Table 1. Simulation configuration.

Case	*$\Phi_{1/2}$ and FOV (degree)*	*No. of LED*	*Coordinates of LED*
1	60	3	(2,2), (4,2), (3,4)
2	70	3	(2,2), (4,2), (3,4)
3	60	4	(2,2), (4,2), (2,4), (4,4)
4	70	4	(2,2), (4,2), (2,4), (4,4)
5	60	5	(2,2), (4,2), (2,4), (4,4), (3,3)
6	70	5	(2,2), (4,2), (2,4), (4,4), (3,3)

DISCUSSION. The analysis is conducted on 6 different cases. Figure 4 depicts the positioning error for each case. Positioning error of 0 indicates the points where localization was failed. As can be shown, the lower value of $\Phi_{1/2}$ and FOV results in the inability of the VLP system to solve the triangulation problems in some areas since RSS measurement by at least three LED is not obtained. The positioning error of corner sides is higher compared to center points since the deployment of lights in the corner points is less dense.

In table 2, the result of simulation for each case is provided. For the lower bound of $\Phi_{1/2}$ and FOV (60 degree), increasing the number of lights can increase the coverage area significantly, while on the other hand, the higher bound of $\Phi_{1/2}$ and FOV can almost support the localization in the whole room even with the minimum number of 3 LEDs. The comparison of each case with similar transmitter configuration and different hardware parameter shows that the performance of the VLP system is largely dependent on the values for $\Phi_{1/2}$ and FOV. One of the performance metrics of a positioning system is scalability (Liu et al. 2007) which ensures the normal performance of positioning even in large scales. The result indicates that the scalability of a VLP system can be largely affected by the selection of these hardware parameters. In the last column, since the covered area for case 1, 3, and 5 is small and thus not representative, the 95th percentile accuracy is omitted.

Table 2. Performance evaluation in different cases

Case	*$\Phi_{1/2}$ and FOV (degree)*	*Percentage of covered area by VLP*	*95th percentile accuracy (cm)*
1	60	52.8	(Not representative)
2	70	99.7	6.2
3	60	61.6	(Not representative)
4	70	≃100	5.7
5	60	89.1	(Not representative)
6	70	100	4.4

