction site. The reliability analyses result of these factors is also presented in Table 4.21

Table 4.21: Conditional Human Factors

S/N	Conditional Human Factors
1	Risk taking ability
2	Fatigue and depletion
3	Belief System
4	Appreciation of the risks associated with the job
5	Noise Level on Site

Table 4.22 shows a Cronbach alpha of 0.678 recorded for the conditional human factors affecting hazard recognition capability of construction workers. This value is relatively

low, even though acceptable. However, the low value can be attributed to the low number of items in the factor (Hair et al, 2010). Looking at the Table critically, deleting any of the items does not yield any increase in the Cronbach alpha value. Therefore, all the items are retained and considered internally consistent in measuring the hazard recognition capability based on the conditional human factors.

Table 4.23: Reliability and Item Total Statistics for Conditional Human Factors

Cronbach's Alpha	No of Items			
0.6782	5			
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Risk taking ability	13.470	8.739	0.527	0.586
Fatigue and depletion	13.670	8.857	0.405	0.642
Belief System	13.550	8.920	0.446	0.621
Appreciation of the risks associated with the job	13.410	9.277	0.461	0.617
Noise Level on Site	13.370	9.698	0.335	0.669

4.4.4 Reliability of project factors variables

Table 4.24 shows the six items under the project factors affecting hazard recognition capability. These factors are mainly concerned with construction project site characteristics such as the layout plan, site configuration and condition, which definitely impacts hazard recognition capability of workers. The reliability analyses result of these factors is also presented in Table 4.24

Table 4.24: Project Factors

S/N	Project Factors
1	Site configuration
2	Productivity and delivery Pressure
3	Project characteristics
4	Site Condition
5	Traffic on site
6	Site layout Plan

As can be seen in Table 4.25, a Cronbach alspha of 0.769 recorded for the project factors affecting hazard recognition capability of construction workers. This value is adequate for reliability.

Looking at the Table also, deleting any of the items does not yield any increase in the Cronbach alpha value. Therefore, all the items are retained and considered internally consistent in measuring the hazard recognition capability of construction workers from the perspective of the project characteristics.

Table 4.25: Reliability and Item Total Statistics for Project Factors

Cronbach's Alpha	No of Items			
0.7691	6			
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Site configuration	18.01	11.993	0.578	0.718
Productivity and delivery Pressure	17.96	11.982	0.565	0.721
Project characteristics	17.92	12.279	0.542	0.728
Site Condition	17.99	12.702	0.455	0.75
Traffic on site	18.13	12.652	0.444	0.753
Site layout Plan	17.96	12.586	0.496	0.739

4.5 Relationships among the Determinants of Hazard Recognition Capability and the Factor-Based Model for Predicting Hazard Recognition Capability of Workers

Table 4.26: Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	561	100.0
	Missing Cases	0	0.0
	Total	561	100.0
Unselected Cases		0	0.0
Total		**561**	**100.0**

a. If weight is in effect, see classification table for the total number of cases.

In Table 4.26, the case processing summary presents the number of cases included in the analysis. It can be seen that a total number of 561 responses were used and there is no missing case in the data.

The output of the logistic regression comes in two sections; block 0 and block 1. Block 0 assesses the extent to which the null model will perform in predicting HRC of workers. This is just the baseline model presented in Table 4.27.

Table 4.27: Logistic Regression Classification Table[a,b] (Block 0)

Observed			Predicted		
			HRC		Percentage Correct
			0	1	
Step 0	HRC	0	0	215	0.0
		1	0	346	100.0
	Overall Percentage				61.7

a. Constant is included in the model. b. The cut value is .500

Table 4.28: Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	0.476	0.087	30.019	1	0.000	1.609

Table 4.28 shows the baseline model for predicting hazard recognition capability of workers. It can be observed that this is the model containing only the constant, without entering the explanatory variable (predictors). This model is constructed based on the nature of the data entered. It can be seen that based on this, the model predicted that the respondents have the capability to recognise hazards. This is because the data consist of greater number of responses tending to the positive. The model also shows that it is true up to 61.7% of times. This is just the baseline model guessing the HRC level of the respondents, which gives some hope that the predictive model is likely to explain higher HRC level of the respondents.

The last other table in the block 0 section is the one containing the variables not in the equation (see AppendixD). That table has all the independent (predictor) variables, showing that they have not been included in the model generated by the block 0 results.

The next section of the results is the Block 1. The first table here presents the Omnibus test of model coefficients (Table 4.29). This gives the result of Likelihood ratio test that indicates the extent to which the inclusion of the predictor variables in influence the model fit. It compares the constant only (the baseline) model to the model with all the predictors of hazard recognition capability included to see whether or not there is any improvement in

the new model. A p-value (sig) of less than 0.05 means that the block 1 model is a significant improvement of the block 0 model.

Table 4.29: Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	583.864	4	0.000
	Block	583.864	4	0.000
	Model	583.864	4	0.000

Considering the significant chi-square recorded, (538.864, df=4, p<.000*),* the new model (with all the predictors) is better than the baseline model, and this suggests that the addition of the explanatory variables improves the accuracy of the model in predicting hazard recognition capability of construction workers.

Table 4.30: Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	162.972[a]	0.647	0.879

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Table 4.30 presents information about the goodness of fit of the model. In standard regression, the coefficient of determination (R^2) value indicates the level of variation explained by the model. For logistic regression, pseudo R square values are used for that purpose. Two measures are given as the Cox & Snell R Square and Nagelkerke R Square. Like R square in multiple regression these values range between '0' and '1' with a value of '1' indicating that the model accounts for 100% of variance in the outcome and '0' that it

accounts for none of the variance. Table 4.30 shows that the model explains between 64.7% (Cox & Snell R Square) and 87.9% (Nagelkerke R Square) of the hazard recognition capability of construction workers.

Moreover, the deviance, or -2 log-likelihood (-2LL) statistic is basically a measure of how much unexplained variation there is in the logistic regression model – the higher the value the less accurate the model. It compares the difference in probability between the predicted outcome and the actual outcome for each case and sums these differences together to provide a measure of the total error in the model. The -2 Log likelihood of 162.972 is reasonably low and indicates good fitness of the model.

Table 4.31 Hosmer and Lemeshow Goodness of Fit Test

Step	Chi-square	df	Sig.
1	1.461	8	.993

Another indicator of the reliability of the model is the Hosmer-Lemeshow goodness of fit test (Table 4.31). In this test, a significance value less than 0.05 indicates poor fitness of the model (Pallant, 2010). The result indicated a chi-square value of 1.461 with a significance level of 0.993 (>0.05) and therefore supports the model.

Table 4.32: Classification Table[a]

Observed			Predicted		
			HRC		
			0	1	Percentage Correct
Step 1	HRC	0	190	25	88.4
		1	13	333	96.2
	Overall Percentage				93.2

a. The cut value is .500

Table 4.32 is the classification table for block 1 which is equivalent to the one in the block 0 section. This table now presents the results indicating how well the model (involving the predictor variables) is able to predict the correct hazard recognition capability levels for each case. In comparison to the one in the block 0, the model correctly classified 93.2% of the HRC cases overall. This is a significant improvement from the 61.7% classification in the baseline model.

Tables 4.33 (a-d) present the key results of the logistic regression models. They give details of the contribution of each of the categories of factors (independent variables) in predicting the hazard recognition capability of workers (dependent variable) in different trades. The tables present the regression coefficients (B), the Wald statistics (to test the statistical significance), the standard errors and the all-important Odds Ratios (Exp (B)) for each variable category in each of the data sets. All factors that record a p-value of less than 0.05 are significant contributors to the predictive ability of the models. The following sections present the Tables containing the variables in the equations of the models pertaining to each data set used in the study. The model developed from the complete data set is presented in Table 4.33 (a) and followed by models developed for the individual data sets for the different trades (Tables 4.33 b, c and d). The remaining results of the individual models for the respective trades are presented in Appendix D.

Table 4.33 (a): Variables in the Equation for the Combined Model

Categories of predictors		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	A-Organisational Factors	4.024	0.495	66.093	1	0.000	55.907	21.192	147.487
	B- Inherent Human Factors	3.088	0.424	53.114	1	0.000	21.939	9.561	50.339
	C-Conditional Human Factors	2.967	0.445	44.438	1	0.000	19.425	8.120	46.469
	D-Project Factors	2.195	0.392	31.397	1	0.000	8.976	4.166	19.341
	Constant	-42.672	4.866	76.915	1	0.000	0.000		

a.Variable(s) entered on step 1: A, B, C, D.

From the table 4.33 (a), it can be observed that based on the coefficients of logistic regression (B), the organisational category has the highest level of predictive power of hazard recognition capability (B=4.024), followed by the inherent human factors category (B=3.088), then the conditional human factors (B=2.967) and lastly the project factors (B=2.195). The logistic regression model for the combined data set is therefore expressed as:

Logit ($HRC_{combined}$) = log (p/(1-p))= -42.672 + 4.024Org + 3.088IHF+3.088CHF+2.195Prj

Table 4.33 (b): Variables in the Equation for the Steel Workers' Model

Categories of predictors		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1a	A-Organisational Factors	3.536	.694	25.923	1	0.000	34.312	8.798	133.819
	B- Inherent Human Factors	3.022	.563	28.855	1	0.000	20.533	6.817	61.848
	C-Conditional Human Factors	2.793	.621	20.255	1	0.000	16.327	4.838	55.094
	D-Project Factors	2.013	.546	13.598	1	0.000	7.484	2.568	21.813
	Constant	-39.351	6.411	37.681	1	0.000	.000		

a. Variable(s) entered on step 1: A, B, C, D.

Table 4.33 (b) presents the results of the logistic regression, it can be observed that based on the coefficients of logistic regression (B), the organisational category has the highest level of predictive power of hazard recognition capability (B=3.536), followed by the inherent human factors category (B=3.022), then the conditional human factors (B=2.793) and lastly the project factors (B=2.013). The logistic regression model for the steel workers' data set is therefore expressed as:

Logit (HRC_{steel}) = log (p/(1-p))= -39.351+ 3.536Org + 3.022IHF+2.793CHF+2.013Prj

Table 4.33 (c): Variables in the Equation for the Roof Workers' Model

							95% C.I.for EXP(B)	
Categories of predictors	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1a A-Organisational Factors	2.182	0.915	5.688	1	0.017	8.868	1.475	53.301
B- Inherent Human Factors	1.933	1.136	2.896	**1**	**0.089**	6.910	0.746	64.037
C-Conditional Human Factors	1.197	1.066	1.261	**1**	**0.261**	3.309	.410	26.711
D-Project Factors	2.059	0.881	5.467	1	0.019	7.840	1.395	44.047
Constant	-25.639	9.373	7.482	1	0.006	.000		

a. Variable(s) entered on step 1: A, B, C, D.

Table 4.33 (c) presents the results of the logistic regression, it can be observed that based on the coefficients of logistic regression (B), the organisational category has the highest level of predictive power of hazard recognition capability (B=2.182), followed by the

inherent human factors category (B=1.933), then the conditional human factors (B=1.197) and lastly the project factors (B=2.195). However, it can be observed that the inherent human factors and the conditional human factors categories are not significant predictors of hazard recognition for the roof workers. This is however a misnomer, which is attributed to the shortage of responses in the category, which made the logistics model inadequate for prediction in this case. The logistic regression model for the roof workers' data set is therefore expressed as:

Logit (HRC_{roof}) = log (p/(1-p))= -25.639+ 2.182Org + 1.933IHF+1.197CHF+2.059Prj

Table 4.33 (d): Variables in the Equation for the Excavation Workers' Model

Categories of predictors		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	A	5.861	1.298	20.399	1	0.000	350.960	27.589	4464.560
	B	3.650	.961	14.437	1	0.000	38.487	5.855	252.978
	C	4.700	1.252	14.096	1	0.000	109.945	9.454	1278.592
	D	2.496	.859	8.445	1	0.004	12.132	2.254	65.316
	Constant	-58.070	12.682	20.966	1	0.000	0.000		

a. Variable(s) entered on step 1: A, B, C, D.

