

A VALIDATION FRAMEWORK FOR CONSTRUCTION WORKERS' UNSAFE BEHAVIOR MITIGATION MEASURE USING AGENT-BASED MODELING AND EMPIRICALLY TRAINED LARGE LANGUAGE MODELS

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ABSTRACT: Unsafe behavior among construction workers is a major cause of construction site accidents. Despite extensive research on identifying its causes and developing mitigation measures, validating these strategies remains challenging due to practical and theoretical barriers. This study proposes a validation framework integrating agent-based modeling (ABM) with large language models (LLM) to simulate and evaluate unsafe behavior mitigation measures. Since unsafe behavior results from complex interactions among multiple factors, effective validation requires a simulation that replicates these interactions. ABM is widely used for modeling agent behaviors, but defining accurate behavioral rules remains a challenge. LLM, trained on vast text data, can generate context-aware, human-like decision-making processes, offering a solution to this limitation. By integrating empirically trained LLM-driven agents with ABM, this study develops a simulation framework to evaluate unsafe behavior mitigation measures. The decision-making model of intentional unsafe behavior, based on the Theory of Planned Behavior (TPB), was first validated through survey data. A hypothetical mitigation method was then formulated and tested using the LLM-ABM simulation. Results demonstrate that measures derived from the validated model effectively reduce intentional unsafe behavior. This framework provides a novel methodology for validating safety interventions, addressing the long-standing challenge of assessing mitigation measures' effectiveness in construction safety research. Future researchers can adopt this approach to enhance the reliability of mitigation measures before real-world implementation.

1. INTRODUCTION

The construction industry is widely recognized as one of the most hazardous industries. According to the International Labour Organization (ILO), 5,486 fatal occupational accidents occurred across all industries in the United States in 2022. Among these, approximately 20% (1,092 cases) took place in the construction industry (ILO, 2023). This high proportion of construction-related fatalities is not unique to the United States. In South Korea, 2,016 fatal occupational accidents occurred in 2023, with 486 cases (about 24%) recorded in the construction industry (KOSIS, 2023). Research has identified unsafe behavior among construction workers as a major cause of accidents. Salminen and Tallberg (1996) reported that more than 80% of construction site accidents result from unsafe behavior by workers. Unsafe behavior is defined as “any action by a worker that deviates from safety regulations or rules” (Derdowski and Mathisen, 2023).

Unsafe behavior can be categorized based on the worker's intention. Unintentional unsafe behavior occurs without the worker's intention, typically due to cognitive failure or routine lapses. In contrast, intentional unsafe behavior (IUB) occurs with deliberate intent, often driven by various factors such as inefficiency or the cumbersome nature of safety equipment (Reason, 1990). Since IUB is intentional, a decision-making process precedes its occurrence. Therefore, understanding the mechanism of IUB through a decision-making model can help identify its underlying causes. Numerous studies have explored the reasons behind unsafe behavior in construction (Chae et al., 2024; Choi et al., 2017; Fang et al., 2016). These studies have successfully identified contributing factors and, in some cases, developed mitigation measures based on their findings. However, the validation of such measures remains limited due to various practical and theoretical challenges, including the difficulty of directly observing unsafe behavior, ethical constraints, the lack of objective measurements, and the challenge of isolating variables in real construction environments.

This research proposes a framework based on large language models (LLM) and agent-based modeling (ABM) to address these challenges in validating unsafe behavior mitigation measures. First, a hypothetical decision-making model for IUB among construction workers was developed based on the Theory of Planned Behavior (TPB). The model was then validated using structural equation modeling (SEM) with survey data collected from Korean construction workers. Based on the validated model, a mitigation method for IUB was formulated. Following the development of the decision-making model and the mitigation measures, a simulation incorporating LLM and ABM was designed. ABM was used to simulate construction workers' IUB as agent behaviors within the simulation, while LLM was employed to replicate workers' decision-making based on contextual information. Recent studies have highlighted the effectiveness of LLMs in generating human-like behavior, supporting their integration with ABM (Gaffarzadegan et al., 2024). The validated decision-making model and survey dataset were used as empirical data to provide contextual information to the LLM. The simulation allowed worker agents to interact with environmental and managerial agents within a given context, enabling the evaluation of the mitigation measure's effectiveness.