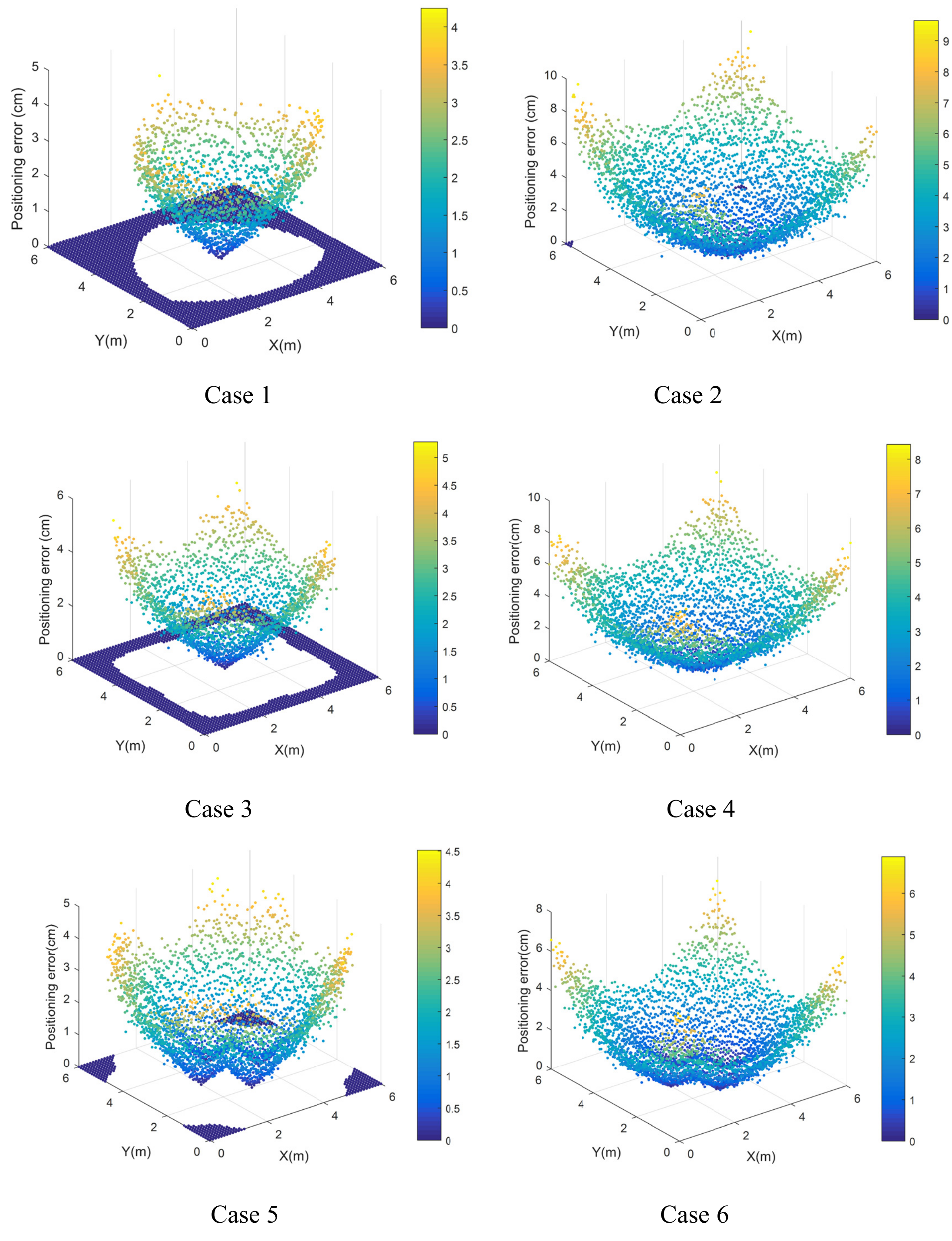
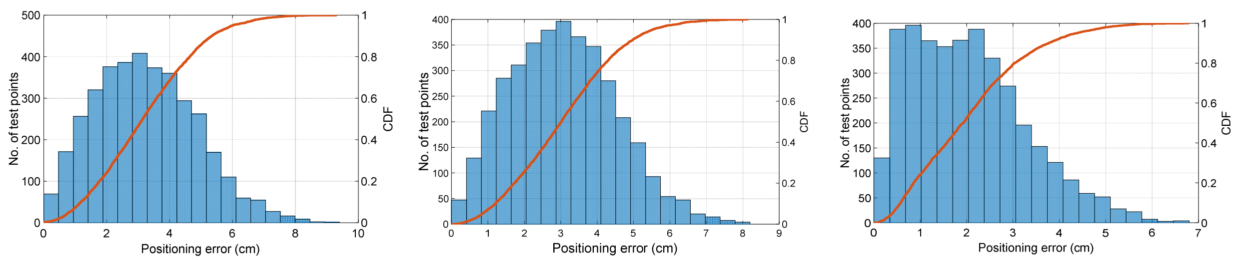


Figure 4. Positioning error and covered area of localization in different cases

In figure 5, the CDF functions, and the histogram plots for case 2, 4, and 6 which represent the cases with 100 percentage of covered area are provided.



a) Case 2 b) Case 4 C) Case 6

Figure 5. Comparison of histogram and CDF for different number of LEDs

LIMITATION. Although the multipath propagation effect in a VLP system, unlike RF-based approaches, is not a major concern, the reflection component of light from objects, walls, and human can deteriorate the accuracy of the system. In this study, the direct line of sight is assumed between the transmitter and the receiver, and the reflection component is not considered. However, this issue is going to slightly affect the accuracy (Li et al. 2014) and not the trilateration algorithm for the coverage ability of the system studied here. Moreover, the receiver is assumed to be perpendicular to the ceiling, and the effect of small tilting angle which can increase the error is not included in the model.