Table 4.33 (d) presents the results of the logistic regression, it can be observed that based on the coefficients of logistic regression (B), the organisational category has the highest level of predictive power of hazard recognition capability (B=4.024), followed by the inherent human factors category (B=3.088), then the conditional human factors (B=2.967) and lastly the project factors (B=2.195). The logistic regression model for the excavation workers' data set is therefore expressed as:

Logit ($HRC_{excavation}$) = log (p/(1-p))= -42.672 + 4.024Org + 3.088IHF+3.088CHF+2.195Prj

To interpret the results of the test for the combined data sets first, all the categories of factors in the combined data set and the other two data sets (steel workers, excavation workers) have proved to be significant predictors of hazard recognition capability of construction workers, as all of them recoded a p value of less than 0.05. Moreover, it can be observed that all of the categories of factors have a positive relationship with hazard recognition capability of construction workers. This is due to the fact that all of them have a positive B value, which means that the more they all increase the likelihood of workers having hazard recognition capability. Any increase in these factors increases the probability of attaining a score of 1, which indicates a worker recognising hazards in the work place.

Looking first at the result for the organisational factors in the combined data set, there is a highly significant overall effect (B=4.024, Wald=66.093, df=1, p<0.000). The B coefficient is significant and positive, indicating that improving the organisational policy and practices for safety and hazard recognition is associated with increased odds of achieving hazard recognition capability of construction workers. The Exp(B) column (the Odds Ratio) indicates that for every unit increase in the level of organisational factors, the odds of workers being capable to recognise hazards increases by 55.907. In other words, workers in organisations where there is good safety policy to support hazard recognition are (55.907) time more likely to recognise hazards than those in organisations with poor safety policy and HR practices.

Previous studies have also reported the significance of organisational factors on workers hazard recognition capability. In this regard, Slates (2008) argued that only leadership and organizational commitment are important in ensuring employee involvement, training, hazard identification and management, if organisations must achieve safety improvement in the hazardous construction scenarios. Organizational systems and policies were also found to impact hazard recognition and the extent of accident and injury causation (Chi, Han, & Kim, 2013). Similarly, the safety management system of a company and the level employee and supervisors involvement have been reported to impact on workers hazard recognition capability(Namian, et al., 2016; Patel & Jha, 2015; Slates, 2008; Tam et al., 2003). These therefore confirm the results of this research.

The effect of inherent human factors is also significant and positive (B=3.088, Wald= 53.114, df=1, p-value=0.000), indicating that workers that measure high in these factors are more likely to achieve good hazard recognition capability than others with low level of inherent personal factors. The odds ratio shows that such workers are 21.939 times more likely to have good hazard recognition capability, keeping other factors constant. This result is in line with the findings of Fang et al., (2016); Yang Miang Goh & Binte Saadon, (2015); Tam et al., (2001); Tam & Fung, (2012); and Tixier et al., (2014) where personal characteristics of construction personnel have been discovered to be directly linked with their hazard perception and safety conduct in performing construction tasks. This result has also been confirmed by previous studies such as Bernardes et al., (2018) who reported the influence of certain human factors in hazard recognition or workers. Similarly, (Campbell

& Smith, 2007; Choe & Leite, 2017; Tixier et al., 2014) have all reported the direct relationship between certain human factors and hazard recognition performance of construction workers. Furthermore, all these studies have wholly or partly confirmed the impact of factors inherent in workers that influence the behaviour and ability of workers to recognize and manage work hazards on construction sites.

In the case of the conditional human factors, the result is also positive and significant (B=2.967, Wald=44.438, df=1 and p-value=0.000), meaning that it is a significant predictor of workers hazard recognition capability. Any improvement in the conditional human factors in a construction worker would yield an increase in his/her ability to recognise hazards at workplace. Moreover, the odds ratio of 19.425 means that for every unit increase in the conditional human factors, the likelihood of workers hazard recognition capability increases by 19.425, all other factors being constant. Several other studies have established a strong correlation between these personal characteristics of the construction personnel and their level of safety level of hazard recognition capability. These include the works of (Kheni et al., 2006; Tam et al., 2003; Tixier et al., 2014).

The result is also similar for the project factors category which is found to be a significant predictor of workers hazard recognition capability (B=2.195, df=1, p=0.000). Comparatively, the project factors category is the least predictor of hazard recognition capability among the four categories of factors having recorded the least regression coefficient value and the least odds ratio of 8.976. Altogether, the four categories of factors have direct relationship with the hazard recognition capability and all are found to be

significant predictors of the construction workers hazard recognition capabilities. The finding on the project factors is also in line with stand of Patel & Jha, (2017) on the significant effects of construction project characteristics on the hazard level of the project. This has also been linked with workers ability to recognise or perceive work hazards on construction sites.

4.5.1 Validation

The validity of the LR prediction model was tested by examining its predictive accuracy against a testing data group. How well the model predicts workers hazard recognition capability within the test group data is determined by the value of the mean absolute percentage error. As shown in Table 4.37, a total of 25 independent sets of testing group data (Set B) was designated for model validation, and the cutoff value was set at 0.5 for the purpose of prediction. It can be seen that the model was able to correctly predict up to 76% of the test group data. The mean absolute percentage error of 24% shows that the model has high amount of external validity.

Table 4.37: Validation Results

HRC Cases	Observed	Predicted	Absolute Percentage Error
1	0	0	0
2	1	0	100
3	1	1	0
4	1	1	0
5	1	1	0
6	0	0	0
7	1	1	0
8	0	0	0
9	0	0	0
10	1	1	0
11	0	0	0
12	1	1	0
13	1	0	100
14	1	0	100
15	0	0	0
16	0	0	0
17	0	0	0
18	1	1	0
19	1	1	0
20	1	0	100
21	0	0	0
22	1	0	100
23	1	1	0
24	1	0	100
25	0	0	0
Error			600
Mean Absolute Percentage Error			24

CHAPTER FIVE

SUMMARY CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary of Major Findings

The preceding pages of this thesis show how the research aim and objectives have been achieved. Based on the results of the study, the summary of the findings and conclusions emanating from them are presented thus:

i. The research established a total of 53 factors influencing hazard recognition capability of construction workers. These factors, as categorised from literature were validated by experts into four groups as personal factors, organisational factors, social and project related factors. There were some consensus among the experts regarding the relevance of most of the factors to hazard recognition capability. Among the 20 personal factors, 12 recorded mean values greater than 3.0, while about 9 of the factors recorded relatively very low standard deviations less than 1. All the sub factors under the social factors category recorded mean values between 2.00 to 2.93, which make them less relevant compared to the personal factors. The 11 sub factors in the organisational factors were rated as 'relevant', with mean scores between 3.8 and 3.2. Similarly, 12 out of the total of 15 sub factors have recorded mean values greater than 3, which means they are mostly 'relevant' to hazard recognition of workers, with little dispersion among the experts. Considering their group mean scores, the organisational factors category was the most

relevant with a mean score of 4.29, followed by the personal factors category with a mean score of 4.00, then project factors category with a mean value 3.40 while the least in the ranking is the social factor category, having a mean score of 2.57. A follow up interview with the experts also confirmed these results.

ii. The extent of influence of the factors on hazard recognition capability of construction workers was also assessed using mean value analysis for each of the groups of respondents. The assessment revealed some similarities in the way the different groups of respondents view the influence of the factors on hazard recognition capability of construction workers. The mean values are closely related for all the factors in the four categories. There is no any major variation in the mean values across the groups. Moreover, the group means for the four categories of factors were also not significantly different for all the groups' responses, even though they differ slightly. For the steel workers, roof workers, professionals and the general combined mean values, organisational factors category is the most influential (mean values of 3.66 for steel workers, 3.69 for excavators, 3.66 for the professionals and 3.57 for the generally combined values). This is followed by the project factors, then social factors and lastly the personal factors category. However, for the roofers and the combined tradesmen responses, there were slight variations in the group means of the factors.

iii. The study has established a structure of the key determinants of hazard recognition capability of construction workers among the factors using

principal component analysis. The structure revealed 30 factors in four components termed organisational factors with 12 items, inherent human factors with 7 items, conditional human factors with 5 items and project factors with 6 items. The factors were also reorganised completely from the previous categorisations that were established from literature and field survey. All the 30 items loaded between 0.74 and 0.50 on the respective components established. No significant variation exist in the structure of the determinants across groups of respondents. These determinants formed a generic selfassessment tool for evaluating hazard recognition capability of construction workers. iv. Using binary logistic regression analysis, relationship among the key determinants of hazard recognition capability of construction workers was established. All the categories of factors have proved to be significant predictors of hazard recognition capability of construction workers, as all of them recoded a p-value of less than 0.05 and have a positive relationship with hazard recognition capability of construction workers considering their positive B value. This implies that any increase in the categories of determinants would yield an increase in workers' hazard recognition capability. Based on the coefficients of logistic regression (B), the organisational category has the highest level of predictive power for hazard recognition capability (B=4.024), followed by the inherent human factors category (B=3.088), then the conditional human factors (B=2.967) and lastly the project factors (B=2.195).

v. The predictive model was also developed correctly classifying up to 93.2% of the HRC cases with a significant chi-square value, (538.864, df=4, p<.000*)*. The model explains between 64.7% (Cox & Snell R Square) and 87.9% (Nagelkerke R Square) of the hazard recognition capability of construction workers and recorded a -2Log likelihood of 162.972 which is reasonably low and indicates good fitness of the model. The model validation revealed that model correctly classified up to 76% of the cases, which is good enough for prediction purposes.

5.2 Conclusions

Based on the findings of the research, the following conclusions were drawn:

1. Hazard recognition capability of construction workers is influenced by a variety of factors related to the personal characteristics of the worker, the organisation in which the worker operates, the nature of projects and the group of people that a person works with. These four broad categories consist of 53 sub-factors with varying degrees of influence on the hazard recognition capability of workers in different trades and construction scenarios. Construction practitioners largely agreed on the relevance of the factors to hazard recognition capability of construction workers. Managers must understand the interplay among the factors in order to establish effective solutions to the challenges of poor hazard recognition of construction personnel.

2. There is a general consensus among construction personnel on the extent of influence of the factors on hazard recognition capability of construction workers. Based on the mean scores, the organisational factors category is the most influential group of factors on hazard recognition, followed by the project factors, then social factors and lastly the personal factors category. The trade dimension of the workers does not influence the consensus among them. This signifies the important role played by an organisation in its safety policy and practices on the workers hazard recognition capability.

3. A structure of the critical factors affecting hazard recognition capability has been established in four components such as the organisational factors, the inherent human factors, the conditional human factors and then project factors. Any efforts towards measuring or improving hazard recognition capability of workers can be channeled to these four components containing 30 critical factors affecting the workers' hazard recognition capability. There is a high degree of reliability among the different components of the determinants established, and thus, a self-assessment tool has been developed from the key determinants. This can be used to assess a worker's hazard recognition capability using different assessment methods.

4. The four components of factors have been established to have a direct positive relationship to hazard recognition of workers and have proved to be significant predictors of the recognition capability of construction workers. The organisational factors are the most significant predictors, followed by the inherent personal factors, then conditional human factors and the least significant predictor

of hazard recognition capability of workers is the project factors. The more favourable the organisational environment is in terms of safety policy and practices of improving hazard recognition, the more capable the workers would be in hazard recognition. Same thing applies to the other three components of the factors in that order, since they all have direct positive relationship to hazard recognition capability.

