UNDERSTANDING AND CONTROLLING THE NON-HELMET USE BEHAVIOR OF CONSTRUCTION WORKERS: AN EMPIRICAL AND SIMULATION STUDY

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M.Phil

The Hong Kong Polytechnic University

2018

The Hong Kong Polytechnic University

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Understanding and Controlling the Non-Helmet Use Behavior of Construction Workers: An Empirical and Simulation Study

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A thesis submitted in partial fulfilment of the requirements

for the degree of Master of Philosophy

September 2017

CERTIFICATE OF ORIGINALITY

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ABSTRACT

The construction industry is regarded as one of the most hazardous and dangerous industries, with one of the highest accident rates. Head traumas are a common serious injury on construction sites and have attracted extensive attention from society. The cause of these injuries is often due to not wearing a safety helmet but the reasons for such unsafe behavior is not yet well understood. Despite the great importance of helmet use, data collection of helmet use and management methods on reducing non-helmet use behavior on construction sites is still in a relatively early stage.

In order to provide valuable learning opportunities for the development of safety performance, therefore, this study aims to understand the root cause of non-helmet use behavior of construction workers from both individual and management levels, and explore how different supervision methods and punishment mechanisms could help to control the unsafe behavior. To achieve these aims, specifically, non-helmet use data was collected and analyzed by a real-time tracking system (Eye on Project) to investigate: (1) the impact of individual factors on non-helmet use behavior; (2) the impact of safety climate and productivity pressure on non-helmet use behavior; and (3) the impact of punishment systems and supervision methods on workers' behavioral patterns.

In order to gain a better understanding of how different types of factors influence non-helmet use behavior, this study has used three main analysis methods to achieve the research objectives: an association rule, system dynamics (SD) and an agent-based modeling system. Several findings were demonstrated by the empirical and simulation analyses: (1) The relationship between the non-helmet use behavior and individual's characteristics have been identified through an association-rule based approach, and the findings could help to establish a risk assessment matrix and advise construction managers or workers with the purpose of preventing the causality patterns. (2) Taking into consideration the impact of safety climate and productivity pressure, the proposed SD model works by understanding the feedback mechanisms involved in non-helmet use behavior when positive action is taken (i.e., safety training, communication and inspection) and the negative components of workplace stress on the safety climate of

construction sites. (3) A better understanding of the effectiveness of multiple supervision methods and punishment amounts on non-helmet use behavior has been achieved based on the agent-based modeling method, and both punishments and supervision act as an effective role in reducing unsafe behavior and can be used as a management tool in practice; However, the negative influences of excessive punishment and supervision should be seriously considered and then prevented.

Through investigating the relationship between contributory factors and non-helmet use behavior, and the impact of punishments and supervision methods, the findings not only provide an effective method for identifying factors related to unsafe behavior on construction sites but also help in developing more efficient and accurate risk assessment strategies. The proposed tool for objectively evaluating the number of individuals and periods of not using helmets on construction sites also overcomes the deficiencies of the traditional recording methods used in previous studies. The final analysis of empirical and simulation results can be used by project managers to implement safety management and stipulate safety rules on construction sites.

KEYWORDS

Non-Helmet Use ; Behavior Patterns ; Construction Workers ; Empirically Study ; Agent-Based Simulation Study

LIST OF PUBLICATIONS

Referred Journal Papers：

Heng Li, Xiaoying Li, Xiaochun Luo, Joanna Siebert. (2017). Investigation of the causality patterns of non-helmet use behavior of construction workers. Automation in Construction, 95-103.

Heng Li, Xiaoying Li, Michael Sing, Martin Skitmore. (2017). Understanding the influence of safety climate and productivity pressure on helmet misuse in construction sites. Safety Science, Under review.

Heng Li, Xiaoying Li, Chen Wang, Samad Sepasgozar. (2017). Agent-based Eye-on-Project (EOP) System for Behavioural Patterns of Engineering Workers: Punishment and Supervision System on Helmet-use. Journal of Management in Engineering, Under review.

ACKNOWLEDGMENT

Two years of academic journey gave me an unforgettable experience, I would like to take this opportunity to thank my teachers, colleagues, friends and family. Without their understanding and support, this thesis could not have been completed.

Firstly, I would like to express my deepest gratitude to my supervisor, Professor Heng LI, for his continuous encouragement, support and valuable guidance throughout my MPhil study. Prof. LI always give me the most appreciated and valuable supervision on my research. I have been fortunate to have such an extraordinary supervisor who has always been available to provide me with selfless support. His great personality also influences me in both academic and personal life.

I would also express heartfelt thanks to my colleagues and friends at the Smart Construction Laboratory and Department of Building and Real Estate within HongKong PolyU. I am very grateful for having an opportunity to work with a group of such outstanding research colleagues, they are Dr. Ting Huang， Dr. Xiaochun Luo, Mr. Xintao Yang, Mr. Xincong Yang, Mr. Waleed Umer, Mr. Maxwell Fordjour, Mr. Wei Lu, Mr. Bo Ye, Mr. Zeli Wang, Mr.Xuzhong Yan, Ms. Liulin Kong, Miss Yantao Yu, Ms. Chao Dong, Miss Qi Fang, MissYixuan Tang, Miss Xiao Xue, Dr. Fan Wang and Miss Ruiqu Ma. Sincere and special thanks also extend to Dr. Dongping Cao, who has helped me much on both research and daily life. I would also like to express my gratitude to the construction workers who participated in my research for their cooperation.

Finally, I owe my loving thanks to my parents. Thanks for their everlasting love and support and they mean everything to me.

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Chapter 1. INTRODUCTION

1.1 Research Background

1.1.1. Safety Performance on Construction Site

Construction is regarded as one of the most hazardous industries around due to its complicated nature and workers' safety issues, consequently garnering extensive critical attention from society (Recarte Suazo and Jaselskis 1993). Although there have been significant reductions in the number and rate of injuries recorded, construction workers still suffer a disproportionate number of serious injuries, which is triple that of other industries (Carter and Smith 2006). According to the Health and Safety Executive (2015), construction workers suffer 10% of major injuries and 31% of fatal injuries across all industries. Moreover, out of almost 4000 worker fatalities in private industries, in the year 2013, 796 or 20.3% were in the construction industry (Occupational Safety and Health Administration 2014).

The worker fatal injury rate in the construction domain is almost four times the average rate across all industries. Approximately 65,000 construction workers suffered from different kinds of injuries at work in 2016 (Executive). In China, the reported number of deaths on construction sites was 2,197 in 2014 and almost 90% of construction accidents were due to human error. The average death rate in the construction industry over the past ten recorded years has also reached the awful figure of 2,600 per year (House). Hence, measures are clearly needed to reduce underlying hazards and enhance safety performances (Flin, Mearns et al. 2000, Hallowell and Gambatese 2009).

Therefore, although there has been a significant improvement in the reduction of injuries, the construction industry is still dealing with a high accident rate, which needs an urgent and effective solution.

Since human behavior is the main cause of accidents on construction sites (Jannadi and Bu-Khamsin 2002), effective control and the management of workers' unsafe behavior have become the key factors to a safe site environment.

1.1.2. Importance of Helmet Use for Construction Workers

Head traumas are a common serious injury in the workplace worldwide, since the head is the part of the human body with the highest potential for serious injury and cause of death (Long, Yang et al. 2015). On construction sites, traumatic brain injuries are usually caused by falls and trench/scaffold collapse. Medical Online, for example, states that about 230,000 Americans suffer traumatic head injuries each year, with more than a fifth dying. Similarly, the Center for Disease Control and Prevention (Center for Disease Control and Prevention 2011) estimates that head injuries account for almost half (49%) of fatal injuries. Moreover, a survey focused on worksite accidents and injuries collected by the Bureau of Labor Statistics (Bureau of Labor Statistics 2009) demonstrated that not wearing head protection results in almost 90% of all traumatic brain injuries. This is particularly the case in the construction industry, which has the highest number of traumatic brain injuries across all industries (i.e. transportation industry, agriculture and primary industry) (Colantonio, McVittie et al. 2009).

The need for wearing helmets in specific areas during working hours is also stipulated by the American National Standards Institute (ANSI). Each construction project promotes the importance of helmets and educates workers in the use of helmets. There are also increasingly focused and tailored prevention strategies in the construction trades to ensure proper helmet use. Helmet use is regarded as a way for contractors to evaluate construction workers' safety performances during their work activities. A series of regulations are in place to ensure that employers provide appropriate head protection and bear the responsibility of supervising its use in conditions where objects might fall from above and strike workers on the head. They might also bump their heads against objects, such as exposed pipes and beams, or there might be accidental head contact with electrical hazards.

Therefore, helmets are an important and widely used piece of 'personal protection equipment' (PPE) on construction sites and it is important to improve safety performances by ensuring the effective use of safety helmets.

1.2 Knowledge Gaps and Research Gaps

1.2.1. Knowledge Gaps

To enhance construction safety, a series of measures have been put forward to encourage workers to wear helmets by both the law and construction managers. Kelm, Laußat et al. (2013) stated that employers should increase helmet use in three ways: (1) education and training, (2) punishment, and (3) enforcement. Previous research was mostly based on the reporting of accidents or near-accidents, which usually just consisted of a description of the individuals involved and the accident itself (Lindberg, Hansson et al. 2010).

Many studies have attempted to find the key factors that lead to this poor performance in the construction industry (Mohamed 2002, Fang, Xie et al. 2004, Wei and Lu 2015). However, the working environment in construction is complicated and constantly changing, so previous research has failed to investigate the dynamic between the risk factors and accidents (Jannadi and Bu-Khamsin 2002). The poor safety performances and their associated contributing factors are highly specific to the environment and workers' behavior and are inherently nonlinear (Gilbert and Troitzsch 2005). Current research continues to count on traditional methods such as questionnaires, data statistics or interviews, which ignore the dynamic interaction between workers and does not improve the safety climate effectively (Mohamed 2002).

As a result, the existing research may simplify the construction workers' real situations in which numerous scenarios must be considered. The limitations of current studies should be addressed by improving the research methodologies and technical methods.

1.2.2. Research Objectives

Drawing on current limited research, this study aims to propose both empirical and simulation methods to develop comprehensive research on understanding and controlling non-helmet use behavior on construction sites. Furthermore, to better understand the different types of contributory factors which result in non-helmet use behavior and to provide systematic and dynamic methods to assess and improve safety performance, this study has proposed three main methodologies to achieve the specific research objective, which has been set as follows:

1) To identify the impact of individual factors on non-helmet use behavior.

2) To identify the impact of safety climate and productivity pressure on non-helmet use behavior.

3) To identify the impact of punishment systems and supervision methods on workers' behavioral patterns.

The association rule is proposed as a data mining technology, which has emerged as a means for identifying patterns and trends of different factor combinations according to the different levels. The application of association rules will combine the designated individuals' risk factors and find the causality patterns of non-helmet use behavior. To have a better understanding of the impact of safety climate and productivity pressure, the implementation of a system dynamics model has been designated to explore nonlinear causes of behavior within a complex system over time and under conditions of feedback and complex combinations of variables. Moreover, the agent-based modeling and simulation concepts have been widely used in the construction management domain and a series of studies have applied a distributed control system usually designed to test the outcome of alternative solutions.

Therefore, the implementation of different research methodologies is necessary and important to achieve the aforementioned three objectives. The proposed methodologies are demonstrated in detail in Chapter 3.

1.3 Overview of Thesis

The rest of this thesis is organized as follows: Chapter 2 provides a brief outline of current research on designated factors and punishment systems for the non-helmet use behavior. Chapter 3 illustrates the research method of the present study including both empirical studies and simulation studies. To achieve the three research objectives, Chapter 4 to Chapter 6 are developed to examine the impact of individual factors on non-helmet use behavior; the impact of safety climate and productivity pressure on non-helmet use behavior and the impact of punishment systems and supervision methods on workers' behavioral patterns. Chapter 7 provides a systemic summary of the major findings and discusses the directions for future work.

Chapter 2. LITERATURE REVIEW

2.1 Individual Factors Related to Non-Helmet Behavior

Since non-helmet use is common unsafe behavior in site conditions, it is important to refer to the contributory factors influencing unsafe behavior. Previous studies classified the key factors leading to unsafe behavior on construction sites. One of the most significant factors influencing unsafe behavior is individual characteristics (Ismail, Doostdar et al. 2012). On an individual level, personal factors, including gender, age, type of work, experience and knowledge, lead to diverse results on helmet use in the workplace (Lombardi, Verma et al. 2009, Lin, Chen et al. 2011, Sing, Love et al. 2014, Lu, Shi et al. 2015). Through an investigation into the psychological processes of construction workers, their decision not to wear safety helmets seems to be deliberate (Zhang and Fang 2013, Shin, Lee et al. 2014). Attitude is one of the significant factors in workers' behavioral intentions (Ajzen 1991). Paying close attention to the workers' mental process (i.e. what an individual can do with their minds) should contribute to a detailed understanding of how their safety attitude influences their behavior (Foa, Steketee et al. 1989). Once the workers have adopted the information that extends beyond their personal experience, they will develop their own safety attitude and make decisions on whether to act according to their formative attitude. Seven factors were identified from previous studies, namely gender, age, work experience, time of day, attitude, motivation, psychological distress and intended acts. The related items of literature are listed in Table 2.1.

Table 2.1 Literature related to individual characteristics

No	Individual contributory factors	Studies
1	Gender	(Buckley, Chalmers et al. 1996, Azadeh-Fard, Schuh et al. 2015) (Messing, Courville et al. 1994, Chi, Chang et al. 2005)
2	Age	(Buckley, Chalmers et al. 1996, Alsamadani, Hallowell et al. 2013, Azadeh-Fard, Schuh et al. 2015) (Cheng, Leu et al. 2012)
3	Work experience	(Chi, Chang et al. 2004, Watanuki and Kojima 2007, Arquillos, Romero et al. 2012) (William McConnell, Gloeckner et al. 2006)
4	Time of day	(López, Ritzel et al. 2011)
5	Attitude and motivation	(Haupt 2003, Chen and Jin 2015)
6	Psychological distress	(Williams, Ochsner et al. 2010)
7	Intended acts	(Watanuki and Kojima 2007, Sherratt, Crapper et al. 2015)

This research mainly focused on the following four factors.

(a) Gender

Construction workers on site are generally predominantly male.and it is therefore, males who are the most likely victims of injuries/fatalities (Chi, Lin et al. 2014). However, when there are the same number of both genders, male workers still have a higher fatality rate than female workers (Lin, Chen et al. 2011, Cheng, Leu et al. 2012). Male workers have a higher fatal occupational injury rate, almost eight times higher, than female workers (Lin, Chen et al. 2008, Zhang, Gkritza et al. 2011), which is consistent with similar studies elsewhere. Lin, Chen et al. (2008) also illustrated that female workers exhibited a correlation between age and number of fatal injuries, while males revealed an inverted U-shaped pattern as the male occupational fatality rate dropped sharply in the 25–34 year-old age group, then increased consistently with advancing age. In addition, Bena, Mamo et al. (2006) state that men also have more secondary accidents.

(2) Age

From previous research,, age is seen to have the most significant impact on injuries in construction, this is also an index on the severity of accidents (Azadeh-Fard, Schuh et al. 2015). In fact, as the age of the injured worker increased, so too did the seriousness of the accident (Camino López, Ritzel et al. 2011). Almost all research found that a young workers' fatality rate was higher than the overall rate (Ehsani, McNeilly et al. 2013), but the older workers' injury rate is the highest one over all (Rabi, Jamous et al. 1998, Salminen 2004). All of these researchers highlighted the actual age range of victims who are most vulnerable to injuries, even fatal accidents on construction sites. For example, López-Arquillos, Rubio-Romero et al. (2015) presented that workers aged between 50–59 years old are the most likely to have a fatal accident, while workers between 25–29 years old are the least likely. Chi, Lin et al. (2014) compared different standardized mortality ratios (SMRs) and found the majority of fatality victims were between 25 and 44 years old. Lin, Chen et al. (2008) showed that over two-thirds (67.6%) of fatal injuries occurred in young male workers aged 44 years or younger due to some special psychological and physical symptoms.