CONCLUSION

Location information of the occupants in indoor environment can improve context-aware applications and provide location-based service. Recent achievements in the field of data communication through LED lights have defined applications, such as indoor positioning. In this paper, the scalability of a LED-based positioning system for a typical office environment was studied. The performance of the system was evaluated through using a trilateration positioning method in different cases with different number of lightings, and specific hardware parameters of LED lights and the receiver. The results show that the scalability of the system is mainly affected by the hardware parameters, and fine-grained location detail can be obtained by ensuring the scalability of the system.

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Modeling the Effect of a Socio-Psychological Process on Construction Workers' Safety Behavior

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Abstract

Although the vast majority of construction accidents are caused by workers' unsafe behavior, the management of safety behavior remains inadequate. To reduce unsafe behaviors, construction managers have mainly relied on external formal controls (e.g., penalties) to prevent a violation of safety rules. However, a number of studies recently demonstrated that social factors such as group norms and social identification play a critical role in shaping workers' safety behavior. Although previous studies have illuminated the social aspect of safety behavior, there is a noticeable paucity of research addressing the mechanism that underlies the link between cognitive process, social influence, and safety behavior. To address this issue, this study aims to understand the effect of workers' socio-cognitive processes on their safety behavior using experimental analyses with computer simulations. An agent-based model was developed to perform experimental analyses by incorporating the theoretical cognitive model of safety behavior and empirical finding regarding social influence. Then, model experiments were conducted to explore the effect of the interaction between the socio-cognitive process and different management interventions on workers' safety behaviors. The results indicate that frequent managerial feedback has a positive but limited influence on workers' safety behavior. In addition, it was also found that workers' safety behavior can be further improved by combining the strict managers' risk acceptance and stimulation of workers' project-based identity. This study contributes to the body of knowledge on construction safety by modeling the socio-cognitive mechanism of safety behavior and exploring how the mechanism interacts with different management interventions.

INTRODUCTION

Despite continuing efforts to reduce the number of accidents, construction remains one of the most dangerous industries in the United States. In 2014, 874 fatal occupational injuries within construction were reported, which is the highest number of all the industries (BLS 2015a). While the construction industry employs 4.1% of the national workforce (BLS 2015b), it accounts for 18.7% of all fatalities in 2014 (BLS 2015a). From the perspective of accident investigation, workers' unsafe behavior has been widely proven to be the leading cause of construction accidents (Hinze 2006). The unique characteristics of the construction industry, however, make it very challenging to improve workers' safety behavior using external formal controls such as penalties. Since all construction projects vary regarding design, location, participants, etc., work conditions differ from one project to another project. Also, the progress in construction projects makes complex and dynamic changes in work condition. Therefore, it is very difficult to establish standardized work procedures and safety rules that cover all the complex and dynamic situations in construction projects (Andersen et al. 2015). Given these limitations of external controls, researchers recently have paid more attention to understanding how workers' unsafe behaviors are produced.

RELATED WORKS

There has been an interest in research that seeks to understand workers' unsafe behavior as the result of human error. Human error is defined as "the misjudgment or inappropriate decision in the cognitive process" (Chi et al. 2013). In this vein, unsafe behavior can be interpreted as the results of workers' inability to adequately perceive and respond to risk in the workplace. If workers underestimate the risk or assess the perceived risk as an acceptable one, workers will perform an unsafe behavior. The risk perception and risk assessment also have been included in the cognitive model of preventive health behavior. Considering that an individual's health behavior is a reaction to potential health risk, individuals' health behavior, much like workers' safety behavior, is a response to potential dangers in the workplace. The health belief model and protection motivation theory noted that an individual's likelihood to take recommend preventive health action is influenced by his/her perceived risk of diseases and perceived benefits and barriers of the recommend behavior (Rogers 1975). The links between risk perception and safety behavior and between risk assessment and safety behavior have been tested in previous studies (Wang et al. 2016).

