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Safety risk assessment and improvement method for precast/ prestressed concrete industry plant

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The Precast/Prestressed Concrete Institute (PCI) is the technical institute for precast/prestressed concrete industry. The plant involves activities such as placing high tensile steel strings inside the concrete products before they harden. This process needs the strings to be "stressed" hydraulically with high tension, which provides possibility of breaking the strand. Hence, employees may face a severe injury around the stressing bed. As various activities take place on the plant at the same time, employees must follow certain safety protocols while being around the plant. Another safety concern on the precast plant is silica exposure.

Occupational Safety and Health Administration (OSHA) has provided various guidelines and tools to minimize silica exposure. Employees need to be careful and follow these safety protocols, otherwise it may lead to severe lung disease. Thus, employees need the appropriate safety training which will motivate them to follow safety protocols rigorously. The Bayesian Network (BN) methodology helps analyze plant structure to understand potential risk factors and causes that can be fixed by the employer paying more attention. The current traditional training methods such as videos, PowerPoint slides, or on-paper training, are not as effective in conveying

the severity of the risky situations. This research focuses on precast plant activities while trying to identify the factors affecting plant safety.

The current results suggest that using the BN study for the factors, such as stressing, chipping, leg injuries, tripping, and suspended loads, that may cause accidents or affect plant safety have a major impact on overall plant safety. Further sections of the dissertation discuss Fault Tree Analysis for risk assessment. It is observed that the BN study outperforms the risk assessment.

Improvisation in safety protocols associated with these factors will help mitigate overall plant risks. In addition, study includes the development of immersive training methods and comparison of the immersive method to current safety training methods. Virtual Reality (VR) training module provides significant evidence to improvement in motivation level compared to traditional training. Knowledge gain concerning the safety protocols proves to be increasing for employees after the VR training method compared to the traditional training methods.

DEDICATION

I would like to dedicate this dissertation to my parents, Anjali Joshi, and Ganesh Joshi, who have been constant source of love and encouragement in my life. I would also like to thank my family Pranjali Kubera and Pravin Kubera for their constant encouragement and support.

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INTRODUCTION

1.1 Precast/pre-stressed concrete industry

Construction is a growing industry, and maintaining safety is a critical part of this growth. Occupational Safety and Health Administration (OSHA) provides guidelines and training programs to construction companies. However, safety is a wide term, and many factors affect plant safety. These factors are not only interrelated but mutually exclusive, as the possibility of injury depends on the existence of multiple factors. Even though it cannot be ensured that all accidents will be avoided, there is an opportunity for some protocols to be improved, which will help with the reduction of accidents. Along with this, collecting data for different types of factors affecting safety can be infeasible as it is difficult to keep track of and collect accidental data. It also differs for each precast plant, according to its safety training methods and employees.

The precast concrete industry produces products by pouring and casting concrete in various molds in a controlled environment to achieve and transport products for specific construction needs. Prestressed products can be defined as the products following procedure for precast concrete but involving steel strings stressed with high tension before the concrete hardens. When strings are stretched before concrete is hardened well, they are known as pre-tensioning products. The typical products include roof slabs, railroad tiles, and wall panels, and so on. On the other hand, post-tensioning products are the products where strings are stretched after the concrete hardens. Post-tensioned concrete is more flexible and helps reduce cracking from shrinkage when the concrete dries.

1.2 Safety risk assessment in precast/pre-stressed concrete industry

Large numbers of people work every day in the precast/prestressed industry. The products designed on the plant are very useful as they are used for low and mid-rise apartment buildings, hotels, beams, piles, railway sleepers, and bridges, and so on. Due to the design and nature of the products, employees are occasionally exposed to hazards. The industry recognizes risks and tries to mitigate them by investing money and time into safety. The employer not only needs to design the training to help employees follow safety procedures, but the training methods should be equally cost-effective and effectively engaging. The risk and loss that occur with risk depend on the level of hazard and how it can be avoided. The goal of quality and safety management is to stop the occurrence of accidents, requiring them to take initiative to prevent accidents from occurring.

The initial methodology to make sure that safety practices are followed is to organize different pieces of training and workshops to help employees stay safe and avoid hazardous incidents. OSHA has provided strict guidelines to various employers to manage operational safety in the concrete manufacturing industry. While management is developing a plant safety management plan, the risk assessment is conducted using the following five-steps [1]. The first step includes setting up a multidisciplinary task force. This step helps to promote general understanding between all departments. The second step is to identify hazards. All task force members are given a tour of the plant during working hours, which helps them experience and understand hazardous communications. After this step, they are asked to identify hazards in the plant. This step is followed by the determination and likelihood of the risks. The severity of the risk is classified into three general categories: minor, moderate, and major (ranging from 1 to 3 respectively). The likelihood is classified as remote, occasional, and frequent (ranging from 1 to 3 respectively). Total risk is equal to the product of severity and likelihood. The risk factor ranges from 1 to 9, where 1 to 3 is low to moderate, 4 to 6 is moderate to severe, and 7 to 9 is severe to extreme. The fourth step plans for safety management. This step decides and modifies the control measures. And for the final step, the process will be implemented. However, this process is not a one-time effort as it needs to be done repetitively. Accordingly, workers are re-trained after a certain amount of time. This process also includes employee feedback, which benefits the training plan with continuous improvisation and that will lead to a decrease in the accident rate.

1.3 Safety training in precast/pre-stressed concrete industry

For the precast/prestressed plant, operations are risky when employees fail to follow certain protocols. Safety training is highly important when it comes to workers' safety. The current safety training approaches for the plant employees include training with videos, training with PowerPoint slides, on-paper training, or on-site training. The video, on-paper, and PowerPoint slides are cost-effective methods for safety training for precast employees. However, these training methods lack employee participation as they are passive forms of training. On the other hand, on-plant training engages employees and helps them learn the importance of following protocols. While on-plant training is more engaging, this training interrupts employees working on the plant, making it less cost-effective.

Virtual Reality (VR) safety training is a platform that combines on-paper and on-site training. The only expense for this training method will include the initial investments for the devices and the module development. Virtual reality modules allow trainees to actively participate in the training. That is proven to be a helpful approach to employees for better understanding and motivation to follow safety protocols.

1.4 Research questions

This study aims to develop the methodology to find an effective way to study, analyze, and improve the safety protocols for the precast/prestressed employees. Based on the gaps from previous studies, this study focusses on addressing the following research questions:

1) Which are the factors causing any injury or accidents on precast/prestressed plant. How can the risk assessment of these factors be conducted? Which methods are the most effective methods to identify which factors/procedures need to be refocused and changed further to ensure precast plant safety?
2) Once these factors are identified, how can plant safety be improved? What additional methodologies or modifications need to be made to the plant to reduce the number of accidents on precast/prestressed plants?
    a) Would these different modifications or improvements provide different results for male and female employees?
    b) Would there be any modification in participant motivation for current and after the modifications?
    c) Is there any difference in employee learning and understanding with modified safety protocols?

1.5 Tentative organization of the study

This study is divided into five sections. Chapter 2 focuses on analyzing the factors affecting plant safety the most. Various factors that affect plant safety are considered at the beginning of the study, and they are interconnected using Bayesian networks to develop a model targeting plant safety. Expert opinions are analyzed using a fuzzy analysis approach to find the individual probability distribution for the Bayesian network. The study provides output in terms of factors that are supposed to be revisited by safety instructors to improve plant safety.

Chapter 3 discusses the new virtual reality (VR) training module that is developed to deliver safety training in a cost-effective yet recurring manner, aiming to reduce common plant injuries. The module is developed using Unity3D and Visual Studio joint platforms and can be interfaced with using the Oculus Rift / Oculus S. The module addresses three major safety concerns in the plant: personal protective equipment (PPE), the tensioning of the strand (the stressing process), and risks associated with the suspended loads. Using the extracted data from the research experiment, the efficiency and effectiveness of the module are tested to understand how effective the module is performing compared to the traditional safety training methods. The efficacy analysis was based on simulation sickness, user experience, and system usability. This analysis showed that the developed VR module is a user-friendly simulator with minimal simulation sickness. Also, an effectiveness analysis was performed based upon a comparative study of this VR training method and the traditional video-based training method. This analysis indicated that VR training is more engaging and provides a better understanding of safety protocols and real-life experience of the precast/prestressed concrete plant.

Chapter 4 focuses on the comparison of current evaluation and training methods with different analysis techniques to compare the analysis techniques and training methods within the VR module. It also presents an outlook comparison of the results from different methodologies. Chapter 5 discusses the similarities and differences of these methodologies in depth.

CHAPTER II

SAFETY ASSESSMENT FOR PRECAST / PRESTRESSED CONCRETE INDUSTRY USING FUZZY-BAYESIAN NETWORK ANALYSIS

2.1 Introduction: Risks associated with precast/ prestressed industry

The precast/prestressed industry is an important branch of the concrete industry. Precast plants turn concrete materials into useful products after rigorous tensioning and de-tensioning. As much as this process is useful for the industry, there is a higher level of risk involved for the employees working on site. For the employees and their safety, companies implement administrative and engineering techniques. However, the employees' awareness plays a significantly important role in avoiding injuries or accidents. According to the NPCA (National Precast Concrete Association) report, there is a yearly average of between 150 to 200 employees severely injured, and more than 100,000 are injured due to construction-related activities [2]. The United States Department of Labor highlighted the number of accidents [3]. One of the incidents reported in June 2009 detailed an employee getting injured by an 8,000 lb. panel as it was being transported; the crane tripped, and the employee was pinned. He sustained a broken pelvis and punctured artery. Another incident was reported in September 2009 when a precast concrete panel rolled over a truck driver and killed one of the employees. In July 2010, an employee was helping set wall panels when he was struck in the head by a falling pipe brace, causing a fatal injury. For a long period, accidents like these were being reported, ranging from minor injuries to death. The OSHA and PCI are trying their best to implement rules and regulations to help avoid these accidents as employers are applying various policies as well [4, 5]. Therefore, it is necessary to investigate the relationship between different protocols and operations on the precast plant and consider safety analysis aiming towards safety and factors affecting safety on the plant. These factors involve safety practices, different operations, as well taking major precautions, and utilizing protection equipment. Sensitive factors can be identified and improved from existing training methods and protocols with this study. The precast industry offers many benefits to the construction industry, such as the easier erection of the building structure, lower project costs, durability and sustainability, lesser material waste, better architecture structure [6, 7].

2.2 Review on Bayesian network / Fuzzy analysis

Past research provides various methodologies for risk management purposes in various industries. Methodologies involved the comprehensive fuzzy evaluation method, neural network, influence diagram, risk-based analysis in safety [8]. This risk analysis methodology contributed to different complex engineering projects [9]. The limitation of these studies is dealing with dependency between variables and having to cope with uncertainty, while the neural network has limitations, such as dealing with changing and dynamic situations [10]. Bayesian Network (BN) combines various aspects effectively to provide the most accurate estimate for the interdependent factors. BN was first introduced in 1980 by Judea Pearl [11]. Bayesian Network has provided enormous contributions in various decision-making processes [12]. Historical data or expert opinions can build parameters of the Bayesian Network [13]. Along with decision-making processes, the Bayesian Network has also been proved very useful for prediction analysis [14].

For the risk assessment study associated with the precast industry, the risk factors can be divided into three sections: Self-awareness by employees, factors that can be fixed using engineering controls, and factors that can be fixed using administrative controls. Even if they are different from each other, they are also interdependent. These risk factors can be divided into two major categories: qualitative and quantitative [15]. Various modeling and problem-solving methods have been used to resolve these issues, such as Fault Tree Analysis (FTA), Comprehensive Fuzzy Evaluation Method (CFEM), influence diagram, neural network, decision tree, and so on. These methodologies also demonstrate their limitations while dealing with complex problems and their dependencies with updating probabilities and related uncertainty [9, 16].

The precast plant is a loud and busy place. The relationship between machines and humans is equally important and has been proven risky in the case of ignorance. The Bayesian Network is proposed to be the most effective tool to model and measure complexity between man-machine relationships [17]. BN deals with qualitative and quantitative data at the same time [18]. BN is proved to be a great tool while dealing with complex problems for failure analysis and reliability of the system [19, 20]. Traditionally, BN provides a prior and posterior probability distribution for each node. This probability distribution deals with real numbers or crisp numbers [21]. In the precast industry, there are various situations where casualties might occur and must be avoided. However, it is difficult to collect uncensored data [22]. Experts or professionals working for safety training and safety analysis over the years can provide better information regarding the odds of occurrence of casualties. Fuzzy set theory is one of the most successful and helpful tools for similar scenarios [23]. The uncertainty can be considered for not only a single number but the interval of the fuzzy numbers. For these uncertain environments, BN and FST can be combined for better reasoning and analysis [24]. The Fuzzy Bayesian Network (FBN) approach is proved to be a tool with great potential to deal with risk factor inter-relationship identification, likelihood calculations, and their interpretation [25]. FBN methods also provide various reliability indexes, which is difficult to obtain using conventional methods [26]. The fuzzy Bayesian Network was first introduced in 1987 [27]. The algorithm provides an effective posterior probability distribution for the variables. However, some variables increase, making it difficult to simulate based on the same algorithm [28].

While working in high-risk environments, it is crucial to have a strong safety protocol. For any process, when a lot of factors are interdependent, there is an increasing possibility of the occurrence of unexpected events. The system gets affected by each of the smaller to larger incidents in the system, allowing the smaller incidents to act as a catalyst and create larger incidents. The result derived from the combination of the fuzzy method with the Bayesian networks has the potential to provide calculated weights for all the possible interactions for the system. The system is discussed in the early stages of the development of the BN concept [29] regarding petrochemical plants. The results showed that the most important factors affected are awareness, preparedness, and flexibility.

In 2013, research was conducted to analyze poor decisions leading to serious consequences. Two important factors are considered for the study: hazards arising from hardware failure and reducing human error through the decision-making process. A study for situation assessment was conducted based on a case from US Chemical Safety, which leads to different maintenance decisions [30].

Bayesian network systems are one of the most systematic approaches for interdependent data analysis. It has been combined and used to investigate relationships between construction projects, such as tunnel-induced damage and hazard mechanisms caused by that [31]. There are limitations on the current probability estimation, and using an expert opinion ensures the reliability of the data using fuzzy assessment. The Fuzzy Bayesian approach can be used for safety analysis in construction projects, which will increase the likelihood of a safe environment in complex procedures. Furthermore, in 2018, important research was conducted using the same approach. Sustainable Waste Bio-Refinery Facilities (WBFs) deal with a system that works with the cooperation and acceptance of different stakeholders; there is a hybrid of expert opinions and statistical results from questionnaires and surveys conducted from stakeholders. This model was claimed to identify the certainty of each node in the model [31].

This section is organized in the following order: The concepts and their mathematics are explained in Section 3; Section 4 discusses the case study, related production process, and analysis of the module as well as further analysis including the methodology used and sensitivity analysis; in section 5, advantages and disadvantages are discussed for the method are proposed; the conclusion is drawn for a given methodology and research in Section 6.

2.3 Modeling the Bayesian network

The primary goal of this study is to identify factors that show a major effect on plant safety and modify current protocols to be more useful. The framework of the study is described in Figure 2.1. Initially, research has been conducted to identify the most applicable procedure to define the relationship between nodes. Based on conceptual research and identification, the Bayesian Network has proved to be the most appropriate tool. Furthermore, the first step was to understand the precast process carefully, understanding factors causing accidents and affecting ‘safety’ on a primary level. This step was followed by the construction of the Bayesian Network (Step 2). The factors identified in Step 1 are used to design networks representing the relationship between those factors and related safety. These nodes function based on their probability distributions. Hence, in Step 3, a questionnaire was designed to represent the likelihood of each factor causing accidents on the plant. Precast safety experts contributed their opinions in terms of ratings from 1 to 5 with one being the least possible for an accident and 5 being the highest possibility of an accident. Using the experts' opinions from Step 3, Step 4 applied collected information to the fuzzy analysis, and output indicates the probabilities for an accident due to each node from the Bayesian Network. In Step 5, these probabilities are applied to the software. These probabilities are further used in Step 6 to work on sensitivity analysis and propagation analysis. This method is aiming to identify the factors most affecting plant safety. This step will help identify and fix issues in the specific parts of the safety process.

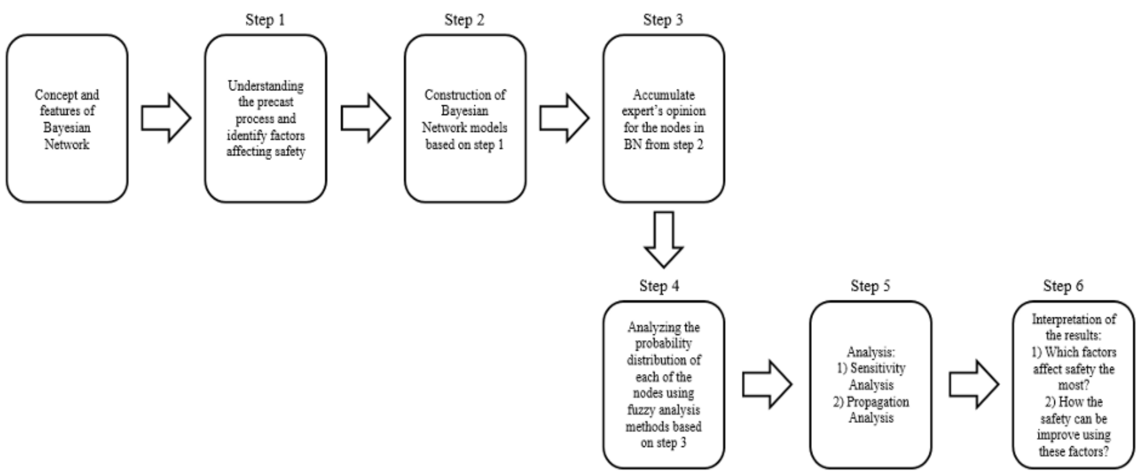


Figure 2.1 The framework of the Bayesian Network Study

2.3.2 Methodology representing the Bayesian network.

While forming the Bayesian Network, various uncertainties and interconnections are taken into consideration. A Bayesian Network is a graphical representation model of these variables, considering their dependencies. These variables are known as 'nodes.' 'Arcs' work as directional arrows indicating which node is dependent on another node. For the dependent relationships, 'parent node' indicates the cause of the event, and 'child node' represents the outcome of an event.