The results of the decision-making model validation identified five causal factors influencing IUB: (a) Manager's attitude—the manager's perspective on worker safety, (b) Attitude toward behavior—the worker's positive or negative attitude toward IUB, (c) Perceived behavioral control (PBC)—the worker's belief in their ability to engage in IUB, (d) Actual behavioral control (ABC)—actual constraints influencing the worker's IUB, and (e) Intention—the worker's intent to engage in IUB. Among these, (a) Manager's attitude and (d) ABC are external factors that can be controlled through intervention. The simulation results using LLM and ABM indicate that both factors significantly contribute to reducing IUB.

Validating the effectiveness of mitigation measures is crucial for practical implementation. However, due to the challenges of conducting experiments in construction settings, research on unsafe behavior mitigation has faced validation difficulties. The proposed LLM-ABM simulation methodology provides a robust framework for testing and validating safety interventions and mitigation measures in construction. This study contributes to the body of knowledge by establishing a rigorous validation methodology for unsafe behavior mitigation. Furthermore, it enhances the integration of ABM and LLM, demonstrating their potential for replicating human behavior in specific contexts.

2. RESEARCH BACKGROUND

2.1 Unsafe Behavior of the Construction Worker

Research on the causes of industrial accidents has identified unsafe worker behavior as one of the primary causes of such incidents (Reason, 1990; Heinrich et al., 1950). Numerous studies have been conducted to investigate the factors underlying unsafe and safe behaviors among construction workers. Choi and Lee (2022) developed a hypothetical model of safety participation, incorporating factors such as safety compliance, project identification, transformational leadership, and communication climate within construction sites. The authors conducted a survey and applied SEM to validate their model. Based on their findings, they proposed future directions for safety management in the construction industry. Fang et al. (2016) introduced the CM-CWUB model, integrating multiple theoretical perspectives. Their study emphasized the importance of the cognitive process, specifically the stages of acquiring information from

the surrounding environment and selecting appropriate responses, in explaining unsafe behavior among construction workers. Similarly, Han et al. (2022) employed grounded theory to explore the causes of unsafe behavior based on an interview dataset. They identified seven categories that capture construction workers' psychological needs and desires leading to unsafe behavior. Based on their findings, they provided preliminary recommendations for safety management in construction sites. These studies offer meaningful insights into the nature of unsafe behavior and suggest potential methods for its mitigation, which could be beneficial for safety management. The methods for mitigation range from abstract suggestions, such as cultivating transformational leadership for promoting workers' project identification levels, to specific recommendation, such as orientation for experienced workers. However, the effectiveness of these proposed methods has not been fully validated. This limitation arises primarily from challenges associated with the validation process. Since the impact of interventions on unsafe behavior must be assessed in real-world construction sites, continuous monitoring of workers' behavior is required—an approach that is practically unfeasible. Additionally, beyond practical constraints, theoretical challenges exist, such as the difficulty of controlling variables in a dynamic construction site environment.