Since workers are working in a social environment, cognitive processes and behaviors would be affected by others. Many researchers noted that workers' safety behaviors are subjective to group-level informal controls (Choudhry et al. 2007). Social norms refer to shared perceptions of what is acceptable behavior or what is not acceptable in a group (Bendor and Swistak 2001). The shared perceptions in an organization are shaped by interactions among the organizational members. Interactions occur not only between workers but also between workers and management (Fang et al. 2015). Workers perceive acceptable unsafe behaviors in the current project by observing the action of management as well as coworkers (Choi et al. 2016). In the same vein, recent researchers have suggested multilevel social influence models which consist of the organizational level and workgroup level (Zohar 2000).

Changes in behavior driven by social influence can be explained by individuals' social identification process. The social identity theory posits that when people strongly identify with a specific group, they try to conform to the group norm because they regard themselves as a representative of the group (Ashforth and Mael 1989). Social identity theorists identified this mechanism as the most fundamental way in which social norms affects behaviors. Choi et al. (2016) proposed and tested a theoretical model that incorporates multilevel social influence (i.e., management and workgroup norm) and social identification process (i.e., project identity) in construction workers' safety behavior context. The results showed separate impacts of workgroup and management norms on workers' safety behavior. Also, workers' social identification with their project intensifies the relationship between management norms and safety behavior and attenuate the association between workgroup norm and safety behavior.

Although previous studies have examined workers' unsafe behavior, there is a noticeable lack of research addressing the mechanism that underlies the link between cognitive process, social influence, and safety behavior. The few studies that have proposed a theoretical model of the cognitive process have not investigated how the cognitive process interacts with the environment. Additionally, previous social influence studies have not uncovered the underlying process of social influence emerging from an individuals' interactions in an organization. Furthermore, there is a limited understanding of how workers react and which group-level phenomena will emerge when different safety management interventions are implemented.

To fill this knowledge gap, this study adopted an Agent-Based Modeling (ABM) which has advantages in generating complex and social phenomena as emerging from individual's interactions in an organization (Macy and Willer 2002). The ABM aims to bridge between micro level of cognitive process, an individual's interactions in an organization, and its impact on safety behaviors. In addition, the thought experiments (Macy and Willer 2002) are conducted to explore the impacts of different safety management interventions on workers' safety behaviors.

MODEL DEVELOPMENT

A set of agent behavioral rules in ABM that incorporate the cognitive process and social influence is summarized in Figure 1.