5. The logistic regression model is highly accurate in predicting hazard recognition capability of construction workers, considering the high level of accuracy established from the model diagnostics. Moreover, the model has been found to have adequate validity in predicting hazard recognition capability of construction workers across different trades.

5.3 Recommendations

Based on the findings of the research, the following recommendations are drawn:

a. Given the poor hazard recognition of construction workers generally encountered in the construction industry, managers should pay attention to the factors influencing hazard recognition capability of workers in order to establish the actual capability of workers before any intervention is designed or administered. This will ensure effectiveness of the interventions for increasing situational awareness of construction workers and reducing accidents on construction projects.

b. Hazard recognition assessment tool should be used on any worker or group before assigning a site responsibility to the worker. This is expected to highlight

areas of deficiency of such workers for proper placement, and will help in addressing construction accidents and fatalities on sites.

c. Construction organisations have the highest responsibility for improving hazard recognition performance of workers. Any organisation that ensures favourable environment for safety management is expected to have workers that are conscious of safety and recognise work hazards better. This therefore calls for improvement in safety management practices of firms in order to ensure good hazard recognition and situational awareness of construction workers.

d. Worker personal characteristics and the circumstances around the worker play significant roles in the worker's hazard recognition capability. Thus managers must make efforts to understand the worker fully in order to envisage how much hazards he/she can recognise in a work environment. This will guide the managers in training and other interventions made towards improving hazard recognition competencies of construction workers.

e. Construction site characteristics should also be made favourable for hazard recognition and management. This will go a long way in ensuring that workers recognise more hazards and avoid accident tendencies while working on sites.

5.4 Further Research

This research has investigated the factors influencing hazard recognition capability of construction workers using opinions of professionals and selected construction trades. This led to the development of a self-assessment tool for evaluation of workers' hazard

recognition capability, after which, a factor based model for predicting hazard recognition capability of construction workers was developed using logistic regression. The model comprises four categories of key determinants of hazard recognition and has been found to have good predictive capability. The generalizability of the findings may be limited to the number of trades considered in the data collection process. Based on the results of this study,

i. Further research may assess the influence of the same factors on hazard recognition capability of workers on other trades, to further confirm the findings of this research which revealed the same influence on the hazard recognition of workers irrespective of trades. ii. The self-assessment tool developed in this research only serves as a preliminary guide for construction managers to gauge the level of hazard recognition capability of workers. It can also be used to assess workers' capability using the 360 assessment approach. Further research can therefore be focused on automating the self-assessment tool and establishing an objective grading system in form of an index or a score that will indicate the exact hazard recognition capability and give a score for a worker. The system may also be developed in such a way that it highlights specific areas of improvement in the workers hazard recognition performance. This would be useful in training and up-skilling of workers for greater performance in hazard recognition and safety management.

iii. The logistic regression model validation reveals the predictive validity of 76%. For hazard recognition assessment, a bit higher predictive validity will help the usability of the model.

Further studies may dwell into improving the predictive validity of the model or developing alternative models using other tools, in order to enhance prediction of hazard recognition capability of workers.

5.5 Contributions to Knowledge

Based on the findings of the research, the following significant contributions to knowledge on hazard recognition and safety performance have been made:

1. The study has established 53 factors affecting hazard recognition capability of construction workers in different trades and origins. The factors were categorised according to four dimensions based on their nature of influence on hazard recognition of workers.

2. The research has also identified the critical determinants of hazard recognition capability of construction workers in four important components.

3. The study has also developed a robust self-assessment tool with high reliability for evaluating hazard recognition capability of workers using different approaches.

4. The research has also developed a model for evaluating hazard recognition capability of construction workers, clearly showing the relationships and interplay among the different dimensions of factors affecting hazard recognition performance of workers.

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APPENDICES

APPENDIX 'A'

Experts' Validation Questionnaire

VALIDATION OF TOOL FOR THE ASSESSMENT OF WORKERS' HAZARD RECOGNITION CAPABILITY

Dear respondent,

This questionnaire is an assessment tool for a PhD research aimed '**developing a tool for evaluating hazard recognition capability of construction workers**'. The statements made in the table below are based on the factors that influence the hazard recognition

capability of construction workers. The tool will be used to measure the level of hazard recognition of construction workers.

As an experienced professional in the construction industry, you are kindly requested to validate the tool for use in the prototype system, on the basis of the following:

Adequacy of the issues covered

Wording of the questions/statements

Relevance of the factors to hazard recognition

Your response would be highly valued and used strictly for the purpose of developing the evaluation tool.

After reading the statements in the questionnaire, you are kindly requested to answer some questions in a table attached at the end of the questionnaire.

Thank you.

Muawiya Abubakar

SECTION 1: PERSONAL DETAILS OF THE EXPERT

1. Nature of job handled by your organization……
2. Professional Affiliation ……
3. Highest Educational Qualification……
4. Position/Job title…..…….
5. Years of Professional Experience…….

(Note: This is the beginning of the questionnaire)

SECTION 2: WORKERS HAZARD RECOGNITION EVALUATION

Q. The Table below presents questions/statements for the evaluation of construction workers' hazard recognition capability. You are requested to kindly assess the relevance of the questions/statements using a scale of 0 – 4, where 0 – Irrelevant, 1 – Unsure, 2 – Fairly Relevant, 3 – Relevant, and 4 - Most Relevant.

Where, in your opinion, the wording is not appropriate, please tick (√) the option, 'Recast'.

EVALUATION OF QUESTIONS FOR THE HAZARD RECOGNITION CAPABILITY EVALUATION OF CONSTRUCTION WORKERS

S/N	**HAZARD RECOGNITION FACTORS**	**Experts' Assessment of Questions**					
A	**PERSONAL FACTORS**	**0**	**1**	**2**	**3**	**4**	**Recast**
A1	I have a positive attitude towards safety in general						
A2	I have the requisite competence (Knowledge and Experience) to safely do my work						
A3	I have undergone safety training to recognize hazards						
A4	I am experienced in using hazard recognition techniques						
A5	I always respond to recognized hazards						
A6	I have a good appreciation of the risks associated to my job						
A7	I have a stable emotional disposition at work						
A8	I have a good visual ability						
A9	I have sound auditory ability						
A10	I don't use Substances (like drugs, alcohol and so on) at work						
A11	I do not have safety complacency at work						
A12	I have a strong risk-taking ability						
A13	Fatigue hampers my hazard recognition ability						
A14	I believe luck can impact hazards recognition						
A15	I only recognize hazards whose risks (consequences) are known to me						
A16	My belief system encourages hazard recognition						
A17	My race and ethnicity impacts my ability for hazard recognition at work						
A18	I have been involved in/witness a construction accident						
A19	Greater number of construction tasks on site hampers my hazard recognition level						
A20	Location of hazards affects my level of recognition						
	Others….. please suggest						
B	**Social Factors**	**0**	**1**	**2**	**3**	**4**	**Recas**

							t
B1	I am influenced by my co-workers on hazard recognition and safety practices						
B2	I adjust my behaviors to align with the norms of my work group/team members						
B3	The size and composition of work crew influence my hazard recognition level						
B4	I can be influenced by the hazard recognition ability of my peers at work						
B5	My coworkers and superiors offer support on hazard recognition at work						
	Others……. Please suggest						
C	**Organisational Factors**	**0**	**1**	**2**	**3**	**4**	**Recas t**
C1	Our organizational safety policy supports hazard recognition and management						
C2	Employees are involved in hazard recognition and safety planning						
C3	We have a healthy Supervisory environment that supports hazard recognition and safety management						
C4	We have Safety Training Programs that enhance workers hazard recognition skills						
C5	Our employees are empowered/motivated to recognize and manage hazards at work place						
C6	We have an organizational structure with responsibilities for hazard recognition and management						
C7	We have a communication system for managing hazard information at work						
C8	We employ various hazard identification (both manual and automated) tools in our projects						
C9	We appraise the hazardous tendencies of all equipment used in our projects						
C10	Our organization undertakes campaigns to promote hazard recognition						
C11	We strongly discourage the use of psychoactive substances by our workers						
	Others…… please suggest						
D	**Project Factors**	**0**	**1**	**2**	**3**	**4**	**Recas t**

D1	The project has a high safety climate that supports hazard recognition						
D2	The project owner and community support hazard recognition and management						
D3	The productivity and delivery pressure of the project does not hamper hazard recognition						
D4	The layout plan of the construction site is made with the aim of improving workers' hazard recognition						
D5	Hazard recognition practices are employed in the project						
D6	The project characteristics (e.g. size, scope, materials, height etc) will not hamper hazard recognition and management						
D7	The project scope and schedule are not likely to change in the process						
D8	Advanced technological tools are used in hazard identification on the project						
D9	The site configuration (e.g. topography, soil condition, access, space, etc) will not hamper hazard recognition						
D10	The site condition (e.g. elements of weather) are not inimical to hazard recognition (by having negative influence of the workers physically and psychologically)						
D11	The project site is maintained in an orderly and tidy manner						
D12	Job specific safety training is provided for workers in the project						
D13	There is no high level of noise in the project site						
D14	There is high amount of traffic on the site						
D15	The project involves the use of mechanical plants and equipment						
D16	No excessive traffic is envisaged on the project site						
	Others… please suggest						

FINAL EVALUATION SHEET

Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Q1. Are the questions easy to understand?					
Q2. Are the components of the assessment adequate enough?					
Questions	**Expert's comments**				

Q3. Which parts of the proposed tool fell short of your expectations? Why?	
Q4. What is your opinion about the adequacy of questions in each category? If not adequate, which section(s)?	
Q5. Do any new questions need to be added? If yes, please specify.	
Q6. In your view, how can this questionnaire be improved before developing the tool?	
Additional comments:	

APPENDIX 'B'
Workers' Survey Questionnaire

RESEARCH QUESTIONNAIRE FOR THE ASSESSMENT OF HAZARD RECOGNITION CAPABILITY OF CONSTRUCTION WORKERS

Dear respondent,

This questionnaire is part of a PhD research aimed at **'Developing a framework for evaluating hazard recognition capability of construction workers**'. You are kindly requested to provide the relevant information that will help in achieving the set objectives of the research. The information provided will be treated confidentially and used strictly for the purpose of the research.

An average of 15 minutes is required to fill the questionnaire.

Your participation will be highly appreciated.

Thank you.

Mu'awiya Abubakar

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Section A: Personal details of the respondents.

6. Nature of job handled by your organization: [ ] Building Construction [ ] Civil engineering construction [ ] Both Building and Civil Engineering works [ ] Others (please specify)……
7. Highest Educational Qualification: [ ] Secondary School [ ] ND [ ] Bachelors

   [ ] Others(please state ……
8. Trainingcertification obtained ……
9. Years of Experience: (please tick)

   [ ] 1 – 5 years

   [ ] 6-10 years

   [ ] 11-15 years

[ ] 16-20 years

[ ] 21-25 years

[ ] 26-30 years

[ ] Above 30 years

10. Worker's trade/nature of job: (tick the appropriate option)

[ ] Work at height (Scaffolding and ladder usage)

[ ] Construction Steel work

[ ] Excavation work

Section B: Evaluation of factors affecting hazard recognition capability of construction workers.

1. Please indicate the extent to which the following factors affect hazard recognition capability of construction workers using a scale of 1 to 5, where 1 – Very Low, 2 - Low, 3 - Moderate, 4 - High, 5 – Very High.