(3) Experience

Several studies have explored the contributing factors to occupational accidents in the construction industry and regarded an individual's work experience as one of the most compelling factors (Chi, Chang et al. 2004, Watanuki and Kojima 2007). Work experience is congruous with the job tenure, which has a negative correlation with the unsafe behavior (William McConnell, Gloeckner et al. 2006). For instance, (López-Arquillos, Rubio-Romero et al. 2015) pointed out that poor work experience is a major accounting factor in fatal accidents on construction sites since a high accident rate occurred among workers within the first few months of job tenure. Analogously, Chi, Chang et al. (2004) correlated comprehensive factors which lead to PPE misuse using SMR analysis and also found that construction workers who have less than 1 year's site experience are under tremendous risk of being heavily injured due to an accident (i.e. hit by falling objects).

The experienced workers, on the other hand, have a better understanding of the safety rules and requirements (Choudhry and Fang 2008). Experienced workers are usually skilful enough to handle any possible contingency and to always be aware of the seriousness of safety responsibility (Gherardi and Nicolini 2002). Although safety training and education have been widely provided to novice workers in recent years, the new employees may still lack safety knowledge because of the unreasonable or outmoded content, which is closely linked to the failure of the current construction situation (Haslam, Hide et al. 2005). Consequently, construction workers customarily rely on their own past experience to evaluate site safety (Bust, Gibb et al. 2008). Furthermore, the older and more experienced workers usually shoulder the responsibility to help promote safety issues as well as promptly identify potential risks, so as to avoid or reduce injuries (Fung and Tam 2013). Fung, Lo et al. (2012) also emphasized the importance of individual experience in general practice and said both construction workers and supervisors rely on their experience to deal with risk assessment. What is noteworthy is that past accident experience is another important element to reducing the accident rate (Gherardi and Nicolini 2002). Workers who have experienced hazards tend to be sensitive about the location where their injury occurred and willing to share their safety knowledge with novices (Alizadeh, Mortazavi et al. 2015). Construction workers with accident records have the lowest rate of occupational accidents while beginners are constantly at a high risk of getting injured (Jeong 1998, Lin, Chen et al. 2008).

(4) Work Time

Previous research also regards work time as one of the components influencing unexpected site accidents. Dembe, Erickson et al. (2005) recognized that accident rates strongly correlated with work hours. More specifically, workers who worked more than 12 hours per day had a higher rate of accidents (37%) and those who had more than 60 work hours every week had a 23% chance of having a terrible accident. It is not too surprising given the fact that fatigue is closely linked to potential risk (Swaen, Van Amelsvoort et al. 2003). Glass and Fujimoto (1994) indicated that long work hours have a fair chance of leading to unsafe and careless behavior, which results in an accident. Haslam, Hide et al. (2005) also stated that although there is no confirmed direct relation between work hours and injures, workers are sure to pay less attention to safety issues because of an unreasonable work load (i.e. taking off PPE while working long operating times without breaks).

2.2 Project and Management Level Factors Related to Non-Helmet Use Behavior

A construction project is a temporary construction process to produce a unique product with a defined schedule and budget. Although each project is established to achieve its own specific goals, the primary goals of all construction projects are a time, budget and quality triangle. When any of these goals are threatened, project managers seek to identify where compensatory adjustments can be made in the other goals (Long, Yang et al. 2015). With the urge for improved productivity, whether because of real (or feared) time or budget slippages, safety performance is an obvious sacrificial candidate. For example, workers tend to eschew safety equipment to improve productivity due to its inconvenience and discomfort. In the face of such pressure, workers often take increasing risks involving to a greater propensity for unsafe behavior (Han, Saba et al. 2014). Therefore, it is necessary to properly balance management schedules and pressure to maintain safety standards.

At a management level, safety management, based on the project's goal, involves developing and executing safety policies and providing PPE to workers (Choudhry and Fang 2008). Zohar (2000) emphasizes the importance of the safety climate in reflecting the priorities of safety management. Safety climate is a managerial factor that refers to workers' attitudes to safety, procedures, and practices in the workplace (Zohar 1980, Neal, Griffin et al. 2000, Zohar 2000, Zohar 2002, Zohar 2003). To investigate their influence on helmet use at a management level, it is first necessary to provide a measure of the safety climate. This has been undertaken in various ways, with Janssens, Brett et al. (1995), for example, categorizing management, work pressure, safety systems and safety level as safety climate. Safety climate provides a good atmosphere for mutual supervision and supports the promotion of the safe behaviors (Cavazza and Serpe 2009, Hon, Chan et al. 2014, Choi, Ahn et al. 2017). In the construction industry, this involves components such as safety training and improved safety awareness (Abreu Saurin, Torres Formoso et al. 2005, Haslam, Hide et al. 2005, Williams, Ochsner et al. 2010).

In this paper, the project and management level factors are summarized as (a) safety attitude, (b) training, (c) communication, (d) safety inspection and (e) workplace stress and(f) co-workers.

Safety attitude

The attitudes of project managers and workers towards safety would affect the safety climate in the organization (Cheyne, Cox et al. 1998). For example, several researchers ascertained that the manager's support for safety practices should be the utmost vital factor in promoting organizational safety (Huang and Hinze 2006). When managers ignore safety rules, they are regarded as providing a negative role model, with workers behaving likewise. Workers will have a poor safety performance if the project managers do not sufficiently care about safety behavior (Fogarty and Shaw 2010).

Safety training

Safety training refers to the frequency, pertinence and thoroughness of training provided to on-site workers (Jiang, Fang et al. 2014). It has long been recognized as an effective form of safety climate for reducing accidents (Ostrom, Wilhelmsen et al. 1993). In order to improve workers' safety awareness and increase their safety knowledge, regular safety training is essential for instilling basic requirements while helping the workers to remember procedures in wearing PPE (Burke, Salvador et al. 2011, Wachter and Yorio 2014). Another dimension that has been examined in the safety climate literature is employee perceptions of their safety training (Zohar 1980, Huang and Hinze 2006). This construct is a measure of the effectiveness of formal orientation programs and follow-up training of safety practices at work (Huang and Hinze 2006). It is important to differentiate between safety climate and the structural elements of a safety management system, such as the existence of policies and procedures (e.g., safety training or available safety equipment) (Hahn and Murphy 2008). Safety training has a positive effect in increasing safety performance (Cohen and Jensen 1984, Reber and Wallin 1984).

Communication

Communication is concerned with information exchange between workers and management over safety problems, including their degree, frequency, and effectiveness (Probst 2004). This is one of the dimensions of a psychological climate (Koys and DeCotiis 1991). The incorporated communication (e.g. discussion of safety issues in meetings) is one of the components of safety climate and conclude that workers with different degrees of communication have different perceptions of workplace hazards (Cheyne, Cox et al. 1998). Moreover, Hofmann and Stetzer (1998) concluded that safety climate and communication (an open, free-flowing exchange about safety-related issues) significantly influences workers' attributions toward the site safety. Similarly, Kaskutas, Dale et al. (2013) also ascertained that unsafe behaviors could be reduced by good and effective communication within the organization.

Safety Inspection

Safety inspection refers to the frequency and thoroughness of management inspection of workers' unsafe behaviors and any hazards associated with construction sites (Tam, Zeng et al. 2004). It is often used as a comprehensive system for supervising whether the workers have followed the safety guidelines. Safety inspection plays a vital role in the safety climate to improve safety performance in the workplace (Yule, Flin et al. 2006). If safety inspections are conducted frequently, that will be enough to make workers feel under pressure; they will then take the initiative to promote safety awareness and act accordingly (Neal, Griffin et al. 2000).

Workplace stress

Workplace stress is defined as an increased demand perceived by individuals or workgroups to perform their work within a given time or budget. This component deals with the degree to which workers feel under pressure to complete work, and the amount of time taken to plan and carry out work (Glendon, Stanton et al. 1994). For example, an urgent working schedule is the biggest factor adversely affecting construction safety performances (Ahmed, Ahmad et al. 1999). Fahlbruch and Wilpert (1999) also ascertained that work pressure is known to be an important aspect of safety climate management involving balancing production and safety demands. With increased competitiveness in the construction industry, workplace stress is very likely to influence the safety climate when the schedule and resources become stretched. Thus, a higher expectation of work production would lead to a negative safety climate.

Co-workers

Workers' behavior is strongly linked to the safety response of co-workers, especially in Chinese construction. Results indicate that the connection between workers and co-workers is much closer compared to the connection with their supervisors (Meliá, Mearns et al. 2008). Theorell, Karasek et al. (1990) also demonstrated that physical job demands, decision latitude and support from co-workers, may result in job strain and further affect personal or workplace safety performance. Meanwhile, when unsafe behavior is discovered, it is possible that the other nearby co-workers will report the offence, which may result in a low level of work satisfaction (Granovetter 2007)

2.3 Punishment System on Construction Sites

Previous research of companies found punishment to be an effective way to increase employees' work motivation, performance, job satisfaction and other desirable attitudinal and behavioral outcomes (O'Reillys and Puffer 1989, Podsakoff, Bommer et al. 2006). Punishment as a form of behavioral control is therefore universal in organization management (Arvey and Ivancevich 1980, Ball 1994, Tam, Zeng et al. 2004, Aksorn and Hadikusumo 2008, Ismail, Doostdar et al. 2012). The construction industry generally adopts an economic punishment method as the main approach to managing the unsafe behavior of construction workers and has developed a series of economic penalty systems (Mitropoulos, Abdelhamid et al. 2005, Poon, Tang et al. 2008). Lingard (2002), also demonstrated that the adoption of certain punishments will increase workers' motivation to conform to appropriate occupational health and safety behavior. Specifically, if the penalty requires the workers to be fined, workers will think twice about committing the same unsafe behavior again.

However, although the punishment system has been proved to play a significant role on the improvement of safe behavior, previous studies focused less on whether there is a superior standard of punishment to prevent unsafe behavior. Meanwhile, even though managers have reinforced the penalty system during recent years, the record of unsafe behavior and the accident rate has still not significantly declined (Teo, Ling et al. 2005). The punishment system did not produce the expected effect. On the one hand, there is no clear evidence of a correlation between punishment and unsafe behavior. On the other hand, excessive amounts of penalties lead to the dissatisfaction of construction workers; some workers will have slack behavior or even withdrawn behavior, which causes new safety problems on construction sites.

Chapter 3. RESEARCH METHOD

3.1 Introduction

The head is the most important human organ and the most vulnerable, as even a moderate impact can cause serious injury or death (Long, Yang et al. 2015). Therefore, the safety helmet is the most crucial form of PPE on a construction site. Data relating to the use of safety helmets on construction sites can be used to estimate the working hours of construction workers and analyze their unsafe behaviors. It is necessary to establish a platform for collecting quantitative data (i.e. whether construction workers have worn a helmet or not) in a convenient and timely manner but without interrupting their normal working activities.

To fully understanding and controlling the non-helmet use behavior on construction sites, this paper proposed both empirically and simulation methods to develop a comprehensive research. The proposed methodologies are demonstrated as following in detail below.

3.2 Association Rule

Association rules were proposed to underline groups of correlated variables that typically occur together defined on transaction. Currently, the association rule is widely used to delve into the relationships of variables from big databases, and to explore potential associations(Cheng, Lin et al. 2010). Independent variables are combined stochastically. The strongest rule is identified by using the malleable association rules. The antecedent is the input controllable variable and the consequent is the variable which are supposed to be predicted, the relationship is always in the form ‘‘If antecedent, then consequent’’(Larose 2014),

An algorithm by Agrawal, Imieliński et al. (1993) is adopted and used to analyze the collected data. In furtherance of finding the valid association rules in a transactional dataset, a specified minimum support and specified minimum confidence are supposed to be designed. The relationship between the variables will be strong if they meet the threshold of minimum support or minimum confidence.

The details of the support-confidence framework following the original definition by Agrawal can be shown as follows: Let $\mathrm{I} = \{i_{1,} \ \ i_{2,}i_{3,\dots,}i_m\}$ be a set of binary attributes (also named items). Let $\mathrm{D} = \{t_{1,} \ \ t_{2} \ _{,}t_{3,\dots,}t_m\}$ be a set of variable transactions (also called the transaction database), where each transaction T is a set of items such that $\mathrm{T} \subseteq \mathrm{I}$. Therefore, every transaction in D contains a subset of the items in I. Meanwhile, each association rule consists of two different sets of items (also named item sets) X and Y, where X is called the antecedent or left-hand-side (LHS) and Y is the consequent or right-hand-side (RHS). The association rule is the implication that $\mathrm{X} \Rightarrow \mathrm{Y}$ where $\mathrm{X}, \mathrm{Y} \subseteq \mathrm{I}$ and$\mathrm{X} \cap \mathrm{Y} \neq \emptyset$. The significance of association rules is usually measured by three indices: support, lift and confidence (Brin, Motwani et al. 1997). The probability that $\mathrm{X} \Rightarrow \mathrm{Y}$ holds in D is defined as support:

$$Support(\mathrm{X} \Rightarrow \mathrm{Y}) = Support(\mathrm{X} \cup \mathrm{Y}, \mathrm{D})$$

The confidence of a rule is the probability that a rule can be true. Confidence can be defined as follows:

$$Confidence(\mathrm{X} \Rightarrow \mathrm{Y}) = Support(\mathrm{X} \cup \mathrm{Y}, \mathrm{D}) \ / \ Support(\mathrm{X}, \mathrm{D})$$

The lift $\mathrm{lift}(\mathrm{X} \Rightarrow \mathrm{Y})$ is the ration of the observed support value to expected support value.

$$Lift(\mathrm{X} \Rightarrow \mathrm{Y}) = Support(\mathrm{X} \cup \mathrm{Y}) \ / \ \big(Support(\mathrm{X})Support(\mathrm{Y})\big)$$

Furthermore, the three indices above demonstrate the strength of such an association rule and the stronger association can be represented by a higher index (Long, Yang et al. 2015).

To set a threshold of such an association rule, the minimum support σ and minimum confidence δ has been set respectively. The association rule must meet the requirement:

$$Support(\mathrm{X} \Rightarrow \mathrm{Y}) \geq \sigma$$

And

$$Confidence(\mathrm{X} \Rightarrow \mathrm{Y}) \geq \delta$$

3.3 System Dynamics (SD) Model

The capability and fitness of System Dynamics (SD) to contribute to the improvement of understanding complex safety systems has been well documented in the literature (Shin, Lee et al. 2014). The SD model can be used to explore nonlinear causes of behavior within a complex system over time and under conditions of feedback and complex combinations of variables. Synchronously, SD is a modeling tool that mainly focuses on a feedback structure and the resulting behavior to understand complex systems in a comprehensive way (Sterman 2000). Bouloiz, Garbolino et al. (2013) adopted the SD model to improve safety performance by exploring causal variables between safety factors involving organizational, technical and human aspects. Blanch, Torrelles et al. (2009) have also developed an SD model to simulate experience-transfer scenarios in the architectural/engineering/construction (AEC) industry; and Han, Saba et al. (2014) have developed an SD model to understand the impact of work pressure on safety performance.

Compared with conventional research methods into unsafe construction behaviors which follow a linear process of factor identification, the SD methodology pays attention to the combined interactions between different contributors within the system (Cooke 2003, Qureshi 2007, Goh, Brown et al. 2010).

Based on this advantage, the SD method has been increasingly used to examine the unsafe behaviors of construction workers in recent years. For example, Shin, Lee et al. (2014) recently developed a SD model of construction workers' mental processes to understand how management incentives influence workers' safety attitudes and safety behaviorss. Jiang, Fang et al. (2014)also presented a SD model which primarily focuses on characterizing how management conditions such as safety inspections and safety training impacts construction workers' physical conditions and then unsafe behaviors.