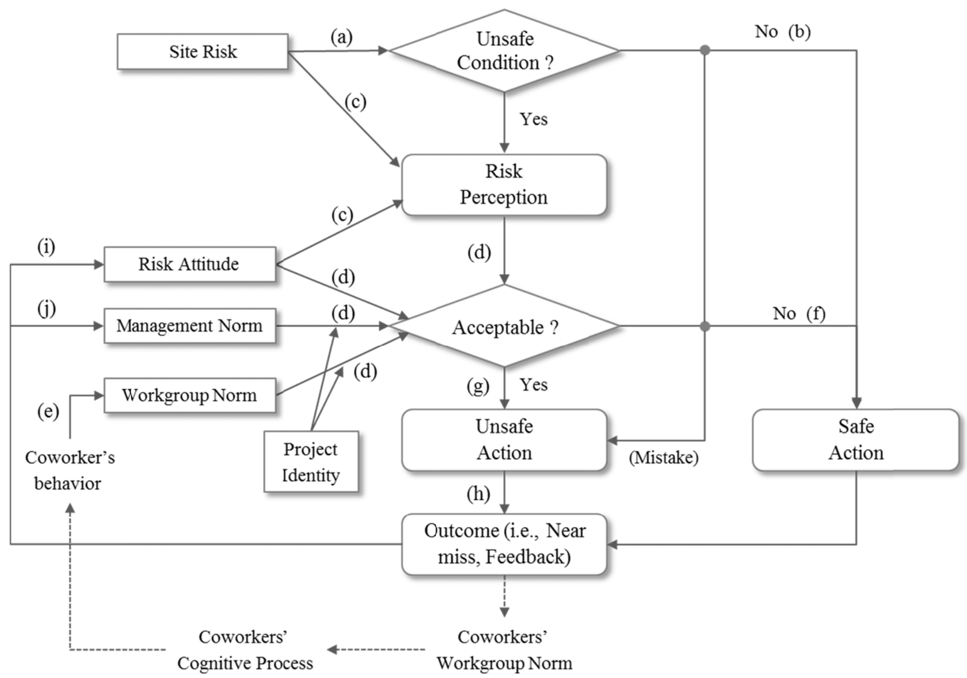


Figure 1. Agent Behavioral Rules

First, an agent (i.e., worker) is provided with a work condition (i.e., safe or unsafe condition). The probability of being under the unsafe condition is determined by the level of site risk (a in Figure 1). The site risk refers to the degree of hazard with the range between 0 and 1 that includes a probability of being exposed to the unsafe condition and the severity of the risk of the unsafe condition. If a worker is under the safe condition and does not make a mistake, he/she will perform the safe action (b in Figure 1). In the case of an unsafe condition, the worker perceives the risk and establish his/her judgment regarding the perceived risk. The risk perception is a subjective assessment of a particular danger that can differ from worker to worker even if both are experiencing the same situation (Hallowell 2010). The subjective risk perception tendency is called the risk perception coefficient, and it is affected by risk attitude (c in Figure 1). If a worker has risk-seeking attitude, the risk perception coefficient will be below 1.0 because the risk-seeking workers underestimate risk around them. Also, even if two workers perceived the same amount of risk, they may have different assessments of the same risk. This is because some workers are willing to accept the perceived risk while others are reluctant to accept the risk. The empirical findings from Choi et al. (2016) are incorporated to determine workers' risk acceptance in this model. As shown in the Equation (1), workers' risk acceptance is influenced by risk attitude, management norm, and workgroup norm. Also, the project identity moderates the association between management norm and risk acceptance and between workgroup norm and risk acceptance (d in Figure 1).

$$RA_i^{(t)} = (1 - w_i)AT_i^{(t)} + w_i\left(pj_i MN_i^{(t)} + (1 - pj_i)WN_i^{(t)}\right) + \varepsilon \qquad (1)$$

Where $RA_i^{(t)}$ is worker i's risk acceptance at time t, $AT_i^{(t)}$ is worker i's risk attitude at time t, $MN_i^{(t)}$ is worker i's management norm at time t, $WN_i^{(t)}$ is worker i's workgroup norm at time t, w_i is worker i's weight on social influence, and pj_i is worker i's project identity.

The management norm refers to workers' perception of managers' risk acceptance. The workgroup norm refers to workers' perception of coworkers' risk acceptance. If a worker observes a coworker's unsafe action in a certain situation, the worker interprets that coworker's risk acceptance as greater than the current risk. If the worker observes the safe action, his/her perception of the coworker's risk acceptance will be lower than the current risk (e in Figure 1). If the perceived risk is not acceptable and the worker does not make a mistake, the worker performs a safe action (f in Figure 1). If the perceived risk is acceptable, the worker performs an unsafe action (g in Figure 1) and it either results in a near miss, or nothing happens (h in Figure 1). The probability of a near miss depends on the severity of the risk which is determined by the site risk. If a near miss occurs, the worker becomes more risk-averse because he/she realizes the possibility of the accident. However, if nothing happens, the worker become more risk-seeking due to the optimistic recovery (Shin et al. 2014) (i in Figure 1). Also, the worker's unsafe action can receive feedback from the managers based on the strictness and frequency of managers' feedback. Workers will not receive feedback from managers if the encountering risk is lower than managers' risk acceptance. In this case, the worker regards the perceived risk as acceptable in the current project and adjusts management norm. If the encountering risk is greater than managers' risk acceptance, the probability of receiving feedback from managers will be determined by the frequency of the feedback. The feedback from manager makes worker's perception of management norm stricter (j in Figure 1).