S/N	Factors	1	2	3	4	5
A	**Personal**					
A1	Knowledge of the job					
A2	Level of experience in the job					
A3	Sound auditory ability					
A4	Safety training to recognize hazards					
A5	Attitude towards safety					
A6	Prior knowledge of the hazards					
A7	Good visual ability					
A8	Safety complacency					
A9	Use of Substances (like drugs, alcohol and so on) at work					
A10	Experience in using hazard recognition techniques					
A11	Stable emotional disposition					
A12	Appreciation of the risks associated with the job					
A13	Risk-taking ability					
A14	Fatigue and depletion					
A15	Involvement in a previous construction accident					
A16	Belief system					
A17	Location of hazards					
A18	Large number of construction tasks on site					

A19	Knowledge of risks (consequences) associated with a hazard					
A20	Race and ethnicity					
B	**Social factors**					
B1	Coworkers' and superiors' support on hazard recognition at work					
B2	Work group norms					
B3	Co-workers' hazard recognition and safety practices					
B4	Hazard recognition ability of peers at work					
B5	The size and composition of work crew					
B6	Supportive environment for hazard recognition and management					
B7	Hazard recognition ability and motivation of peers					
C	**Organisational factors**					
C1	Organizational safety policy					
C2	Safety Training Programs in the organisation					
C3	Organizational structure with responsibilities for hazard recognition and management					
C4	Use of incentive programs to motivate and empower employees for hazard recognition and management					
C5	Hazardous nature/tendencies of equipment used in projects					
C6	Organisational communication system for managing hazard information at work					
C7	Supervisory environment					
C8	Employee involvement in hazard recognition and safety planning					
C9	Organizational campaign to promote hazard recognition					
C10	Use of hazard (both manual and automated) identification technites					
C11	Organisational policy on the use of psychoactive substances by workers					
D	**Project factors**					
D1	The project owner and community support for hazard recognition and management					
D2	The use of mechanical plants and equipment in the project					
D3	Hazard recognition practices employed in the project					
D4	Job specific safety training provided for workers in the project					
D5	The project site house-keeping practices					
D6	Project safety climate					
D7	Traffic on project site					
D8	The layout plan of the construction site					
D9	The productivity and delivery pressure of the project					
D10	Project characteristics (e.g. size, scope, materials, height etc)					
D11	The site configuration (e.g. topography, soil condition, access, space, etc)					
D12	The site condition (e.g. elements of weather which may have negative influence of the workers physically and psychologically)					
D13	Project scope and schedule change					
D14	Noise level in the project site					

	Use of advanced technological tools in hazard identification on the project					
D15	Hazard recognition method / tool adopted					

If you are interested in the final outcome of the research, please provide your information below, and it would be shared with you.

Name:……..

Organisation:…….....

Address:……..

Email/Phonenumber:……

APPENDIX 'C'

Professionals' Survey Questionnaire

RESEARCH QUESTIONNAIRE FOR THE ASSESSMENT OF HAZARD RECOGNITION CAPABILITY OF CONSTRUCTION WORKERS

Dear respondent,

This questionnaire is part of a PhD research aimed at **'Developing a framework for evaluating hazard recognition capability of construction workers**'. You are kindly requested to provide the relevant information that will help in achieving the set objectives of the research. The information provided will be treated confidentially and used strictly for the purpose of the research.

An average of 15 minutes is required to fill the questionnaire.

Your participation will be highly appreciated.

Thank you.

Mu'awiya Abubakar

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Section A

Personal details of the respondents.

11. Nature of job handled by your organization: [ ] Building Construction [ ] Civil engineering construction [ ] Both Building and Civil Engineering works [ ] Others (please specify)……
12. Highest Educational Qualification: [ ] ND [ ] HND [ ] Bachelors [ ] Masters [ ] PhD
13. Position/Job title: [ ] Safety Manager [ ] Construction Manager [ ] Others (please specify)……..
14. Years of Professional Experience: (please tick)

    [ ] 1 – 5 years

[ ] 6-10 years

[ ] 11-15 years

[ ] 16-20 years

[ ] 21-25 years

[ ] 26-30 years

[ ] Above 30 years

Section B: Evaluation of factors affecting hazard recognition capability of construction workers.

2. Please indicate the extent to which the following factors affect hazard recognition capability of construction workers using a scale of 1 to 5, where 1 – Very Low, 2 - Low, 3 - Moderate, 4 - High, 5 – Very High.

S/N	Factors	1	2	3	4	5
A	**Personal**					
A1	Knowledge of the job					
A2	Level of experience in the job					
A3	Sound auditory ability					
A4	Safety training to recognize hazards					
A5	Attitude towards safety					
A6	Prior knowledge of the hazards					
A7	Good visual ability					
A8	Safety complacency					
A9	Use of Substances (like drugs, alcohol and so on) at work					
A10	Experience in using hazard recognition techniques					
A11	Stable emotional disposition					
A12	Appreciation of the risks associated with the job					
A13	Risk-taking ability					
A14	Fatigue and depletion					
A15	Involvement in a previous construction accident					
A16	Belief system					
A17	Location of hazards					
A18	Large number of construction tasks on site					
A19	Knowledge of risks (consequences) associated with a hazard					
A20	Race and ethnicity					
B	**Social factors**					
B1	Coworkers' and superiors' support on hazard recognition at work					

B2	Work group norms					
B3	Co-workers' hazard recognition and safety practices					
B4	Hazard recognition ability of peers at work					
B5	The size and composition of work crew					
B6	Supportive environment for hazard recognition and management					
B7	Hazard recognition ability and motivation of peers					
C	**Organisational factors**					
C1	Organizational safety policy					
C2	Safety Training Programs in the organisation					
C3	Organizational structure with responsibilities for hazard recognition and management					
C4	Use of incentive programs to motivate and empower employees for hazard recognition and management					
C5	Hazardous nature/tendencies of equipment used in projects					
C6	Organisational communication system for managing hazard information at work					
C7	Supervisory environment					
C8	Employee involvement in hazard recognition and safety planning					
C9	Organizational campaign to promote hazard recognition					
C10	Use of hazard (both manual and automated) identification technites					
C11	Organisational policy on the use of psychoactive substances by workers					
D	**Project factors**					
D1	The project owner and community support for hazard recognition and management					
D2	The use of mechanical plants and equipment in the project					
D3	Hazard recognition practices employed in the project					
D4	Job specific safety training provided for workers in the project					
D5	The project site house-keeping practices					
D6	Project safety climate					
D7	Traffic on project site					
D8	The layout plan of the construction site					
D9	The productivity and delivery pressure of the project					
D10	Project characteristics (e.g. size, scope, materials, height etc)					
D11	The site configuration (e.g. topography, soil condition, access, space, etc)					
D12	The site condition (e.g. elements of weather which may have negative influence of the workers physically and psychologically)					
D13	Project scope and schedule change					
D14	Noise level in the project site					
	Use of advanced technological tools in hazard identification on the project					
D15	Hazard recognition method / tool adopted					

If you are interested in the final outcome of the research, please provide your information below, and it would be shared with you.

Name:……

Organisation:…….

Address:……

Email/Phone number:……

APPENDIX 'D'
RESULTS OUTPUT FROM SPSS

D1: RESULTS OF FACTOR ANALYSES (PRINCIPAL AXIS FACTORING AND PRINCIPAL COMPONENT ANALYSIS)

D1A: RESULTS OF PRINCIPAL AXIS FACTORING

TABLE D1A1: KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.937
Bartlett's Test of Sphericity	Approx. Chi-Square	13669.012
	df	1378
	Sig.	0.000

TABLE D1A2" Communalities

	Initial	Extraction
KnowlgOftheJob	.594	.523
LevelOfExpernce	.560	.467
SoundAuditoryAblty	.441	.388
SafetyTrningToRecogniseHzrds	.524	.455
AttitudeTowardsSafety	.490	.387
PriorKnwledgeOfHazrds	.505	.397
GoodVisualAblty	.347	.265
SafetyComplacency	.322	.184
UseOfSubstances	.263	.094
ExpernceInUsingHzrdRecTechs	.469	.345
StableEmotionalDisposition	.469	.351
AppreciatnOfRsksAssociatedWthTheJob	.486	.357
RskTakingAbilty	.413	.395
FatgueAndDepletion	.408	.308
InvolvmntInPrevConstAccdnts	.364	.201
BeliefSystm	.377	.307
LocatnOfHzrds	.426	.285
LargeNoOfConstTasks	.377	.256
KnowldgeOfRiskAssociatedWithHazrds	.397	.268
RaceAndEtnicity	.266	.101
CoworkerAndSupriorsSpprt	.450	.293
WrkGrpNorms	.474	.298
CowrkrsHzrdRecPrctices	.534	.430
HzrdRecognAbltyOfPeers	.569	.395
SizeAndCompofWrkCrw	.434	.288
SpprtveEnvirnmnt	.563	.403
HzrdRecgMotivationOfPeers	.575	.469
OrgSaftyPolicy	.620	.586
SftyTrngProgInOrg	.631	.567
OrgStructre	.661	.591
UseOfIncentvToMotivate	.607	.565

HzrdousNatureOfEqpt	.553	.494
OrgCommSyst	.588	.553
SupervisoryEnv	.483	.356
EmployeInvolvmnt	.630	.581
OrgCampaignToPromotHR	.577	.486
UseOfHzrdIdntTechns	.599	.511
OrgPoliOnPsychoactiveSbstc	.366	.223
PrjctOwnrAncCmmntySpprt	.547	.497
UseOfMechPlnts	.485	.370
HRPractices	.196	.111
JobSpecificSaftyTrng	.619	.554
HouseKeepngPrctces	.490	.340
PrjctSftyClimate	.531	.400
TrfficOnSite	.450	.323
SiteLayOutPlan	.418	.326
PrdctvtyAndDelivryPress	.469	.423
PrjctXtics	.504	.424
SiteConfig	.517	.474
SiteCondtn	.469	.340
PrjctScopeAndSchedChng	.524	.359
NoiseLevelOnSite	.448	.287
HRMthod	.535	.437

Extraction Method: Principal Axis Factoring.

TABLE D1A3: Total Variance Explained

Factor	Initial Eigenvalues	Extraction Sums of Squared Loadings	Rotation Sums of Squared Loadings [a]

	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	15.627	29.484	29.484	15.049	28.394	28.394	13.021
2	2.829	5.338	34.823	2.225	4.198	32.593	5.699
3	2.158	4.072	38.895	1.560	2.943	35.535	7.273
4	1.845	3.480	42.375	1.254	2.366	37.902	9.720
5	1.652	3.116	45.491				
6	1.381	2.605	48.096				
7	1.311	2.473	50.569				
8	1.254	2.366	52.935				
9	1.185	2.235	55.170				
10	1.135	2.142	57.312				
11	1.087	2.050	59.362				
12	1.042	1.967	61.329				
13	.969	1.828	63.157				
14	.946	1.785	64.941				
15	.904	1.705	66.646				
16	.864	1.630	68.276				
17	.829	1.564	69.840				
18	.791	1.492	71.333				
19	.735	1.388	72.720				
20	.729	1.375	74.095				
21	.679	1.281	75.376				
22	.662	1.249	76.625				
23	.636	1.200	77.825				
24	.634	1.196	79.021				
25	.597	1.127	80.148				
26	.562	1.061	81.209				
27	.551	1.040	82.249				
28	.522	.986	83.235				
29	.510	.961	84.196				
30	.498	.939	85.135				
31	.482	.909	86.044				
32	.470	.887	86.932				
33	.465	.877	87.809				
34	.439	.827	88.636				
35	.430	.811	89.447				
36	.417	.787	90.234				
37	.408	.770	91.004				
38	.392	.739	91.743				
39	.374	.706	92.448				
40	.357	.673	93.121				