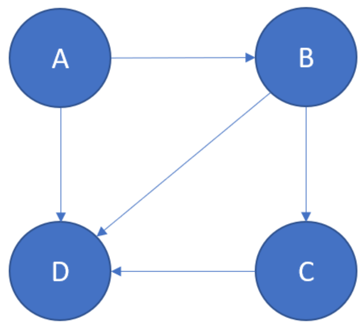


Figure 2.2 Bayesian Network structure

Node A (Figure 2.2) is a parent node for node B and D; B is a parent node for C; B is a child node for A; C is a child node for B; and D is a child node for node A, B, and C.

Each node has its possibility for the occurrence of the event; it is denoted by P(x) for node x. For instance: P(A) represents the probability of event A occurring. The Bayesian Network describes this relationship between nodes that captures dependency between variables. Each node with a parent node will indicate conditional probabilities [32]. It has prior probability distribution, which also takes into the value of the existence of the parent node and considering all the possible combinations of the parent nodes. Thus, the joint probability for distribution for Bayesian Network with nodes can be described as.

$$P(x_1, x_2, \dots \dots x_n) = \prod_{i=1}^{n} P(x_i | p_a(x_i)) \qquad (2.1)$$

The probability of B depends on the probability of A. The prior probability of B can be noted as P(B) and the posterior probability of B can be stated as P (B|A). The mathematical formation of the probability is as described in equation 2.2.

$$P(B|A) = \frac{P(A,B)}{\mathrm{P(A)}} \tag{2.2}$$

Similarly, the probability of D will depend on the probability of A, B, and C. Posterior probability for D is the conditional probability for D given A, B, and C. And it is the ratio of the joint probability of A, B, and C to the probability of A, B, and C, and it is denoted by P (D|A, B, C). However, nodes B and C also contain parent nodes so they have conditional probabilities [33], which will be denoted as P(B|A) and P(C|B). Mathematical representation for the joint probability of A, B, C, and D can be described as equation 2.2.

$$P(A,B,C,D) = \mathrm{P(A)} * P(B|A) * P(C|B) * P(D|A,B,C) \tag{2.3}$$

Simplifying equation 2.3 using algebraic operations further provides the posterior probability of D given the probability of A, B, and C as equation 2.4.

$$P(D|A,B,C) = \frac{P(A,B,C,D)}{\mathrm{P(A)} * P(B|A) * P(C|B)} \tag{2.4}$$

Applying results from equation 2.2 in equation 2.4. It results as (2.5).

$$P(D|A,B,C) = \frac{P(A,B,C,D)}{\mathrm{P(A,B)} * P(C|B)} \tag{2.5}$$

2.3.3 Methodology representing the Fuzzy Logic.

Once the Bayesian Network is designed with an appropriate structure, the network targets one of the nodes and checks the effect of all other factors on that specific node [31]. However, to proceed with this, all the connections need to be weighted as accurately as possible. There are various ways to do that through Boolean logic, crisp logic, finding and fitting appropriate distribution for each node, and so on [30]. However, the most appropriate way to measure weight can be the one that has the potential to deal with conditional uncertainties between nodes. These uncertainties are described as chances of the event happening. They are indicated as the weight, W_{ij}; shows chances of reaching node j given that the current stage is node i. W_{ij} takes a value between 0 and 1. The information available to extract this information is through an expert's advice. A fuzzy concept is the most accurate tool to find the weight. The mathematical theory was explained [34], and the theory was proposed in 1965 by Zadeh [35]. Fuzzy sets a defined as ‘‘a membership function mapping the elements of a domain, space, or universe to the unit interval (0, 1)’’ [34].

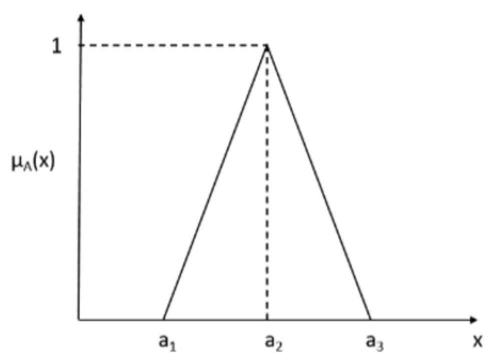


Figure 2.3 Triangular Fuzzy model representation

This figure shows a smaller Bayesian Network. It represents the structure of the Bayesian Network including nodes, arcs, and directions of the dependencies. Further information regarding this image can be found on page 12.

A fuzzy set A in R is called a fuzzy number if it satisfies the following conditions:

(a) A is normal,

(b) A(x) is a closed interval for every a ϵ (0, 1],

(c) The support of A is bounded.

The general characteristic of a fuzzy number is represented in Figure 3. According to the figure, A(x) denotes the membership function of x in the fuzzy set A. This shape of the fuzzy number is referred to as a ‘‘triangular’’ fuzzy number and denoted by the triple (l, m, u). In general, a fuzzy set is a fuzzy number if its height is one (in which case it is said to be normal), it is a convex subset of the real line, and it has only one core [36].

2.3.4 Modeling a Bayesian Network with Fuzzy Analysis

Section 2.1 discusses the nodes associated with the precast process and their interdependencies. The tools that have been used for this data collection include the questionnaires considering independent and conditional probability distributions. The questionnaire includes five sub-sections. The first section discusses only safety concerns with only one variable. The probability of event A occurring is denoted by P(A), such as if the person is wearing specific personal protection equipment, or the person is following necessary safety protocols at a specific situation, or the necessary cleaning was well done. All these variables are binary; they only have two possibilities: yes or no. The next section includes two variables, one independent and one dependent. The probability of event B occurring given that event A has already occurred is denoted by P(B|A). For instance, chipping can be considered as a dependent variable, and chipping safety with h respect to risk on the eyes is primarily dependent on if the person was wearing eye protection or not. Hence, wearing glasses becomes an independent variable for this probability. In this case, there are two binary variables with two possible outcomes of each event. That becomes 22 possible outcomes for the conditional probabilities. Further, three variables indicate that the probability of occurring event C gave that probability A and B have occurred (P(C|A, B)). This scenario has 23 possible outcomes from the incident. Similarly, for the incidents depending on three previous incidents and their outcomes has 24 possibilities.

Effectively, probabilities are calculated based on historical data. However, in this case, it is difficult to track the number of accidents that have occurred so far and their odds of occurring again in the future. Hence, the fuzzy methodologies are an appropriate tool to estimate these possibilities based on the questionnaires and surveys described. The questionnaires are designed with the help of experts, which includes a wide range of possibilities that may cause accidents on the precast plant. These surveys are presented to three safety experts from the precast industry for their opinion. These three experts present their opinion regarding this process on a scale of 1 to 5 with 1 indicating the least likely scenario for the accident and 5 for the most likely scenario for the accident to occur. The likelihood is further analyzed using a triangular fuzzy analysis [37]. In this method, the rankings for certain events are analyzed into probabilities using the beta distribution in the following steps:

Step 1: Consider the ranking for each variable individually. Independent nodes and different dependent nodes. Using a table with a five-point triangular fuzzy scale (Table 2.1), they are ranked 1 to 5.

Table 2.1 Five-Point Triangular Fuzzy Scale

Rank	Linguistic Expressions	Fuzzy Numbers
1	Negligible Possibility	(0.75,1,1)
2	Less Possibility	(0.5,0.75,1)
3	Moderate Possibility	(0.25,0.5,0.75)
4	Highly Possible	(0,0.25,0.5)
5	Possible	(0,0,0.25)

Step 2: In each expert's opinion, identify the fuzzified numbers obtained from fuzzy sets (l, m, $\boldsymbol{\mu}$).

Step 3: There are various conventional methods to defuzzify the fuzzy numbers. Theorem using beta distribution obtaining crisp numbers for corresponding fuzzy numbers is a simple yet effective method in this case [37].

If random variable X follows beta distribution, the probability distribution for X is obtained as below:

$$f(x) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha) * \Gamma(\beta)} * x^{\alpha-1} * (1-x)^{\beta-1} \quad 0<x<1$$
$$= 0 \qquad \text{otherwise} \tag{2.6}$$

The mean of the beta distribution is:

$$\mu = \frac{\alpha}{(\alpha + \beta)} \text{ where, } \alpha, \beta > 0 \text{ and parameters of the distribution} \tag{2.7}$$

Consider the triangular fuzzy set a = (l, m, u). To analyze crisp numbers from the given fuzzy set, the set will be projected over a new interval (0, 1). That will be as follows:

$$a' = \left(\frac{l-l}{u-l}, \frac{m-l}{u-l}, \frac{u-l}{u-l}\right)$$
$$= (0, \frac{m-l}{u-l}, 1) \tag{2.8}$$

Projecting it on the interval (0, 1), the parameters of the distribution are defined as:

$$\alpha = \frac{m-1}{u-1} + 1 \; and \; \beta = \frac{u-m}{u-l} - 1 \tag{2.9}$$

From equations 4, 5, 6,

$$\mu' = \frac{m+u-2l}{3\,(u-l)} \tag{2.10}$$

This is the mean of bets distribution to corresponding fuzzy numbers for the interval (0, 1). Transferring to the interval (l, u), obtains the following equation:

$$\mu a = \mu' + (u - l) + l \qquad (2.11)$$

Step 4: As there are three experts' opinions available, average μ_a for all three experts and average the numerical value.

Once all the proportions are obtained, they are used as inputs in the Bayesian module. Further sensitivity analysis takes place.

2.4 Bayesian network case study

2.4.1 The precast output production process

For the precast/prestressed industry, the process starts from customer demand and ends at the delivery of the precast product (Figure 2.4). In this study, safety is the focus while designing the Bayesian Network. The focus of the study is on the product setup. Various safety concerns are considered in these sections of the process.

The nodes or factors considered in the Bayesian Network are:

- If the person follows safety procedures,
- If the person wears PPEs and still suffered the injury,
- If any of the procedure was in progress which the person should have been aware of, such as the stressing process, suspended loads, chipping, grinding.
- Any external factors, such as if silica were present in the environment more than the recommended amount when the catastrophic event occurs and played a role in the injury,
- And for the injuries, it considers all major sections of the body getting injured due to the plant operations, including hands, legs, head, back injury, death, and so on.

Different nodes are related to one of the above sections.

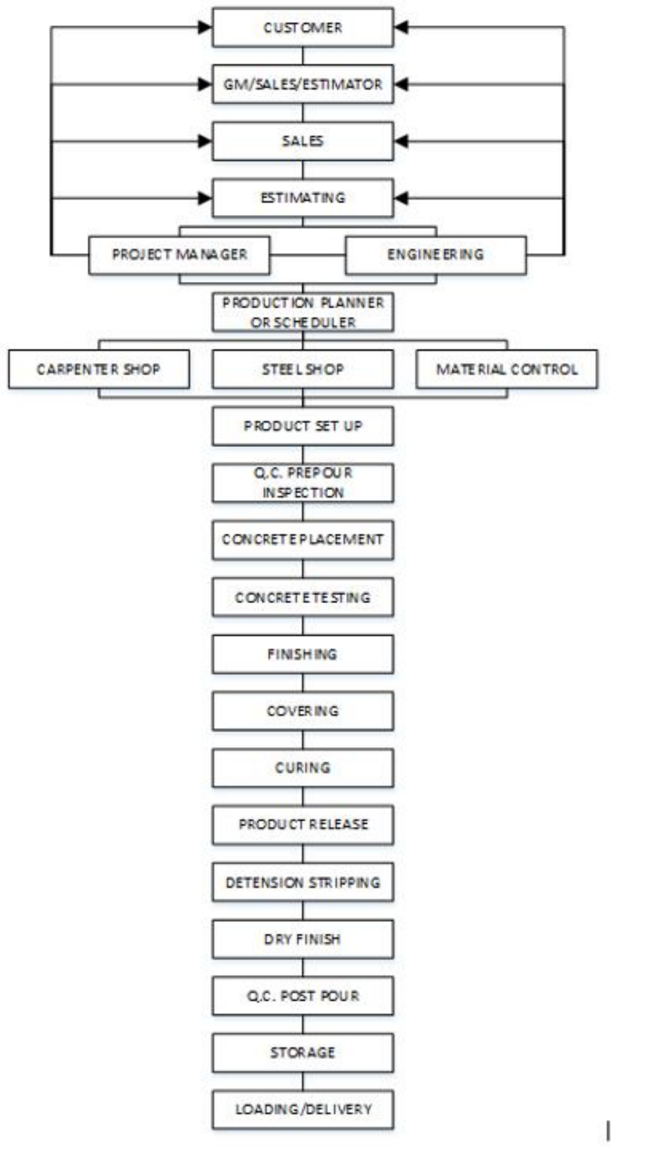


Figure 2.4 Process chart for precast production

The figure explains the production process on the precast plant. The chart explains details about the processes at the precast plant which will help with risk identification.

2.4.2 Description of the study

Risk can be defined as a loss of injury. It can also be expressed as a financial digit, while occasionally the cost can be beyond what can be measured. When a person starts working on a precast plant, they are required to follow certain procedures, such as attending mandatory safety training, wearing Personal Protection Equipment (PPE), learning about signs and indications on the plant such as alarms, or lights, and reaching out to their supervisor for specific operations and so on. However, it does not completely prevent accidents. There are various sections and stages in the precast process where such incidents may occur. Due to this, it is difficult to control them by looking at a broad picture. The Bayesian Network is a useful tool to narrow it down to important processes. The Bayesian Network focuses on the 'Safety' approach of the plant, keeping in mind the causes of various accidents on the plant. The manufacturing procedure is explained in detail in Section 2.2.1. Based on that procedure, there are different branches of the process that might contain more risk than other branches. The Bayesian Network will help analyze which methods or nodes affect the safety node the most. The network built is as shown in Figure 2.5. Each of these nodes needs the input of probabilistic distribution. This probability distribution is derived using a fuzzy analysis.

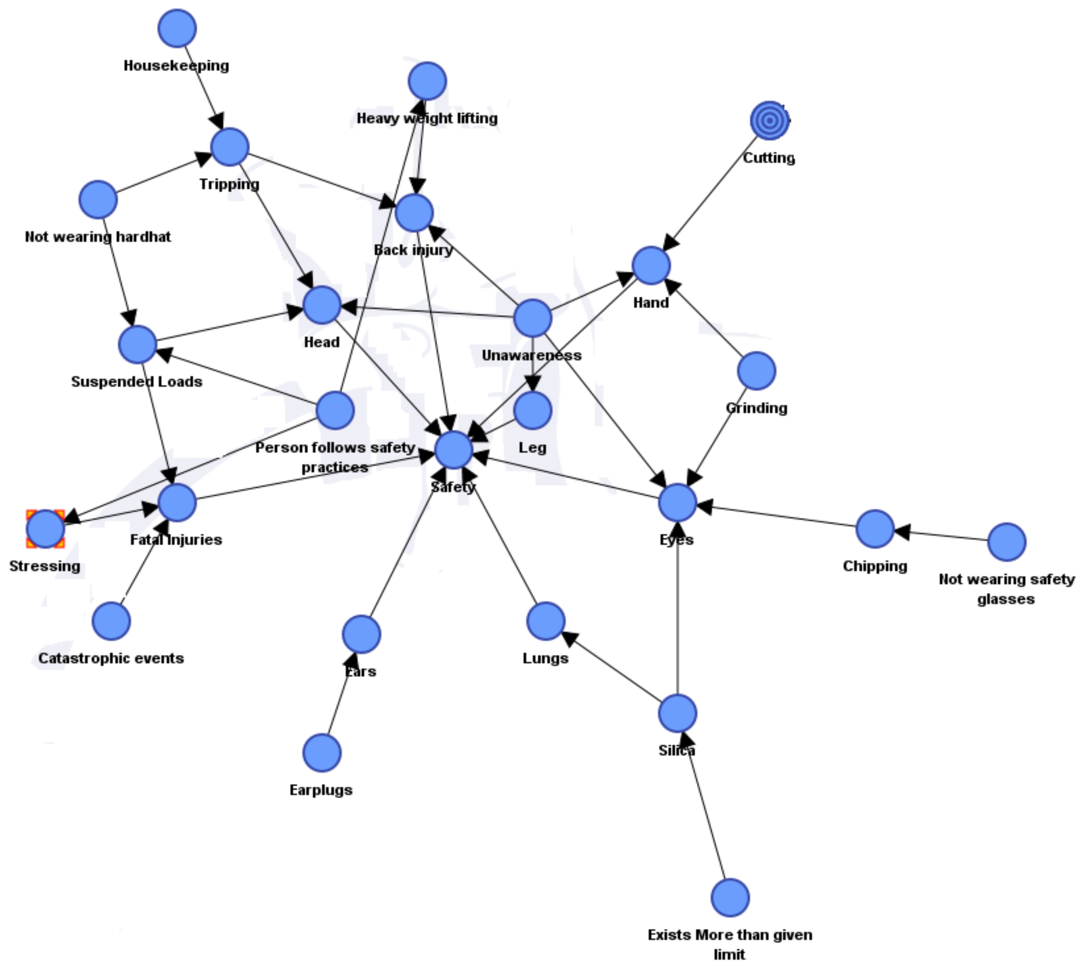


Figure 2.5 Bayesian Network for the case study

There are 26 nodes in this module. The nodes are categorized into 5 sections: one variable or independent nodes, two variables, three variables, four variables, and five variables. One variable node is the nodes that do not have a child node yet include only one variable and has discrete probability distribution with only two outcomes of either true or false. In this section, true indicates that the node was true, and false indicates that the node was not taken care of. For example, one may look at the node ‘earplugs.’ If the probability distribution is false, the person was not wearing earplugs, and if it is true, the person was wearing earplugs (Figure 2.6).