3.4 Agent-Based Modeling (ABM) System

Computer simulation is regarded as an efficient tool to mimic the real-world behaviors of the real-world and efficiently resolves costly or impossible experimentation in the real world (Marzouk and Ali 2013). The agent-based model allows researchers to study complex adaptive systems and consists of a series of independent decision-making units which are called agents (Bonabeau 2002). An agent-based model is a distributed control system and is usually designed to test the outcome of alternative solutions. Palaniappan, Sawhney et al. (2007) pointed out that agent-based modeling (ABM) can model human behaviors in a bottom-up approach and is an appropriate technique for developing computational models to manage construction safety behaviors. The key features of an agent-based model for a construction safety system are as following: (i) agents which have properties and rules in diversified types; (Watanuki and Kojima) agents' relationships and interaction with other agents and the environment and; (iii) agents' environment and methods, where agents interact with other agents and interact with the environment (Macal and North 2010). With the aforementioned features, agent-based modeling provides a realistic representation of the system and efficiently solves the nonlinear relationships on construction sites.

In fact, agent-based modeling (ABM) has been widely used in the construction management domain (Watkins, Mukherjee et al. 2009, Choi and Lee 2018). In particular, several studies have applied agent-based modeling and simulation concepts in construction to dynamically study safety issues (Palaniappan, Sawhney et al. 2007). For example, Sawhney, Bashford et al. (2003) used an agent-based simulation experiment to work out the complex relationship between construction safety culture and the adaptation of construction workers. Another agent-based simulation experiment was also conducted to demonstrate the relationship between workers' safety behaviors and reward systems on construction sites (Walsh and Sawhney 2004). Khosravi, Asilian-Mahabadi et al. (2013) demonstrated a model which aims to explore factors affecting unsafe behaviors from the perspective of safety supervisors. Another implementation of agent-based modeling (ABM) aims to study the interaction between organizational and human factors, and their effects on construction performance (Du and El-Gafy 2012).

3.5 Non-Helmet Use Behavior Inspection System: EOP

3.5.1. Current Methods and Technologies on Helmet Use Inspection

Previous researchers have attempted to understand the major causes of non-helmet use behaviors on construction sites. However, it is hard to obtain data about non-helmet use behaviors (i.e. time spent without wearing a helmet, periods of the day where it is more likely to occur, and a correlation between personality and non-helmet use behaviors). Due to the hysteresis of accident prediction and warning functions in the construction sector, the research is always based on accident reports instead of real-time data. For example, statistics on the lack of PPE use during daily construction processes have always emphasized self-reports of construction staff by construction site managers (Sherratt, Crapper et al. 2015). Incident reporting systems (IRSs) are also widely used for post hoc analysis, which provides proactive analysis for safety management (Saurin, Formoso et al. 2015). The current analysis is mainly based on reporting that cannot visually display workers' unsafe behaviors and their updated risk. Therefore, current studies may fail to provide effective safety analysis for such a complex industry such as construction.

Because of the dangers present on construction sites, the use of safety protection equipment, such as PPE, has gained much of attention from researchers. The current method of worker supervision using PPEs is simply visual surveillance by supervisors or construction managers. However, this method is ineffective and time-consuming, since such surveillance is executed only at scheduled times. In the past few decades, studies have moved away this manual method of supervision to the use of advanced remote sensing, which negates the need for human interference entirely. Kelm, Laußat et al. (2013), for example, use various existing commercial automated identification (ID) and information technologies (IT) to design a mobile RFID to check the use of PPE by workmen. Barro-Torres, Fernández-Caramés et al. (2012) have introduced an advanced cyber-physical system (CPS) to check in real time whether a PPE is worn by workers based on an structure composed of a wireless local area network and a body area network. The helmet is a widely used piece of personal protective equipment (PPE) on construction sites which can directly reduce the risk of head injury or prevent workers from injuring themselves from falling items (Cloute, Mitchell et al. 2008, Williams, Ochsner et al. 2010, Wagner, Kim et al. 2013). Proactive research is urgently needed to promote the workers' safety (Kines, Andersen et al. 2010).

Therefore, it is necessary to develop methods and technologies to inspect helmet use based on real-time and visual data. Meanwhile, performance should be not only evaluated in terms of the behaviors itself, but also from the workers' common characteristics of non-helmet use.

3.5.2. An Overview of the System

The EOP was mainly designed to collect the time data of workers' helmet use (including frequency and duration) and analyze their behavioral patterns when they are occupied with their jobs. The real-time data collection and uploading system was built with Bluetooth technology. As noted in the literature review above, radio frequency (Williams and Solutions)-based technologies, such as RFID, are commonly used to record and upload data currently collected from safety helmets. However, these technologies are too bulky to carry everywhere during construction. Moreover, they consume a large amount of power, which makes them impractical for long-term usage. The tradeoff between different characteristics such as range, accuracy, ease of deployment on construction sites, costs of purchase, as well as use and maintenance ,must also be considered (Li, Chan et al. 2015).

The EOP developed in this study is divided into two parts: (1) a Bluetooth endnote device and (2) a data collector with a low-power Bluetooth protocol. The Bluetooth device with a coin cell battery is attached to the inside shell of the safety helmet and connected to a silicone single-point detector placed on the sweat pads of the safety helmet. Meanwhile, to protect workers from suffering potential discomfort, the Bluetooth device produced is very small and thin. Therefore, the device is still suitable for workers' daily on-site work compared to the other technologies mentioned earlier. Although a Bluetooth device is attached to the inside shell of the helmet, it will not affect physical health which was verified during the design period. Moreover, the privacy of workers was also considered. Detection of safety helmet use occurs when the detector is touched. In this way, the device can capture the period the helmet is worn and store the data in its memory for regular transmission to an external location. The Bluetooth device attached to the safety helmet is shown in Fig 3.1.

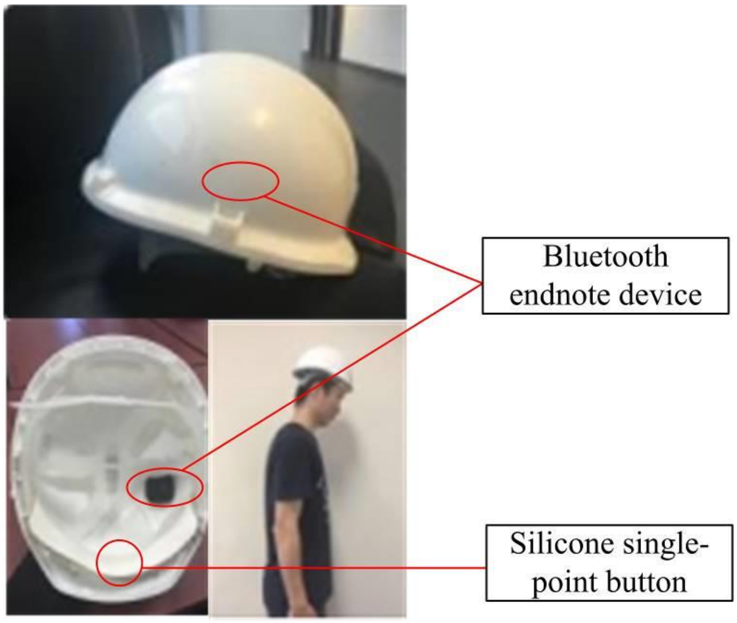

Fig 3.1 Structure of the safety helmet

Fig 3.2 represents the framework of the EOP. The data collector can be fixed in any place and is mainly used to establish an automatic connection with the device, read the data stored in the device and then transmit the data to a server by GPRS. Under normal circumstances, the auto-connection between the device and collector can be established due to the wide communication coverage of low consumption Bluetooth. The process moves in circles. When data appears in the memory of the device within scanning range, the collector reads and uploads it. It then re-scans continuously until the next broadcast within the scanning range. To negate the effects of false touches, an exception is made when a connection of only a few seconds is sensed.

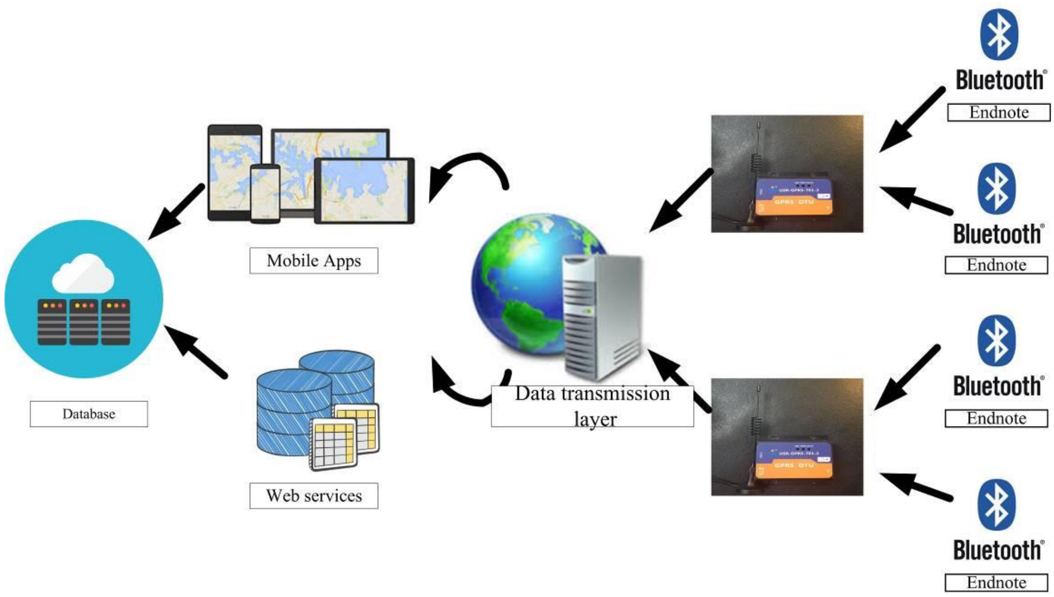

Fig 3.2 Framework of the EOP

3.5.3. System Operational Procedure

A typical operational procedure of EOP consists of three stages: preparation, running and data analysis. In preparation, (1) the data collector is placed in a fixed area for workers passing on time (such as the construction site entrance), and the data transmission distance from endnote to collector is 30 m (if workers' active areas exceed this range, it is necessary to deploy more than one collector to the site); (2) the workers' personal information (including ID, age, gender and work experience) are established and updated, the characteristics can be differentiated by the workers' ID's; and (3) the relationship between endnote and endnote carriers is established through the association of the worker-ID and helmet-ID, which can realize the combination between workers' personal characteristics and their performance in helmet use.

The data collection was realized by the record from the collector's physical ID, the helmet's physical ID and the time that the helmet was on and off with EOP. Part of the helmet use records from EOP is shown in Fig 3.3. When running EOP, we can obtain the time data of helmet use by inspecting record by record. A single helmet record contains the data collector ID, Helmet ID, duration of use and duration of non-helmet use for one time. The duration of non-helmet use is equal to the difference between the [Take-off Time] for this record and the [Take-on

Time] for the next record during their work time. Thus, the frequency and duration of the workers' non-helmet use can be acquired during the period of data collection.

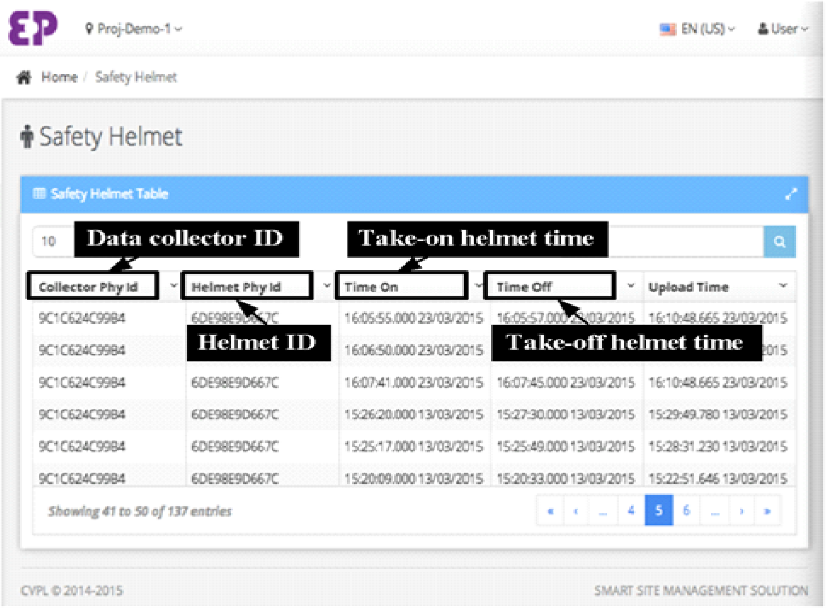

Fig 3.3 Example of helmet use records from EOP

Finally, when the helmet use records and worker information has been collected, the workers can be categorized into risk levels according to the frequency and duration of non-helmet use and by using association rules to explore the characteristics and contributors involved. More details of this procedure are given in the sections below. These characteristics are the foundation to the worker's risk level assessment during the construction period.

Chapter 4. IMPACT OF INDIVIDUAL FACTORS ON NON-HELMET USE BEHAVIOR: ANALYSIS BASED ON ASSOCIATION RULE

4.1 Introduction

This section reports a field experiment investigating workers' common characteristics of non-helmet use and then assessing workers' risk levels on construction sites. In this section, the EOP is used as the non-helmet-use behavior inspection system in an experiment. The features and operational procedures are introduced in detail. Association rules were used as a data analysis method to find the obscure combination of risk factors hidden in the data collected. Many data mining techniques have been used for safety analysis in recent years (Geurts, Wets et al. 2003, Geurts, Thomas et al. 2005, Cheng, Lin et al. 2010). Meanwhile, a risk assessment matrix system was obtained by the association rules above, with levels classified by characteristics. The significance of this section is to propose a more intuitional way to find and demonstrate risk contributors.

The framework of the system implementation procedures is demonstrated in Fig 4.1.

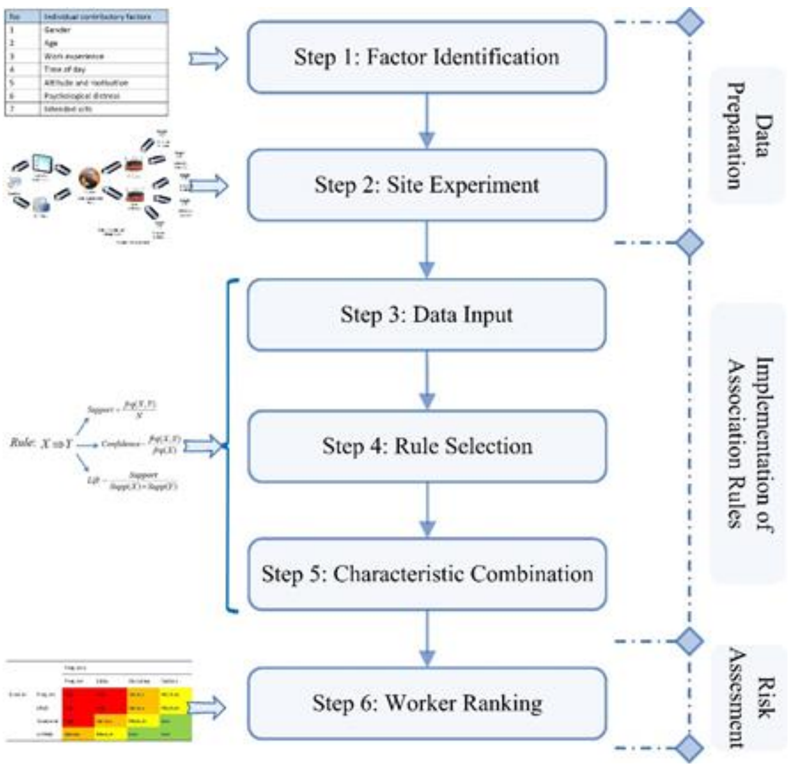

Fig 4.1 Framework of the implementation procedures

4.2 Factors Designated in the Study

As previously mentioned, this study mainly focuses on four risk factors: gender, age, experience and time of day. "Sex-linked differences" are always found in relation to occupational accidents, and the accident rates between male and female workers show that women suffer fewer accidents than men (Messing, Courville et al. 1994). Age is regarded as a significant contributor to construction injuries. Cheng, Leu et al. (2012) state that the most commonly injured group are people aged 35–44 years old (31%), while it is apparent that workers older than 55 and younger than 24 are the most likely to be involved in fatal accidents. Given that experience represents the workers' own proficiency, (Arquillos, Romero et al. 2012) show that poor work experience is a major factor affecting the fatal accident rate on construction sites. Meanwhile, López, Ritzel et al. (2011) analyze the severity of occupational accidents suffered by construction workers at different hours of the day, and illustrate that the interval of time between 13:00 and 17:00

has a significantly higher rate of severe and fatal accidents than any other period; this is termed the “lunch effect”.