2.2 Decision-making Model of Intentional Unsafe Behavior

IUB can be defined as an activity that deviates from safety regulations or rules and is carried out with intentionality. Since IUB is an intentional behavior, a decision-making process must precede its occurrence. Therefore, a decision-making model of IUB can provide valuable insights into the underlying reasons for IUB and the relationships between its causal factors. TPB is a psychological framework used to describe and predict intentional behavior across various contexts (Ajzen, 1991). TPB has been applied to analyze unsafe behavior in construction settings (Fang et al., 2016; Fogarty and Shaw, 2010). Given that IUB typically results from deliberate and reasoned decisions, TPB provides a strong foundation for modeling such behavior. In this context, TPB is particularly suitable as it focuses on intention as the key predictor of behavior, influenced by psychological and social factors. The TPB model assumes four causal factors that influence intention, as well as the relationship between intention and actual behavior. Attitude toward behavior refers to an individual's positive or negative perception of a specific behavior. Subjective norm represents the perceived social pressure from significant others regarding the behavior. While both attitude toward behavior and subjective norm directly predict intention, PBC and ABC moderate these relationships. PBC refers to an individual's perceived ability to perform the behavior, whereas ABC encompasses the actual factors that determine whether the behavior can be carried out. Although the original TPB has demonstrated strong predictive power for behavior, some contextual factors are omitted from the model (Fishbein and Ajzen, 2011). While incorporating additional factors may improve predictive performance in specific contexts, the authors argued that such modifications should be limited to context-specific applications and should not be included in the general model. Building upon these theoretical foundations, this study develops a hypothetical decision-making model for IUB. Figure 1 illustrates the proposed model, which incorporates two additional factors: past behavior—referring to previous unsafe behavior that did not result in an incident—and manager's attitude—reflecting the manager's stance on worker safety. Intention factor directly predicts the intentional unsafe behavior, while ABC factor moderates this relationship. Subjective norm, attitude toward behavior, and past behavior factors predict intention, while PBC factor moderates these relationships. Manager's attitude is assumed as an exogenous variable that predict subjective norma and attitude toward behavior.

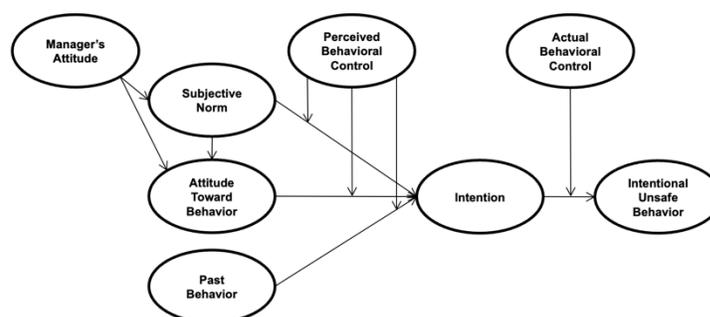


Figure 1: Hypothetical model of decision-making process

2.3 Integration of Large Language Model and Agent-based Modeling

ABM is a computational modelling approach used to simulate interactions among autonomous agents within a system. In ABM, agents behave according to predefined rules, making decisions and interacting with other agents in the simulation (Choi and Lee, 2018). ABM is widely employed to simulate human behavior under specific conditions and to analyze the effects of behavior, decision-making processes, and interactions among agents (Gao et al., 2024). However, defining rule-based decision-making processes remains a challenge (Simon, 1957). To address this limitation, researchers have sought to integrate new tools capable of generating human-like behavior, such as LLM. LLM, which are artificial intelligence models trained on vast text datasets, have demonstrated the ability to replicate human-like behavior (Park et al., 2022; Ghaffazadegan et al., 2024). Studies have demonstrated that LLM effectively replicate general human behavior. However, generating specific behaviors, such as IUB, may require additional contextual information to ensure that LLM accurately represent behavior within the environment. Figure 2 describe the LLM-ABM integration process. Agent exists within ABM, receiving information about the conditions from scenarios. An agent transfers the information about the current status of its attribute to the LLM model, while LLM model utilizes the information for the decision-making process. After decision-making, the output of the LLM model (i.e., decisions and adjustments to attributes) transfer back to the agent.