The next section is for two variables, where the probability needs to be analyzed conditioning the existence of the other variable, such as 'Tripping given Housekeeping.' This type of variable has further conditional probability distribution. The probability distribution for that looks like Figure 2.7. The first cell (ear false, earplugs false) can be interpreted as there is a 33% possibility that ear injury did not occur given that person was NOT wearing the earplugs. The second cell (ear true, earplugs false) states that there is a 67% possibility that a person had an ear injury given that they were not wearing earplugs.

False	True
86.000	14.000

Figure 2.6 The probability distribution for one variable

Earplugs	False	True
False	33.000	67.000
True	67.000	33.000

Figure 2.7 A conditional probability distribution for two variables

Similarly, sections 3, 4, and 5 deal with the probability distribution of one variable conditioning on two, three, and four other variables, respectively.

2.5 Uncertainty analysis

2.5.1 Sensitivity analysis

While previous sections focused on finding the accurate conditional probabilities, this section will focus on analyzing the network to identify the factors that need to be identified for safety improvisations on the plant. At first, using the tool, the direct effect of all the nodes on safety is calculated. The standardized total effect of each node on safety practices is arranged in descending order. Six of the factors result in major direct effects on safety, including stressing process, wearing safety glasses, chipping, tripping, and suspended loads. And one of the injuries that seem to have the largest effect on the safety process is leg injuries. For the Bayesian Network 'Target' can be set to find ultimate probabilities. This can provide information when one of the nodes is set as a 'target' and identify how all other factors change. 'Safety' is set as a target node and can check how other factors affect it. In this case, all true value stands for an accident caused and the false value indicates that an accident did not occur. Therefore, safety needs to be checked for false which can be interpreted as safety not being compromised. The effect of all the factors is defined in Figure 2.8.

The Total Effects (TE) are estimated as the derivative of the target node concerning the corresponding node. It can be expressed as

$$TE(X, Y) = \frac{\partial y}{\partial x} \tag{2.12}$$

Standardize total effect (STE) represents the effects multiplied by the ratio of the standard deviation of the respective node to the standard deviation of the "target." It can be represented by the following equation:

$$STE(X, Y) = \frac{\partial y}{\partial x} * \frac{\sigma x}{\sigma y} \tag{2.13}$$

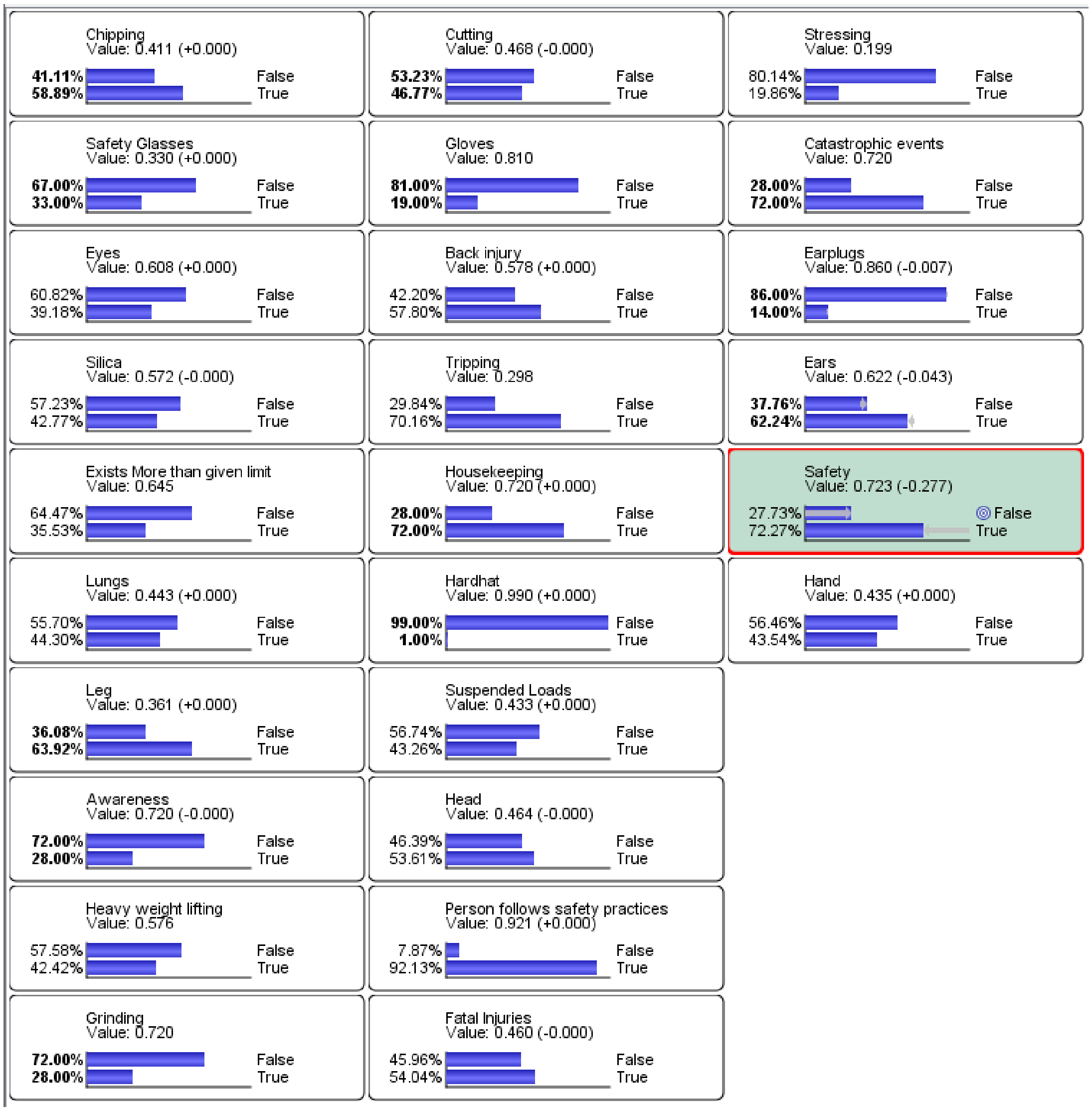


Figure 2.8 Direct effects of the factors

Safety can be turned to 100% to check how other factors react. When safety is tuned to being 100% effective, proportions for hand injuries, ear injuries, and earplugs have a large impact, and this is what needs to be changed. A similar sensitivity analysis is performed on the other 5 factors. The most affected factors and their results are summarized in Table 2.2.

Table 2.2 Factors indicating a higher direct effect on safety

Factors	Head	Hand	Back	Eyes	Following Safety Practices	Heavy Weightlifting	Silica	Aware	Housekeeping	Hard Hat	Safety Glasses	Grinding
Stressing			T		T	T						
Chipping				T			T	T			T	T
Leg	T	T	T					T				
Tripping	T		T						T			
Suspended Loads	T	T	T		T	T				T		

Safety is most affected due to five factors: stressing, chipping, leg injuries, tripping, and suspended loads. The further investigation provides information about other aspects directly related to these five factors.

2.5.2 Uncertainty analysis

The Bayesian Network is based on the hypothesis given supporting evidence. It is a probability calculation based on reasoning. The distribution of the fuzzy analysis depends on logic or opinion applied by the experts. When a relationship is a cause to an effect, then it is known as 'Normative Reasoning.' That indicates what would be the proper results system had it been computed from the network. However, when the effect to cause is measured, human intuition can be flawed or biased. The network considers a variety of relationships, making it is necessary to perform propagation analysis on the given nodes.

All parent nodes are considered; these are safety glasses, awareness, silica level, earplugs, gloves, grinding, catastrophic events, hardhat, a person following safety practices, and housekeeping. All parents' nodes are set in such a way that the plant system would seem perfect. All the nodes are on status 'True' except for catastrophic events and grinding. This indicates that safety glasses, earplugs, gloves, and hardhats are worn, safety practices are being followed, no grinding is in progress, silica level is within limits provided by OSHA, employees are aware of surrounding on the plant, and no catastrophic event occurred during the time. However, even in the perfect system, there was no huge effect on safety indicating that these are not the only factors affecting safety on the plant.

Further, safety is observed for each node. Rest nodes indicate true indicates that accidents occur and false indicates that accidents did not occur due to those particular scenarios. And the contribution to the change of ‘Plant Safety’ due to each of the factors or each kind of accident is noted. Respectively the changes are Back-injury: 0.28%; Head injuries: 0.81%; Hand injuries: 2.10%; Ear or hearing injury: 3.85%; Eye’s injury: 4.76%; Lung’s injury: 8.92%; Leg injuries: 9.14%; Fatal Injuries: 11.41%. Intuitively fatal injuries seem to have the biggest impact on plant safety.

2.6 Discussion and conclusion

The analysis of uncertainty on the precast plant is an essential issue. Not only do these accidents affect companies in terms of the financial aspect, but it also causes loss to the employees. However, the precast plant is a very loud and busy place. It is difficult to identify the exact factors affecting safety on a larger scale. Data collection for such accidents and sub-categorizing them according to different systems is a possible yet not easily completed task. Because all the operations are nested, dependent on each other, and have a high possibility of part of the data becoming censored, the conditional probabilistic approach proves a useful tool in this case. Fuzzy analysis resolves the issue for data collection as expert's opinions are not very difficult data to be collected, rather than tracking the accidents. The tools used for this identification are inexpensive and can be modified after each level of safety improvement.

Using the above tools, it can be concluded that factors directly affecting safety are ear injuries, earplugs caution, stressing process, chipping process, leg injury, tripping incidents, suspended loads. The factors further directly having an impact on these factors have an indirect effect on safety. They are head injuries, hand injuries, back injuries. There can also be issues with people following safety practices, such as using, lifting heavy objects, lacking personal awareness, or wearing PPE. Along with this, in the plant, there are potential issues with housekeeping, the existence of silica particles more than the recommended level, and grinding. These issues should be addressed and focused on further within a specific plant. Various techniques can be further applied to improve safety using these factors. For instance, there is a piece of evidence indicating that the presence of some of the PPE is an issue. The training can be improved in a way that employees will never fail to wear their PPE before entering the plant. For various muscle injuries, some ergonomics techniques can be applied for either an administrative approach or an engineering approach. For back-injury, techniques may be used to analyze what part of the process is incorrect by the employee that causes muscle issues, and those techniques can be analyzed and improved. Once factors are identified, it depends on the organization to improve techniques to ensure employee safety.

This study has all the above advantages; while on the other hand, it does have a few limitations. The opinion provided by experts is subjective and the opinions may differ from plant to plant or company to company. Though most of the precast plants follow similar protocols, yet they might differ from each safety expert's opinions. However, the questionnaires can be updated, and these issues can be resolved further by considering feedback from a larger number of experts. This study can be further expanded to include the financial aspect of each loss. If almost accurate costs can be estimated for each accident and loss, the inclusion of it to the model can provide prevention of loss, while also making it possible to forecast how many additional expenses the company needs to consider for the coming terms. We believe that the current study and even extension of the current study will provide a valuable tool for the safe approach of the precast plants. The study was focused on how the Bayesian Network can be helpful to analyze and identify the risk factors on the precast plant. The results obtained from the study indicate that most accidents occur with stressing, chipping, leg injuries, tripping, and suspended loads. Hence, the safety training or protocols can be focused on these factors to improve overall plant safety. Further investigation will take place in Chapter 4. Different similar methods and testing their effectiveness will help improve the study and its outcomes.

CHAPTER III

IMPROVING PRECAST/ PRESTRESSED PLANT SAFETY TRAINING METHODS USING VIRTUAL REALITY TECHNOLOGY

3.1 Introduction: Current precast/ prestressed plant safety protocols and VR

The employees of the precast/ prestressed concrete industry are occasionally exposed to hazardous situations in the plant because of design characteristics and the production process of the precast/Prestressed concrete product. To mitigate these hazards and protect employees from harm, the Occupational Safety and Health Administration (OSHA) has provided guidelines for safety training approaches [38, 39] and the Precast/Prestressed Concrete Institute (PCI) follows these guidelines to provide safety and loss prevention programs [40]. According to a report from the NPCA (National Precast Concrete Association), each year on average more than 100,000 employees are injured in the construction industry due to safety unawareness in the U.S. [41, 42]. The precast/prestressed concrete industry represents less than 5% of the total construction industry. According to PCI guidelines, workplace safety regulations are established to recognize the hazards and to avoid workplace injuries. Training programs are designed to educate employees on the risks and train them on required safety procedures. Accident investigations determine the root causes of accidents and allow corrective action to be taken to prevent the same accidents or injuries from reoccurring [43].

Industries and companies invest a large amount of money and time to ensure that accidents and injuries are prevented. Traditional precast concrete safety training methods include video training, on-site training, and lecture presentations. These approaches can be either very costly or unengaging [44]. For instance, lectures, PowerPoint presentations, and video training are cost-effective but not engaging for most employees. On-site training is engaging but expensive because it requires professionals to train employees in the plant which interrupts plant operations and affects productivity. There is a need to provide a new training approach to satisfy both cost and engagement requirements for the precast concrete industry, and Virtual Reality (VR) helps to meet these two criteria.

VR technology has grown since 1990. VR was initiated in media and grew in interest through Hollywood science fiction movies, and even TV sitcoms [45]. VR is now becoming a well-known training tool with many benefits, including no risks involved, training in real-life scenarios, retention improvement, better employee engagement, and flexible training time [46]. Interaction, desirable but practical approach, breaking the bounds of reality, and tangible settings are the four most important objectives for using VR in training [47]. In this study, we propose a VR-based training approach to conduct safety training in the precast/ prestressed concrete industry. Implementation of a VR-based safety training approach is cost-effective as it only requires investing one time for the facility and VR module development. It is also immersive because the participant will have a feeling of being in the "Virtual Plant" while wearing the VR headset. This VR module is designed using the Unity3D and Visual Studio joint platforms. The developed VR module can be accessed using Oculus Rift or Oculus Rift S. C# is the primary programming language used to build the module.

This module provides training for three fundamental safety protocols: personal protective equipment, suspended loads, and the stressing process. Audible alarms in the plant, such as alarm/light indications for suspended loads and alarms for the stressing process, can easily be unheeded by employees while focusing on their normal routines and tasks. The VR module immerses new employees in a plant setting, training them to become familiar with these audible alarms and the hazards that they warn of in a no-risk environment. To evaluate the performance of the proposed VR module, we applied two types of analysis: efficacy and effectiveness. Efficacy analysis includes three measures: simulation sickness, system usability, and user experience, while effectiveness analysis compares the VR approach with traditional approaches. Two groups of participants were recruited from a college in the study. One group applied a traditional video training approach, and the other group used the VR training approach. A post-test was conducted to check their understandings of safety protocols.

3.2 Literature for the safety training on precast/ prestressed plant

3.2.1 Traditional safety training methods for employees

Precast concrete systems have several advantages over other construction systems, such as high quality, low project cost, and better sustainability [48]. The precast concrete industry makes significant contributions to the economy and labor employment [49]. However, due to the design and required production processes of its products, employees are occasionally exposed to hazards in precast/ prestressed concrete plants. Prior research [50] indicated that more than 50% of accidents are caused because of unsafe acts which could be mitigated by effective training programs. Workers and employees are expected to be always well trained and vigilant in this industry [51, 52]. An injury not only affects the employee but the employer as well.

A variety of risks exist in a precast plant, such as dangers from suspended loads, moving equipment, trips, and falls, injures from improper lifting, the stressing process, etc. [53]. In this industry, the stressing process is done by placing high tensile steel tendons in the desired profile to be cast into the concrete and tensioning them with a hydraulic jack to a high load (30kip). This process is dangerous, and though it is extremely rare, failures can occur. Employees must follow safety protocols so that they are protected during these rare failures.