4.3 A Method for Assessing Workers’ Risk Level

The data analysis of non-helmet use can be divided into two steps: (1) using the association rules to analyze the characteristics of workers who neglect helmet use; and (2) using the risk assessment matrix to evaluate the risk levels of workers; workers who have a higher risk being the target during construction work.

Risk assessment has traditionally involved quantifying the risk of an incident based on two or more variables, such as the probability of a risk (frequency), and the impact or consequence of the risk occurring (severity). However, this risk assessment method is always focused on the risk of an activity, which represents the amount of injuries expected to occur as the result of a potential accident associated with an activity. In our current research we intend to analyze the characteristics of workers that lead to non-helmet use and assess their risk level based on the helmet use data. Therefore, the risk of non-helmet use means the amount of non-helmet use in terms of frequency and duration.

Two-dimensional risk assessment matrices have been widely used to define different levels of risk. The color codes in this matrix correspond to various levels of risk (low, medium and high). However, this matrix has been criticized for being too subjective and qualitative. In this research, assigning numerical values for frequency and duration based on the association rules can provide quantitative risk values for the matrix.

4.4 A Case Study of Non-Helmet Use Behavior

4.4.1. Overview of the Experimental Construction

The non-helmet use behavioral data was collected for the Shenzhen project “The Peninsula”, and compiled with the Eye on Project (EOP). The ongoing project is a housing estate with 44,481.2 m^2 floor space and a construction period from May 2015 to December 2017 (32 months). A total of 43 workers participated in the second and third construction phases of the project from the 23 November 2015 to 21 January 2016. 19 workers worked on-site without head protection at least once in the experiment, resulting in 483 incidents recorded by EOP. Table 4.1 summarizes the categories of workers' characteristics in the experiment.

Table 4.1 Descriptive statistics of non-helmet use data from EOP

Characteristic	Level	Description	Count	Percentage
Gender	male	GEN1	14	72.36%
	female	GEN2	5	27.64%
Age	<24	AGE1	1	5.26%
	24-34	AGE2	3	15.79%
	35-44	AGE3	9	47.37%
	45-54	AGE4	5	26.32%
	≥55	AGE5	1	5.26%
Work Experience	<1	EXP1	2	8.94%
	1-5	EXP2	3	16.67%
	6-10	EXP3	6	30.49%
	>10	EXP4	8	43.90%
Time of day for frequency of non-helmet use	[9:00,12:00]	TIM 1	35	7.32%
	(12:00,15:00]	TIM2	345	71.36%
	(15:00,18:00]	TIM3	103	21.32%
Time of day for duration of non-helmet use	[9:00,12:00]	TIM1	204	13.61%
	(12:00,15:00]	TIM2	841	56.10%
	(15:00,18:00]	TIM3	454	30.29%

4.4.2. Non-Helmet Use Workers's Characteristics

To create association rules for the characteristics and contributory factors of non-helmet use in the EOP database, the researchers carried out an *a priori* algorithm with 9 sets of data. According to the principle of association rules, the first was to set the minimum value of support, confidence and lift based on the actual situations. Workers' characteristics were expressed by rules as the combinations of different characteristics. In this investigated project, the daily lunch rest period was 12:00-13:00, and the helmet and non-helmet use data during this period has already been excluded in the data analysis section.

However, the resulting rules for frequency and duration of non-helmet use were diverse and independent, which produced two evaluated results from the two dimensions of frequency and duration. Next, we selected rules that simultaneously exhibit the frequency and duration results. In this study, a total of 32 rules were obtained as shown in Table 4.2

Table 4.2 Overlapped rules from the frequency and duration of non-helmet use

Rule ID	Consequent	Antecedent	Frequency			Duration		
			Support(%)	Confidence(%)	Lift	Support(%)	Confidence(%)	Lift
1	EXP1	GEN2	26.91	72.55	1.40	28.69	56.33	1.03
2	EXP1	GEN2 and TIM2	21.17	81.24	1.56	21.16	56.38	1.03
3	TIM2	GEN2 and AGE4	19.84	90.19	1.13	12.27	72.56	1.06
4	TIM2	AGE3 and EXP1	18.85	84.09	1.06	19.68	69.74	1.02
5	EXP1	GEN2 and AGE4 and TIM2	17.90	90.01	1.73	8.90	59.20	1.09
6	GEN1	AGE5 and EXP1	9.63	100.00	1.37	3.25	100.00	1.40
7	EXP2	TIM3 and AGE4	7.35	53.51	1.29	9.12	58.25	1.53
8	GEN1	TIM3 and AGE4	7.35	73.51	1.01	9.12	71.36	1.00
9	GEN1	AGE2	6.28	100.00	1.37	11.07	87.00	1.22
10	EXP2	TIM3 and AGE4 and GEN1	5.40	50.00	1.21	6.51	50.34	1.32
11	EXP2	TIM3 and GEN2	4.57	74.78	1.80	5.91	55.81	1.46
12	AGE3	GEN2 and EXP2 and TIM2	3.97	55.00	1.83	9.17	52.90	1.34
13	GEN1	EXP3	3.91	100.00	1.37	6.77	99.02	1.39
14	GEN1	AGE2 and EXP1	3.42	100.00	1.37	5.11	100.00	1.40
15	EXP1	TIM1 and GEN1	3.36	81.07	1.56	3.96	64.80	1.19
16	AGE4	TIM1 and EXP1 and GEN1	2.72	62.04	1.17	2.57	55.17	1.53
17	GEN1	EXP3 and TIM2	2.70	100.00	1.37	5.16	98.71	1.38
18	EXP1	TIM1 and AGE3	2.07	82.69	1.59	2.08	68.09	1.25
19	GEN1	EXP3 and AGE3	2.05	100.00	1.37	5.20	100.00	1.40
20	GEN1	TIM1 and AGE4	1.97	100.00	1.37	2.72	72.36	1.02
21	EXP1	TIM1 and AGE4 and GEN1	1.97	85.86	1.65	1.97	71.91	1.32
22	GEN1	AGE2 and EXP1 and TIM2	1.89	100.00	1.37	2.50	100.00	1.40
23	GEN2	TIM1 and AGE3 and EXP1	1.71	68.61	2.55	1.42	60.94	2.12
24	GEN1	AGE2 and TIM3 and EXP2	1.53	100.00	1.37	2.52	72.81	1.02
25	GEN1	AGE2 and TIM3 and EXP1	1.53	100.00	1.37	2.61	100.00	1.40

26	GEN1	EXP3 and AGE3 and TIM2	1.27	100.00	1.37	4.07	100.00	1.40
27	AGE3	EXP3 and TIM3	1.21	63.93	2.12	1.62	69.86	1.78
28	GEN1	EXP3 and TIM3	1.21	100.00	1.37	1.62	100.00	1.40
29	AGE3	EXP3 and TIM3 and GEN1	1.21	63.93	2.12	1.62	69.86	1.78
30	AGE3	TIM1 and GEN2	1.17	100.00	3.32	1.62	53.43	1.36
31	EXP1	TIM1 and GEN2	1.17	100.00	1.92	1.62	100.00	1.83
32	AGE3	TIM1 and GEN2 and EXP1	1.17	100.00	3.32	1.62	53.43	1.36

4.4.3. Workers's Risk Level Assessment

To obtain a more accurate result from the association rules, we selected two indices, support and lift, to overcome the inaccuracies of a single index. In this case study, support and lift intervals from the two dimensions, frequency and duration, are set according to the same regulation. The support and lift intervals both range from 1 to 100. Both frequency and duration can represent the probability of repetitive non-helmet use. Thus, the matrices of frequency and duration descriptors are the same, as shown in Table 4.3. In Table 4.3, the green cells show the unlikely probability levels, the yellow cells correspond to occasional levels of probability, whilst the orange cells are the rules that occur sometimes with likely probability levels and the red cells represent the most frequent levels of probability. According to Table 4.4, 32 rules are classified into frequent, likely, occasional and unlikely levels from the frequency and duration of non-helmet use.

Table 4.3 Frequency or duration descriptors of non- helmet use

		Support (%)			
		[1,2)	[2,4)	[4,7)	[7,100]
Lift	[1.4,100)	Occasional	Likely	Frequent	Frequent
	[1.2,1.4)	Unlikely	Occasional	Likely	Frequent
	[1.1,1.2)	Unlikely	Unlikely	Occasional	Likely
	[1.0,1.1)	Unlikely	Unlikely	Unlikely	Occasional

Table 4.4 Thirty-two rules classified by frequency levels

Level	Rule ID for frequency	Rule ID for duration
Frequent	1; 2; 5; 6; 7; 11	6; 7; 9; 10; 11; 12
Probable	3; 9; 10; 12; 15; 18	13; 14; 16; 17; 19
Occasional	4; 8; 13; 14; 17; 19; 21; 23; 27; 29; 30; 31; 32	1; 2; 3; 4; 5; 8; 18; 22; 23; 25; 26; 27; 28; 29; 31;
Remote	16; 20; 22; 24; 25; 26; 28	15; 20; 21; 24; 30; 32

We combined the 32 rules in Table 4.3 from the frequency and duration dimensions of non-helmet use. Table 4.4 shows the risk levels and color codes based on the frequency and duration, which represent the impact of the four factors (i.e., age, experience, gender, and time of day) on workers' non-helmet use. Risk is classified into extreme, high, moderate and low levels. The green cells show the low risk levels, the yellow cells correspond to moderate levels of risk, while the orange cells denote high risk and the red, extreme levels of risk. For example, the rule that is classified as an extreme level of risk is the combination of the frequency level and duration level. The high risk level events are those that are classified as both frequent and unlikely. The 32 rules are reclassified by the risk levels and listed in Table 4.6 according to the classification of risks in Table 4.5. Based on this result, the workers who neglect to use helmets can easily be found.

Table 4.5 Risk assessment matrix for non-helmet use rules

		Frequency			
		Frequent	Likely	Occasional	Unlikely
Duration	Frequent	Extreme	Extreme	High	Moderate
	Likely	Extreme	Extreme	High	Moderate
	Occasional	Extreme	High	Moderate	Low
	Unlikely	High	Moderate	Low	Low

Table 4.6 Thirty-two rules classified by risk levels

Risk	Rule ID	Consequent	Antecedent	Risk	Rule ID	Consequent	Antecedent
Extreme	1	EXP1	GEN2	Moderate	15	EXP1	TIM1 and GEN1
	2	EXP1	GEN2 and TIM2		16	AGE4	TIM1 andEXP1 and GEN1
	5	EXP1	GEN2 and AGE4 and TIM2		21	EXP1	TIM1 and AGE4 and GEN1
	6	GEN1	AGE5 andEXP1		23	GEN2	TIM1 and AGE3 andEXP1
	7	EXP2	TIM3 and AGE4		27	AGE3	EXP3 and TIM3
	9	GEN1	AGE2		29	AGE3	EXP3 and TIM3 and GEN1
	10	EXP2	TIM3 and AGE4 and GEN1		30	AGE3	TIM1 and GEN2
	11	EXP2	TIM3 and GEN2		31	EXP1	TIM1 and GEN2
	12	AGE3	GEN2 andEXP2 and TIM2		32	AGE3	TIM1 and GEN2 andEXP1
High	3	TIM2	GEN2 and AGE4	Low	20	GEN1	TIM1 and AGE4
	4	TIM2	AGE3 andEXP1		22	GEN1	AGE2 andEXP1 and TIM2
	8	GEN1	TIM3 and AGE4		24	GEN1	AGE2 and TIM3 andEXP2
	13	GEN1	EXP3		25	GEN1	AGE2 and TIM3 andEXP1
	14	GEN1	AGE2 andEXP1		26	GEN1	EXP3 and AGE3 and TIM2
	17	GEN1	EXP3 and TIM2		28	GEN1	EXP3 and TIM3
	18	EXP1	TIM1 and AGE3				
	19	GEN1	EXP3 and AGE3				

4.5 Data Analysis and Result

In the extreme-risk section, it is apparent that [EXP1] is the consequence of the highest proportion of non-helmet use. [GEN2] and [EXP1] have a stronger relationship than other rules, i.e. 1, 2 and 5. The extreme level of risk indicates that workers with these characteristics are more prone to experience construction accidents. The high-risk category provides another consequence where being a male ([GEN1]) worker is the biggest contributory factor to non-helmet use behavior. Workers with less than five years of work experience ([EXP1]), and who work between 9:00 am and 12:00 am ([TIM1]), have factors of approximately equal impact, while [TIM1] accounts for a high average support value, which can be found in rule 3 and rule 4. Workers with a high level of risk have an influential role on the whole work team as they tend to affect their colleagues' behavior.

There are several comprehensive factors that mutually influence the moderate level, such as less than five years of work experience ([EXP1]), workers aged from 35 to 44 years old ([AGE3]), male workers ([GEN1]) and [AGE3] leadership of all the impacts. Moderate level workers are stable and less prone to taking dangerous actions. These workers are considered minimal risk takers. The low level is composed of a singular component of male workers ([GEN1]). This is due to the skill (or lack thereof) of these workers in the pilot study.

Compared with the workers that have patterns of a combination of individual factors leading to unsafe behavior, the characteristic of 24 workers who are following the rule and wearing their helmets are converging on the following aspects: below 35 years old ([AGE1], [AGE2]) and with over 5 years' work experience ([EXP3], [EXP4]). Moreover, those working after 3pm tend to pay more attention to helmet use.

This chapter is mainly focused on the mining association rule between sets of workers' characteristics of non-helmet use. The progressive methods proposed can automatically obtain important characteristics and contributory factors with the records of non-helmet use. By using the two evaluation indexes as support and lift, more accurate information of the combination of workers' characteristics can be obtained to analyze the potential causes of serious accidents.

Chapter 5. IMPACT OF SAFETY CLIMATE AND PRODUCTIVITY PRESSURE ON NON-HELMET USE BEHAVIOR:ANALYSIS BASED ON SYSTEM DYNAMICS MODEL

5.1 Introduction

This section will provide a means of systematically understanding the causes of non-helmet use behavior on construction sites under a safety climate and productivity pressure. The methodology of System Dynamics (SD) is adopted to model the project system on the individual, management and project levels, and then integrate the links between primary contributors, which belong to the three levels, and non-helmet use behavior. The Eye on Project System (EOP) is developed to target the amount and frequency of the non-helmet use behavior on construction sites, calibrating the SD model being developed. This is followed by a demonstration in which the model is used to examine the likely effects of different safety policy regimes under productivity pressures to identify the most appropriate for ameliorating non-helmet use behavior.

5.2 Understand Complex Safety System Using System DynamicsPrinciples of system dynamics (SD)

This study aims to develop an SD model to comprehensively understand how factors related to external environments and personal characteristics collectively influence construction workers' unsafe behavior which is automatically detected by a real-time intelligent safety helmet. The factors are examined in detail in this section and are categorized into three levels:

Level 1- *Project Level*: The requirements of a specific project, the key project goal being the most important consideration influencing unsafe behavior with the opposing objectives of safety and productivity tending to create adverse conditions;

Level 2- *Safety management strategies*, such as safety training and safety climate, primarily concerned with the specific project;

Level 3- *The diverse characteristics of individuals*, with age, gender, type of work and work experience being dominating factors.