41	.348	.657	93.779
42	.342	.646	94.425
43	.327	.618	95.042
44	.323	.609	95.652
45	.307	.580	96.232
46	.293	.554	96.785
47	.282	.532	97.317
48	.266	.501	97.819
49	.260	.491	98.310
50	.248	.468	98.778
51	.236	.445	99.223
52	.212	.399	99.622
53	.200	.378	100.000

Extraction Method: Principal Axis Factoring.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

TABLE D1DA4: Factor Matrix[a]

	Factor			
	1	2	3	4
EmployeInvolvmnt	.731	-.143	-.100	-.129
OrgStructre	.723	-.218	-.124	-.081
UseOfIncentvToMotivate	.695	-.204	-.188	-.073
JobSpecificSaftyTrng	.694	-.032	-.267	-.019
HzrdousNatureOfEqpt	.691	.018	-.077	-.104
OrgCommSyst	.682	-.075	-.245	-.150
OrgSaftyPolicy	.671	-.203	-.295	-.086
PrjctOwnrAncCmmntySpprt	.661	-.002	-.163	-.185
UseOfHzrdIdntTechns	.658	-.199	-.080	-.181
HzrdRecgMotivationOfPeers	.651	-.209	-.026	-.007
OrgCampaignToPromotHR	.644	-.125	-.185	-.146
SftyTrngProgInOrg	.635	-.198	-.350	.047
CowrkrsHzrdRecPrctices	.626	-.154	.120	.001
SpprtveEnvirnmnt	.625	-.115	-.008	.004
HRMthod	.623	-.040	-.134	-.171
HzrdRecognAbltyOfPeers	.609	-.116	.093	.054
PrjctSftyClimate	.593	.180	-.036	.118
SupervisoryEnv	.590	-.086	-.018	.022
SafetyTrningToRecogniseHzrds	.582	-.199	.042	.274
ExpernceInUsingHzrdRecTechs	.574	-.058	.097	-.045
StableEmotionalDisposition	.563	-.021	.181	-.032

AttitudeTowardsSafety	.562	-.106	.097	.223
HouseKeepngPrctces	.556	.118	-.082	.102
UseOfMechPlnts	.554	.250	-.001	.018
KnowlgOftheJob	.550	-.157	.152	.416
LevelOfExpernce	.549	-.160	.144	.346
PriorKnwledgeOfHazrds	.546	-.184	.148	.209
CoworkerAndSupriorsSpprt	.539	-.007	.034	.046
SizeAndCompofWrkCrw	.515	.096	.047	.107
WrkGrpNorms	.513	-.087	.165	.002
SoundAuditoryAblty	.503	-.100	.174	.308
AppreciatnOfRsksAssociatedWthTheJob	.497	-.004	.285	-.169
KnowldgeOfRiskAssociatedWithHazrds	.482	.115	.015	.149
LocatnOfHzrds	.471	.120	.216	-.048
PrjctScopeAndSchedChng	.470	.319	.084	-.171
SiteLayOutPlan	.442	.336	-.023	.130
OrgPoliOnPsychoactiveSbstc	.439	-.003	-.138	-.105
LargeNoOfConstTasks	.435	.177	.184	-.046
TrfficOnSite	.414	.385	-.053	-.006
SafetyComplacency	.410	-.006	.126	-.006
GoodVisualAblty	.410	-.021	.257	.175
NoiseLevelOnSite	.393	.274	.132	-.202
InvolvmntInPrevConstAccdnts	.386	.113	.139	-.138
BeliefSystm	.383	.026	.331	-.222
FatgueAndDepletion	.377	.175	.289	-.226
HRPractices	.314	.052	-.004	-.099
UseOfSubstances	.225	.194	-.049	-.058
SiteConfig	.270	.559	-.257	.147
PrdctvtyAndDelivryPress	.297	.541	-.108	.173
PrjctXtics	.355	.430	-.243	.232
SiteCondtn	.400	.420	-.052	-.024
RaceAndEtnicity	.190	.200	.147	-.056
RskTakingAbilty	.403	.080	.434	-.196

Extraction Method: Principal Axis Factoring.

a. 4 factors extracted. 5 iterations required.

TABLE D1A5: Pattern Matrix[a]

	Factor			
	1	2	3	4
OrgSaftyPolicy	.806	-.010	-.127	.021

OrgCommSyst	.746	.069	-.001	-.054
SftyTrngProgInOrg	.741	.061	-.269	.122
UseOfIncentvToMotivate	.717	-.039	-.034	.099
OrgCampaignToPromotHR	.695	-.004	.028	-.015
OrgStructre	.689	-.074	.030	.137
UseOfHzrdIdntTechns	.671	-.123	.127	.028
EmployeInvolvmnt	.667	-.028	.105	.080
JobSpecificSaftyTrng	.663	.173	-.092	.067
PrjctOwnrAncCmmntySpprt	.649	.093	.112	-.075
HRMthod	.612	.046	.109	-.046
HzrdousNatureOfEqpt	.526	.119	.147	.060
HzrdRecgMotivationOfPeers	.509	-.082	.056	.243
OrgPoliOnPsychoactiveSbstc	.446	.077	.035	-.045
SpprtveEnvirnmnt	.423	.001	.087	.229
SupervisoryEnv	.384	.033	.067	.225
CowrkrsHzrdRecPrctices	.334	-.083	.192	.304
ExpernceInUsingHzrdRecTechs	.306	-.010	.219	.199
CoworkerAndSupriorsSpprt	.253	.091	.111	.238
HRPractices	.225	.064	.142	-.024
SiteConfig	.001	.725	-.110	-.051
PrdctvtyAndDelivryPress	-.124	.671	.007	.069
PrjctXtics	.046	.646	-.173	.110
SiteCondtn	.080	.476	.172	-.046
SiteLayOutPlan	.019	.453	.082	.171
TrfficOnSite	.094	.452	.153	-.013
UseOfMechPlnts	.182	.338	.174	.123
PrjctSftyClimate	.203	.331	.066	.243
HouseKeepngPrctces	.264	.276	.009	.208
UseOfSubstances	.113	.216	.097	-.072
RskTakingAbilty	-.056	-.087	.623	.122
FatgueAndDepletion	.027	.038	.536	-.022
BeliefSystm	.067	-.116	.529	.049
AppreciatnOfRsksAssociatedWthTheJob	.152	-.087	.468	.126
NoiseLevelOnSite	.108	.199	.411	-.101
PrjctScopeAndSchedChng	.151	.285	.376	-.082
LocatnOfHzrds	.055	.098	.357	.175
LargeNoOfConstTasks	.032	.158	.336	.134
InvolvmntInPrevConstAccdnts	.137	.069	.328	.014
StableEmotionalDisposition	.198	-.001	.294	.243
RaceAndEtnicity	-.082	.148	.265	.020

SafetyComplacency	.133	.017	.200	.190
KnowlgOftheJob	-.015	.057	-.069	.742
LevelOfExpernce	.039	.029	-.031	.664
SoundAuditoryAblty	-.018	.052	.028	.608
SafetyTrningToRecogniseHzrds	.216	.004	-.079	.555
PriorKnwledgeOfHazrds	.138	-.051	.056	.525
AttitudeTowardsSafety	.143	.049	.026	.497
GoodVisualAblty	-.096	.029	.194	.457
HzrdRecognAbltyOfPeers	.292	-.018	.141	.331
KnowldgeOfRiskAssociatedWithHazrds	.106	.245	.049	.286
WrkGrpNorms	.194	-.054	.228	.274
SizeAndCompofWrkCrw	.136	.204	.107	.274

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.[a]
a. Rotation converged in 10 iterations.

TABLE D1A6: Structure Matrix

	Factor			
	1	2	3	4
OrgStructre	.758	.223	.372	.543
OrgSaftyPolicy	.757	.250	.245	.450
EmployeInvolvmnt	.752	.273	.431	.513
UseOfIncentvToMotivate	.746	.237	.317	.505
OrgCommSyst	.740	.332	.342	.408
JobSpecificSaftyTrng	.725	.403	.295	.467
SftyTrngProgInOrg	.714	.272	.137	.473
UseOfHzrdIdntTechns	.700	.175	.401	.450
OrgCampaignToPromotHR	.697	.259	.337	.410
PrjctOwnrAncCmmntySpprt	.689	.353	.409	.378
HzrdousNatureOfEqpt	.674	.378	.451	.460
HRMthod	.651	.299	.385	.373
HzrdRecgMotivationOfPeers	.649	.181	.355	.550
SpprtveEnvirnmnt	.599	.240	.369	.516
CowrkrsHzrdRecPrctices	.572	.177	.435	.560
SupervisoryEnv	.561	.250	.341	.488
ExpernceInUsingHzrdRecTechs	.521	.224	.433	.466
PrjctSftyClimate	.501	.485	.366	.467
HouseKeepngPrctces	.494	.424	.305	.433
CoworkerAndSupriorsSpprt	.479	.277	.350	.454
OrgPoliOnPsychoactiveSbstc	.463	.244	.247	.253
HRPractices	.298	.190	.256	.181
SiteConfig	.188	.676	.117	.075
PrdctvtyAndDelivryPress	.168	.643	.207	.154
PrjctXtics	.272	.629	.112	.220
SiteCondtn	.307	.553	.353	.180
TrfficOnSite	.323	.536	.345	.209
SiteLayOutPlan	.326	.528	.313	.320
UseOfMechPlnts	.459	.493	.420	.378
UseOfSubstances	.194	.274	.194	.084
RskTakingAbilty	.267	.133	.615	.312
AppreciatnOfRsksAssociatedWthTheJob	.408	.158	.557	.381
FatgueAndDepletion	.272	.226	.553	.214
BeliefSystm	.294	.101	.539	.270
PrjctScopeAndSchedChng	.379	.450	.510	.223
NoiseLevelOnSite	.308	.356	.488	.171
LocatnOfHzrds	.358	.281	.484	.371
StableEmotionalDisposition	.476	.229	.479	.477
LargeNoOfConstTasks	.323	.315	.456	.321

InvolvmntInPrevConstAccdnts	.320	.234	.419	.240
RaceAndEtnicity	.105	.213	.286	.109
KnowlgOftheJob	.418	.201	.235	.720
LevelOfExpernce	.432	.187	.258	.682
SafetyTrningToRecogniseHzrds	.512	.185	.238	.653
SoundAuditoryAblty	.377	.196	.276	.620
PriorKnwledgeOfHazrds	.458	.141	.307	.617
AttitudeTowardsSafety	.470	.227	.304	.604
HzrdRecognAbltyOfPeers	.546	.215	.397	.556
GoodVisualAblty	.276	.166	.340	.483
WrkGrpNorms	.442	.160	.406	.467
SizeAndCompofWrkCrw	.423	.354	.346	.444
KnowldgeOfRiskAssociatedWithHazrds	.390	.367	.293	.426
SafetyComplacency	.344	.179	.341	.352

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

TABLE D1A8: Factor Correlation Matrix

Factor	1	2	3	4
1	1.000	.370	.455	.597
2	.370	1.000	.341	.232
3	.455	.341	1.000	.393
4	.597	.232	.393	1.000

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

D1B: **RESULTS OF PRINCIPAL COMPONENT NALYSIS**

TABLE D1B1: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.937
Bartlett's Test of Sphericity	Approx. Chi-Square	13669.012
	df	1378
	Sig.	0.000