Safety training is key to mitigate hazards and avoid injuries. OSHA has provided guidelines for safety training approaches [54, 55]. NPCA, OSHA, and PCI also have introduced various visual materials for training [56]. These training procedures include printed material, video lectures, and onsite training. Onsite training is commonly used but is not the most efficient approach because it interferes with daily production [57, 58]. While printed material and video can provide some visual understanding of risks and safety protocols, due to a lack of immersion, they are not always as effective as onsite training. Hence, there is a need to develop a new safety training approach to satisfy both cost-effective and immersion requirements.

3.2.2 Virtual reality safety training methodology

Virtual Reality has drastically changed training practices during the past decade. Some VR modules were milestones and great success stories. For example, one of the most important implementations of VR is in phobia therapy, such as anthrophobia [59, 60], public transport phobia [61], and speech therapy [62]. Apart from helping subjects overcome their fears, it has been proven that VR has a positive impact on personality [63]. Other important applications of VR include military training [64] and entertainment [65, 66]. Motivation and immersion are the properties of VR helping with a better understanding of a concept in a 3D environment [67, 68]. A high level of immersion plays a significant role in ensuring the success of VR implementations. Visual immersion is defined as 'how close the system's visual output is to real-world visual stimuli', so it may differ from person to person [45, 62]. Hence, immersion is considered as one of the critical elements while designing a training or operation VR module. Various VR development platforms have different effects on immersion levels which need to be considered in VR module development [69].

VR has been used in a variety of training settings. When the tasks to be trained are dangerous in real life, a computer-generated reality can be a useful alternative [68]. For example, surgeries have critical training issues. There are many risks involved in existing training procedures. VR can provide a great alternative in surgical training. It improves the conceptual understanding of medical students regarding surgical operations in a risk-free manner [59].

A project designed by Intel focuses on VR training solutions that will supplement existing training tools [45]. The project considers four important aspects of the business for Intel: product development and engineering, sales, marketing, and training and education. Product development uses VR assistance to consider a customer's opinion closely in on-going product development. A virtual room gives customers the experience of upcoming sales products. Training can be provided to students and employees worldwide at the same time which is more effective in VR than conference calls and meetings. Intel believed that VR would help reduce training costs, increase trainee attention, motivate trainees, and increase training return on investment. A VR system is one of the most useful tools while analyzing volume visualization. In this case, volume visualization is referred to as a graphical representation of objects or data sets in three dimensions. This confirmed understanding of participants is proportional to the level of immersion [70].

VR has also been employed in the mining industry. Beginning in 2014, VR simulation was used to avoid accidents and fatalities in the coal mining industry, and it has been proven to be useful and productive. The study not only discussed VR safety training for coal mining workers but also provided some exercises to enhance the understanding of safety protocols [71].

In extreme scenarios where real-life training is not feasible, VR training is a great substitute. Safety knowledge of an aviation life preserver is one of them. Airlines need to understand how passengers may behave in an emergency. It is infeasible to develop a real-life training setting and VR training helps airlines understand safety protocols as real-life scenarios without interrupting any on-site procedures [72].

The implementation of VR in training and education settings is promising. Compared to other 3D methods, VR requires fewer facilities. VR only requires the headset and virtual hands for the operation of the module [73], while many 3D methods need additional hardware for support, such as a keyboard, a mouse, and external devices. VR representation of the site and details included in the training are more efficient and reliable than traditional training methods such as videos and on-paper training [74, 75]. Another advantage of VR over other systems is real-time stimuli [76].

Construction training is the second-largest application of VR after healthcare [48]. Prior research has been conducted to use game technologies to improve the training performance in construction plants [77, 78]. These modules include many activities on an interactive platform to help the trainee to understand safety concerns while becoming familiar with construction plant operations [79]. Construction plant operations are further focused on in the precast industry. Further study was conducted in 2014 to train precast workers for the installation process [80]. This study provided detailed information regarding safety in Industrialized Building Systems using precast components, which lead to zero accidents in Penang. Precast safety depends on the hazard recognition capacity of workers. One study has been conducted for two years where the objectives were to develop a high-fidelity VR environment that would help workers identify hazards more quickly and to evaluate the effectiveness of the strategy used [81, 82]. Results suggested that hazard recognition improved by 27% with this study.

Several measures are used to evaluate the performance of a developed VR module. Measures used to identify the level of immersion of the VR module are known as efficacy measures. Three efficacy measures are used for this study: simulation sickness, system usability, and user experience. Questionnaires measuring efficiency are also designed to measure the quality of learning [83, 84]. These questionnaires are simulation sickness questionnaires (SSQ) [85], the system usability scale (SUS) questionnaire [86], and presence questionnaires (PQ) [87]. While working in VR, participants may experience some level of simulation sickness. Using SSQ, simulation sickness analysis provides a simulation sickness score. This score is used to determine if the module is safe for further study, or if it will be problematic. SUS helps determine user expectations from the developed VR module by using a system usability score. SUS helps with the understanding of the user's overall experience with the module and whether it helped the user to reach the desired learning objectives. PQ is used to evaluate the user experience. This tool helps to understand the satisfaction level of the participants after completing the training module.

3.2.3 Existing research gaps based on the literature.

After reviewing the relative studies, the following gaps are found:

1) Most of the VR-based training modules in the construction field discuss operation procedures. However, to the best of our knowledge, there is no safety training approach developed using VR in the precast industry.
2) Although VR-based training modules for construction workers are available, there are no studies that have studied the immersion level and investigated the efficacy of a VR module.

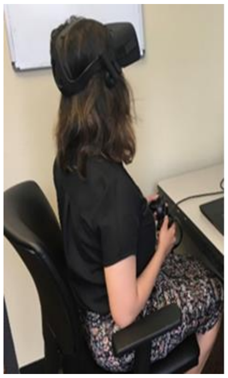
3.3 Research questions

The study aims to introduce an effective and innovative way to provide safety training for precast/ prestressed employees. Efficacy evaluation of a VR module uses three tools: SSQ, SUS, and PQ. Effectiveness assessment of a VR module uses two measures: motivation survey and knowledge gain. The following research questions represent the study objective:

1) Is the average SSQ score of the proposed VR safety training module within the acceptable range?
2) Is the average PQ score of the proposed VR safety training module within the acceptable range?
3) Is the average SUS score of the proposed VR safety training module within the acceptable range?
4) Would the VR safety training module affect participants' knowledge gain in safety protocol?
5) Would the VR safety training module affect participants' motivation in learning safety protocol?
6) Is there any difference between males and females in learning safety protocols using the proposed VR module?

3.4 Description of virtual reality safety training module

The primary goal of developing a VR safety training module should be to help precast concrete employees effectively gain knowledge of safety protocols, which will then reduce the quantity and severity of accidents in a precast plant. This training module is developed using the Unity and Visual Studio joint platform. The primary programming language used is C#. The training module can be viewed and operated using Oculus Rift/ Oculus s. To experience the developed virtual world, the participant will need to wear the Oculus headset. Participants can navigate the module using touch controllers. By using the left controller, the participant can move forward and backward, while the right controller helps to rotate 90 degrees (Fig. 3.1a). Each controller is represented as a virtual hand. These two virtual hands can be used to perform tasks in the virtual world. The audio and visual instructions are provided whenever necessary. Fig. 3.1b shows the VR module development hardware facility.



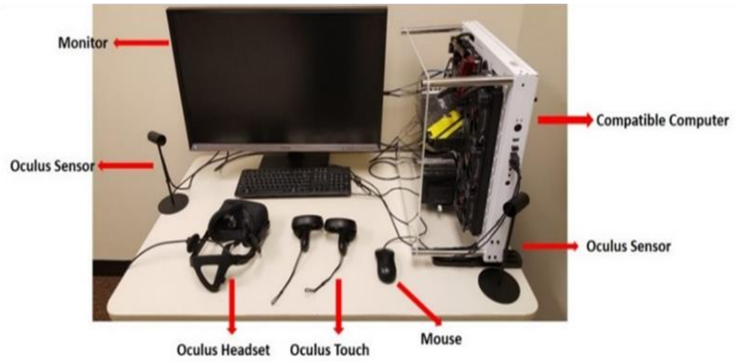


Figure 3.1 Virtual Reality facility

The figure has part a) VR Headset and controller, and b) VR developed facility.

The module includes four major sections: audio/video instructions, Personal Protective Equipment (PPE), suspended heavy loads, and the stressing process. Below Fig. 3.2 presents these four sections.

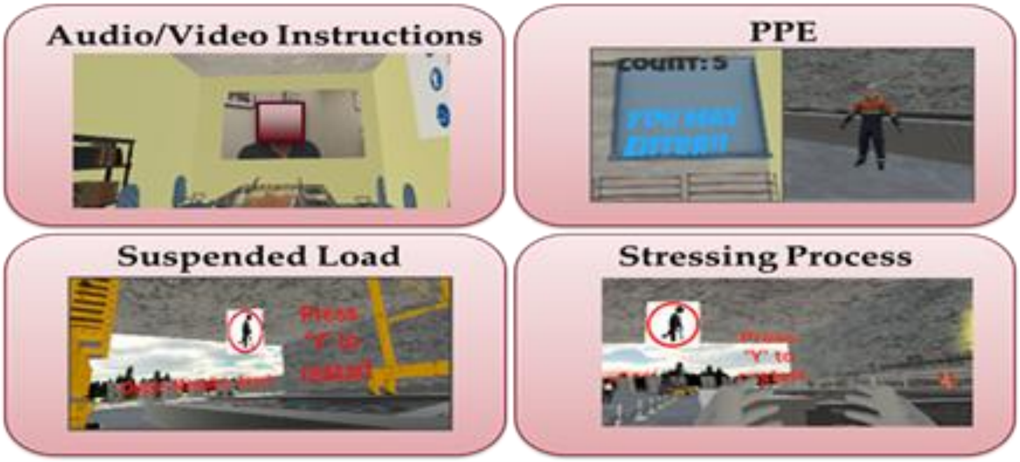


Figure 3.2 VR Training model

The four major sections of the model are: a) Audio and visual instructions of the model; b) Personal Protection Equipment model; c) The risk management while suspended loads are in process; d) The precautionary measures when stressing process is in progress

The VR safety training module begins with a virtual employee standing outside a precast plant (Fig. 3.3). The participant can control the virtual hands to experience the VR module contents. He/she is instructed regarding navigation in the module. It is essential to go through an orientation to have an initial understanding of safety issues and job hazards before entering the plant. After entering the reception area of the plant, the participant is asked to enter a conference room to receive an orientation. The orientation video presents overall hazardous situations in the plant and an overview of the module.

Figure 3.3 Module environment overview

The overall module overview of the plant environment

3.4.2 Personal protection equipment

After successful completion of the orientation, the participant can proceed to the plant. However, the plant door remains closed. To open the plant door, the participant needs to pick up all appropriate personal protective equipment using virtual hands. The primary purpose of this module is to make employees aware of exactly which PPE is necessary before entering the plant. The participant needs to pick up all the necessary PPE among all equipment assigned in the module (as shown in Fig. 3.4). The essential PPE includes a hard hat, safety gloves, safety glasses, steel-toed boots, and earplugs. Audio indicators and a counting tool indicate if the appropriate PPE is being picked up. The audio indication differentiates the right PPE from the wrong. Once all the right PPE is picked up, the message on the wall will indicate that "You May Enter.", which indicates the participant has completed this section.

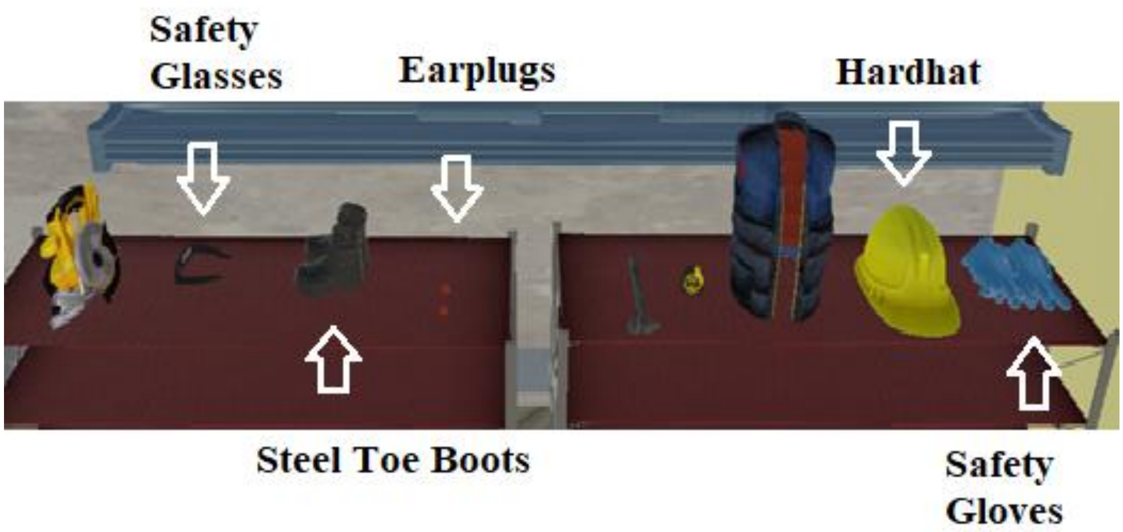


Figure 3.4 Personal Protection Equipment

The PPE module contains some correct PPE and some incorrect PPEs. Participants need to identify the correct PPE.

3.4.3 Plant overview, suspended loads, and the stressing process

A precast plant is inherently a noisy and busy place. Due to the design of the precast/prestressed concrete product itself and the requirements of its production process, employees are occasionally exposed to hazards. Employees and equipment are constantly moving around the plant (as shown in Fig. 3.5a). The participants must be aware of their surroundings while navigating the plant environment. The visual instructions on the plant wall include informative videos for suspended loads, the stressing process, and overall plant safety. The participant can play these videos while exploring the plant. In addition to these videos, the participant is expected to answer questions while walking around the plant using virtual hands (as shown in Fig. 3.5b).

Large concrete panels are the finished products of the precast plant and are produced on casting forms known as beds. Overhead cranes or traveling cranes (MI Jacks) carry the finished panels from the beds and take them to the storage area (as shown in Fig. 3.5c). When the concrete panels are lifted and being transported, the participant is strictly prohibited from being around the crane and its suspended load. The crane indicates this process is underway with specific audible and visual alarms that are activated when suspended loads are being carried. The participant must stay a minimum of 10 feet away from the crane and the suspended load being carried. If the participant moves too close to the crane, he/she will be instructed to restart the module indicating failure of this part of their safety training.

The plant includes three casting beds. An alarm and a yellow flashing light will indicate if one of the beds is conducting the stressing process. The participant needs to recognize that stressing is underway and avoid walking into the stressing safety zone. If the participant enters the stressing safety zone, he/she will be asked to restart the module (as shown in Fig. 3.5d), which notifies the participant of failure of this part of their safety training. All the audio and visual indications such as videos, alarms, flashing lights, and voice instructions can be updated for each plant in a negligible amount of time as C# provides that flexibility.

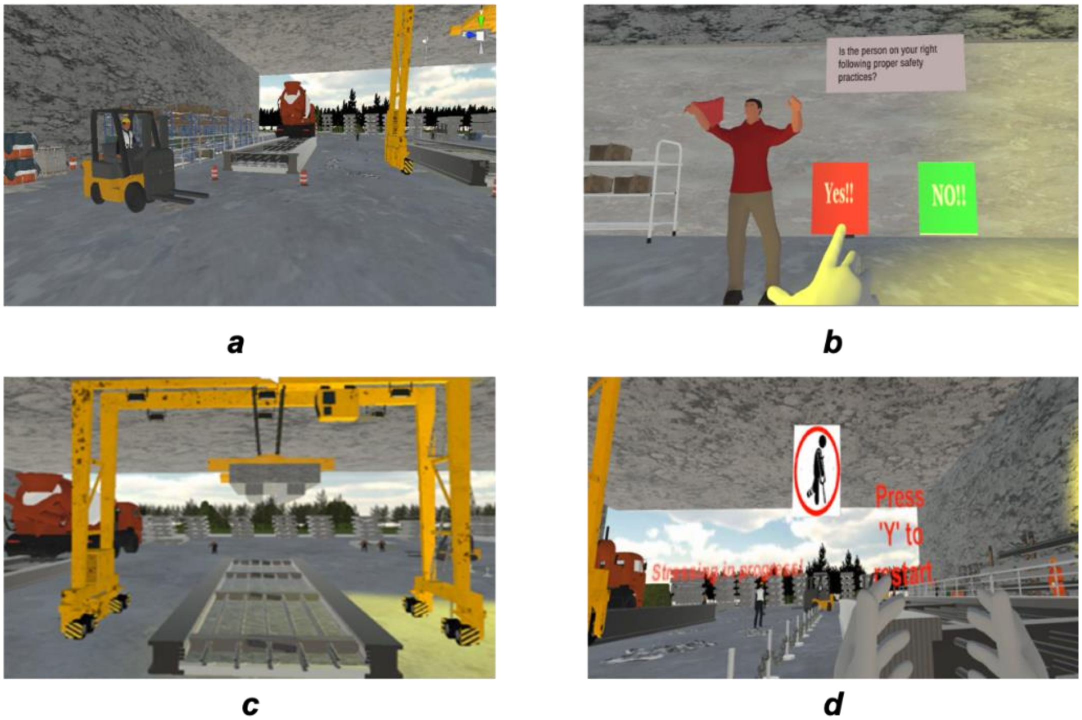


Figure 3.5 The plant overviews

Place plant overview includes a) Plant Overview; b) Practice Questions; c) Suspended Loads; d) Stressing Process.