In this SD modeling work, unsafe behavior on construction sites is influenced by three integral levels of contribution, instead of being isolated individual or organizational factors. Figure 5.1 illustrates this based on the identification of the project, management and individual loops involved.

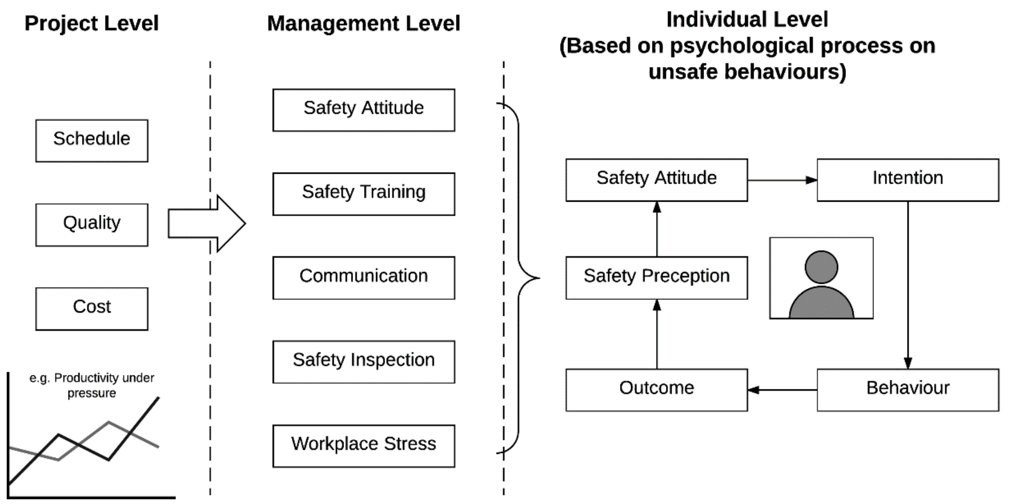

Fig 5.1 Conceptual Model on the Safety Performance

5.3 System Dynamics (SD) Modeling

5.3.1. The Structure of System Dynamics (SD) Modeling

Based on the conceptual model, as shown in Figure 5.1, the developed SD model for the feedback loop of the non-helmet use behavior is shown in Figure 5.2. It consists of two separate causal loops within the three levels previously mentioned, comprising of:

Loop B1 (Balancing Loop): (non-helmet use behavior→ (+) safety incidents→ (+) safety perception→ (+) workers' attitude towards safety→ (+) intention to wear safety helmet→ (-) non-helmet use behavior) is constructed based on the psychological processes involved in the workers' decision making ("*individual level*" as shown in Figure 1). Near misses are hazardous situations, events or unsafe acts where the sequence of events could have caused an accident if they had not been interrupted (Small, Wuerz et al. 1999), and non-helmet use behavior is regarded here as a key resource for near misses.

Loop R2 (Reinforced loop): (Project Manager's attitude toward safety → (+) Worker's attitude towards safety → (+) increment on safety climate) demonstrates the interdependent relationship between the three levels in the conceptual model. The safety attitudes of both project manager and workers would have a positive effect on the safety climate of the construction site.

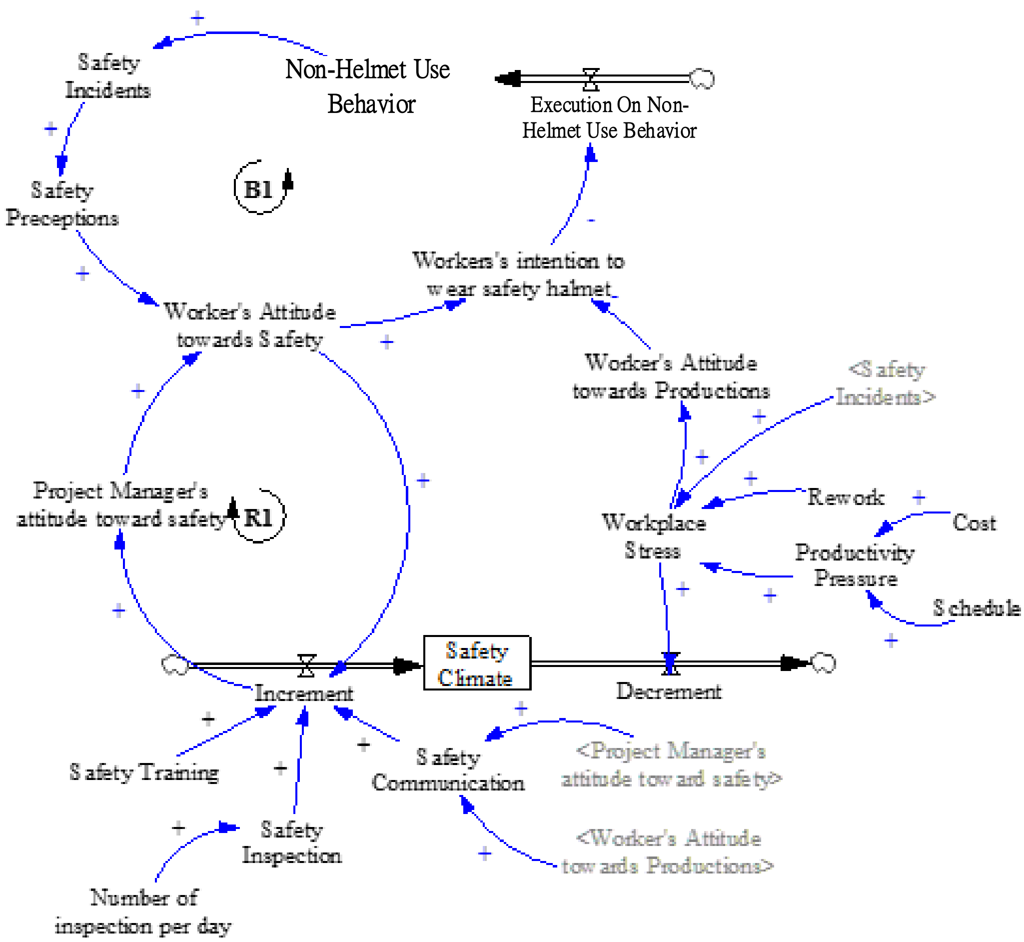

Fig 5.2 System Dynamics Model

In sum, the SD model embodies the understanding gained from the feedback processes on the three levels of individual, management and project contributions. This permits the identification of the actions and policies with the greatest potential to provide the desired range of safety performances in helmet use while maximizing the promotion on the positive safety climate factors (i.e., safety training, safety communication and safety inspection) and minimizing the negative impact of productivity aspirations.

5.3.2. Data Collection and Analysis

To assess the correlations with the associated variables in the SD model, 91 completed questionnaire surveys were collected from different types of construction workers including: concreters, steel fixers, crane operators, form fixers and scaffolders. The questionnaire focused on safety perception, worker's attitude towards safety, worker's attitude towards production, work pressure and safety climate (see Table 5.1). Another 13 group managers were requested to complete the second part of the questionnaire, i.e. the manager's attitude towards safety. Other variables in the SD model were retrieved from historical data of the subdivision of work from the project data and literature. For example, according to (Breierova and Choudhari 1996), only one serious injury and ten minor injuries resulted from 600 near-miss incidents. The final correlation coefficients among the mentioned variables in the model were using the statistical software SPSS ver.210. For the second part, as it is used to validate the SD model, a one-week demonstration was conducted on a real construction project with five workers and two managers.

The questionnaire survey involved a variety of project goals, safety climate dimensions and individual variables, using data collection methods such as project reports, surveys and interviews. Worker safety perceptions, safety and production attitudes (at the individual level), attitudes of managers to safety, safety training, safety communication and work pressure (as components of safety climate) and time and cost pressure (as project-level variables), were examined for their intercorrelations and to understand the causal feedback processes involved in non-helmet use behavior. Quality goals were not taken into consideration, as they are hard to measure over short periods.

To measure individual level variables, worker safety perceptions, attitudes towards safety and attitudes towards production; a questionnaire on a 5-point Likert scale ranging from 0 (strongly disagree) to 5 (strongly agree) was produced, as shown in Table 5.1. The questionnaire was distributed to workers during safety meetings at the beginning of each day of construction work. The responses were converted into fractions by dividing by five and the final score converted into a percentage.

Table 5.1 List of questions on individual variables

Safety perception	
1	How concerned are you about suffering a head injury at work?
2	What is the likelihood you might suffer a head injury at work?
3	Taking the potential head injuries into consideration, what is the likelihood you will act in an effective protective manner?
4	I am clear about my responsibilities for workplace safety.
Attitude towards safety	
1	When I am at work, I think safety is the most important thing.
2	When I am at work, I wear safety helmets to prevent injury.
3	I take care of safety problems at work.
Attitude towards project goals	
1	I sometimes ignore safety measures for the sake of production.
2	I sometimes I do not wear a safety helmet to improve the production rate.
3	I take care of production problems at work.
Work Pressure	
1	I think the current workload is beyond my ability.
2	I think it is impossible to meet the workload requirements.
Safety Climate	
1	Do your workmates think safety is the priority?
2	Do your workmates regard wearing a helmet as an efficient way to prevent accidents?
3	Do your workmates care about safety problems during construction work?
4	What is the likelihood that your group will remind each other of the safety risks during construction work?

The data relating to safety climate comprises of two sections: the questionnaire survey of the attitudes of both managers and workers towards safety, and the observation and calculation of other components (e.g., safety training, safety communication, safety inspection and work pressure). For the survey on effectiveness of leadership attitudes, the two managers responded to the same questions as those put to the workers listed in the questionnaire. Safety training, safety communication and safety inspection were tested independently, each being evaluated within the total numbers of labor hours. As with safety training records, the number of safety training hours on a site was also recorded and converted into a percentage unit by dividing the total number of labor hours. Safety communication was measured by the number of hours in daily meetings and converted into a percentage unit. safety inspection was measured as the percentage of estimated inspected time to the total number of labor hours.

Project data consists of both planned and actual costs, and production per day as recorded in the demonstration unit. The production pressure is calculated by dividing the actual production (i.e. cost and time) per day by the planned production per day. The results are summarized in Figure5.3.

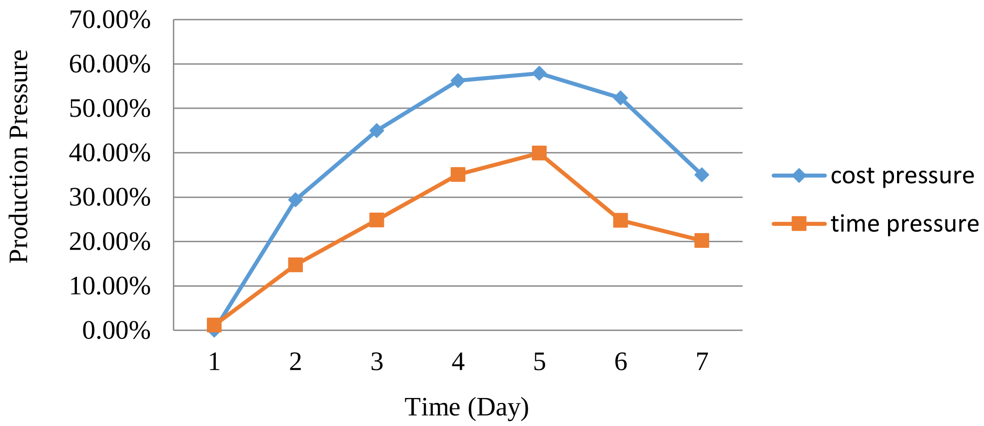

Fig 5.3 Daily cost and production over the demonstration period

5.4 Model Validation Test

The model is validated by comparing its predictions of the rate of non-helmet use behavior with actual data collected from EOP. This shows a similarity between the simulated and actual rate of non-helmet use behavior per worker during one day in Figure 5.4. Following (Sterman 1984), a validation test is used to analyze and decompose the sources of error. This involves the use of the Mean Absolute Percentage Error (MAPE) for prediction comparisons (Martin and Witt 1989), with where N is the number of days of the non-helmet use behavior $(t = 1, \dots, n)$; S_t is the simulated value at time t; and At is actual value at time t.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{S_t - A_t}{A_t}\right|$$

The range of MAPE can be used to classify the model's predictions, with less than 10 percent denoting 'high accuracy', 10-20 percent 'comparable accuracy', 20-50 percent 'reasonable accuracy', and higher than 50 percent 'low accuracy' (Lewis 1982, Martin and Witt 1989). In this case, with a MAPE of 17.80%, the model is taken to predict worker non-helmet use behavior with at least a reasonable level of accuracy.

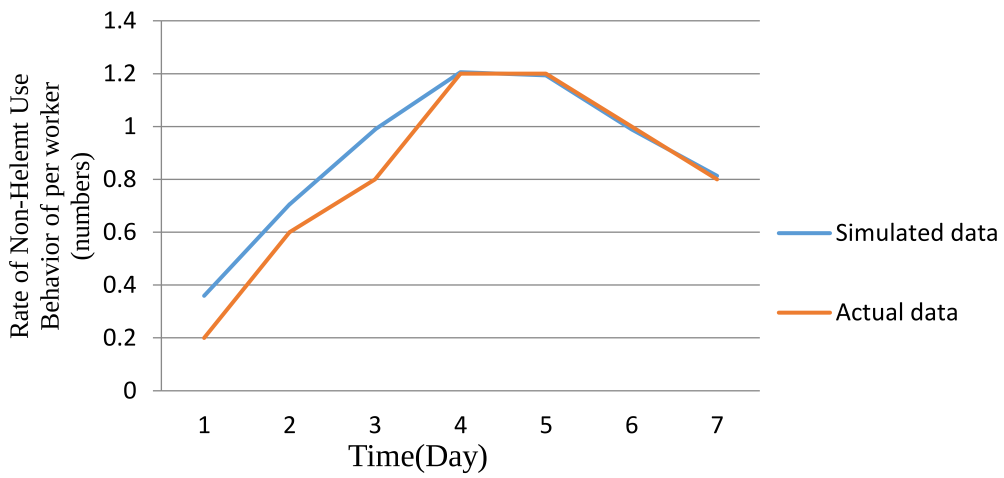

Fig 5.4 Simulation results over time: comparison between simulated and actual data

5.5 Data Analysis and Result

The ultimate goal of the model is to determine the policies needed to prevent non-helmet use behavior in order to improve construction safety and reduce the rate of incidents on site. The key purpose is to determine whether the components of a safety climate can mitigate the pressure of production goals. As illustrated in Fig. 5.5, and as expected, time and cost pressures reduce the level of the safety climate and lead to negative attitudes towards safety by increasing the probability of non-helmet use behavior. As a result, safety training, safety communication, safety inspection and the attitudes towards safety of both managers and workers, are in turn jeopardized by this 'safety climate decrement', as it is only by improving the safety climate that workers can be induced to increase their use of safety helmets. This is leading to a downward spiral of a non-helmet use behavior safety climate that can only be mitigated by management intervention in the form of a correct policy selection.