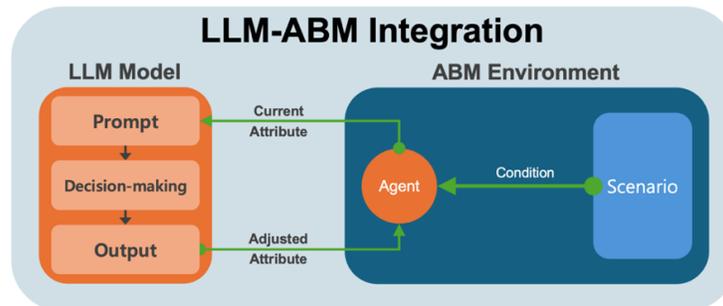


Figure 2: Hypothetical model of decision-making process

3. DECISION-MAKING MODEL OF INTENTIONAL UNSAFE BEHAVIOR

This section presents the validation results of the decision-making model for IUB. The hypothetical model was validated using SEM and survey data. A detailed explanation of the validation process requires a dedicated journal paper; however, in this study, only a brief summary is provided, as the primary focus is on proposing a framework rather than discussing the validation of the IUB decision-making model. Based on the hypothetical decision-making model of IUB, a five-point Likert scale survey questionnaire was developed. The survey was conducted among Korean construction workers across eight different construction sites. A total of 444 responses were collected, and after a filtering process, 340 responses were used for model validation. The validation results indicate that past behavior and subjective norm do not significantly influence IUB. Consequently, these factors were omitted, and the decision-making model of IUB was refined. Figure 3 presents the final model, including path coefficients and significance levels.

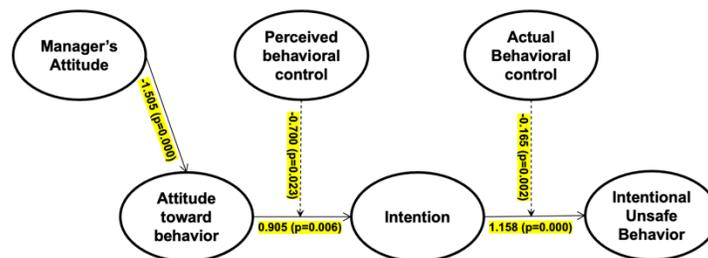


Figure 3: Decision-making model of IUB

In the context of construction workers' IUB, manager's attitude can be exemplified by productivity pressure or safety climate as perceived by workers. Attitude toward behavior reflects the overall safety climate among workers, while PBC represents workers' self-efficacy regarding IUB. ABC in the construction context can be illustrated by the presence of surveillance systems on-site.

The path coefficients in the decision-making model of IUB include both positive and negative values. This variation arises because certain survey questions could not be designed to depict a positive relationship with IUB. For instance, ABC, which represents external constraints that restrict unsafe behavior, inherently cannot have a positive relationship with IUB. As a result, manager's attitude, PBC, and ABC were defined as having negative relationships with IUB, while attitude toward behavior and intention were defined as having positive relationships with IUB. Among the five causal factors of IUB, attitude toward behavior, PBC, and intention are categorized as intrinsic factors, as they originate from a construction worker's cognitive and perceptual processes. In contrast, manager's attitude and ABC are classified as extrinsic factors, as they originate from external conditions in the construction environment. Since extrinsic factors stem from the construction site environment, they are controllable through external interventions, whereas intrinsic factors are more difficult to regulate as they are shaped by individual workers' cognition and perception.

Based on these findings, the authors propose that interventions targeting extrinsic factors may effectively reduce IUB. Specifically: Improving manager's attitude (e.g., enhancing the quality of safety-related toolbox meetings, providing more safety information to workers), and Enhancing ABC factors (e.g., increasing surveillance system usage, notifying workers about the presence and purpose of surveillance systems)

4. VALIDATION FRAMEWORK BASED ON LLM-ABM INTEGRATED SIMULATION

4.1 Validation Framework

Figure 3 presents the proposed validation framework based on the LLM-ABM integrated simulation.