3.5 Experimental design

3.5.1 Experimental setup

Thirty-two students from Mississippi State University participated in this experiment, including both graduate and undergraduate students. Twenty of them were female and twelve were male. The participants were further divided into two groups for the study purpose: The Video group and the VR group. Participants were randomly selected for the experiment and randomly assigned to one of the groups. Sixteen students participated in the video experiment and another sixteen students participated in the VR experiment. The Oculus Rift headset, touch controllers, and VR compatible computer with VR safety training installed were the essential tools used to perform this experiment. Participants were asked to wear the Oculus Rift headset and navigate using touch controllers. Fig. 3.6 presents the experiment procedure.

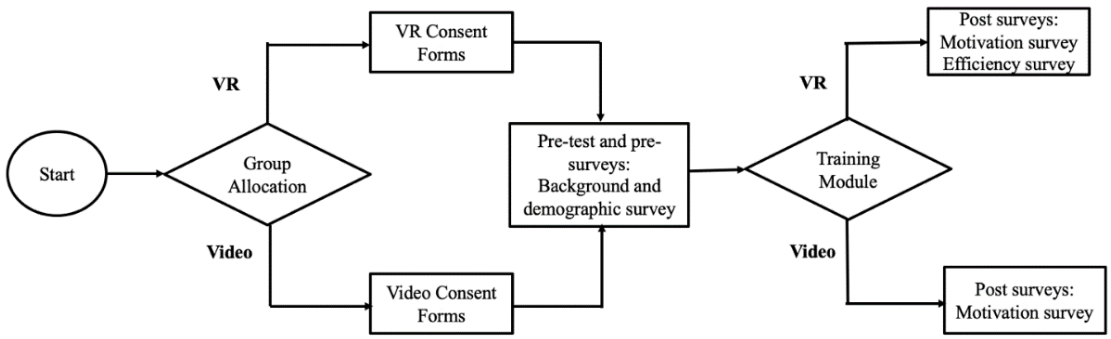


Figure 3.6 Flow chart for the experiment

Participants reported their feedback by answering questionnaires. Questionnaires included pre and post-test knowledge, a motivational survey, and efficacy measures. Pre and post-tests were used to analyze the knowledge gain of participants in the two different groups. The motivation survey indicated how much motivation was achieved through each training method. Efficacy measures collected information regarding the efficacy of the module, including SSQ, SUS, and PQ.

For the Video experiment group, nine were female and seven were male, while for the VR group, eleven were female and five were male. Initial data collection included a consent form and background questionnaires. Background questionnaires included gender, the participant's field of study, level of knowledge in VR, and race. According to the background survey, none of the participants held an above-average knowledge of the precast/ prestressed industry, 87% of the VR participants had prior knowledge of VR, and only 31% of the participants had prior knowledge of construction safety protocols.

3.5.2 Experimental setup

After checking in for participation, students were assigned to either the VR group or the traditional training experiment group. This provided randomness for the experiment. In the traditional training case, the student was assigned to the Video group; they were asked to fill out a video consent form, primary questionnaires, which included a background questionnaire, pre-test, and motivation questionnaires. Next, they were asked to watch 17 minutes of a PCI safety training video. They were asked to go through the video carefully, and then complete the rest of the questionnaires. These questionnaires were used to analyze their understanding of the safety training content, how much knowledge they received, and the amount of motivation and confidence they felt after completing the training.

When a student was assigned to the VR group, they were asked to fill out similar preliminary questionnaires as the traditional training group did. Next, they were shown how to navigate and use the VR module to participate in the safety training. Once participants started navigating in the VR module, they followed the instructions and paths to complete the VR training. They primarily needed to perform the tasks as shown in Fig. 3.7.

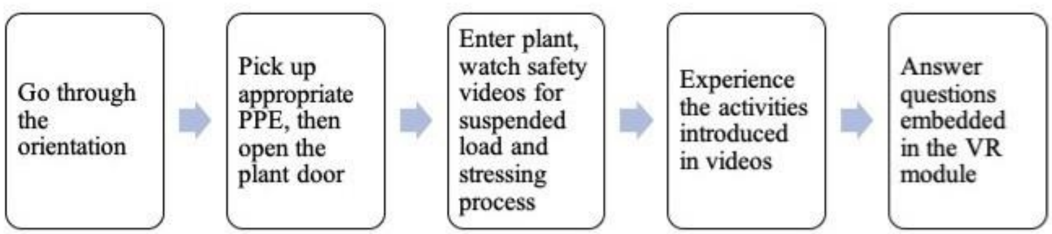


Figure 3.7 Primary activities after wearing VR headset

3.6 Efficacy and effectiveness analysis

3.6.1 Efficacy analysis

Efficacy measures the quality of the immersion in a developed VR simulation [47, 48]. Various questionnaire evaluation approaches are developed to analyze the quality of performance of the VR system. The most used approaches are SSQ, SUS, and PQ. SSQ indicates the level of discomfort encountered by the participants and has been used to determine if the VR module needs to be modified. SSQ measures sixteen symptoms and requires participants to report the level of discomfort from 0 to 4 (0, 1, 2, and 3 being none, slight, moderate, and severe, respectively). Symptoms are categorized for each of the discomfort levels caused by VR. Nausea (questions 1,6,7,8,9,15,16) deals with symptoms related to gastrointestinal distress; oculomotor disturbance (questions 1,2,3,4,5,9,11) indicates symptoms related to visual observations such as eye strain and headache; and disorientation (questions 5,8,10,11,12,13,14) indicates dizziness and vertigo. Each of these symptoms are estimated with their respective scores, and the total score indicates if the module can cause problems overall. Each of the scores for symptoms are calculated by adding the question scores within each group and multiplying the sum by the weights of the symptom. The weights for nausea, oculomotor disturbance, and disorientation are 9.54, 7.58, and 13.92, respectively. The total SSQ score is calculated by summing the group's scores and multiplying that total by the weight of 3.74. Table 3.1 represents conclusions corresponding to each possible score.

Table 3.1 SSQ score calculations score and conclusions overview

SSQ Score	Overview
0	No symptoms
< 5	Negligible symptoms
5 ~ 10	Minimal symptoms
10 ~ 15	Significant symptoms
15 ~ 20	Significant symptoms
20 ~ 25	Symptoms are concern
> 20	A problem simulator

The simulation sickness assessment provides a better understanding of the VR module concerning the experience of the participants. An SSQ score above 20 indicates that the VR module is a problem simulator, and immediate actions need to be taken. Table 3.2 represents the test group's assessment for each symptom in the proposed VR safety module. The overall score is 14.96, which means the developed VR safety module has significant symptoms indicating the need for further modification, but that the module is still useful.

Table 3.2 Simulation sickness analysis results

Symptoms	Weights	Scores	Participants Indicating Negligible Simulation Sickness
Nausea	9.54	23.32	70.4%
Oculomotor Disturbance	7.58	18.53	70.4%
Disorientation	13.9	42.79	40.7%
Total	3.74	14.96	52%

Based on the study conducted, the results indicate "safe" use of the VR module with respect to oculomotor disturbance, nausea, and disorientation. More than 70% of the participants reported negligible or no symptoms for nausea and oculomotor disturbance and more than 40% reported negligible or no symptoms for disorientation. For the overall experiment, more than 50% of the participants reported negligible or no symptoms of simulation sickness. The most important factors to be considered are sample size and the experience of the participants. A sample size of 200 is considered an effective sample size, especially when the sample is being divided in half for the comparison of groups [52]. Hence, results may be stabilized by increasing the sample size from 32. Another factor is the relevancy of the sample size. Expanding this study further to include participants from precast plants should provide more stabilized results. Using relevant participants in the study will be an effective test to determine how effective the VR module is compared to traditional training methods.

System Usability is a measure to analyze expectations from the system. SUS questionnaire consists of 10 items [53, 50]. Each response scale ranges from 0 to 5 (0 being the lowest and 5 being the highest). The questions are divided into 2 groups: positively worded and negatively worded. Seven questions are worded positively (1,2,3,4,5,7,9) and 3 are worded negatively (6,8,10). For the positively worded questions, scores are calculated by subtracting 1 from the response. For a negatively worded response, the score is subtracted from 5. The total SUS is obtained by summing all the responses and multiplying by 2.5.

The System Usability score represents usability expectations from the VR module. A total SU score of 68+ suggests that users experienced above-average satisfaction from the module. Table 3.3 represents the results for SUS performance reported by the test group. The total SUS is 64, which is close to average. However, the participants scored above average for all positively worded questions and two out of the three negatively worded questions. Further, a student's t-test was conducted with a 5% level of significance to test the hypothesis, if male and female participants experience similar system usability. Results indicate that for two-tailed tests (p-value 0.59) the hypothesis is accepted. Male and female participants experience the same level of usability experience.

Table 3.3 System Usability results

#	Questions	Average	SD
1	I think that I would like to use this VR module to learn safety protocols.	4.4	0.6992
2	I want to use VR in other courses.	3.9	1.1972
3	I found this VR module was easy to use.	3.1	0.9944
4	The VR modules helped me to establish the linkage between the protocols for safety and practice.	4.3	1.0593
5	I found the various functions (e.g., sound, pictures, control) in this VR module were well-integrated.	3.7	1.0593
6	I thought there was too much inconsistency in this VR module.	2.3	1.0593
7	I would imagine that most people would learn to use this VR module very quickly.	3.5	1.4337
8	I think I would need the support of a technical person to use this VR module.	3.6	1.3375
9	I felt very confident using this VR module.	2.3	1.3375
10	I should learn more VR base knowledge before I use the VR module.	3.4	0.8433

User experience evaluates the convenience of using the product. Participants explain their experience through PQ [49, 51]. PQ provides an estimation for the following experiences: involvement, immersion, visual fidelity, interface quality, and sound. The questionnaire consists of twenty-two questions with nine involvement questions (1,2,3,4,5,6,7,10,13), six immersion questions (8,9,14,15,16,19), two visual fidelity questions (11,12), and three sound questions (20,21,22). Each question is rated on a 7-point scale (0 to 6). Summing all the responses generates the PQ score, and the total score ranges from 0 to 114. The reported average score for the precast training VR module is 3.85. Out of five sub-scales, above-average scores are reported for involvement, visual fidelity, and sound. Immersion and interface quality are reported as below average. These factors should be addressed moving forward while improving the module.

Table 3.4 User Experience

Sub-scales of PQ	Items	Average Score
Involvement	1, 2, 3, 4,5, 6, 7, 10, 13	4.12
Immersion	8, 9, 14, 15, 16, 19	3.73
Visual Fidelity	11, 12	4.30
Interface Quality	17, 18	2.60
Sound	20, 21, 22	3.82

A pilot study in a precast plant was also conducted. The purpose of this study was to investigate the impact of the module on professionals. Fifty-one industry employees participated in this study. The data consisted of five females and forty-six males. Six of the participants had average prior experience in VR, nine had little prior experience, and 36 had no prior experience. The overall response provided by professionals confirmed that the VR module has the potential to engage new employees better than the traditional training methods. Higher engagement will help individuals retain more information. This should reduce accidents and help lower turnover in the precast industry.

3.6.2 Effectiveness analysis

Effectiveness analysis consists of two evaluation methods: motivation and knowledge gain. Motivation analysis focuses on the level of motivation achieved by the participants after each training method. This section focuses on different comparisons amongst dependent and independent groups of participants using t-test and Wilcox tests. Two sample t-test helps analyze the hypothesis that the population means of both groups are equal. One of the assumptions of t-tests assumes that both sample groups are independent, the variables are approximately normally distributed, and the population variances are equal.

The test hypothesis can be stated as the dataset is normally distributed, and the level of significance is considered as 5% for all the tests. If results provide a p-value < 0.05, it confirms that the data is NOT normally distributed. Hence, both groups should be following normal distributions with parameters (μ_1, σ_1) and (μ_2, σ_2). These samples need to be independent, and their variances need to be equal ($\sigma_1 = \sigma_2$). The F-test is used to check the equality of the variances. These tests are also applicable to the acceptance or rejection criteria as above. While testing the normality assumption for these independent sets of the group, primarily the Shapiro-Wilk test and Kolmogorov-Smirnov tests are included in the study. If one of the assumptions of the t-test is not fulfilled, then it can be said that the test would not perform as it otherwise should. Hence, it may lead to a false rejection of the null hypothesis.

In such cases, the Wilcox rank-sum test (for independent samples) and Wilcox-signed-rank (for paired samples) test have been applied on the same data to verify the results. These are non-parametric tests with a similar hypothesis as t-tests for independent and paired samples, respectively. Besides, for all the tests, the Q-Q plot represents how close the sample distribution is to the theoretical distribution. Q-Q plot is a scatterplot by plotting two sets of quantiles against each other. It helps with the visual representation of the distribution of both sets and how comparable are those to each other. The further sections describe these test results and conclusions obtained from each dataset and statistical tests.

3.6.2.1 Motivation analysis

The motivational questionnaires are organized in such a way that they analyze the motivation generated through different training methods. Fig. 3.8 summarizes the motivation results of the two training approaches. Motivation surveys test how much each method motivates the participants to follow safety practices. 14 questions are designed to test their motivational level. The participants are randomly divided into two different groups. These groups are divided based on the training methods participants are assigned to, traditional training group and VR training group. These groups are compared using two-sample t-tests. Table 3.5 confirms normality assumptions and if the t-test would be the appropriate test in this case. The hypothesis listed for these specific tests states that the data is normally distributed. Considering the same level of significance, p-value < 0.05 would suggest that distributed data fits other non-normal distribution.

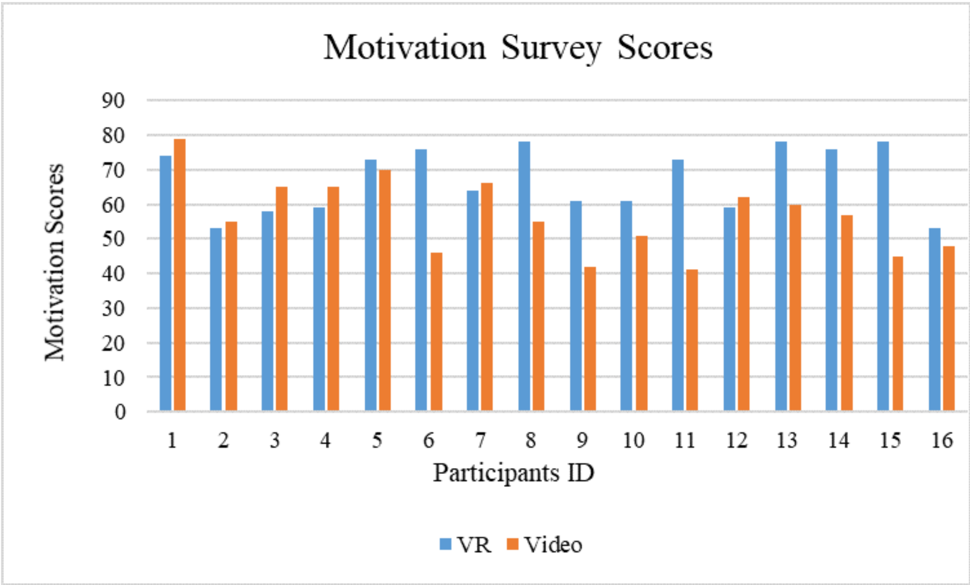


Figure 3.8 Motivation survey results

Table 3.5 Normality assumption tests for VR and Video training method from motivational analysis

		p-value	Normally Distributed?
VR	Shapiro-wilk	0.0212	No
	Kolmogorov-Smirnov	0.1923	Yes
Video	Shapiro-Wilk	0.7790	Yes
	Kolmogorov-Smirnov	0.9341	Yes

From table 3.5 it can be concluded that the traditional training data seems normally distributed with both tests. While the VR training data proved to be normally distributed using

Kolmogorov-Smirnov. Furthermore, the F-test analyzes if both the groups provide evidence for equal population variances. This test hypothesizes that both groups have equal population variances, and a p-value < 0.05 will result in rejection of that hypothesis. However, F-test ($F = 0.75$, p-value = 0.59) concludes that both the population variances can provide ratio as 1. For comparison of the training method, the student's t-test and Wilcoxon rank-sum test are used to test if the VR training method is cause a significantly better motivation level than the video-based training method. The null and alternative hypotheses are listed below.

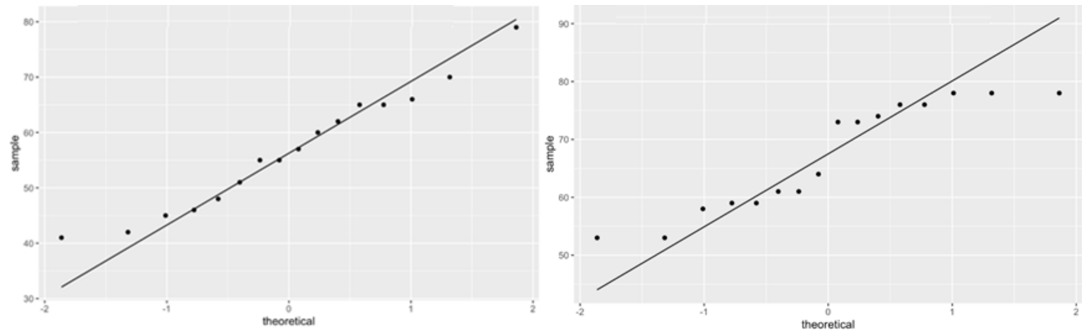
H_o: The motivation level achieved by the traditional video training method is equal to the VR training method.