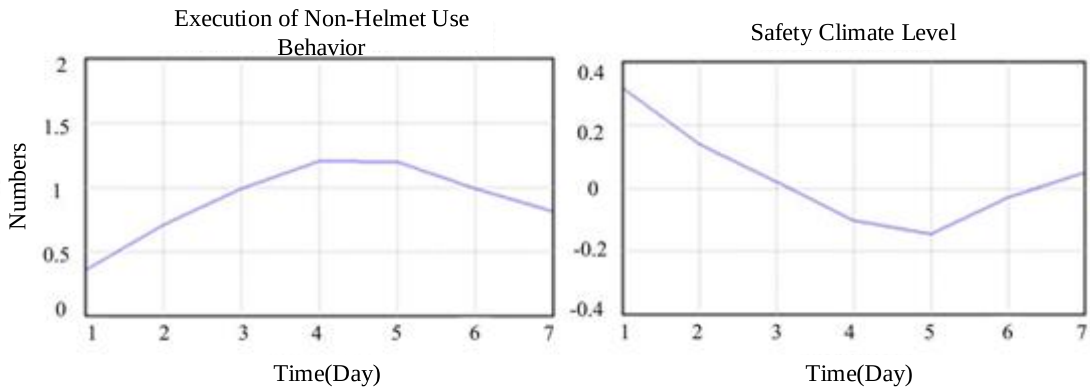

Fig 5.5 Helmets misuse behavior and safety climate sensitivity analysis

Sensitivity analysis is used to determine the impact of changes on parameters, policies and on outcomes, and helps to clarify the dynamics of real systems (Breierova and Choudhari 1996). To understand the effects of production pressure on the components of safety climate under different policy regimes, the impacts of the variables involved are analyzed by altering their weights in the SD model.

Previous work by (Zohar 2002) used principal component analysis to classify the impact of safety climate, resulting in the identification of three factors of Preventative Action (PA), Reactive Action (RA) and Prioritization (P). To investigate the effects of these factors in the SD model, we developed five policy 'packages' as shown in Table 5.2. Package 1 maintains a balance between PA and RA; Package 2 and Package 3 reinforce the PA and RA respectively; Package 4 prioritizes safety climate increments (e.g., safety training, safety communication, safety inspection) over safety climate increments as work pressure; whilst in comparison, Package 5 prioritizes project production goals over safety goals.

Table 5.2 Parameters of the five safety climate policy packages

Components	Package1 (PA+RA)	Package2 (PA)	Package3 (RA)	Package4 (P1)	Package 5 (P2)
Safety training weight	1	1.5	0.5	1	1
Safety communication weight	1	1.5	0.5	1	1
Safety inspection weight	1	0.5	1.5	1	1
Manager's attitude towards safety weight	1	0.5	1.5	1	1
Worker's attitude towards safety weight	1	0.5	1.5	1	1
Time pressure weight	0.4	0.4	0.4	0.4	0.4
Cost pressure weight	0.4	0.4	0.4	0.4	0.4
Incidents weight	0.2	0.2	0.2	0.2	0.2
Safety climate increment weight	1	1	1	1	0.5
Safety climate decrement weight	1	1	1	0.5	1

The SD model's predicted outcomes for the five policy 'packages' are shown in Figure 5.6, with all policies producing increased non-helmet use behavior up to 4-5 hours of the day and diminishing thereafter. Package 4 is the most effective policy, underlining the importance of positive safety climate to show that safety prioritization reduces the rate of non-helmet use behavior. This is followed by Packages 1 and 2, indicating preventative action (safety training and safety communication) to be the next most important policy in preference to reactive policies. On the other hand, if production is prioritized for the whole project, the rate of non-helmet use behavior increases significantly, especially during periods of increased work pressure.

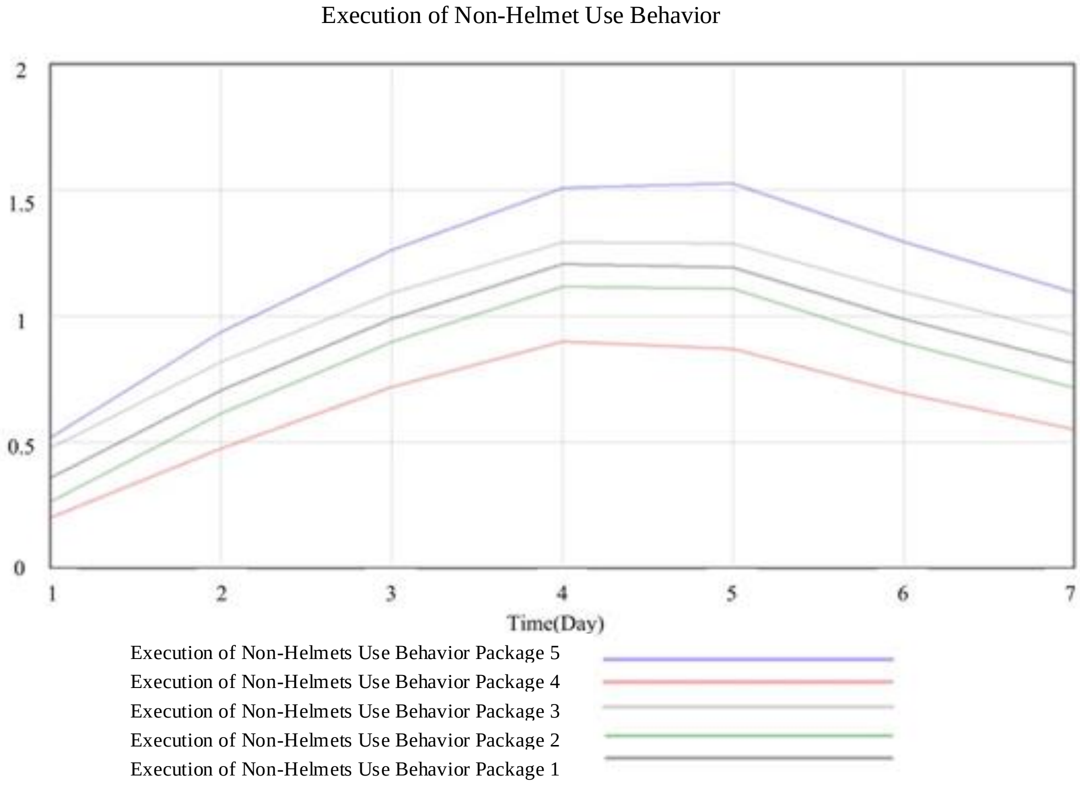

Fig 5.6 Result of sensitive analysis on safety climate policies

5.6 Chapter Summary

This chapter utilizes the system dynamics modeling to simulate the construction works at the project, management, and individual levels to understand the dynamics relationship of safety climate, pressures of productivity and such unsafe behavior. Using the data collected from the Eye on Project, the proposed SD model can be calibrated for simulating the influence of safety climate and productivity pressures on the helmet in construction sites. The findings indicated that the system's potential to help develop policies to mitigate the negative influences of work pressure and reduce helmet misuse.

Chapter 6. IMPACT OF PUNISHMENT SYSTEM AND SUPERVISION METHOD ON WORKERS' BEHAVIORAL PATTERNS:ANALYSIS BASED ON AGENT-BASED MODELING

6.1 Introduction

To get a better understanding of the relationship between construction workers, this section uses an agent-based modeling method（ABM）in which the system is controlled through the interaction of multi-agents. Agent-based systems act on a bottom-up approach and use a computational model of autocephalous agents which move and interact with others and the environment (Wagner and Agrawal 2014). In addition, the modeling and simulation seeks to create a closer relationship with the real work phenomenon and solve research problems by testing multiple environment-specific scenarios (Wilensky and Rand 2015). The implementation of ABM allows us to study the emerging behavior of workers on a changing construction site, which, as a consequence of an integrated system, is defined by interactions among individual workers, safety supervisors, safety helmets and the punishment system.

In summary, this section uses an ABM model and a real-time tracking safety helmet designed by the researchers to: 1) investigate the changing tendencies in workers' behavioral patterns under different punishments; 2) observe the changes in workers' behavioral patterns under different supervisor inspection levels and penalties; and3) study the variation in workers' behavioral patterns under traditional supervision methods (i.e. impeachment from co-workers and safety supervisors on-site) and information from the real-time tracking safety helmets.

6.2 Agent-Based Simulation System

The ABM system in this section is conducted by using a combination of NetLogo☒(an agent-based modeling and simulation development environment) and Java programming languages. The following section will describe the research design, including both the real-time tracking safety helmets and the agent-based modeling, in which the designated autonomous agents interact with each other and their environment.

The prototype ABM system in this section is designed to model the changing patterns of construction workers' behavior. It allows for the changing of construction workers' behavior with a dynamic of different combinations including: punishment systems, inspection methods and inspection levels. The adopted agents in this section include: construction workers, co-workers, safety supervisors, safety-helmets and a punishment mechanism. To set the parameters of the agents, a questionnaire has been handed out to different types of construction workers from four construction projects in ShenZhen, China, which may have different safety problems and solutions. The questionnaire contains three main parts: 1) workers' information (e.g., worker type, work duties, age, education level, work experience, physical conditions, average monthly income and penalties); 2) perceived unsafe behavior assessment factors (e.g., work time saved, perceived psychological earnings, prospect of rewards, perceived potential degree of risk) and; 3) factors which determine work satisfaction levels (e.g., impeachment from co-workers, inspection levels and inspection methods). The response to each attitudinal question was designed on a five-point Likert scale, under the categories 'strongly agree', 'agree', 'neither agree nor disagree', 'disagree' and 'strongly disagree'. 200 questionnaires were distributed to workers during safety meetings at the beginning of each day of construction. 184 completed questionnaires were collected and 178 questionnaires were valid.

The main research questions in this model are: 1) What is the impact of different amounts of punishment on the changing of workers' behavioral patterns? 2) What is the variation trend of workers' behavioral patterns under different supervised inspection levels and penalties? 3) How do workers' behavioral patterns change under different combinations of inspection methods i.e. impeachment from co-workers, safety supervisors on site and real-time tracking intelligence safety helmets?

Based on the key features of ABM mentioned above, the following description of this model is based on three components: (i) agents which have properties and rules in diversified types; (Watanuki and Kojima) agents' interaction with their environment and (iii) individual autonomous agents interacting with other agents.

The structure of this case study has been demonstrated in Figure 6. 1.

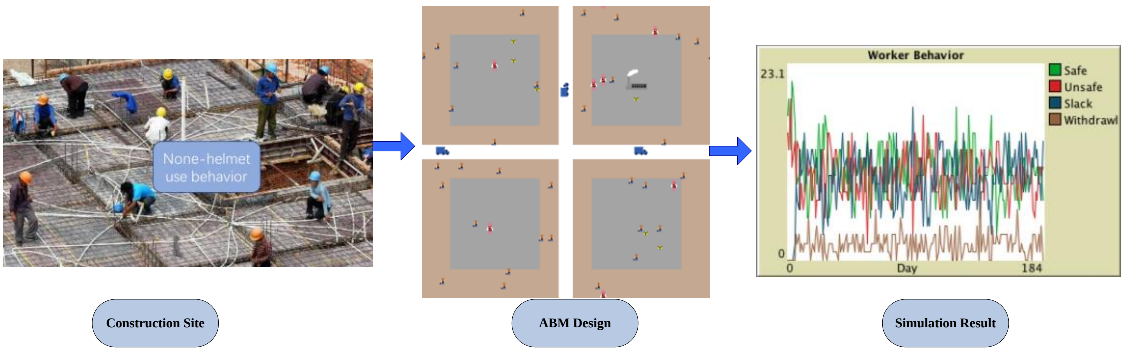

Fig 6.1 The structure of the case study

6.3 Agents and Environment Setup

The virtual construction site is comprised of 100 construction workers and 10 safety supervisors. The number of input variables can be monitored by a slider named workers-num and supervisors-num. Two logic variables have been designed, which are named 'safety-helmet' and 'co-worker', respectively. When the 'safety-helmet' button turns on, the lack of safety-helmet use behavior will be recorded in real-time. Meanwhile, when the 'co-worker' variable turns on, the workers will report the surrounding 'co-workers' lack of helmet use behavior to safety supervisors. According to the collected questionnaires, the average income of on-site employees is 5000 RMB per month. Therefore, the penalty amount in this study has been set by the author at 0 to 500. Hwang (2012) demonstrated that construction equipment challenges safety management by raising the risk of accidents by a considerable amount. Therefore, the simulated construction site consists of three trucks and a tower crane, which contribute to the potential dangers. Each simulation process covers 300 working days.

The behavioral patterns of construction workers are divided into four categories: 1) Safe behavior: construction workers show strong safety consciousness and wear a safety helmet to protect their own safety during work time; 2) Unsafe behavior: construction workers fail to follow the safety rules and do not wear a safety helmet, which indirectly or directly results in an accident; 3) Slack behavior: construction workers' intentional absenteeism and slack behavior at work, resulting from a particular cause; 4） Withdrawal behavior: construction workers feel low satisfaction about their working environment and choose to resign or demit from their current work. The objective of a penalty system should not only be to focus on preventing unsafe behavior, but also on the need to act efficiently to avoid potential slack or withdrawal behavior, which would raise new problems in construction （i.e. inefficient operations, labor loss and a poor safety climate） .

6.3.1. Non-Helmet Use Behavior : Cost and Benefit Analysis

Drawing on a widely-used rule in the construction industry known as Heinrich's Law: for every major accident that causes injury at a work station, there are 29 accidents that cause minor injuries and 300 accidents that cause no injuries (what are often termed 'incidents') (Geller 1990, Ward 2012). The probability of the accident rate has been set at 1/300 in this study. The probability of non-helmet use behavior being detected is $p(B)$. If workers choose not to wear a helmet during work time, it usually comes with two consequences. First, the non-helmet use behavior is found by supervisors or the Eye on Project, then, the targeted worker will be fined for violations according to the punishment mechanism (Swaen, Van Amelsvoort et al.). Secondly, if the non-helmet use behavior is not recorded, workers will be able to finish their essential work early to earn work time saved (ST). During conditions of high temperatures, working outdoors without a safety helmet will also make workers feel more comfortable (CW). Furthermore, managers will reward advanced schedule progress and workers will obtain extra rewards, which is defined as the prospect of reward (PR). However, non-helmet use behavior is always associated with negative benefits. Workers will suffer from the psychological stress of being punished by the construction regulations (PS). Furthermore, when workers act with poor safety, they will also be under the mental stress from the assessment of potential accident （PA）. As a record of poor safety performance, the economic effect on construction industries can be devastating after suffering from an accident (Sawacha, Naoum et al. 1999). Therefore, the economic loss (EL) also calculates negative benefits. All the variables mentioned can be categorized into two kinds of contributing factors: named Benefit (B) and cost (C), respectively. The details of the categorization can be seen in Table 6.1.

Table 6.1 The categorization of designated factors

	Factors ID	Contributory Factors
Benefit (B)	WTS	Working time saved
	CW	Comfortable working conditions
	PR	Prospect of reward
Cost (C)	PM	Punishment mechanism
	PS	Psychological stress
	PA	Potential accident
	EL	Economic loss

The equation of non-helmet use behavior benefits can be defined as:

$$B = [1 - p(B)] * PR + (1 - 1/300) * (WTS + CW)$$

In the same way, the equation of non-helmet use behavior cost can be defined as

$$C = (1 - 1/300) * (PS + PA) * PM + 1/300 * EL$$

Using the strengths of the behavioral decision theory, which was demonstrated by Lima and Dill (1990), an individual behavior selection process depends on the judgment stages of different behavioral gains. The emergence of construction workers' behavior is decided by the difference between non-helmet use behavior benefits and cost. When predicted behavioral benefits are greater than the predicted cost of the behavior, the construction workers tend to act safely. In contrast, workers will choose not to wear a helmet. Therefore, when benefit > cost, construction workers will pay attention to using the safety helmet. On the contrary, the probability of unsafe behavior will increase when benefit < cost.

The probability of non-helmet use behavior is adjusted by comprehensive factors during the actual simulation process (including the application of the intelligence helmet, punishment mechanism and safety supervisors' inspection level, etc.). Slack behavior and withdrawal behavior by construction workers is indicated by the work satisfaction level. Assuming that the initial score for work satisfaction is 20, the results of the questionnaire demonstrated that 0.14% of workers will tend to show withdrawal behavior and 0.57% of workers will show slack behavior when the work satisfaction score is lower than 1. When the work satisfaction level ranks from 1 to 2, the proportion of slack behavior reaches 0.16% and there is no withdrawal behavior. 0.1% of workers will show slack behavior when the satisfaction level ranks from 2 to 5, with no tendency of withdrawal behavior either.