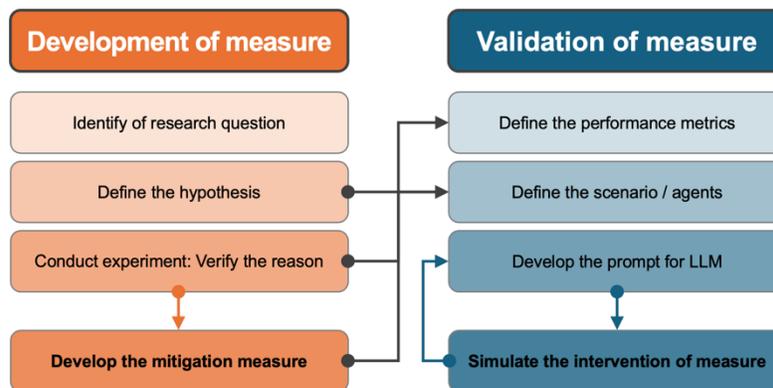


Figure 3: Proposed validation framework

The left side of the figure illustrates the typical research process for developing a mitigation measure. The process begins with identifying the research question (e.g., What is the reason of IUB of construction workers?). Once the research question is established, the hypothesis is formulated, and relevant information about the research topic is gathered (e.g., Hypothetical decision-making model of IUB). After defining the hypothesis, an experiment is designed and conducted to investigate the causes of unsafe behavior (e.g., Survey conducted to construction workers). Based on the experimental results, a mitigation measures are developed (e.g., Manager's attitude and ABC). The information and knowledge acquired during the development of the measure serve as a foundation for building a simulation to validate its effectiveness. To develop a simulation for validation, performance metrics for measuring the effectiveness of the mitigation measure must be established. These performance metrics vary depending on the characteristics of the mitigation measure being evaluated. After defining the performance metrics, the scenario and agents within the simulation must be specified. At this stage, existing knowledge about unsafe behavior and its causal factors is incorporated into the simulation design. Once the simulation is structured,

prompts for the LLM must be developed. This is an iterative process, requiring continuous prompt engineering based on feedback from preliminary simulations. After refining the LLM prompts, the simulation can be utilized to assess the effectiveness of the mitigation measure.

4.2 LLM-ABM Integrated Simulation

A brief introduction to the development of the mitigation measure was provided in Section 3. Based on the experimental results, the authors assumed that enhancing the manager’s attitude and ABC could serve as an effective mitigation measure for IUB. Using this information, a simulation was developed to validate the measure. The IUB factor was selected as the performance metric, meaning that the decision of LLM-driven agents regarding whether to engage in unsafe behavior was used to assess the measure’s effectiveness. The next step involved defining the scenario and agents within the simulation. The scenario represents a specific set of initial conditions and external factors within the simulation. To validate the effect of ABC, two scenarios were defined: one with a low-level of perceived surveillance in the construction site and another with a high-level. In the low-level scenario, the initial value of the ABC factor was set lower, indicating that the agent’s intention to engage in unsafe behavior was less influenced by behavioral control. This scenario represents a construction site with an underdeveloped surveillance system, where workers are less likely to be monitored and thus more prone to IUB. In contrast, the high-level scenario featured a higher initial ABC value, simulating a site with a mature and active surveillance system. Here, the increased behavioral control more strongly moderates the intention to engage in unsafe acts, thereby reducing IUB.

Agents are autonomous entities that behave and interact within the simulation environment. In this simulation, two types of agents were defined. The first is the manager agent, which was introduced to evaluate the impact of the manager’s attitude. This agent provides safety information to the worker agent at each step, with the quality of the information varying based on the manager’s attitude. The manager’s attitude was classified into two levels: low and high.

The second type of agent is the worker agent, which has five attributes: attitude toward behavior, PBC, ABC, intention, and IUB. The behavior of the worker agent follows a three-step process. First, the worker agent adjusts its attitude toward behavior based on its interaction with the manager agent. Next, it updates its intention value based on the adjusted attitude toward behavior and the moderating effect of PBC. Finally, considering the updated intention value and the moderating effect of ABC, the worker agent determines the value of its IUB attribute. Figure 4 illustrates the interaction between the agents and the scenario described above.