TABLE D1B2: Communalities

	Initial	Extraction
KnowlgOftheJob	1.000	.556
LevelOfExpernce	1.000	.500
SoundAuditoryAblty	1.000	.458
SafetyTrningToRecogniseHzrds	1.000	.501
AttitudeTowardsSafety	1.000	.424
PriorKnwledgeOfHazrds	1.000	.436
GoodVisualAblty	1.000	.340
SafetyComplacency	1.000	.209
UseOfSubstances	1.000	.134
ExpernceInUsingHzrdRecTechs	1.000	.365
StableEmotionalDisposition	1.000	.379
AppreciatnOfRsksAssociatedWthTheJob	1.000	.412
RskTakingAbilty	1.000	.482
FatgueAndDepletion	1.000	.411
InvolvmntInPrevConstAccdnts	1.000	.257
BeliefSystm	1.000	.397
LocatnOfHzrds	1.000	.327
LargeNoOfConstTasks	1.000	.302
KnowldgeOfRiskAssociatedWithHazrds	1.000	.315
RaceAndEtnicity	1.000	.157
CoworkerAndSupriorsSpprt	1.000	.315
WrkGrpNorms	1.000	.336
CowrkrsHzrdRecPrctices	1.000	.455
HzrdRecognAbltyOfPeers	1.000	.420
SizeAndCompofWrkCrw	1.000	.323
SpprtveEnvirnmnt	1.000	.425
HzrdRecgMotivationOfPeers	1.000	.495
OrgSaftyPolicy	1.000	.617
SftyTrngProgInOrg	1.000	.596
OrgStructre	1.000	.612
UseOfIncentvToMotivate	1.000	.590
HzrdousNatureOfEqpt	1.000	.516
OrgCommSyst	1.000	.579
SupervisoryEnv	1.000	.376
EmployeInvolvmnt	1.000	.604
OrgCampaignToPromotHR	1.000	.521
UseOfHzrdIdntTechns	1.000	.551
OrgPoliOnPsychoactiveSbstc	1.000	.263
PrjctOwnrAncCmmntySpprt	1.000	.535

UseOfMechPlnts	1.000	.400
HRPractices	1.000	.136
JobSpecificSaftyTrng	1.000	.582
HouseKeepngPrctces	1.000	.376
PrjctSftyClimate	1.000	.436
TrfficOnSite	1.000	.384
SiteLayOutPlan	1.000	.393
PrdctvtyAndDelivryPress	1.000	.512
PrjctXtics	1.000	.504
SiteConfig	1.000	.554
SiteCondtn	1.000	.408
PrjctScopeAndSchedChng	1.000	.425
NoiseLevelOnSite	1.000	.371
HRMthod	1.000	.483

Extraction Method: Principal Component Analysis.

TABLE D1B3:Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	15.627	29.484	29.484	15.627	29.484	29.484	8.444	15.933	15.933
2	2.829	5.338	34.823	2.829	5.338	34.823	5.781	10.907	26.840
3	2.158	4.072	38.895	2.158	4.072	38.895	4.136	7.803	34.644
4	1.845	3.480	42.375	1.845	3.480	42.375	4.098	7.731	42.375
5	1.652	3.116	45.491						
6	1.381	2.605	48.096						
7	1.311	2.473	50.569						
8	1.254	2.366	52.935						
9	1.185	2.235	55.170						
10	1.135	2.142	57.312						
11	1.087	2.050	59.362						
12	1.042	1.967	61.329						
13	.969	1.828	63.157						
14	.946	1.785	64.941						
15	.904	1.705	66.646						
16	.864	1.630	68.276						
17	.829	1.564	69.840						
18	.791	1.492	71.333						
19	.735	1.388	72.720						
20	.729	1.375	74.095						

21	.679	1.281	75.376
22	.662	1.249	76.625
23	.636	1.200	77.825
24	.634	1.196	79.021
25	.597	1.127	80.148
26	.562	1.061	81.209
27	.551	1.040	82.249
28	.522	.986	83.235
29	.510	.961	84.196
30	.498	.939	85.135
31	.482	.909	86.044
32	.470	.887	86.932
33	.465	.877	87.809
34	.439	.827	88.636
35	.430	.811	89.447
36	.417	.787	90.234
37	.408	.770	91.004
38	.392	.739	91.743
39	.374	.706	92.448
40	.357	.673	93.121
41	.348	.657	93.779
42	.342	.646	94.425
43	.327	.618	95.042
44	.323	.609	95.652
45	.307	.580	96.232
46	.293	.554	96.785
47	.282	.532	97.317
48	.266	.501	97.819
49	.260	.491	98.310
50	.248	.468	98.778
51	.236	.445	99.223
52	.212	.399	99.622
53	.200	.378	100.000

Extraction Method: Principal Component Analysis.

TABLE D1B4: Component Matrix[a]

	Component			
	1	2	3	4
EmployeInvolvmnt	.736	-.153	-.103	-.168
OrgStructre	.728	-.231	-.132	-.108
UseOfIncentvToMotivate	.701	-.218	-.199	-.107
JobSpecificSaftyTrng	.701	-.040	-.293	-.064
HzrdousNatureOfEqpt	.700	.014	-.089	-.134
OrgCommSyst	.688	-.082	-.250	-.189
OrgSaftyPolicy	.675	-.215	-.308	-.141
PrjctOwnrAncCmmntySpprt	.669	-.008	-.176	-.237
UseOfHzrdIdntTechns	.666	-.217	-.085	-.232
HzrdRecgMotivationOfPeers	.661	-.236	-.039	-.018
OrgCampaignToPromotHR	.653	-.140	-.195	-.192
SftyTrngProgInOrg	.640	-.213	-.376	-.002
CowrkrsHzrdRecPrctices	.638	-.180	.126	.012
SpprtveEnvirnmnt	.637	-.137	-.017	.018
HRMthod	.634	-.048	-.151	-.236
HzrdRecognAbltyOfPeers	.621	-.143	.090	.076
PrjctSftyClimate	.606	.195	-.065	.164
SupervisoryEnv	.603	-.105	-.032	.017
SafetyTrningToRecogniseHzrds	.591	-.230	.012	.315
ExpernceInUsingHzrdRecTechs	.588	-.073	.106	-.043
StableEmotionalDisposition	.576	-.031	.213	-.017
AttitudeTowardsSafety	.574	-.131	.074	.267
HouseKeepngPrctces	.570	.126	-.123	.144
UseOfMechPlnts	.567	.277	-.015	.042
LevelOfExpernce	.557	-.187	.111	.377
PriorKnwledgeOfHazrds	.557	-.219	.127	.249
KnowlgOftheJob	.557	-.179	.113	.449
CoworkerAndSupriorsSpprt	.554	-.016	.028	.083
SizeAndCompofWrkCrw	.530	.106	.043	.172
WrkGrpNorms	.527	-.108	.209	.055
SoundAuditoryAblty	.513	-.124	.162	.391
AppreciatnOfRsksAssociatedWthTheJob	.510	-.010	.356	-.160
KnowldgeOfRiskAssociatedWithHazrds	.496	.130	-.006	.226
LocatnOfHzrds	.485	.135	.271	-.009
PrjctScopeAndSchedChng	.482	.367	.102	-.220
SiteLayOutPlan	.454	.381	-.053	.198
OrgPoliOnPsychoactiveSbstc	.453	-.006	-.175	-.164

LargeNoOfConstTasks	.449	.208	.238	-.012
SafetyComplacency	.425	-.009	.169	.007
GoodVisualAblty	.423	-.031	.296	.270
NoiseLevelOnSite	.404	.325	.173	-.269
InvolvmntInPrevConstAccdnts	.400	.139	.196	-.199
FatgueAndDepletion	.388	.207	.386	-.263
HRPractices	.327	.062	-.001	-.161
SiteConfig	.275	.603	-.307	.143
PrdctvtyAndDelivryPress	.303	.595	-.152	.207
SiteCondtn	.411	.481	-.075	-.049
PrjctXtics	.362	.469	-.308	.240
TrfficOnSite	.425	.444	-.071	.020
RaceAndEtnicity	.199	.259	.223	-.033
UseOfSubstances	.235	.254	-.060	-.103
RskTakingAbilty	.412	.086	.522	-.180
BeliefSystm	.394	.029	.439	-.220

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

TABLE D1B5: Rotated Component Matrix[a]

	Component			
	1	2	3	4
OrgSaftyPolicy	.744	.225	.034	.111
OrgCommSyst	.700	.173	.141	.198
UseOfIncentvToMotivate	.694	.296	.109	.088
SftyTrngProgInOrg	.693	.288	-.094	.157
OrgStructre	.685	.332	.167	.063
EmployeInvolvmnt	.676	.278	.241	.109
OrgCampaignToPromotHR	.670	.186	.155	.118
UseOfHzrdIdntTechns	.669	.217	.239	.010
JobSpecificSaftyTrng	.661	.248	.068	.281
PrjctOwnrAncCmmntySpprt	.646	.128	.232	.218
HRMthod	.623	.129	.225	.165
HzrdousNatureOfEqpt	.573	.240	.268	.242
HzrdRecgMotivationOfPeers	.558	.393	.169	.027
SpprtveEnvirnmnt	.482	.384	.186	.104
OrgPoliOnPsychoactiveSbstc	.466	.068	.116	.165
SupervisoryEnv	.455	.352	.171	.125
ExpernceInUsingHzrdRecTechs	.393	.330	.306	.087
HRPractices	.271	.034	.216	.124
KnowlgOftheJob	.194	.712	.044	.098

LevelOfExpernce	.228	.661	.074	.075
SoundAuditoryAblty	.146	.645	.106	.101
SafetyTrningToRecogniseHzrds	.341	.616	.029	.069
PriorKnwledgeOfHazrds	.287	.579	.135	.013
AttitudeTowardsSafety	.286	.561	.118	.115
GoodVisualAblty	.040	.518	.253	.076
HzrdRecognAbltyOfPeers	.396	.452	.233	.071
CowrkrsHzrdRecPrctices	.430	.434	.286	.018
WrkGrpNorms	.271	.411	.305	.025
KnowldgeOfRiskAssociatedWithHazrds	.200	.390	.118	.329
SizeAndCompofWrkCrw	.231	.388	.186	.290
CoworkerAndSupriorsSpprt	.334	.366	.192	.179
RskTakingAbilty	.074	.210	.657	-.008
FatgueAndDepletion	.119	.060	.617	.113
BeliefSystm	.140	.163	.591	-.044
AppreciatnOfRsksAssociatedWthTheJob	.246	.256	.535	.003
NoiseLevelOnSite	.196	-.031	.498	.289
PrjctScopeAndSchedChng	.248	.013	.464	.385
LocatnOfHzrds	.157	.288	.431	.182
InvolvmntInPrevConstAccdnts	.215	.079	.431	.139
LargeNoOfConstTasks	.124	.236	.414	.242
StableEmotionalDisposition	.308	.362	.381	.089
RaceAndEtnicity	-.047	.069	.330	.203
SafetyComplacency	.208	.281	.285	.077
SiteConfig	.071	-.015	-.026	.741
PrdctvtyAndDelivryPress	-.011	.096	.070	.706
PrjctXtics	.135	.143	-.074	.678
SiteCondtn	.173	.017	.256	.559
TrfficOnSite	.165	.088	.222	.547
SiteLayOutPlan	.121	.260	.148	.538
UseOfMechPlnts	.282	.244	.264	.438
PrjctSftyClimate	.309	.365	.162	.426
HouseKeepngPrctces	.344	.334	.095	.370
UseOfSubstances	.147	-.045	.162	.290

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 7 iterations.