H_1: The VR training method results in a higher motivation level than the traditional video training method.

Table 3.6 Summary of hypothesis-testing independent t-test and Wilcox rank-sum test

	Sample size	Sample mean	Sample S.D.	T-test for independent samples		Wilcox rank-sum test	
				Test statistics (t)	p-value	(w)	p-value
VR	16	67.13	10.84	2.91	0.003	190	0.02033
Video	16	56.69	9.41				

The conclusion obtained with both tests suggests a similar conclusion. Table 3.6 represents the hypothesis test summary. There is sufficient evidence to reject the null hypothesis with the help of a t-test ($t = 2.91$, p-value = 0.003). It concludes that the VR training method results in a higher motivation level than the traditional training method. The level of motivation may be sensitive, and it may differ with the method of training used by employees. Further study needs to be conducted to confirm this hypothesis.



(a) Motivational survey for traditional training method

(b) Motivational survey for VR training method

Figure 3.9 Create a short, Motivational analysis tests distribution for (a) traditional training method and (b) VR training method

Figure 3.9 represents the Q-Q plot for motivational analysis and how traditional training methods and VR training methods performed while testing the sample. To test the impact of gender on the motivation hypothesis, a similar approach was used with the gender dataset for each of the two datasets. The null and alternative hypotheses are listed below.

H_0: Male and female participants gain the same level of motivation from the VR module.

H_1: Male and female participants gain a different level of motivation from the VR module.

To perform this test, table 3.7 is obtained from a normality test. The table supports the hypothesis that all sample groups are normally distributed except for female VR participant groups.

Table 3.7 Summary for normality tests (Gender analysis for a motivational survey)

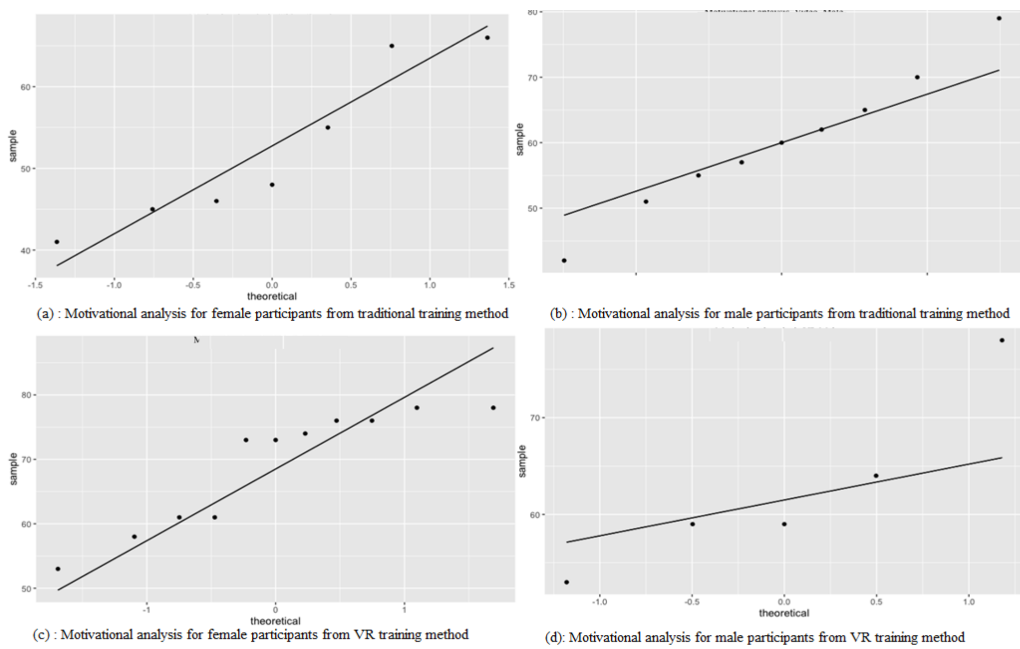
			p-value	Normally Distributed?
VR	Male	Shapiro-Wilk	0.3535	Yes
	Male	Kolmogorov-Smirnov	0.3937	Yes
	Female	Shapiro-Wilk	0.02973	No
	Female	Kolmogorov-Smirnov	0.00663	No
Video	Male	Shapiro-Wilk	0.9997	Yes
	Male	Kolmogorov-Smirnov	0.9966	Yes
	Female	Shapiro-Wilk	0.2326	Yes
	Female	Kolmogorov-Smirnov	0.2692	Yes

Table 3.8 represents all the tests for testing variances and t-test. However, as normality assumption failed for the Female VR participants group, the Wilcox rank-sum test is also performed on the dataset.

Table 3.8 Summary for tests: Equal variances; unequal variances t-tests, Wilcoxon rank-sum test

	Equal variance		T-test for independent variables		Wilcox rank-sum test	
	F-test: p-value (Conclusion)	Gender	(t)	p-value	(w)	p-value
VR	0.8274 (Equal variance)	M	2.31	0.23	36.5	0.3324
		F				
Video	0.8725 (Equal variance)	M	2.14	0.15	19	0.2033
		F				

The video training method results (w = 19, p-value = 0.20) indicate that the hypothesis cannot be rejected, and it can be said that the motivation achieved by male and female participants are not significantly different from each other. Similarly, for the VR training method (w =36.5, p-value = 0.3324), the hypothesis will not be rejected at a 5% level of significance. It can be claimed that gender is insignificant for the motivation gained by the participants. However, referring to figure 3.10, the plots show variations between different gender and methods, this can be tested in the future with a larger data size for more accurate results.



(a) : Motivational analysis for female participants from traditional training method

(b) : Motivational analysis for male participants from traditional training method

(c) : Motivational analysis for female participants from VR training method

(d): Motivational analysis for male participants from VR training method

Figure 3.10 Motivational analysis scores for both training methods

Motivational analysis tests include: (a) female participants from traditional training method; (b) male participants from traditional training method; (c) female participants from VR training method; (d) male participants from VR training methods

3.6.2.2 Knowledge gain analysis

This questionnaire is designed to test the participant's knowledge of the safety protocols after participating in the training. This questionnaire discusses different safety training protocols explained in both video and VR training. Figure 3.11 represents the knowledge gain level between participants' pre- and post-module. Comparing pre-tests and post-tests results, the minimum score of both the VR and Video groups was increased from 5 to 6 after the training has completed. The highest score reported by participants post-training was from the VR training group.

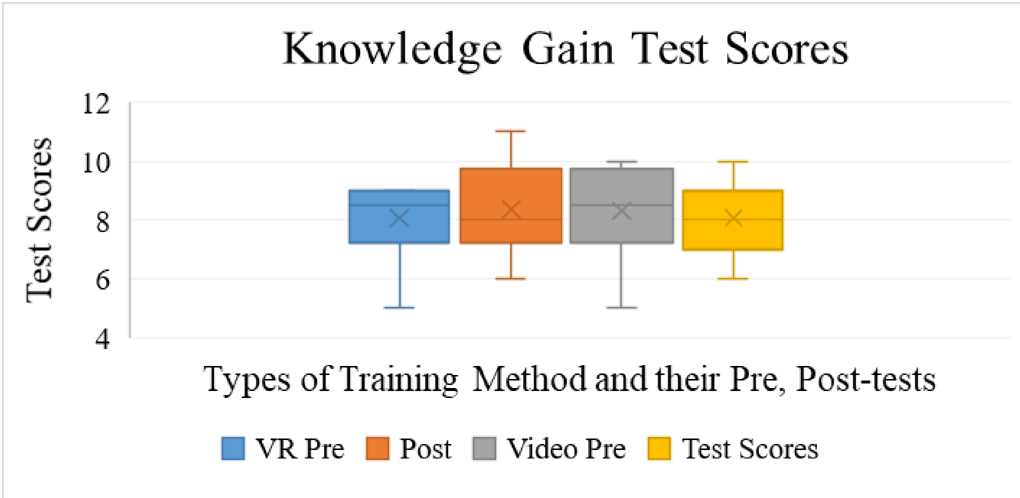


Figure 3.11 Knowledge gain tests for VR and video experiments

The knowledge gained by participants is another important constraint from the study. The average score provided by all participants was 6. The data is divided into two groups for comparison of knowledge gain: knowledge gain by participants studying the traditional training module and scores gained by participants performing VR training module. The first hypothesis to be tested is if the level of knowledge gain is not significantly different for training methods.

As described at the beginning of this section, if the pre-requisite assumptions are proved to be valid, then an independent t-test will be considered, otherwise, Wilcoxon rank-sum test results would be considered for more appropriate conclusions. Table 3.9 represents the normality assumptions for the specific tests at the significance level of 5%.

Table 3.9 Summary for normality tests (Both training methods to test knowledge gain)

		p-value	Normally Distributed?
VR	Shapiro-Wilk	0.4607	Yes
	Kolmogorov-Smirnov	0.2964	Yes
Video	Shapiro-Wilk	0.07991	Yes
	Kolmogorov-Smirnov	0.06352	Yes

Table 3.9 confirms that VR and traditional training method samples for knowledge gain are normally distributed. To test if their variances are equal F-test results (F=1.38, p-value=0.5367) indicate that the population variances for both groups are equal. These results are summarized in table 3.10 to test the following hypothesis.

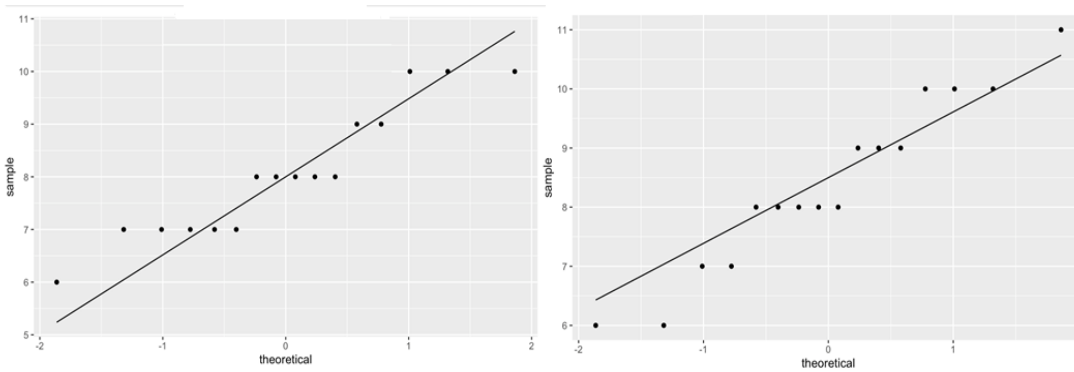
H_o: VR and video training methods are not significantly different for knowledge gain

H_1: VR and traditional training methods have significantly different implications on the knowledge gain of the participants.

Table 3.10 Summary for tests: Equal variances; unequal, equal variance t-tests, Wilcox rank-sum test below

Training method	F-test, p-value (Conclusion)	T-test for independent variables		Wilcox rank sum test	
VR	1.38 (Variances are equal)	(t)	p-value	(w)	p-value
Video		0.6546	0.2588	146	0.4983

The t-test suggest (t= 0.6546, p-value = 0.2588) that the null hypothesis cannot be rejected. The training method is not reflecting significant effects on the level of score obtained by participants. Q-Q plot for the study represented in figure 3.12 represents the distribution of two samples using samples and assumed. And this can be further tested including a larger sample size.



(a) Knowledge gain for traditional training method

(b) Knowledge gain for VR safety training method

Figure 3.12 Knowledge gain for traditional method and VR training method

After testing the differences from different training methods, a one-tailed paired t-test and Wilcox signed-rank tests are used to confirm the extension of this hypothesis. Table 3.11 represents if the difference between post and pre-test are normally distributed, followed by table 3.12 with hypothesis testing summary. To test if the participants performed any significant improvement in post-test analysis, compared to pre-test analysis, the following hypothesis is considered:

H_0: Knowledge gain after the safety training module is equal to the pre-training knowledge.

H_1: Knowledge gain after the safety training module is significantly higher than the pre-training knowledge.

Table 3.11 Summary for normality tests (for the difference of post and pre-test)

		p-value	Normally Distributed?
VR	Shapiro-Wilk	0.2209	Yes
Video	Shapiro-Wilk	0.01965	No

Table 3.12 Paired hypothesis test summary: t-test, Wilcoxon signed-rank test

		Paired t-test		Wilcoxon signed-rank test	
	Sample size	(t)	p-value	(w)	p-value
VR	16	-1.05	0.16	52.5	0.2909
Video	16	0.65	0.26	14.5	0.3586

This tests if the average knowledge gain by the VR training method is better than the traditional training method. Based on the results shown in Table 3.10 for VR and video, this hypothesis is rejected, and it can be concluded that knowledge gain with the VR and video training methods shows indifferent results in this study.

Gender is another attribute, that has been compared for this study. Similar to the motivational analysis, this test evaluates whether gender is independent of the level of score obtained by participants for both the training methods.

H_o: Knowledge gained by male participants is equal to knowledge gain by female participants.

H_1: Knowledge gained by male participants is significantly different than knowledge gains by female participants.

Table 3.13 represents the assumption tests for the gender comparison in VR and traditional training methodology. While table 3.14 represents the analysis summary including F-test for independent variance, paired t-test, and Wilcox rank-sum test.

Table 3.13 Summary for normality tests

			p-value	Normally Distributed?
VR	Male	Shapiro-Wilk	0.314	Yes
	Male	Kolmogorov-Smirnov	0.515	Yes
	Female	Shapiro-Wilk	0.3815	Yes
	Female	Kolmogorov-Smirnov	0.3849	Yes
Video	Male	Shapiro-Wilk	0.1099	Yes
	Male	Kolmogorov-Smirnov	0.08825	Yes
	Female	Shapiro-Wilk	0.2729	Yes
	Female	Kolmogorov-Smirnov	0.1031	Yes

Summary for normality testing for gender analysis for knowledge gain survey

Table 3.14 Summary for normality tests

	Equality of variance		T-test for independent variables		Wilcox rank-sum test	
	F-test; p-value (Conclusion)	Gender	(t)	p-value	(w)	p-value
VR	0.1859 (Equal variance)	M	2.31	0.23	30.5	0.7721
		F				
Video	0.2078 (Equal variance)	M	2.14	0.15	39	0.4432
		F				

Equal variances, unequal variances t-tests, Wilcoxon rank-sum test

Gender is independent of the level of knowledge gained by participants regarding the safety protocols. Further, a similar t-test was used to check whether on average men gained more experience compared to female participants. Figure 3.13 represents the differences in the sample trends for different methods, and a different gender. Due to the small sample size, the study does not provide any significant evidence to support the hypothesis. All the hypotheses are summarized in Table 3.15.

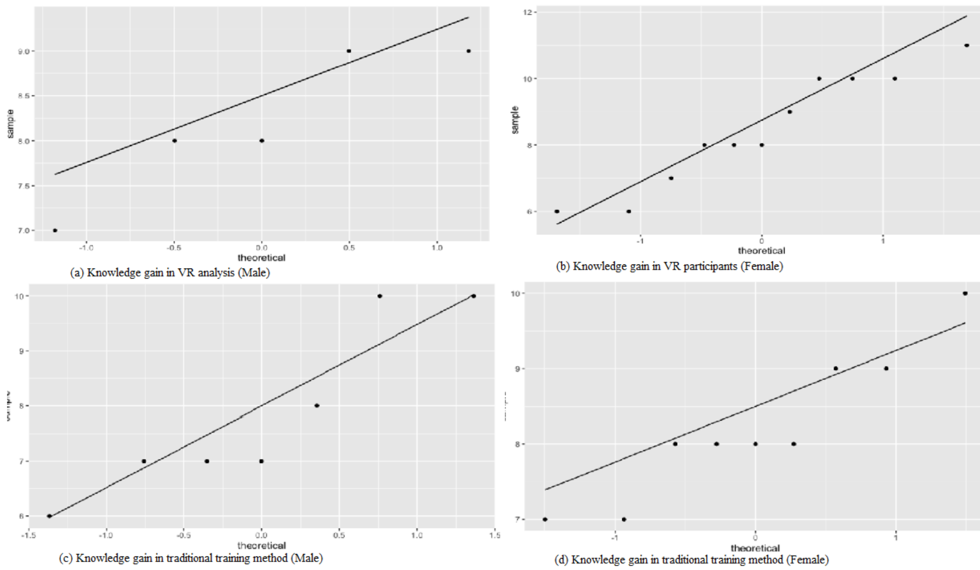


Figure 3.13 Q-Q plot for knowledge gain analysis

Knowledge gain analysis tests for (a) male participants from VR training method; (b) female participants from VR training method; (c) male participants from traditional training method; (d) female participants from the traditional training method

Table 3.15 Summary of hypothesis testing

Tests	Null Hypothesis	Acceptance/ Rejection of Hypothesis
1	The motivation Level achieved by male and female participants is not significantly different (VR)	Fail to reject
2	The motivation Level achieved by male and female participants is not significantly different (Video)	Fail to reject
3	The motivation level achieved by VR is not significantly different than the traditional method	Reject the null hypothesis
4	Knowledge gain by VR is not significantly different than knowledge gain by traditional training modules.	Fail to reject
5	Knowledge gain with the training module is not significantly higher than pre-existing knowledge (VR)	Fail to reject
6	Knowledge gain with the training module is not significantly higher than pre-existing knowledge (VR)	Fail to reject
7	Knowledge gained by male participants is not significantly different than female participants (VR)	Fail to reject
8	Knowledge gained by male participants is not significantly different than female participants (Video)	Fail to reject

Test 4 to 8 from table 3.15, of the analysis, indicate that the participants gain more knowledge after training is completed in both cases. However, results from knowledge gain tests reveal that the knowledge gained by the traditional training method is lower than the knowledge gained by VR training methods. Even though statistical tests did not prove the training method to be significantly better, the results and graph indicate better performance in the VR training method. Performing the study on a larger sample size may lead to a more informed decision in the future. Further tests can be conducted to see if gender and knowledge gain by participants have a dependent relationship. In both training methods, results indicate that the knowledge gain by participants is independent of the gender of the participants.