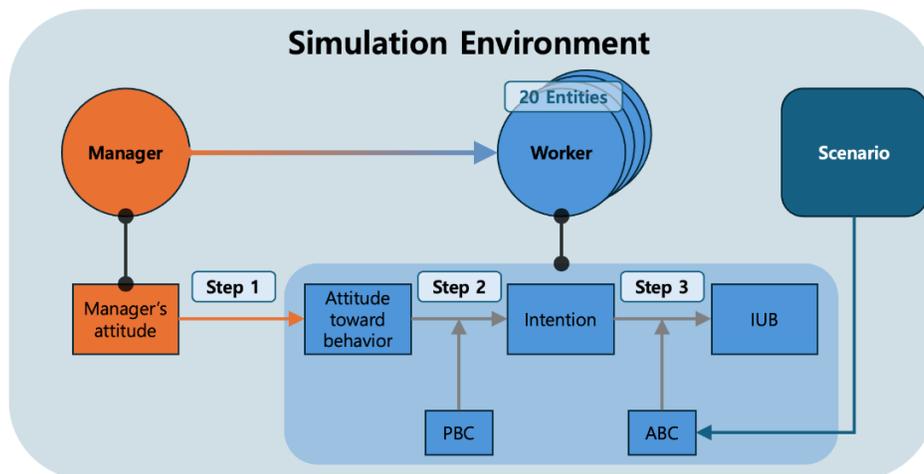


Figure 4: Description of interaction among the agents and the scenario

The prompt for the LLM was developed in three parts. The first part provides an explanation of the decision-making model of IUB, including information about its factors and the coefficient values of the paths. It is also specified that these coefficient values were derived from a five-point Likert scale survey dataset and

analyzed using SEM. The second part contains information about the current state. At each step, the adjusted values of the attitude toward behavior, intention, and IUB attributes were updated for the worker agent. The final part consists of instructions that describe the required actions of the worker agent.

The initial values of the attributes were randomly assigned based on the mean and standard deviation data from the survey dataset. Once the initial values were set, at each step of the simulation, information about the worker agent's status was provided to the LLM. Based on this status and the given instructions, the LLM determined the agent's action (i.e., steps 1–3 in Figure 4). After each worker agent completed an action, the updated attribute values were recorded and transferred to the next step. Each step in the simulation represents a safety intervention by the manager. The number of worker agents was set to 20 to allow for further statistical analysis. A total of 12 steps were applied, with the first three steps, including the initial step, omitted from the dataset to prevent potential issues caused by outliers in the initial settings (i.e., burn-in process).

4.3 Model Algorithm

The simulation model was developed using Python and consists of four stages. Figure 5 illustrates the flowchart of the model algorithm. In the first stage, the necessary Python libraries were imported, and the functions used throughout the simulation were defined. The second stage involved defining the simulation scenario, agents, and prompts. The third stage focused on executing the simulation. As described earlier, at each step, worker agents made decisions based on the LLM and updated their attributes. These updated attributes were then collected and transferred to the next step. After completing all 12 steps, the data was visualized and saved. For the LLM model, GPT-3.5 Turbo was used with a temperature setting of 0.1.

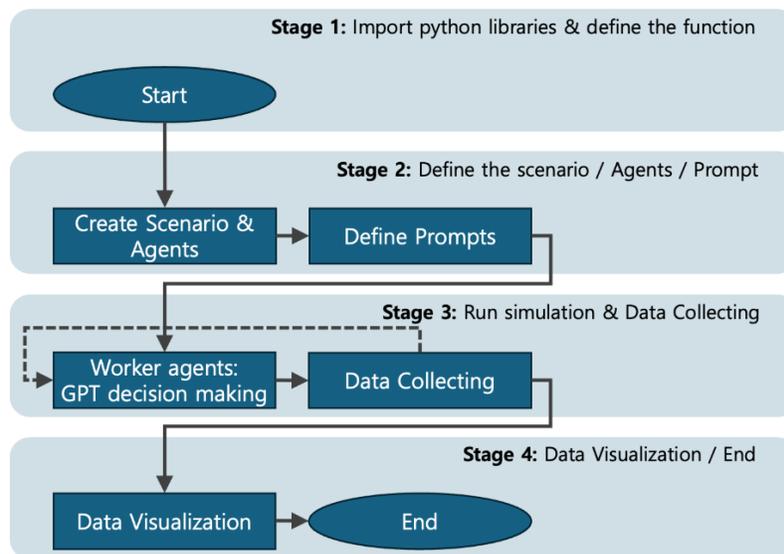


Figure 5: Flowchart of model algorithm

4.4 Simulation Result

The simulation aims to measure the effectiveness of two mitigation factors. First, perceived surveillance, which is defined as a scenario in the simulation. A high ABC condition represents a situation where the perceived surveillance level is high, resulting in a weaker relationship between intention and IUB. Conversely, a low ABC condition indicates a low perceived surveillance level, leading to a relatively stronger relationship between intention and IUB. The manager's attitude factor is controlled in the simulation with two categories: low and high. A high manager's attitude condition signifies that the manager places a strong emphasis on safety, leading to a weaker attitude toward IUB. A low manager's attitude condition represents a weaker emphasis on safety, resulting in a stronger attitude toward IUB. The results are categorized into four groups in a 2×2 configuration. The least effective scenario is the low ABC – low manager's attitude