EXPERIMENT

In order to investigate how the socio-cognitive mechanism of safety behavior interacts with different safety management interventions, impacts of three parameters (i.e., strictness of managers' risk acceptance, the frequency of managers' feedback and project identity) on the safety behavior were explored. Those three parameters represent various managerial interventions for improving workers' safety behavior at a construction site. The range of managers' risk acceptance and feedback frequency is determined from 0.5 to 0.9, thus excluding excessively lenient risk acceptance and infrequent feedback from managers, both of which fail to reflect safety management practices. However, the project identity had a broad range of value (i.e., 0.1 to 0.9) in the experiment.

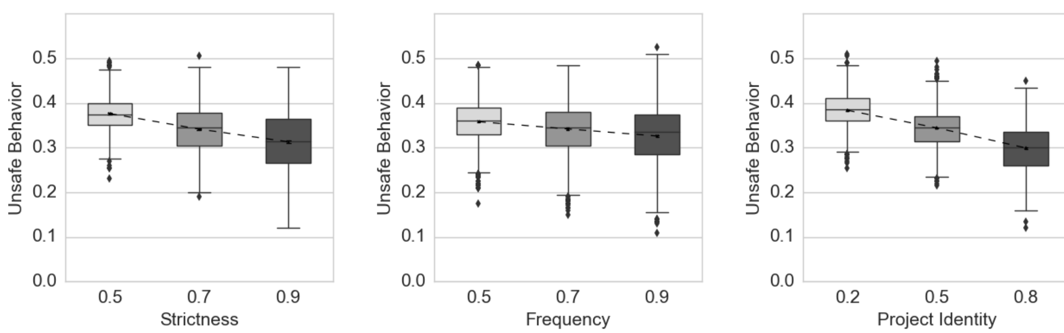
Common settings of other parameters for simulations are represented in Table 1. In this model, construction project with 20 crews, each of which has 10 workers, is simulated. Every worker can observe all other members within a crew, but they have only a slight chance to exchange social influence across crews (Ahn et al. 2013). The value of weight on social influence is driven by the results of Choi et al. (2016). The value for the risk perception coefficient and initial risk attitude is randomly assigned based on the uniform distribution to reflect the heterogeneity of the individuals. The mean of risk perception coefficient is determined less than 1.0. because people tend to underestimate the external conditions and overestimate their capability to control or prevent accidents (Wang et al. 2016).

Table 1. Common Settings for Simulations

Parameter	Setting	Description
Number of workers	200	10 crews x 20 workers
Simulation days	150	150 days
Site risk	0.5	Modest level of site risk
Probability of network connection between workers	Within crew: 100%	Everyone in one crew can observe each other
	Across crew: 3%	Workers have a small chance to observe across crews
Risk perception coefficient	Uniform distribution [0.6, 1.2]	w_i in Equation (1)
Initial risk attitude	Uniform distribution [0.1, 0.9]	Varied risk attitude ($AT_i^{(t)}$ in Equation (1))

RESULT AND DISCUSSION

The experiment runs thirty simulations for each configuration of the three parameters, totaling 21,870 individual simulation runs. Figure 2 and 3 represent the result of the experiments. Figure 2 illustrates the direct impact of the three safety management interventions on workers' safety behavior. The Kruskal-Wallis test, which is a non-parametric mean comparison method, is conducted. As shown in Figure 2, all the interventions reduce workers' unsafe behaviors.