Motivation surveys are designed to understand and compare different scenarios and test which situations or training methods motivate participants for following safety protocols more efficiently. Referring to table 3.15, test 3 supports the claim that the motivation level achieved by the VR training method is significantly higher than traditional training methods. This can be further investigated if the module is including further sections of the safety training program are added. Higher motivation leads to better achievement, helps achieve efficiency levels, and builds stability in employee actions. In this case, higher motivation should lead to all the above results in terms of safety. Employees will be more efficient and stable in terms of safety protocols on the plant. Test 1 (Table 3.15) checks if the gender has any significant difference concerning motivation gain using both training methods. Motivation achieved by the traditional training method is indifferent to the gender of the participants. However, the VR training method reports gender and motivation level as dependent factors. Hence, it is concluded that male and female trainees will gain a different level of motivation while participating in the VR training method.

Immersion is the most important advantage of the VR system. However, with its immersive nature, the VR module needs to satisfy efficiency criteria. This includes if the module causes any simulation sickness and if the user is comfortable using a VR environment. This leads to an improved level of understanding of the user from the module. If efficiency measures indicate any issues, the module needs to be improved. The results of the study show that most participants did not face any issues with simulation sickness while using the VR module. Usability experience indicates how satisfactory the performance that candidates reported was. A SUS score greater than 68 indicates a satisfactory Usability performance. The test group results provide a total SUS of 64, which concludes that the usability experience reported by participants is below a satisfactory level. Other results regarding experience show that the positive and negative wordings of questionnaires have an impact on this. A Student's t-test results accept the hypothesis that both male and female participants reported the same level of satisfaction for the usability study. The last measure considered for this study tests the presence of participants during the study. This study divides all the factors which enhance the performance of the VR module into five sub-scales. Involvement, visual fidelity, and sound for the module resulted to be issue-free and proves the efficiency of the module. Immersion and interface quality are less than satisfactory. All the above analyses may provide more accurate and unbiased results in the future when this study is conducted on a larger number of participants or by utilizing participants from the precast/prestressed concrete industry in the study.

3.7 Conclusion and further modifications

The primary purpose of the module is to help new precast/ prestressed concrete industry employees understand safety protocols more accurately. Which will help with avoiding accidents compared to traditional training methods. The pilot study proves that participants have higher motivation after participating in the VR training method. An increase in their motivation level will help them to learn more safety protocols and follow them whenever necessary. Knowledge gain in the pilot study shows that the understanding of the participants differs for each training method. Most of the participants reported a satisfactory experience in a usability study. The third efficiency measure analyzed five sub-scales of presence. Out of five factors, involvement, visual fidelity, and sound are satisfactory. However, immersion and interface quality can have improved. The pilot study conducted in the precast plant indicates that this module has the potential to minimize the number of accidents. Hence, including more safety modules in the future should be considered.

However, this study has the potential to be improved. The sample size or the number of participants involved in the study is small. If more participants are included in the study, it will lead to more accurate results [88]. Another limitation of this study seems to be the background of the participants. Participants involved in the study are students. With another primary study conducted on the precast plant, it can be hypothesized that professional participants with precast knowledge will provide more accurate results. The pilot study in the plant and the feedback provided by participants support that the professional population will be more sensitive to the training method. The overall response provided by professionals indicates that the VR module has the potential to engage and help new employees retain more information. This should reduce accidents and help lower turnover in the precast industry.

To create this module, the Unity 3D platform and Oculus Rift were used. There are other software packages involved in similar studies. Even with Unity, newer versions can be exported for further studies. Instead of the Oculus Rift, there are upgraded Oculus platforms that may be more effective and convenient to use such as oculus quest and oculus quest 2. Future research will continue to work on these limitations and modify the technique used. VR training can be expanded to teach other operations in the plant in addition to the safety training such as the stressing process.

CHAPTER IV

SAFETY ASSESSMENT FOR PRECAST/ PRESTRESSED INDUSTRY USING FAULT TREE ANALYSIS AND COMPARISON OF BAYESIAN NETWORK ANALYSIS

In the previous chapters, this study described how the precast plant safety analysis is conducted by combining the Fuzzy analysis with the Bayesian Network study. In the next sections, this research focuses on using an alternative methodology to analyze the precast/prestressed plant safety and comparing the different methodologies. The alternative approach used to conduct this analysis is Fault Tree Analysis (FTA). This methodology is used to analyze the abnormal events while considering all the necessary layers in the study, leading to the top event, which is plant safety.

4.1 Introduction

Fault Tree Analysis (FTA) is a graphical representation of the problem or issues to understand and analyze the root cause of the problem. This methodology takes into consideration the reliability of each related event and the level of event failures that cause a system failure. Similar to the Bayesian Network study, this methodology understands and analyzes the factors pursuing an interdependent relationship with the root cause of the problem. The primary purpose of the FTA tool is to identify the safety and reliability of the system. The structure of the Fault Tree is a graphical hierarchy structure that represents a top-down approach, meaning the topmost approach can be treated as the 'target,' or the factor is focused on the study. The further levels of the graph are related to each other based on their direct and indirect relationships with the topmost event. They are also considered sub-layers of the study. Fault Tree Analysis is a widely used methodology to measure the risk analysis approaches [89]. By using FTA, the proposed hierarchical approach and graphical representation were developed to show the connection between the fault and its origin [91].

Generally, FTA starts with a system failure, called the top event, and then works backward from the top of a tree, to determine the root problem caused by the top event [92]. The analysis result shows how individual component failures will be combined to cause an overall system failure. After a Fault Tree is constructed, the FTA is carried out in both a qualitative and quantitative analysis [93]. As described in this section, qualitative analysis is usually evaluated by reducing Fault Trees to minimal cut sets. Thus, the final product will consist of few basic events to cause the top events. For quantitative analysis, the probability of top events occurrence and other reliability indexes will be calculated through mathematical equations. The results of quantitative analysis explain the reliability of the system. Generally, quantification analysis for static Fault Trees does not consider uncertainty in failure data. If the uncertainties are not solved, the result of quantitative analysis is not accurate. There are many different fuzzy numbers of methodologies proposed to solve uncertain failure data in FTA.

For any complex system, it is feasible if the probability of system reliability is known. If system reliability is not certain and many factors are dynamic or changing, it is worth finding the system failure probability. If most factors or environments are changing or dynamic, then it is difficult to find the failure probability [94]. In such cases, the Fault Tree Analysis approach can provide the closest estimate for the system. Various studies that use the FTA approach to resolve the system failure issue are conducted.

FTA can be qualitative as well as quantitative. Qualitative FTA parameters can be converted to the Boolean approach, while a quantitative approach can find the probability distribution to analyze the reliability and probabilities of the failure in each level of the tree. The research has been conducted [95] to analyze applied qualitative methodologies utilizing FTA to determine the weak path for the robot manipulator, while studies have been conducted using a quantitative approach [96] to understand the safety and reliability of the robotic system. The study was conducted for extension of a Fault Tree Analysis to build the model "Galileo." It uses a Fault Tree Analysis to provide a decision analysis method with the interface of package-orientation programming [97]. In 2006, research was conducted to analyze the problems with circuit board assembly [98]. The research focuses on undesirable events at every stage of the circuit and calculates fault intervals of the system components, resulting in the most critical component of the system. This study focuses on Printed Circuit Board Assembly (PCBA). For a regular pipeline, failure events considered are leakage, rupture, cuts, and so on. The Fault Tree Analysis method was used in 2005 to analyze the failure of oil and gas transition for the pipeline [99]. Posbist Reliability Theory includes binary stage assumption. This can be interpreted, as there are only two stages to switch between reliable and non-absolutely reliable [100]. These two stages can pursue values 0 and 1, rather than probabilities between 0 and 1. In other words, the system and components contain two crisp states, fully functioning and completely failed. Based on the binary reliability of each component, the reliability of the system can be derived. This is not the only study focusing on FTA using binary systems. Another study was conducted to further study Binary Decision Diagrams (BDD); these are like Posbist Reliability Theory [101]. The results of the study conclude that BDD diagrams are the most efficient and accurate means of study for systems, especially for the study of circuit systems.

As described in all these studies, traditionally FTA is used to test the reliability of failure possibility in the system given the issues with hardware systems levels. However, for the precast/prestressed industry, employees are an equally important section of the system. The errors that occurred due to employee activities also need to be taken into consideration. The study indicates [102] that human involvement leads to 20% to 90% errors in systems. This research focuses on precast/prestressed plant safety. Hence, it cannot be as straightforward as a circuit system. Each component cannot necessarily pursue only binary outputs. The system contains various stages; these stages are dynamic and depend on many factors. Therefore, finding the probability distribution for each component would provide appropriate results for the final output as described in Chapter 2 of this study.

All the above case studies describe how research conducted in different expertise is using the Fault Tree Analysis method. Even if these methods are aiming for similar outcomes, most of the research focuses on FTA with expert knowledge and fuzzy evaluation of binary methods. These methods lack flexibility and need some updates to estimate more complex systems. They analyzed the FTA approach considering events possibility as Likert scale or a yes/no system. Further, with experts' opinion, the fuzzy analysis provides an approximation of the real-world analysis. It is beneficial if, instead of opinion, the analysis is based on data set analysis, or real-world observations. This research overcomes these limitations and improves the effectiveness of the results.

4.2 Safety assessment and implementation of the Fault Tree analysis

The fault Tree Analysis (FTA) technique is utilized to analyze the high-risk systems for identifying hazards. FTA is a tree that combines required Boolean logic involving the relationships between components. FTA is a widely used approach in various industries [103]. The switch is built using logical gates, primarily and/or gates, and is connected to different events from the system to analyze the topmost event, which can be described as the target of the study [104]. Factors and their possibility of reliability or failure need to be considered and calculated from past events. In this study, those probabilities are analyzed using the fuzzy analysis approach. It is a powerful technique to identify the root cause of undesired events in system failure. FTA is also useful for situations like manufacturing system process/fault diagnosis. FTA is the better fault detection tools because of its following characteristics [105, 106, 107]:

a) FTA can be used to analyze specific faults by levels. It provides clearer graphical representations of the system. It is useful to analyze the significance of each level and its impact on the top level.
b) FTA identifies the reasons for failure, while analyzing the effects of the failure on the system.
c) FTA is a clearer representation of the process and issues associated with it for those management authorities in the process who never participated in the system/process design.
d) The analysis provides better insight into system behavior, which leads to the identification of weak links between design and helps take corrective measures.

Typically, for building Fault Tree Analysis, the builder must understand the concept fully. The inputs for tree components are assumed to be probability distributions or exact failure rates. However, especially in the precast industry, it is difficult to obtain the past data for each accident in complete detail. There are various stages and factors involved, and there are no records for all the activities on the plant when injuries are not severe. Hence, to deal with the process with insufficient information and uncertain situations, the fuzzy analysis approach can fill in the missing gaps in this research.

Some studies have already focused on the application and combination of fuzzy theory and Fault Tree Analysis [108, 109]. The authors propose a way to obtain fuzzy sets of the system failure when known components include membership functions. Another outcome of the research was obtained for the method using fuzzy numbers instead of relative frequencies of basic events. The basic events were considered as fuzzy numbers. Another study was conducted in 1997 which confirmed this approach for fuzzy tree analysis [110]. A similar approach was studies of details for analyzing the printed circuit boards in 2006 [111]. The production of printed circuit boards needs a lot of processing, while the demand needs hundreds or thousands of products with higher quality and reliability. The Fuzzy Fault Tree is constructed considering three major types of faults: manufacturing, human, and performance faults.

Not only manufacturing but the studies have shown that Fault Trees are even important tools for risk analysis. Risk analysis is an essential activity for any organization, from medical to a nuclear power plant. All the processes needing a safe and reliable approach must be analyzed before beginning any progress. Hence, FTA has been a widely used and analyzed methodology for the risk assessment for any processes [112]. FTA analysis differs for each set of problems, and it provides quite different solutions for every problem. The gates used for FTA analysis are shown in Figure 4.1.

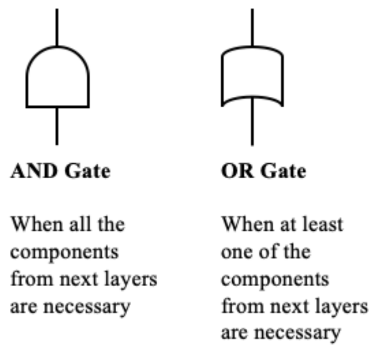


Figure 4.1 Types of logic gates used for the study

These represent the most common gates, which are AND, OR, and NOT gates. The tree utilizes the top-down approach, which is a representation of the system. The top-most event is the outcome and conclusion, while the bottom layers show the dependencies of other factors or from the top event. Figure 4.2 provides an example of a Fault Tree for the system. Assuming event A is the focused event, the reliability level of event A depends on the occurrence of event B and C both, while the occurrence probability of event B is contributed by either event D or E, and so on.

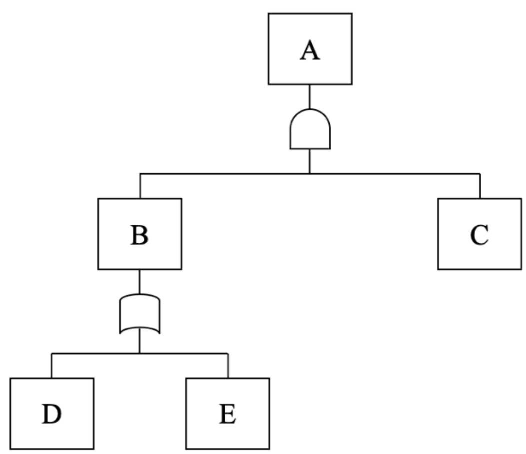


Figure 4.2 Example of fault tree analysis

It is important to consider and understand the dependencies between different events. One must recognize primary events for successful analysis of accident scenarios and effective safety process decision-making [113]. This chapter performs five steps to implement the Fuzzy Fault Tree Analysis for the precast plant. The necessary steps are:

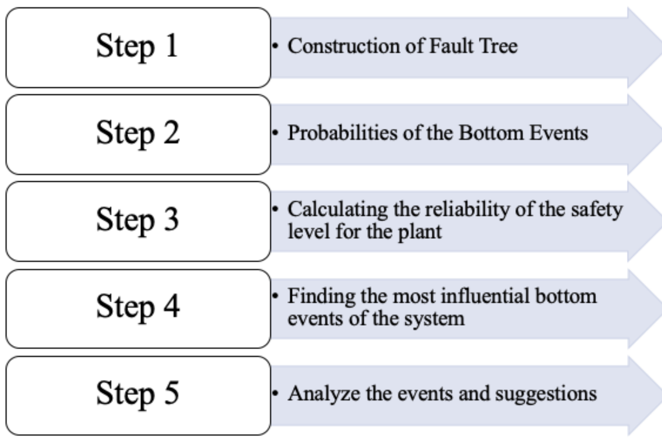


Figure 4.3 Fault tree analysis process

Step 1: Construction of Fault Tree

To construct an FTA diagram using the logic gate and represent the whole process, the process needs to be defined from bottom to top events. The diagram for a precast plant using logic gates is represented in Figure 3. The top event represents plant safety, followed by the first layer of the events, which represents the direct serious possible injuries related to objects or organs of employees. And the third and fourth layer represents the direct relationship or causes between the components or injuries.

Step 2: Probabilities of the bottom events

In this step, considering the expert's opinion, probabilities are calculated. In Chapter 2 of this study, the fuzzy analysis helped convert the expert's opinion to the reliability values. For each of the components related to injury, it calculates the probability of events not occurring. For instance, if the tree indicates the eyes, the probability will indicate that, even after the following events occurred, it did not lead to an eye injury.

Step 3: Calculating the reliability of the safety level for the plant.

Once all probabilities are extracted and collected, this step focuses on calculating reliability for the safety plant. The precast plant is a very busy and noisy place, and employees need to be careful about many factors. Hence, the reliability tree considers various factors and injuries associated with all the included factors. The Fault Tree Analysis process is mathematically expressed in Section 4.2.2 of this chapter. However, once the event probability is calculated for plant safety, the sensitivity analysis is conducted for step 4.

Step 4: Finding the most influential bottom events of the system.

Sensitivity analysis considers the FTA probability of the targeted factor and helps analyze and understand the effects of each factor on the target when the factors and gate reliabilities are absent in the system. This will provide influence on the reliability of each factor on the final event.

Step 5: Analyze the events and suggestions.