TABLE D1B5: Component Transformation Matrix

Component	1	2	3	4
1	.682	.527	.385	.330
2	-.340	-.293	.274	.851
3	-.486	.291	.752	-.336
4	-.427	.743	-.459	.233

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

D2: RELIABILITY ANALYSES RESULTS

Case Processing Summary

		N	%
Cases	Valid	561	100.0
	Excluded[a]	0	0.0
	Total	561	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.927	12

Item Statistics

	Mean	Std. Deviation	N
OrgSaftyPolicy	3.69	1.101	561
SftyTrngProgInOrg	3.63	1.104	561
OrgStructre	3.55	1.096	561
UseOfIncentvToMotivate	3.47	1.103	561
OrgCommSyst	3.57	1.122	561
EmployeInvolvmnt	3.59	1.026	561
OrgCampaignToPromotHR	3.59	1.057	561
UseOfHzrdIdntTechns	3.47	1.108	561
PrjctOwnrAncCmmntySpprt	3.38	1.102	561
JobSpecificSaftyTrng	3.61	1.087	561
HRMthod	3.56	1.123	561
HzrdousNatureOfEqpt	3.65	1.036	561

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
OrgSaftyPolicy	39.09	79.399	.723	.920
SftyTrngProgInOrg	39.15	80.236	.674	.922
OrgStructre	39.22	79.519	.720	.920
UseOfIncentvToMotivate	39.30	79.583	.711	.920
OrgCommSyst	39.20	79.212	.717	.920
EmployeInvolvmnt	39.18	80.378	.727	.920
OrgCampaignToPromotHR	39.19	80.933	.670	.922
UseOfHzrdIdntTechns	39.30	80.159	.676	.921
PrjctOwnrAncCmmntySpprt	39.39	80.325	.671	.922
JobSpecificSaftyTrng	39.17	80.043	.698	.921
HRMthod	39.21	80.928	.624	.924
HzrdousNatureOfEqpt	39.12	81.482	.655	.922

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
42.78	94.796	9.736	12

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
42.78	94.796	9.736	12

ANOVA with Cochran's Test

		Sum of Squares	df	Mean Square	Cochran's Q	Sig
Between People		4423.808	560	7.900		
Within People	Between Items	45.672	11	4.152	78.397	.000
	Residual	3549.411	6160	.576		
	Total	3595.083	6171	.583		
Total		8018.892	6731	1.191		

Grand Mean = 3.56

Reliability Statistics

Cronbach's Alpha	N of Items
.833	7

Item Statistics

	Mean	Std. Deviation	N
KnowlgOftheJob	3.90	1.041	561
LevelOfExpernce	3.92	.963	561
SoundAuditoryAblty	3.68	1.021	561
SafetyTrningToRecogniseHzrds	3.71	1.121	561
AttitudeTowardsSafety	3.68	.982	561
PriorKnwledgeOfHazrds	3.73	1.037	561
GoodVisualAblty	3.85	.960	561

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
KnowlgOftheJob	22.57	18.489	.655	.798
LevelOfExpernce	22.55	19.102	.643	.801
SoundAuditoryAblty	22.79	19.215	.579	.811
SafetyTrningToRecogniseHzrds	22.76	18.520	.587	.810
AttitudeTowardsSafety	22.79	19.300	.600	.808
PriorKnwledgeOfHazrds	22.74	19.063	.586	.810
GoodVisualAblty	22.61	20.777	.427	.833

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
26.47	25.439	5.044	7

ANOVA with Cochran's Test

		Sum of Squares	df	Mean Square	Cochran's Q	Sig
Between People		2035.091	560	3.634		
Within People	Between Items	37.552	6	6.259	60.929	.000
	Residual	2037.019	3360	.606		
	Total	2074.571	3366	.616		
Total		4109.663	3926	1.047		

Grand Mean = 3.78

Case Processing Summary

		N	%
Cases	Valid	561	100.0
	Excluded[a]	0	0.0
	Total	561	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.678	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
RskTakingAbilty	13.47	8.739	.527	.586
BeliefSystm	13.67	8.857	.405	.642
FatgueAndDepletion	13.55	8.920	.446	.621
AppreciatnOfRsksAssociatedWthTheJob	13.41	9.277	.461	.617
NoiseLevelOnSite	13.37	9.698	.335	.669

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
16.87	13.158	3.627	5

ANOVA with Cochran's Test

		Sum of Squares	df	Mean Square	Cochran's Q	Sig
Between People		1473.648	560	2.632		
Within People	Between Items	32.166	4	8.042	37.423	.000
	Residual	1896.634	2240	.847		
	Total	1928.800	2244	.860		
Total		3402.448	2804	1.213		

Grand Mean = 3.37

Case Processing Summary

		N	%
Cases	Valid	561	100.0
	Excluded[a]	0	0.0
	Total	561	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.769	6

Item Statistics

	Mean	Std. Deviation	N
SiteConfig	3.59	1.004	561
PrdctvtyAndDelivryPress	3.63	1.021	561
PrjctXtics	3.68	.990	561
SiteCondtn	3.60	1.015	561
TrfficOnSite	3.46	1.040	561
SiteLayOutPlan	3.64	.985	561

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SiteConfig	18.01	11.993	.578	.718
PrdctvtyAndDelivryPress	17.96	11.982	.565	.721
PrjctXtics	17.92	12.279	.542	.728
SiteCondtn	17.99	12.702	.455	.750
TrfficOnSite	18.13	12.652	.444	.753
SiteLayOutPlan	17.96	12.586	.496	.739

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
21.59	17.020	4.126	6

ANOVA with Cochran's Test

		Sum of Squares	df	Mean Square	Cochran's Q	Sig
Between People		1588.556	560	2.837		
Within People	Between Items	15.804	5	3.161	23.962	.000
	Residual	1834.196	2800	.655		
	Total	1850.000	2805	.660		
Total		3438.556	3365	1.022		

Grand Mean = 3.60

RESULTS OF LOGISTIC REGRESSION

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	561	100.0
	Missing Cases	0	0.0
	Total	561	100.0
Unselected Cases		0	0.0
Total		561	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
0	0
1	1

BLOCK 0

Classification Table[a,b]

Observed			Predicted HRC_TRANS		Percentage Correct
			0	1	
Step 0	HRC_TRANS	0	0	215	0.0
		1	0	346	100.0
	Overall Percentage				61.7

a. Constant is included in the model.
b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.476	.087	30.019	1	.000	1.609

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	A	272.225	1	.000
		B	216.315	1	.000
		C	140.524	1	.000
		D	105.180	1	.000
	Overall Statistics		354.568	4	.000

Block 1 Method: Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	583.864	4	.000
	Block	583.864	4	.000
	Model	583.864	4	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	162.972[a]	.647	.879

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	1.461	8	.993

Contingency Table for Hosmer and Lemeshow Test

		HRC_TRANS = 0		HRC_TRANS = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	55	54.997	0	.003	55
	2	55	54.863	0	.137	55
	3	54	53.758	2	2.242	56
	4	34	36.239	21	18.761	55
	5	15	12.880	44	46.120	59
	6	2	1.839	53	53.161	55

	7	0	.276	25	24.724	25
	8	0	.107	66	65.893	66
	9	0	.038	55	54.962	55
	10	0	.002	80	79.998	80

Classification Table[a]

			Predicted		
			HRC_TRANS		Percentage
Observed			0	1	Correct
Step 1	HRC_TRANS	0	190	25	88.4
		1	13	333	96.2
	Overall Percentage				93.2

a. The cut value is .500

Variables in the Equation

								95% C.I.for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1[a]	A	4.024	.495	66.093	1	.000	55.907	21.192	147.487
	B	3.088	.424	53.114	1	.000	21.939	9.561	50.339
	C	2.967	.445	44.438	1	.000	19.425	8.120	46.469
	D	2.195	.392	31.397	1	.000	8.976	4.166	19.341
	Constant	-42.672	4.866	76.915	1	.000	.000		

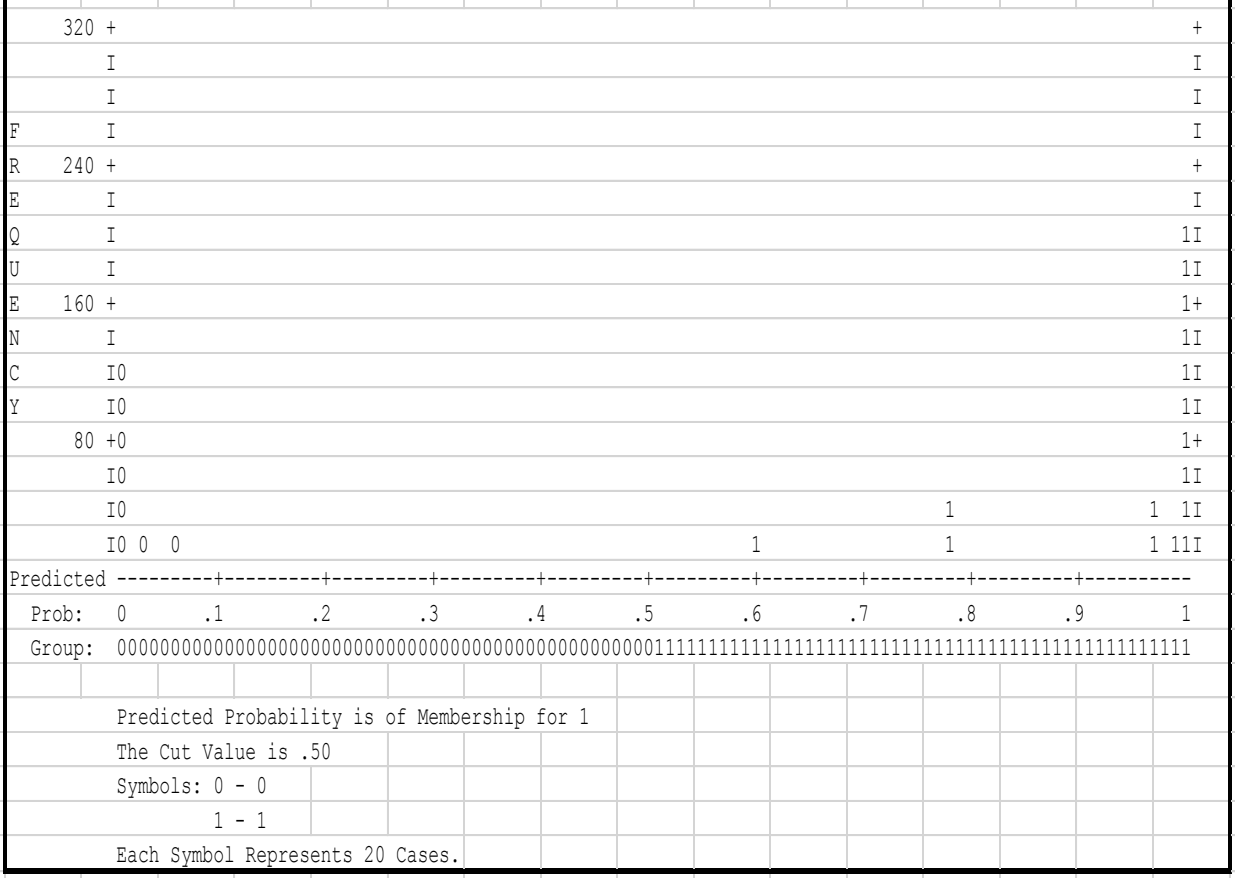
a. Variable(s) entered on step 1: A, B, C, D.

Correlation Matrix

		Constant	A	B	C	D
Step 1	Constant	1.000	-.832	-.797	-.819	-.711
	A	-.832	1.000	.511	.620	.431
	B	-.797	.511	1.000	.558	.451
	C	-.819	.620	.558	1.000	.436
	D	-.711	.431	.451	.436	1.000

Step number: 1

Observed Groups and Predicted Probabilities



Predicted Probability is of Membership for 1

The Cut Value is .50

Symbols: 0 - 0

1 - 1

Each Symbol Represents 20 Cases.