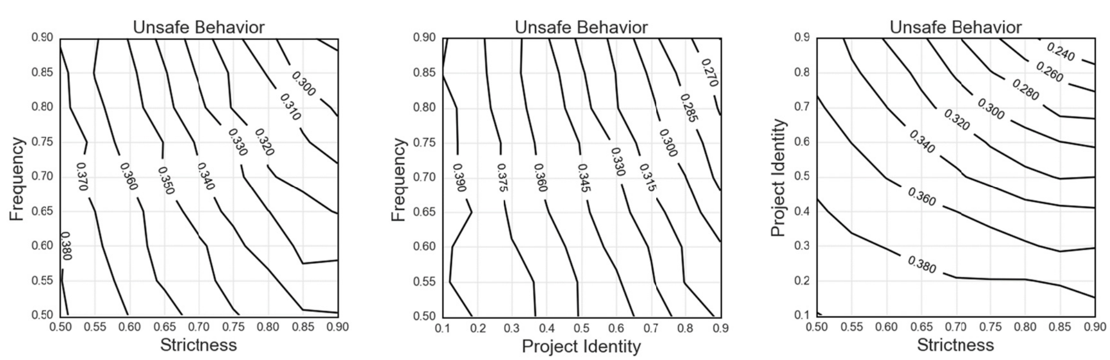


(a) Strictness (b) Frequency (c) Project Identity

Figure 2. Direct Effect of Management Interventions

First of all, there are significant differences in the mean of unsafe behavior in each level of strictness (*Mean*(High) = 0.313, *M*(Medium) = 0.342, *M*(Low) = 0.376, H = 594.31, $p < 2.90 \times e^{-16}$). The result implies that the strictness of managers' risk acceptance is directly related to workers' perception of management norms because workers receive more feedback from managers if the managers have stricter risk acceptance. Also, the mean of unsafe behavior in each level of feedback frequency varies significantly and exhibits meaningful differences (*M*(High) = 0.326, *M*(Medium) = 0.342, *M*(Low) = 0.358, H = 58.60, $p < 1.94 \times e^{-14}$), although the mean differences are less than the previous intervention. More frequent feedback makes workers' perception of management norm more aligned with managers' risk acceptance because workers have more chances to be aware of managers' risk acceptance (Neal et al. 2000). Finally, the mean of unsafe behavior was once again found to be significantly different for each level of project identity (M(High) = 0.299, M(Medium) = 0.344, M(Low) = 0.384, H = 887.17, $p < 6.03 \times e^{-19}$). The stimulation of workers' social identification with the project can lead workers' risk acceptance to be more aligned with management norm because workers' social identification with their project intensifies the relationship between management norm and safety behavior and diminishes the association between workgroup norm and safety behavior (Choi et al. 2016). Since the project identity has a broader range than other parameters (i.e., strictness of managers' risk acceptance and frequency of managers' feedback), the project identity shows greater mean differences than other parameters.

Figure 3 represents the effects of interactions between the safety management interventions. Figure 3(a) shows the result of a parameter sweep between the strictness of managers' risk acceptance and frequency of managers' feedback. The x-axis indicates the strictness, and the y-axis represents the frequency. The contour line represents the level of unsafe behavior. As shown in Figure 3(a), while a strong negative relationship is found between the strictness and unsafe behavior, the relationship between frequency and unsafe behavior is not salient. The impact of frequency on unsafe behavior seems trivial in low strictness condition, but it comes more salient in high strictness condition. Figure 3(b) shows the result of parameter sweep between the project identity and frequency. The result demonstrates that although the direct effect of frequency was significant, the impact becomes limited when it is combined with project identity. The result of the parameter sweep between the strictness and project identity is presented in Figure 3(c). The result shows the significant interaction effects between the strictness and project identity. The impact of strictness on unsafe behavior becomes stronger as the project identity increases and vice versa. In low project identity condition, stricter managers' risk acceptance cannot elicit behavioral changes in workers' safety behavior because workers are reluctant to follow the managers' feedback. The stricter managers' risk acceptance would be effective in high project identity condition because workers are more willing to be aligned with managers' feedback with strong project identity. The relatively limited effect of frequency indicates that managers establishing strict risk acceptance and promoting workers' social identification with their project should be given priority to improving workers' safety behavior. Considering that managers in construction projects already have somewhat strict risk acceptance, and construction workers' social identification with their project is relatively weak, promoting workers' project identity has immense potential to improve workers' safety behavior.



(a) Strictness (b) Frequency (c) Project Identity

Figure 3. Effects of Interactions between Management Interventions