6.3.2. Definition of the Interaction among Simulation Agents

The simulation system in this research is composed of dynamic interaction among heterogeneous agents. Simulation agents are one of the significant characteristics of ABM. The definition of agents designated in this agent-based model is: interaction among construction workers, an intelligence safety helmet, and supervisors and co-workers, which are elaborated as follows:

Construction workers

Workers will adjust their behavioral patterns to determine the boundaries of whether or not to carry out unsafe behavior based on the probability of other workers' unsafe behavior being found out. The change in behavioral patterns and the work satisfaction level will also be influenced by impeachment from co-workers, which will be explained in the following:

Intelligence safety helmet

If the intelligent safety helmet is turned on, real-time tracking can be achieved through the implementation of the Eye on Project and workers will be supervised during their whole work time. On the one hand, workers will show more compliance with the provision of helmet wear due to the non-helmet use behavior being recorded in real-time. On the other hand, workers will suffer from more psychological stress when equipped with the intelligent safety helmet.

Safety supervisor

The boundaries of supervisors depend on the number of supervisors and the inspection-range. Once supervisors' inspection is turned on, the safety supervisor will take on the responsibility of recording the non-helmet use behavior. The inspection-range varies from 1 to 20 m and the cognitive distance is investigated from the real construction site. Workers will adjust their behavior when the number of safety supervisors increases or the distance between safety supervisors and workers shortens. The sensitivity of workers will decrease when the range is extended. However, unsafe behavior will not be informed immediately and management for safety supervisors will be hysteresis.

Co-worker

When workers behave unsafely on a construction site, they will be faced with the possibility of being reported by co-workers. Therefore, the existence of potential impeachment within the group will influence and improve behavior due to the probability of a poor safety performance being detected. At the same time, the work satisfaction level will be lowered, which will lead to an increase in slack and withdrawal behavior, and further result in a high labor turnover rate.

6.4 Simulation Process and Results

The ABM system demonstrated above provides a general and customizable agent-based model for a behavioral pattern simulation of construction workers on site. Two experiments have been conducted to investigate the workers' behavioral patterns that emerge under different parameter combinations of punishment amount and supervision methods.

Experiment 1: The behavioral patterns emerge under different combinations of intelligent safety helmet use and impeachment from co-workers.

The punishment amount is the proportion of average income, which varies from 0% to 10% in increments of 0.5. Five feature points are selected for further investigation into the behavioral patterns. The safety supervisors' inspection level in the first experiment has been fixed at the lowest level. Since there are two possible outcomes for each logical variable (true or false), four combinations of these two safety supervision methods have been arranged. Table 6.2 demonstrates workers' behavioral patterns when the intelligent helmet and impeachment from co-workers operate simultaneously. Table 6.3 and Table 6.4 show the consequences of the unitary implementation of the intelligent safety helmet or impeachment from co-workers. The emergence of workers' behavioral patterns when both supervision methods are not required are shown in Table 6.5.

Table 6.2 Behavioral pattern under helmet on and impeachment on

Helmet ON & Impeach ON						
Behavioral pattern	Proportion of average income					
	0%	0.5%	1%	2%	5%	10%
Safe behavior	85.2	86.8	88.3	90.2	92.2	94.7
Unsafe behavior	11.8	9.2	7.3	5.2	2.3	0
Slack behavior	1.8	2.1	2.4	2.9	2.4	2.7
Withdrawal behavior	1.2	1.9	2	1.7	2.1	3

Table 6.3 Behavioral pattern under helmet on and impeachment off

Helmet ON & Impeach OFF						
Behavioral pattern	Proportion of average income					
	0%	0.5%	1%	2%	5%	10%
Safe behavior	83.9	86.2	86.3	87.1	87.9	89.7
Unsafe behavior	12.8	11.1	10.7	10.4	9.9	2.3
Slack behavior	1.9	1.6	1.8	1.3	1.2	4.1
Withdrawal behavior	1.4	1.1	1.2	1.2	1	3.6

Table 6.4 Behavioral pattern under helmet off and impeachment on

Behavioral pattern	Helmet OFF & Impeach ON Proportion of average income					
	0%	0.5%	1%	2%	5%	10%
Safe behavior	78.3	82.5	84.9	86.7	87.3	88.7
Unsafe behavior	12.2	11.8	9.9	8.2	7.9	1
Slack behavior	3.9	3.5	3.4	3.6	3.5	4.4
Withdrawal behavior	2.4	2.2	1.8	1.5	1.3	5.9

Table 6.5 Behavioral pattern under helmet off and impeachment off

Behavioral pattern	Helmet OFF & Impeach OFF Proportion of average income					
	0%	0.5%	1%	2%	5%	10%
Safe behavior	73.2	75.5	79.2	81.9	83.4	85.1
Unsafe behavior	23.1	19.9	15.5	11.8	9.5	2.7
Slack behavior	2.1	2.6	2.9	3.4	3.9	4.9
Withdrawal behavior	1.6	2	2.4	2.9	3.2	7.3

For investigating the effects of different parameters on combinations, the simulated result has been classified by behavioral patterns.

Figure 6.2 gives a detailed comparison of the safe behavior emergence proportion under different combinations of two supervision methods. As shown, the best safety performance can be achieved when both safety-supervision methods are adopted. This is followed closely by the combination of helmet on and impeach off. The proportions of safe behavior in both combinations are very close when the punishment amount is below 0.5% of the average income. If there is no intelligent safety helmet on the simulated construction site, the ratio of a single supervision method is approximately the same as when the punishment mechanism varies from 2% to 10%. Most workers have a worse safety performance when only the impeachment system is put into effect as an uncritical punishment. When no supervision methods are adopted, the simulation result shows the lowest safety behavior rate, which is almost 10 percent lower compared to the best safety performance. Furthermore, the proportion of safe behavior under all four combinations increases significantly with the enhancement of punishment. Therefore, the increase in the amount of punishment plays a crucial role in the improvement of safe behavior.

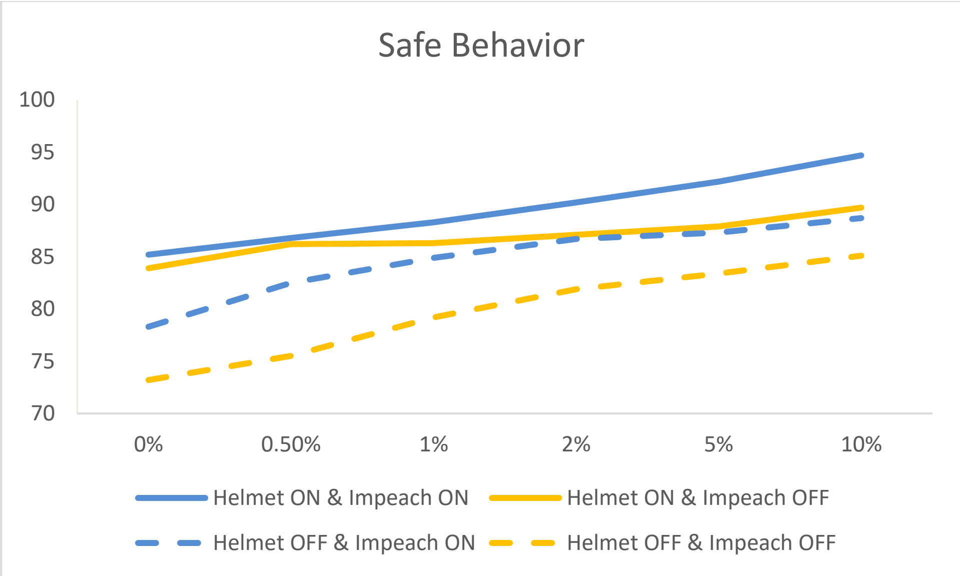

Fig 6.2 Behavior Patterns of Experiment 1-Safe Behavior

As can be seen in Figure 6.3, there is a dramatic decline in unsafe behavior when the punishment amount gradually increases. Moreover, no unsafe behavior occurs when workers face the highest amount of punishment under the existence of both supervision methods. The difference between the four combinations is mainly reflected in the range of 0% to 5%, which is when most unsafe behavior appears i.e. the intelligent safety helmet is turned off and co-workers choose not to report the violations. Compared with the high proportion under no supervision methods, the other three-parameter combinations show a similar rate when the punishment mechanism doesn't work and then fluctuates. At meanwhile, the proportion of unsafe behavior sharply declined when the punishment amount was over 5% of construction workers' average income.

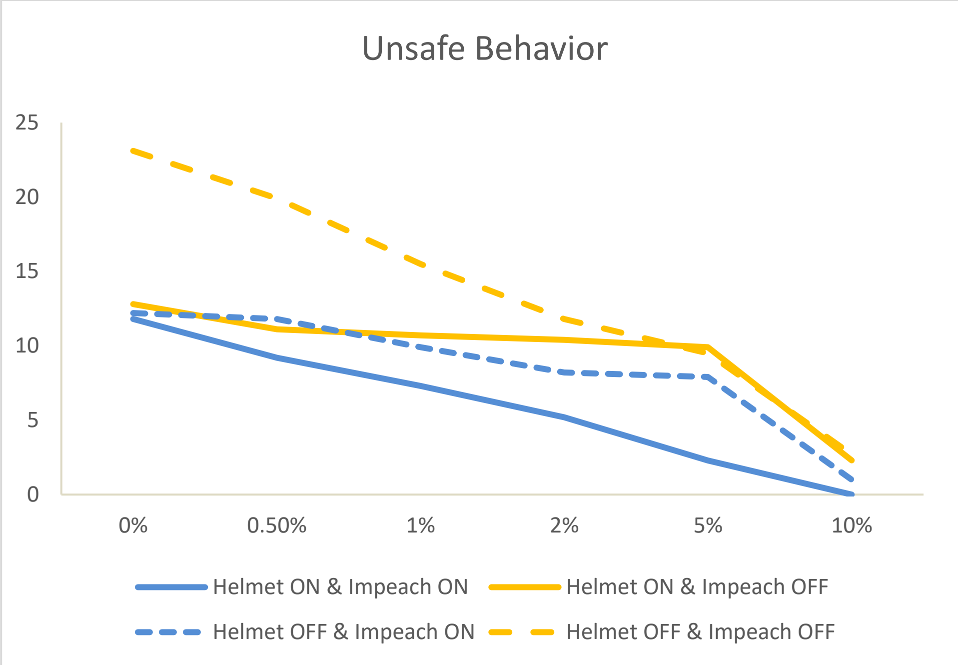

Fig 6.3 Behavior Patterns of Experiment 1-Unsafe Behavior

Figure 6.4 and Figure 6.5 show a similar tendency of slack behavior and withdrawal behavior. As can be seen in the figures, compared with the implementation of the impeachment system, the proportion of slack behavior and withdrawal behavior is lower overall when the intelligent safety helmet has been adopted. In contrast to safe behavior and unsafe behavior, when the two supervision methods coexist simultaneously, the proportion of both types of behavior is higher than the situation under a single supervision method. This mainly results from a lower work satisfaction level when the workers feel that they are being ‘watched’ all the time.

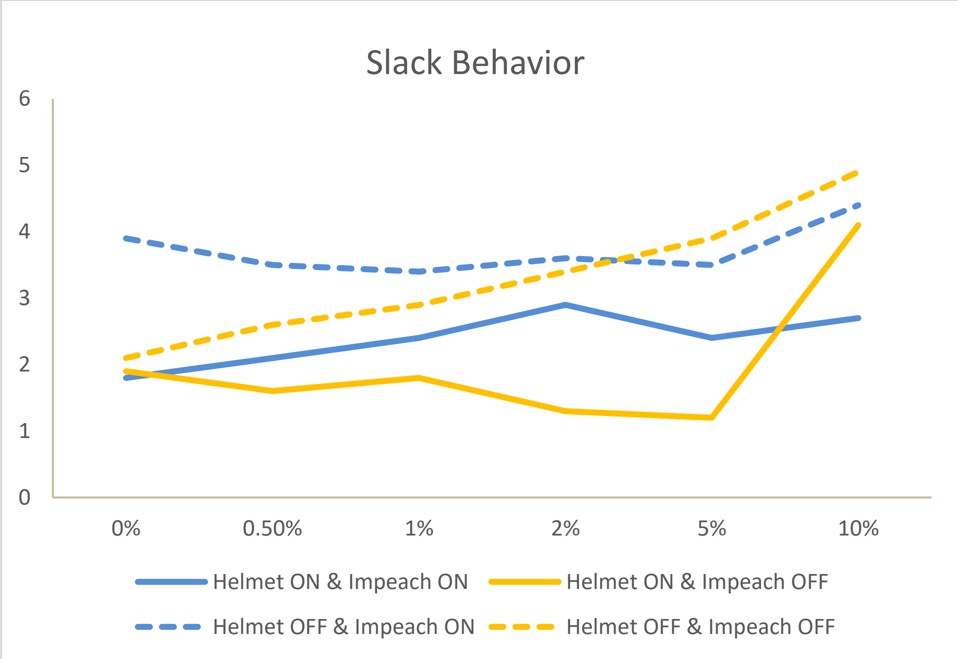

Fig 6.4 Behavior Patterns of Experiment 1-Slack Behavior

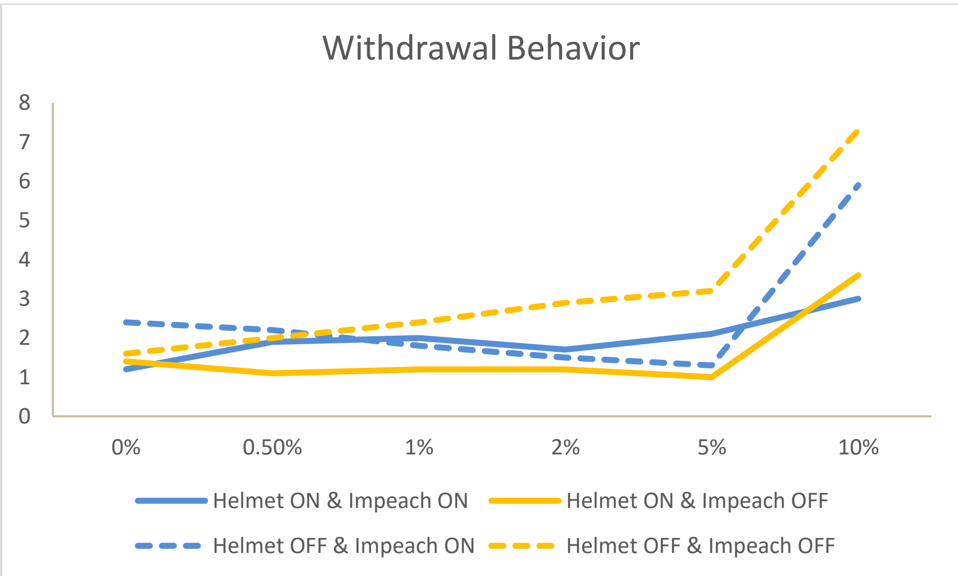

Fig 6.5 Behavior Patterns of Experiment 1-Withdawal Behavior

Experiment 2: The behavioral patterns emerge under different combinations of supervisors' inspection levels and punishment amounts.

The parameters of punishment amounts are the same as the first experiment.The number of construction workers was set to 100. To analyze the effect of safety supervisors on site, the designed section of this experiment takes no account of the intelligent safety helmet and impeachment from co-workers. The inspection level consists of the number of safety supervisors and the distance between the supervisors and workers. The number of supervisors varies from 1 to 10 in increments of 1 and the supervised range is varied from 1 to 20m in increments of 1m. Three inspection levels are selected for further investigation into the behavioral patterns: lowest level (two safety supervisors), medium level (five safety supervisors) and highest level (ten safety supervisors). The simulation results can be seen in Table 6.6.