condition, whereas the most effective scenario is the high ABC – high manager’s attitude condition. The descriptive statistics of the collected data are presented in Table 1. Step 3 marks the starting point for analysis, as the first three steps were omitted due to the burn-in process. The descriptive statistics indicate that the average IUB level decreased across all groups. This reduction occurs because the current simulation does not incorporate external factors that could increase the likelihood of IUB. However, despite this limitation, the effectiveness of the mitigation methods can still be observed.

Table 1: Descriptive statistics of collected IUB data

| Step | Group | Mean | Std.dev. | Sample Size |
|------|------------------------------------|-------|----------|-------------|
| 3 | Low ABC – Low manager’s attitude | 1.306 | 0.272 | 20 |
| | Low ABC – High manager’s attitude | 1.413 | 0.444 | 20 |
| | High ABC – Low manager’s attitude | 1.278 | 0.367 | 20 |
| | High ABC – High manager’s attitude | 1.113 | 0.361 | 20 |
| 12 | Low ABC – Low manager’s attitude | 0.881 | 0.249 | 20 |
| | Low ABC – High manager’s attitude | 0.638 | 0.263 | 20 |
| | High ABC – Low manager’s attitude | 0.676 | 0.340 | 20 |
| | High ABC – High manager’s attitude | 0.576 | 0.286 | 20 |

The visualization of the data is presented in Figure 6. The results were plotted based on the dataset from steps 3 to 12. The black line in each sub-figure connects the averaged data points, while the dotted black line represents the estimated slope of the averaged data points. The value of the slope is noted on the upper left side of each sub-figure. The visualization indicates that the IUB value decreases for every group, which aligns with the descriptive statistics. Additionally, the slope values show that the least effective group has a smaller value compared to the other groups, which is consistent with the characteristics of the groups.

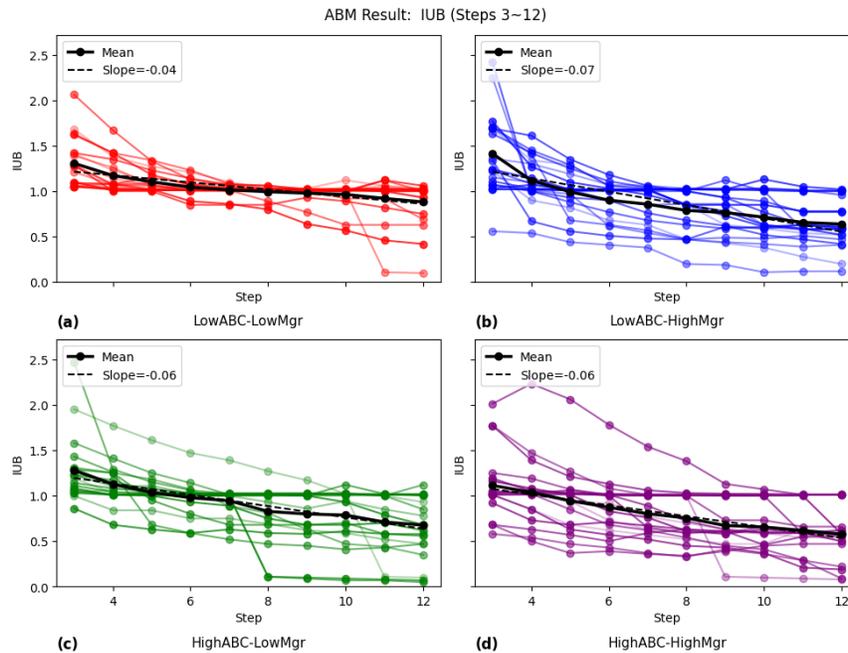


Figure 6: Visualization of the data collected during the simulation.