This step will analyze and summarize all the analysis provided above to conclude and suggest the factors on the precast plant in need of updating. Some factors may have more influence on plant safety than others. Identifying and working on the improvisation of these factors is an essential outcome of the study.

4.2.2 Safety assessment and probability calculations

Fuzzy Operations

In Fuzzy Fault Tree Analysis, the probabilities of all events are calculated using fuzzy analysis. Chapter 2, Section 2.3 describes the process obtained to extract the probabilities using experts' opinions to utilize and analyze the Fault Tree Analysis. Hence, it is essential to obtain arithmetic operations for "AND" and "OR gates of the Fault Tree. The probability calculations under n-array inputs are different for AND and OR gates.

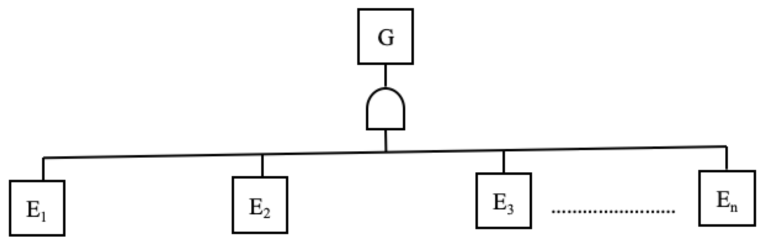


Figure 4.4 AND Gate structure for n-events

The probabilities for n-array OR gate with multiple events such as E_1, E_2,….., E_n are shown in Figure 3. The corresponding probabilities of the reliabilities of the n events are P_1, P_2, P_3,……, P_n. The final probability distribution for the whole gate includes multiple events that can be defined as shown by Equation 4.1. The whole gate includes multiple events that can be defined as shown by Equation 4.1.

$$G(AND) = P1 * P2 * P3 * \dots Pn \tag{4.1}$$

The fuzzy probabilities under the n-array OR gate with events E_1, E_2, E_3,…..,E_n and corresponding probabilities P_1, P_2, P_3,…,P_n can be calculated as Equation 2.

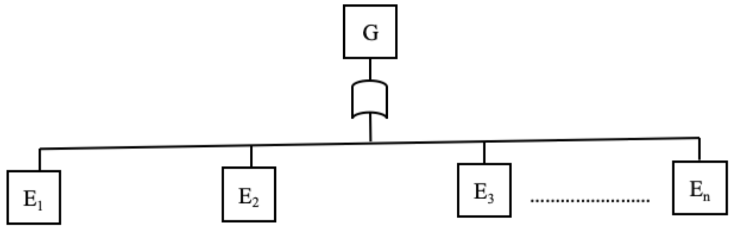


Figure 4.5 OR Gate structure for n-events

$$G(OR) = 1 - [(1 - \mathrm{P1}) * (1 - P2) * (1 - P3) * \ldots * (1 - Pn)] \quad (4.2)$$

Methodology

The FTA analysis has been structured based on the study of the plant system and the reliabilities associated with it. The description provided in Chapter 2, Section 2.3 discusses the system, its dependencies, and the logical relationships between them. Based on the analysis, the Bayesian Network is designed and analyzed in Section 2.4; this section discusses the construction of the system using the Fault Tree structure. The different levels of the Fault Tree represent the different levels of association between factors and the target variable. The first level of the tree represents the target variable, which is plant safety reliability. It is followed by major injuries and employee organ injuries. The next level determines the different factors from the system and how they contribute to the injury associated with the second level of the structure, and so on with the further levels. All the levels relate to each other using the AND or OR gate. However, the final level of events in the Fault Tree structure is built using only basic events. The final structure layer 1 of the Fault Tree is shown in Figure 4.6.

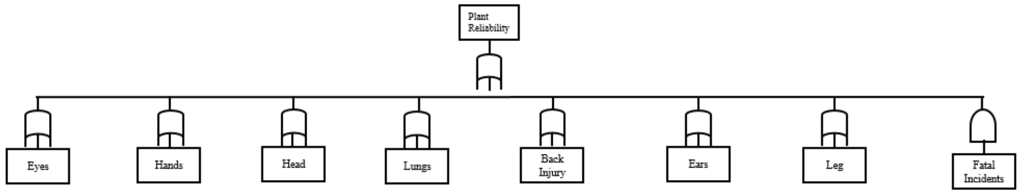


Figure 4.6 Top event and the second layer of the fault tree

Failure and reliability probabilities of these events are calculated in Chapter 2, Section 2.4 using fuzzy set analysis. The next step is substituting these probabilities for the Fault Tree Analysis and future study. The required probabilities are only for the bottom level, or the basic events. These probabilities further provide the prospects for the gate structure and connecting the target variable in this study. Once the probabilities are substituted, the tree is analyzed to check the final probability distributions of the Fault Tree. Figure 4.6 represents the tool structure used for the study.

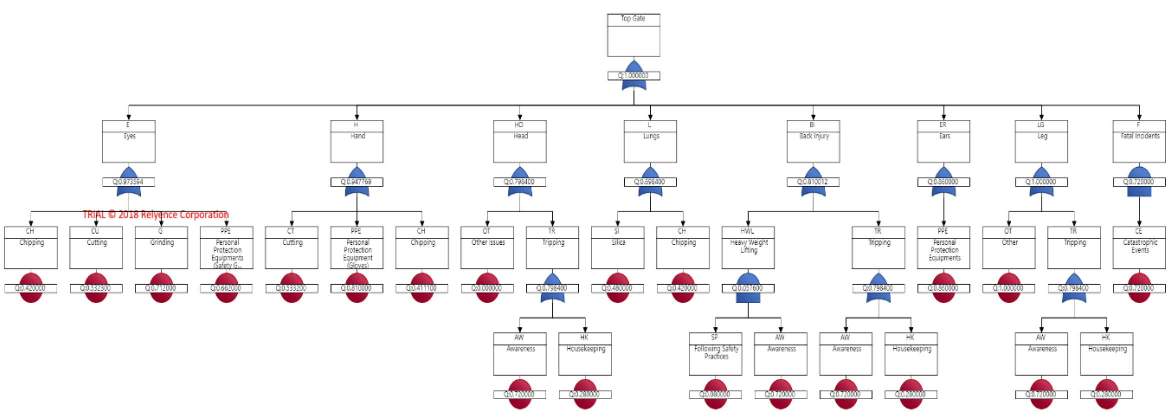


Figure 4.7 Final FTA structure

After the extracted probabilities from the Fuzzy Analysis are substituted in the Fault Tree, the resulting probability for the overall plant safety indicates that the precast plant is entirely safe. Therefore, this is the attempt made by the safety managers to keep the plant 100% safe. However, the sensitivity analysis needs to be considered by switching each reliability probability of the event to 0 and 100 to check which factor of plant safety fluctuates the most.

Reliability concerning plant safety is assessed by switching the reliabilities of each event to its minimum and its maximum. Table 4.1 shows the effect of these events on resultant plant safety. The table explains the difference and the increase or decrease in the final safety reliability, based on each event not being careful. The table is represented using some major factors and their sensitivity on the safety plant reliability as well as their effect on corresponding safety reliability.

Table 4.1 Important factors and change in reliability

Event #	Event	Increase in Plant Safety	The decrease in Plant Safety	No Change in Plant Safety	The decrease in the Gate Reliability
1	Chipping			X	X (6%)
2	Cutting			X	X (3%)
3	Grinding			X	X (2%)
4	Personal Protection Equipment (Gloves)			X	X (5%)
5	Cutting			X	X (12%)
6	Personal Protection Equipment (Safety Glasses)			X	X (12%)
7	Chipping			X	X (3%)
8	Awareness			X	X (72%)
9	Housekeeping			X	X (28%)
10	Silica			X	X (50%)

As the table described, even after having various completely safe factors, or no errors or accidents, the Fault Tree does not result in any reliability change in the plant safety. However, it indicates that the changes in each factor decrease the corresponding major gates in the second layer of the Fault Tree. Hence, according to the current expert's opinion, the overall plant safety does not seem to be impacted even if some factors do not stay reliable. However, the second layer can help us analyze what factors are affected the most and what factors need to be focused on. Sensitivity analysis provides the reliability level of the following events, which affects most of the second layer of the Fault Tree, which are aware of the employees, following personal protection equipment, silica exposure, and catastrophic events. The following section will discuss the results extracted from using Fault Tree Analysis methodologies and similar analyses performed using the Bayesian Network study.

4.3 Comparison of FTA with BN analysis

This section discusses the comparison of the study conducted using Bayesian Network and Fault Tree Analysis. The variables and factors considered for both analysis studies are like each other. However, the results do not provide similar outputs.

4.3.1 Bayesian network results summary

Recalling Chapter 2, the Bayesian Network study indicates the relationship and dependencies between variables and different factors affecting the precast/prestressed industry. The study included 26 variables with different possibilities and dependencies between the variables that may impact precast plant safety. The study also concluded that the factors directly affecting safety are ear injuries, leg injuries, and tripping incidents as well as earplugs caution, the stressing process, the chipping process, and suspended loads. The following factors further directly have an indirect impact on safety: head injury, hand injury, back injury, lack of eye protection, lack of following safety practices, lifting heavy objects, more than the recommended level of silica particles, personal awareness, housekeeping, wearing PPE, and grinding. The limitations of the study include the opinion provided by experts as the opinions regarding each case and situation is subjective. Also, the opinions differ from plant to plant and company to company. Hence, most of the precast plants follow similar protocols, yet they might differ across each expert's opinions. However, the questionnaires can be updated, and these issues can be resolved further by considering feedback from a larger number of experts.

4.3.2 Fault Tree analysis summary

The FTA analysis study is also conducted. Results indicate the most affecting factors and include a similar approach to the Bayesian Network study. The network considers all the dependencies. To find dependencies amongst Fault Tree variables, each event or variable is connected through different groups of gates on each level. However, for each level and gate, different even similar events need to associate separately to each gate from the second layer. From the Fault Tree analysis, none of the factors seem to have direct effects on plant safety. The factors initially performing with low reliability include silica levels, chipping activity, following safety practices, and activities related to heavy weightlifting along with activities like chipping, cutting, and housekeeping. However, the factors seeming to have been reduced from layer 2 include awareness, personal protection equipment, grinding activities, and cutting activities. Hence, the study indicates that related damage to the lungs and heavy lifting activities may occur more on the plant.

4.3.3 Comparison of BN and FTA methodology and results

Both methods used for safety analysis are modern analytical processes for safety assessment. Table 4.2 indicates clear differences and similarities between the two studies [114].

Table 4.2 Comparison of the study

Method	Amount of Information Required	Type of Information Required	Focus	Quantifiable
Fault Tree Analysis	Low	Components, Logical Relationship, Failure Data	Reliability	Yes
Bayesian Network	High	Components, Conditional Probability Tables	Reliability	Yes

Changes in the BN events directly affect the target, which is plant safety, while changes in the FTA events did not directly impact the top-event, which is plant reliability. Following this, Table 4.3 represents the comparison of two studies and they almost perform with the same results.

The first column of the table indicates the reliability score of the events, which has been initially low.

Table 4.3 Summary and Results

Activities	Initially Weak Reliabilities	Have a huge direct effect on plant safety (BN)	Have a huge direct impact on plant safety (FTA)	Have a huge impact on the corresponding gate (FTA)
Back Injury	X			
Housekeeping	X			
Silica Exposure Level	X	X		X
Chipping	X			
Cutting	X			
Awareness		X		X
Personal Protection Equipment		X		X
Heavyweight Lifting	X	X		X
Grinding		X		X
Head Injuries				X

The Bayesian Network mathematics behind the structure is more complex than the Fault Tree analysis. It is seen that the gates AND and OR have the formula, which simply multiplies the respective probabilities or reliability proportions and add them together. Hence, when we have many events, the one individual probability does not make any impact on final plant reliability and the effects of these in sensitivity analysis are straightforward and easy to see. These impacts are affected on large-scale gates when one of the reliabilities gets low. The table also compares sensitivity testing with the Bayesian Network study.

4.4 Summary and conclusions

The study illustrated the techniques to capture some types of uncertainties on the precast plant activities and risk assessment. This chapter compares both techniques and models to analyze the similarities and differences in the analysis [115]. Even though both methods resulted in approximately similar analysis and results, it seems that BN can analyze more appropriately, especially complex structures, like plant safety. BN takes prior beliefs into account better than FTA. BN considers inter-dependencies of the various factors nested within each other. The primary conclusion of the study can be summarized as follows [116]:

1) Comparing both methodologies, BN can update prior probabilities yielding posterior probabilities.
2) The BN can provide more reliable measures of the events by providing configuration for each event that provides more information about both occurrences non-occurrence of events. However, FTA deals with the reliability of the events to conclude the reliability of the plant safety.
3) Each of the Fault Tree events can be measures on the BN structure. However, each BN variable cannot relate to the other using FTA. BN handles uncertainty without having to modify the structure every time.

Overall, BN is a much more flexible structure than FTA. BN fits the various scenarios that may lead to an accident. Its abstractive reasoning and ability to handle uncertainty make it more capable to handle real-life accidental analysis.

CHAPTER V

CONCLUSION AND FUTURE WORK

This chapter summarizes the dissertation by outlining the research summary and indicating the future research directions. This chapter is divided into two sections. First, this chapter discusses the summary of the study and the conclusions drawn from the study. The second section discusses the limitations and future work.

5.1 Research summary and conclusions

This dissertation focused on modern techniques to assess precast plant safety. One major difference between the Fault Tree Analysis (FTA) and Bayesian Network (BN) techniques is the structure and organization of the different events. The Fault Tree uses logical operations and assumes all operations are binary, while the Bayesian Network can accept the probability distribution of different events. Another major difference that the structure causes are the probability distributions and interdependencies of the variables. While the Fault Tree structure has more straightforward mathematical explanations for the results, the Bayesian Network deals much better with the uncertainty and complexity of the variables. BN deals with the conditional probabilities of the events, which dominates the analysis with logical gates. Due to a lack of real data from accidents, the probabilities are extracted using expert opinion and fuzzy analysis technique.

Although both methodologies provide similar results, the probability distribution for each possible factor on the precast plant indicates that considering expert's opinions, there are some factors on the plant which already have a lower reliability level and need improvement. These factors include housekeeping, heavy weightlifting procedures, silica exposure, chipping, and cutting activities. The plant needs to focus on the activities and make sure they improve their reliability while employees are present and working. Both studies suggest that awareness, use of personal protection equipment, heavy weightlifting, grinding activities, and head injuries affect overall plant safety the most. As suggested in Chapter 3, these factors can be improved by introducing more interactive training models. The model will help employees gain more awareness regarding plant procedures and safety protocols.

5.2 Limitation and future work

The study also has the following limitations within the study:

1) Chapter 2 analyzed the Virtual Reality (VR) Module which does not provide sufficient evidence for all the studies. However, plots are performing some differences in the data and the sample size is causing bias in statistical studies.
2) For the Virtual Reality module, the current participants are university students. Hence, the motive of the participants will vary from the precast plant employees, who would be more focused on the study and safety training. The participant's background may also limit the study from providing accurate results concerning the module.
3) The study could not use the accidental data for the probability calculations. Extracting data using expert's opinions to find the probabilities can be subjective as it may depend on each plant or each expert.
4) The FTA study does not interconnect the events as BN study. The BN allows representation of interdependencies and makes the network more realistic. However, for FTA study, some events might be repetitive if they are connected to more than one logical gate.

5) FTA study only needs the reliability probabilities of the event, while the BN study needs conditional probabilities for various events.
6) There can be more events depending on each plant that can be included in the study.
7) Even though similar events are added to both structured analyses, the sensitivity testing in the BN study has direct effects on plant reliability. However, the sensitivity testing on the FTA does not indicate any direct effects on the top-event. While events are considered in larger numbers, the Fault Tree is not sensitive to the presence or absence of each variable.

Future studies can be conducted to overcome these limitations. The study does indicate that the Bayesian Network is superior and more flexible in this case. However, this study can be extended for more accurate results by including future work such as:

1) More Participants and professional participants for the VR study

   For the Virtual Reality (VR) module, the additional data may provide more accurate results. As the plots and statistical tests do not provide the same results, the additional samples would be able to reduce bias in the data. While current participants are university students, the more accurate results might be obtained as professionals from the precast plant would be more sensitive for the study.

2) Real-life data / Additional experts

   Real-life accidental data is always helpful for accurate analysis. This study consists of three experts and their opinions to extract the probability distribution of each event. As an expert's opinion can be subjective and different for each plant, in the future it can be tested if an increasing number of experts will be able to provide more generalized results.

3) Different methodologies for the safety assessment

The study proves that the BN study is more suitable for the data structure and purpose for the study. The BN can be compared and tested further with different methodologies and study structures.

4) More critical Situations in the VR module

The most important benefit of the VR module is to simulate situations that may otherwise be difficult to train in real life. Hence, the VR module can simulate more critical situations to provide more effective and engaging safety training for the employees.

5) Reduction in the variables

It is seen that the FTA provides no direct effects on the top-event when there are many events involved. Feature selection may provide more accurate results for FTA study.

The motivation of the study is to assess the risk in such a way that precast plants will be a safer place for employees to work. Even though it can be assessed and implemented, employees can be careful and avoid accidents by being aware and following safety protocols. This study has introduced the analysis technique as well as an engaging training method that may help employees be more self-aware.

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