Casewise List[b]

Case	Selected Status[a]	Observed HRC_TRANS	Predicted	Predicted Group	Temporary Variable Resid	ZResid
99	S	1**	.138	0	.862	2.496
169	S	0**	.969	1	-.969	-5.623
200	S	1**	.062	0	.938	3.902
285	S	1**	.059	0	.941	3.984
389	S	0**	.969	1	-.969	-5.623

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.

b. Cases with studentised residuals greater than 2.000 are listed.

E1: RESULTS OF LOGISTIC REGRESSION FOR THE SEPARATE DATA SETS

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	260	100.0
	Missing Cases	0	.0
	Total	260	100.0
Unselected Cases		0	.0
Total		260	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
0	0
1	1

BLOCK 0: BEGINNING BLOCK

Iteration History[a,b,c]

Iteration		-2 Log likelihood	Coefficients Constant
Step 0	1	345.514	.477
	2	345.509	.486
	3	345.509	.486

a. Constant is included in the model.

b. Initial -2 Log Likelihood: 345.509

c. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Classification Table[a,b]

		Predicted		
		HRC_TRANS		Percentage Correct
	Observed	0	1	
Step 0	HRC_TRANS 0	0	99	.0
	1	0	161	100.0
	Overall Percentage			61.9

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.486	.128	14.497	1	.000	1.626

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	A	120.253	1	.000
		B	98.753	1	.000
		C	51.815	1	.000
		D	65.689	1	.000
	Overall Statistics		171.868	4	.000

BLOCK 1: METHOD = ENTER

Iteration History[a,b,c,d]

Iteration		-2 Log likelihood	Coefficients				
			Constant	A	B	C	D
Step 1	1	154.679	-10.149	.997	.796	.543	.583
	2	108.175	-17.752	1.696	1.432	1.082	.901
	3	90.036	-25.742	2.404	2.046	1.698	1.272
	4	84.101	-33.233	3.039	2.587	2.299	1.666
	5	83.048	-37.995	3.428	2.925	2.684	1.933
	6	83.002	-39.281	3.530	3.017	2.787	2.009
	7	83.001	-39.351	3.535	3.022	2.793	2.013
	8	83.001	-39.351	3.536	3.022	2.793	2.013

a. Method: Enter

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 345.509

d. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	262.507	4	.000
	Block	262.507	4	.000
	Model	262.507	4	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	83.001[a]	.636	.865

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	.766	7	.998

Contingency Table for Hosmer and Lemeshow Test

		HRC_TRANS = 0		HRC_TRANS = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	26	25.992	0	.008	26
	2	26	25.794	0	.206	26
	3	25	24.501	1	1.499	26
	4	15	16.141	13	11.859	28
	5	6	5.534	20	20.466	26
	6	1	.913	26	26.087	27
	7	0	.094	38	37.906	38
	8	0	.028	33	32.972	33
	9	0	.002	30	29.998	30

Classification Table[a]

		Predicted		
		HRC_TRANS		Percentage
	Observed	0	1	Correct
Step 1	HRC_TRANS 0	85	14	85.9
	1	6	155	96.3
	Overall Percentage			92.3

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	A	3.536	.694	25.923	1	.000	34.312	8.798	133.819
	B	3.022	.563	28.855	1	.000	20.533	6.817	61.848
	C	2.793	.621	20.255	1	.000	16.327	4.838	55.094
	D	2.013	.546	13.598	1	.000	7.484	2.568	21.813
	Constant	-39.351	6.411	37.681	1	.000	.000		

a. Variable(s) entered on step 1: A, B, C, D.

Correlation Matrix

		Constant	A	B	C	D
Step 1	Constant	1.000	-.757	-.802	-.815	-.663
	A	-.757	1.000	.428	.502	.240
	B	-.802	.428	1.000	.605	.456
	C	-.815	.502	.605	1.000	.411
	D	-.663	.240	.456	.411	1.000

Casewise List[b]

Case	Selected Status[a]	Observed	Predicted	Predicted Group	Temporary Variable	
		HRC_TRANS			Resid	ZResid
130	S	0**	.856	1	-.856	-2.442
169	S	0**	.965	1	-.965	-5.228

200	S	1**	.061	0	.939	3.927

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.

b. Cases with studentized residuals greater than 2.000 are listed.

E12: LOGISTIC REGRESSION FOR STEEL WORKERS' DATA SET

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	62	100.0
	Missing Cases	0	.0
	Total	62	100.0
Unselected Cases		0	.0
Total		62	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
0	0
1	1

BLOCK 0: BEGINNING BLOCK

Iteration History[a,b,c]

Iteration		-2 Log likelihood	Coefficients
			Constant
Step 0	1	76.437	.774
	2	76.413	.816

	3	76.413	.817

a. Constant is included in the model.

b. Initial -2 Log Likelihood: 76.413

c. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

Classification Table[a,b]

		Predicted		
		HRC_TRANS		Percentage Correct
	Observed	0	1	
Step 0	HRC_TRANS 0	0	19	.0
	1	0	43	100.0
	Overall Percentage			69.4

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.817	.275	8.791	1	.003	2.263

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	A	26.082	1	.000
		B	17.830	1	.000
		C	5.489	1	.019
		D	15.490	1	.000

	Overall Statistics	30.296	4	.000

BLOCK 1: METHOD = ENTER

Iteration History[a,b,c,d]

Iteration		-2 Log likelihood	Coefficients				
			Constant	A	B	C	D
Step 1	1	45.483	-6.791	.922	.304	.228	.560
	2	36.950	-12.493	1.361	.723	.432	1.121
	3	33.911	-18.372	1.727	1.247	.702	1.626
	4	33.154	-23.031	2.016	1.687	.997	1.927
	5	33.066	-25.262	2.158	1.898	1.167	2.041
	6	33.065	-25.630	2.182	1.932	1.196	2.059
	7	33.065	-25.639	2.182	1.933	1.197	2.059
	8	33.065	-25.639	2.182	1.933	1.197	2.059

a. Method: Enter

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 76.413

d. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	43.348	4	.000
	Block	43.348	4	.000
	Model	43.348	4	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	33.065[a]	.503	.710

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	2.840	8	.944

Contingency Table for Hosmer and Lemeshow Test

		HRC_TRANS = 0		HRC_TRANS = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	6	5.978	0	.022	6
	2	5	5.275	1	.725	6
	3	2	3.082	4	2.918	6
	4	4	2.851	4	5.149	8
	5	2	1.238	4	4.762	6
	6	0	.396	6	5.604	6
	7	0	.139	6	5.861	6
	8	0	.032	6	5.968	6
	9	0	.008	6	5.992	6
	10	0	.001	6	5.999	6

Classification Table[a]

		Predicted		
		HRC_TRANS		Percentage Correct
	Observed	0	1	
Step 1	HRC_TRANS 0	13	6	68.4
	1	2	41	95.3
	Overall Percentage			87.1

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	A	2.182	.915	5.688	1	.017	8.868	1.475	53.301
	B	1.933	1.136	2.896	1	.089	6.910	.746	64.037
	C	1.197	1.066	1.261	1	.261	3.309	.410	26.711
	D	2.059	.881	5.467	1	.019	7.840	1.395	44.047
	Constant	-25.639	9.373	7.482	1	.006	.000		

a. Variable(s) entered on step 1: A, B, C, D.

Correlation Matrix

		Constant	A	B	C	D
Step 1	Constant	1.000	-.607	-.743	-.668	-.628
	A	-.607	1.000	.254	.186	.202
	B	-.743	.254	1.000	.310	.251
	C	-.668	.186	.310	1.000	.336
	D	-.628	.202	.251	.336	1.000

Casewise List[b]

Case	Selected Status[a]	Observed	Predicted	Predicted Group	Temporary Variable	
		HRC_TRANS			Resid	ZResid
263	S	0**	.926	1	-.926	-3.538

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.

b. Cases with studentized residuals greater than 2.000 are listed.

E13: RESULTS OF LOGISTIC REGRESSION FOR ROOF WORKERS' DATA SET

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	176	100.0
	Missing Cases	0	.0
	Total	176	100.0
Unselected Cases		0	.0
Total		176	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
0	0
1	1

BLOCK 0: BEGINNING BLOCK

Iteration History[a,b,c]

Iteration		-2 Log likelihood	Coefficients Constant
Step 0	1	242.531	.182
	2	242.531	.182

a. Constant is included in the model.

b. Initial -2 Log Likelihood: 242.531

c. Estimation terminated at iteration number 2 because parameter estimates changed by less than .001.

Classification Table[a,b]

			Predicted		
			HRC_TRANS		Percentage Correct
	Observed		0	1	
Step 0	HRC_TRANS	0	0	80	.0
		1	0	96	100.0
	Overall Percentage				54.5

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.182	.151	1.451	1	.228	1.200

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	A	81.209	1	.000
		B	63.773	1	.000
		C	63.302	1	.000
		D	18.440	1	.000
	Overall Statistics		116.758	4	.000

BLOCK 1: METHOD = ENTER

Iteration History[a,b,c,d]

Iteration		-2 Log likelihood	Coefficients				
			Constant	A	B	C	D
Step 1	1	105.859	-9.299	.965	.646	.910	.183
	2	66.947	-17.673	1.846	1.181	1.509	.573
	3	47.802	-27.998	2.913	1.820	2.233	1.100
	4	39.366	-39.704	4.085	2.545	3.132	1.663
	5	36.676	-50.452	5.140	3.198	4.017	2.158
	6	36.265	-56.598	5.727	3.563	4.559	2.434
	7	36.250	-58.008	5.855	3.647	4.694	2.493
	8	36.250	-58.070	5.861	3.650	4.700	2.496
	9	36.250	-58.070	5.861	3.650	4.700	2.496

a. Method: Enter

b. Constant is included in the model.

c. Initial -2 Log Likelihood: 242.531

e. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	206.281	4	.000
	Block	206.281	4	.000
	Model	206.281	4	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	36.250[a]	.690	.923

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	.487	7	.999

Contingency Table for Hosmer and Lemeshow Test

		HRC_TRANS = 0		HRC_TRANS = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	19	19.000	0	.000	19
	2	20	19.996	0	.004	20
	3	19	18.883	0	.117	19
	4	15	15.438	2	1.562	17
	5	6	5.979	12	12.021	18
	6	1	.657	19	19.343	20
	7	0	.042	17	16.958	17
	8	0	.003	20	19.997	20
	9	0	.000	26	26.000	26

Classification Table[a]

			Predicted		
			HRC_TRANS		Percentage
	Observed		0	1	Correct
Step 1	HRC_TRANS	0	77	3	96.3
		1	3	93	96.9
	Overall Percentage				96.6

a. The cut value is .500

								95% C.I.for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1[a]	A	5.861	1.298	20.399	1	.000	350.960	27.589	4464.560
	B	3.650	.961	14.437	1	.000	38.487	5.855	252.978
	C	4.700	1.252	14.096	1	.000	109.945	9.454	1278.592
	D	2.496	.859	8.445	1	.004	12.132	2.254	65.316

	Constant	-58.070	12.682	20.966	1	.000	.000		

a. Variable(s) entered on step 1: A, B, C, D.

Correlation Matrix

		Constant	A	B	C	D
Step 1	Constant	1.000	-.907	-.808	-.855	-.715
	A	-.907	1.000	.590	.741	.612
	B	-.808	.590	1.000	.614	.479
	C	-.855	.741	.614	1.000	.390
	D	-.715	.612	.479	.390	1.000

Casewise List[b]

Case	Selected Status[a]	Observed HRC_TRANS	Predicted	Predicted Group	Temporary Variable Resid	ZResid
373	S	1**	.141	0	.859	2.463
385	S	1**	.141	0	.859	2.463
389	S	0**	.983	1	-.983	-7.606

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.

b. Cases with studentized residuals greater than 2.000 are listed.