Table 6.6 Behavioral pattern under three inspection levels

Proportion of average income / Behavior pattern	Lowest Level						Medium Level						Highest Level					
	0%	0.5%	1%	2%	5%	10%	0%	0.5%	1%	2%	5%	10%	0%	0.5%	1%	2%	5%	10%
Safe behavior	82.5	85.3	84.9	86.7	87.3	89.7	88.2	87.8	88.3	88.2	89.2	90.7	85.9	86.2	86.3	87.1	87.9	89.7
Unsafe behavior	13.1	9.8	9.9	8.2	7.9	3.3	9.4	9.1	8.2	8.3	7.3	2.2	7.8	6.2	5.7	5.4	4.9	2.3
Slack behavior	3.3	3.5	3.2	3.6	3.8	4.7	1.8	1.9	2.4	2.4	2.3	4.3	4.4	5.6	5.8	5.4	5.2	2.8
Withdrawal behavior	1.1	1.4	2	1.5	1.0	2.3	0.6	1.2	1.1	1.1	1.2	2.8	1.9	2	2.2	2.3	2	5.2

These findings are further explained in Figures 6.6 to 6.9, which extensively show the proportion of behavioral patterns under different combinations of parameters. As shown in Figure 6.6, the proportion of safe behavior under all three inspection levels generally increases as the punishment follows the upward trend. The best safety performance was achieved at the medium inspection level. Under these circumstances, 90% of workers chose to act safely when facing the highest amount of punishment. When there are only two supervisors, the workers show a poor awareness of safety, especially under a low amount of punishment. However, when the punishment amount is over 2% of the average income, the lowest inspection level and highest inspection level play the same role in safety management.

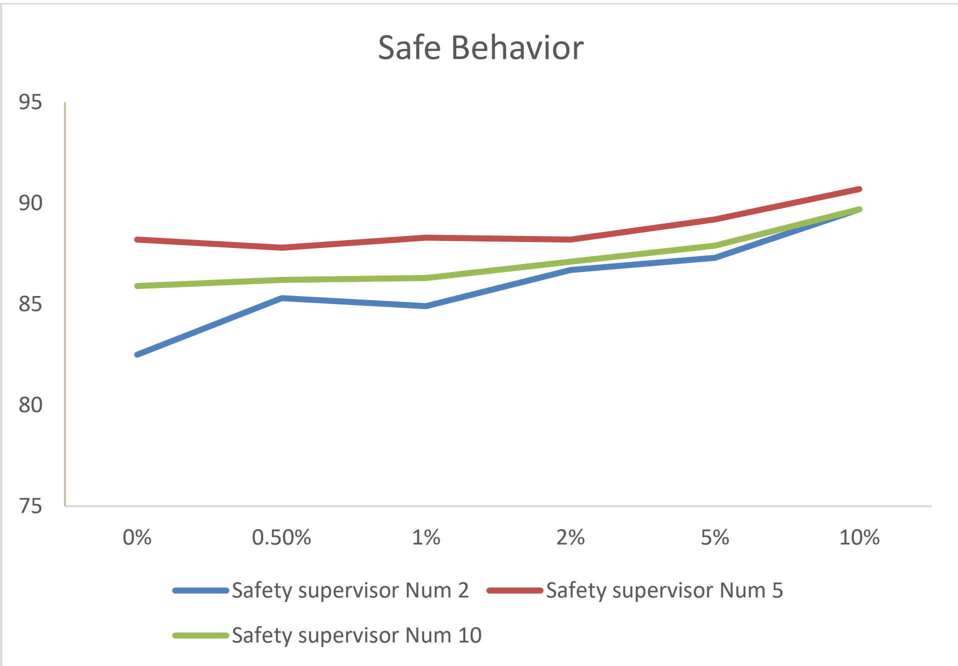

Fig 6.6 Behavior Patterns of Experiment 2-Safe Behavior

Figure 6.7 demonstrates the variation tendency of unsafe behavior patterns. Following an increase in the punishment amount, the unsafe behavior showed a downward trend overall. This means that inspection levels showed a strong correlation with the improvement of safety performance and reflected this achievement by strengthening the supervised level. A worse safety record was performed under a low and medium level, and the unsafe behavior was significantly less when having a high inspection level.

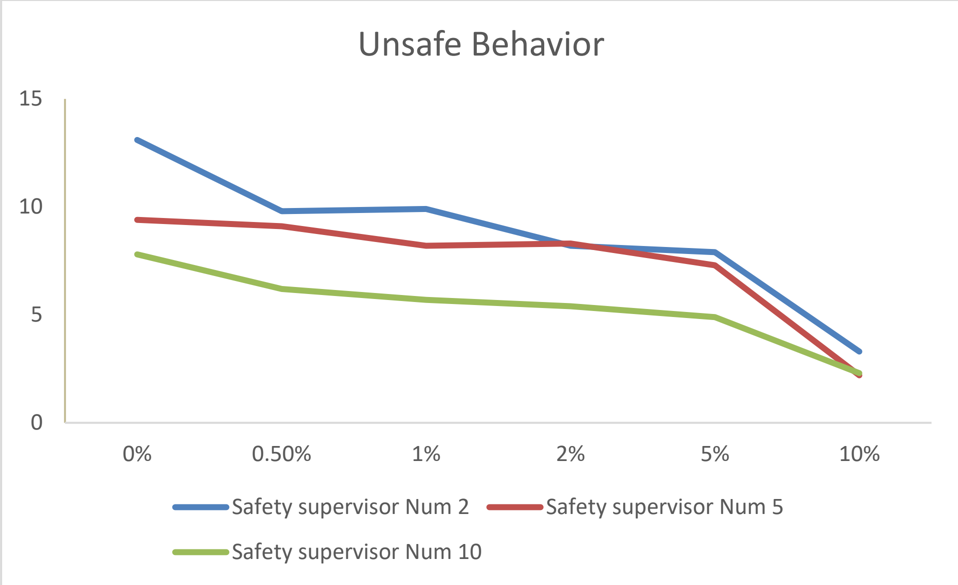

Fig 6.7 Behavior Patterns of Experiment 2-Unsafe Behavior

The tendency for slack behavior and withdrawal behavior shows a negative correlation with the increase in the number of safety supervisors. When the punishment amount is less than 5% of the average income, although workers will be more inactive and want to withdraw with the strengthening of inspection, this only accounted for a minority of workers and has little influence on the safety performance. However, once the punishment is over 5% of the average income, there is a noticeable growth in two behavioral patterns. Despite a reduction in slack behavior under the highest inspection level, the proportion of people withdrawing reached nearly 6%, which leads to a potential deterrent to a safety climate.

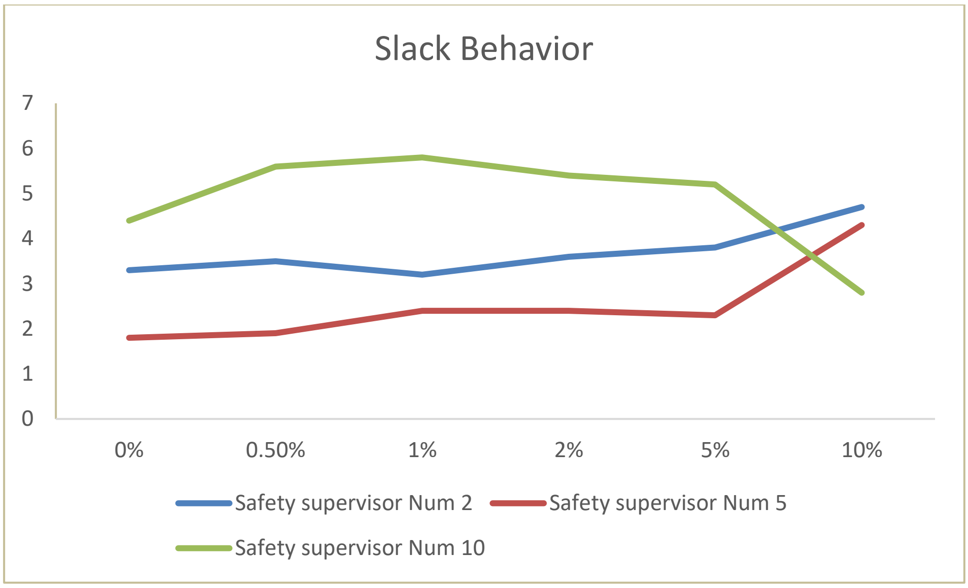

Fig 6.8 Behavior Patterns of Experiment 2-Slack Behavior

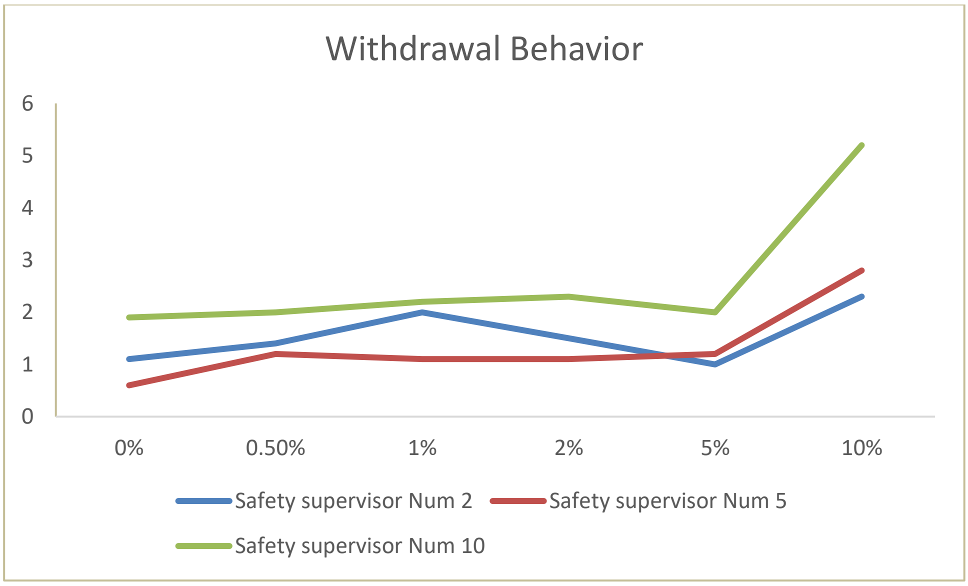

Fig 6.9 Behavior Patterns of Experiment 2-Unsafe Behavior

6.5 Chapter Summary

This charpter has developed a method to monitor construction workers' helmet misuse behavior in which ABM was integrated with real-time experimental data and questionnaire survey data. The proposed agent-based modeling (ABM) simulatied the construction workers' behavioral patterns under the impacts of punishment system and supervision method to understand the dynamics in reasoning. Compared with the safety supervisors' observations and impeachments from co-workers, workers paid more attention to safety wearing the intelligent helmet that recording real-time non-helmet-use behavior. The behavioral patterns, not only safety and unsafe behaviors but also existing slack behavior and withdrawal behavior, lead to negative results in construction management. Neglecting to wear a safety helmet can result in serious injuries on construction sites, yet the intricate causes of such unsafe behavior have not been understood. Eye-on-Project system revealed great potential in mitigating non-helmet-use behaviors and negative influences of punishment system and supervision method.

Chapter 7. CONCLUSION

7.1 Summary of Major Findings

This study aims to use both empirical and simulation methods to develop a comprehensive research on understanding and controlling non-helmet use behavior on construction sites. To achieve this research aim, both questionnaire data and real-time data, facilitated by the Eye on Project (EOP) system, were collected and analyzed to sequentially investigate: (1) the impact of individual factors on non-helmet use behavior; (2) the impact of safety climate and productivity pressure on non-helmet use behavior and; (3) the impact of a punishment system and supervision methods on workers' behavioral patterns. The major findings of these investigations are demonstrated as follows:

(1) With regards to the impact of individual factors on non-helmet use behavior, the contributory factors influencing non-helmet use on construction sites has been successfully investigated. This study specifically provides an association-rules based approach for working out the relationship between the contributing factors and non-helmet use behavior. The hidden relationship between non-helmet use behavior and contributary factors have been identified. This proposed approach not only provides an effective method for identifying factors related to unsafe behavior on construction sites, but also develops a more efficient and accurate risk assessment strategy. The final analysis of data mining results will be used to provide and stipulate safety rules on construction sites. The findings could help to establish a risk assessment matrix between leading factors and non-helmet use behavior, and advise construction managers or workers on how to prevent the causality patterns.

(2) Taking into consideration the impact of safety climate and productivity pressure on non-helmet use behavior, this study further presents an SD model to understand the feedback mechanisms involved in the misuse of helmets under positive actions (i.e., safety training, communication and inspection) and negative

components of workplace stress on the safety climate of construction sites. It explores the causes of non-helmet use behavior involving the project, management and individual levels, instead of simply considering individual or organizational factors adopted in previous research. The developed SD model is able to identify appropriate measures for improving the safety culture on construction sites, for example, safety training and communication is found as being more effective than simple reactive actions such as increased safety inspections.

(3) In relation to the impact of punishment systems and supervision methods on workers' behavioral patterns, this paper successfully provides a better understanding of the effectiveness of multiple supervision methods and punishment amounts on non-helmet use behavior based on the agent-based simulation method. A distinct characteristics of this study is that the investigated behavioral patterns not only include safe and unsafe behavior, but also slack and withdrawal behavior which will also produce negative results in construction management. The simulation results reveal that both punishment and supervision are effective methods in reducing unsafe behavior and can be used as a management tool in practice. However, project managers should try to avoid the negative influences of excessive punishments and supervision.

7.2 Contributions

The main contributions practical implications of this study are as follows:

Firstly, this study has empirically investigated the causality patterns of the non-helmet use behavior of construction workers by proposing an association-rules based approach. . The proposed method can be utilized to assess risks in the workplace quantitatively. An important consideration concerns the use of the results of the two dimensions, frequency and duration, to explore the characteristics of workers who easily neglect helmet use and to make decisions that improve their safety and prevent the occurrence of fatal injuries. With the help of these matrices, the common characteristics of workers with poor safety performance levels can be centralized.

Secondly, the proposed SD simulation model illustrates the dynamic and interactive relationship between safety climate and non-helmet use behavior in feedback loop diagrams. Following its calibration and validation by comparing the simulated and actual rate of helmet misuse per worker, the model is used to demonstrate how the negative impact of productivity pressure on the safety performance under a variety of safety climate policies. Understanding the relationship between non-helmet use behavior and safety climate under workplace stress also helps to reduce the gap between system theory and construction practice. Meanwhile, the model described in this paper provides a general and customizable agent-based model for a behavioral pattern simulation of construction workers on site. This has also provided a simulation model for managers to conduct experiments to predict the effectiveness of each option.

Thirdly, Another characteristic of the present study lies in the use the EOP system to collect the objective and real-time data on the non-helmet use behavior of construction workers. The real-time tracking safety helmet can identify and store the data by monitoring real-time non-helmet use behavior and thus improve the reliability of the analysis results of the present study, which is different from previous studies based on subjective or post-accident behavior data retrieved from questionnaire surveys or accident reports. The findings of the present study have also demonstrated the potential of the EOP system in improving construction safety culture and morale, which can contribute to a wide use of the system to monitor and train the safety-related behaviors of on-site construction workers in the future.

7.3 Limitations and Future Research Directions

This study also has several limitations that could be addressed in future research. Currently, the real-time EOP system used in the study can only identify the non-helmet use behavior data and as well as the information on the age, gender and individual experienceof the monitored construction workers. However, several other important factors, such as the real-time location of the construction workers, can not be identified at present and are thus not included in the study. Through integrating the EOP system with other technologies (such as real-time location technologies), future studies can attempt to more comprehenvevely monitor and analyze the unsafety behaviors of on-site construction workers.Another limitation of the present study relates to the sample size of the empirical data, which was collected only in the context of the Chinese construction industry. Based on the research method provided in the present study, future research could collect larger-scale data in more diversified cultural and institutional contexts to further validate the findings of this study.

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