To compare the performance of the mitigation measure, a pairwise t-test was applied to the dataset from step 12. Based on the four groups, six unique pairs were categorized for the pairwise t-test. The notation of each group in Table 2 follows the notation used in Figure 6. In the pairwise t-test, the difference in values between groups was used for comparison. Specifically, the value of group 2 is subtracted from that of group 1. Thus, a positive value in the t-statistic column of Table 2 indicates that the value of group 1 is larger than that of group 2, meaning group 1 with a higher level of IUB (i.e., group 1 is less effective). The results

showed that the performance of the low ABC – low manager’s attitude group was the least effective. However, comparisons between the other group pairs did not show any significant differences, meaning there is no difference between the method of enhancing only one factor or both factors.

Table 2: Result of pairwise t-test between groups

| Group 1 | Group 2 | t-statistic | Significance | df |
|------------------|-------------------|-------------|--------------|----|
| Low ABC-Low Mgr | Low ABC-High Mgr | 3.000* | 0.005 | 19 |
| Low ABC-Low Mgr | High ABC-Low Mgr | 2.175* | 0.037 | 19 |
| Low ABC-Low Mgr | High ABC-High Mgr | 3.606* | 0.001 | 19 |
| Low ABC-High Mgr | High ABC-Low Mgr | -0.395 | 0.695 | 19 |
| Low ABC-High Mgr | High ABC-High Mgr | 0.720 | 0.476 | 19 |
| High ABC-Low Mgr | High ABC-High Mgr | 1.012 | 0.318 | 19 |

*Significance level <0.05

5. DISCUSSIONS AND CONCLUSIONS

Since unsafe behavior is recognized as the major causes of accidents, many studies have attempted to identify the underlying reasons for such behavior and develop mitigation measures. However, validating measures remains both practically and theoretically challenging, resulting in many methods remaining unverified. This paper proposes a novel framework for validating unsafe behavior mitigation measures through a simulation integrating ABM and LLM. Based on the knowledge acquired during the development of the mitigation measure, an ABM-LLM integrated simulation can be constructed for validation. A preliminary experiment, which utilized survey data and a decision-making model of IUB to train the LLM for generating realistic behavior within the ABM simulation, demonstrated that simulations built upon this framework can effectively measure the performance of mitigation measures.

The simulation results indicate that the proposed framework can be used to validate unsafe behavior mitigation methods. However, it failed to distinguish the relative effectiveness of individual factors. The comparison between the low ABC – high manager’s attitude group and the high ABC – low manager’s attitude group did not show any statistically significant difference. Similarly, the comparison involving the high ABC – high manager’s attitude group also did not yield statistical significance. This result may stem from either the equally strong performance of both factors reaching an upper performance bound or the failure to accurately measure the effectiveness of each individual factor.

Based on these limitations future research should include further experimentation with a more refined simulation setup and a detailed analysis of the mitigation process, including the qualitative evaluation of GPT-generated responses regarding the reasoning behind each decision, would be beneficial. Additionally, the instructions provided to the LLM should be improved in future studies. LLMs are designed to comprehend natural language rather than mathematical equations. However, in this preliminary experiment, the LLM was provided with information on the decision-making model of IUB, including the coefficient values of the paths between factors. This may have led to errors in generating human-like behavior while considering the actual decision-making processes of construction workers.

This study contributes to research on understanding unsafe behavior and developing mitigation measures by introducing a novel framework that addresses the challenges of the validation process. By applying this framework, researchers can design simulations capable of analyzing the effectiveness of mitigation measures. One of the barriers to implementing novel strategies on construction sites is the difficulty in quantitatively predicting their benefits. This uncertainty may lead to reluctance among decision-makers to develop and adopt new safety protocols. By utilizing the proposed framework, practitioners can estimate the expected performance of safety protocols in addressing unsafe behavior, thereby supporting more informed and proactive decision-making. Furthermore, this study highlights the potential of integrating LLMs with ABM, which could be further developed to replicate more complex human behavior in specific contexts.

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