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Impact assessment of reinforced learning methods on construction workers' fall risk behavior using virtual reality

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A R T I C L E I N F O

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A B S T R A C T

Given the nature of construction activities, construction workers usually work in a collaborative way. Thus, interpersonal influences among workers play a crucial role in forming and affecting construction workers' safety behaviors. The social learning literature indicates that interpersonal learning occurs in two opposing ways – positive reinforcement by demonstrating preferred behaviors, and negative reinforcement by demonstrating negative consequences of inappropriate behaviors. Amid theoretical disagreements in the social learning literature, it remains unclear in the construction safety literature how the two reinforced learning methods affect construction workers in safety training. To fill the gap, a human-subject experiment (n = 126) was conducted to investigate people's social learning behaviors in a hazardous construction situation – walking between two high-rise buildings. The experiment utilizes a multi-user Virtual Reality (VR) system with a motion tracking feature. Participants were randomly assigned to one of three groups: control group (no instruction was given), not-falling group (participants observed an avatar demonstrating appropriate walking behaviors), and falling group (participants watched an avatar quickly walking across a plank and falling off). Indicators, including walking time on the plank, walking speed, and gaze movement, were recorded and analyzed to quantify the effects of the two reinforced learning methods. The results indicate that demonstrating information with positive consequences (not-falling group) encourages people to follow the demonstration and maintain normal walking in a hazardous situation. Showing information with negative consequences (falling group) induced participants to walk faster and more irregularly, which further led to more mistakes and unsafe behaviors. This study demonstrates the effectiveness of using VR in safety studies and provides recommendations for better safety training programs.

1. Introduction

The construction industry is one of the most dangerous industries in the United States. In 2016, fatal accidents claimed 4693 workers in private industry and 21% of those were in the construction industry [72]. Falling accident is the number one killer on construction job sites. Nearly 38.7% of the total deaths and injuries in construction projects were caused by falling [72]. Further investigation has found that 80–90% of the accidents were caused by human errors and unsafe behaviors [17,36,41]. As a result, it is critical and urgent to understand how human errors contribute to fatal falling accidents.

Given the nature of construction activities, construction workers often work in groups on construction sites. The interpersonal relationships between construction workers play an important role in forming or changing safety behaviors [110]. The collaborative nature of construction activities has led to an emphasis on safety climate (i.e., the perceived group norms and values placed on safety in an organization) in the construction safety literature [18]. Researchers have found that a positive safety climate may reduce unsafe behaviors [53,68,109], improve safety performance [31], and reduce workers' psychological stress [15]. To create a positive safety climate, some researchers assert that a positive safety climate can be created by learning from negative events [46] or negative consequences [76]. In contrast, other researchers believe that a positive safety training process improves safety performance by reinforcing safer activities in the workplace [103]. This disagreement is rooted in social learning theory's theoretical divergence. According to social learning theory [8], a new behavior can be acquired through the observation of other people's behaviors. This behavioral acquisition occurs through two methods: positive reinforcement or rewards, and negative reinforcement or punishments [7].

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Fig. 1. safety training module on a construction site.

Social learning theory also indicates that consequences (positive reinforcement or negative reinforcement) facilitate people's learning in an anticipatory way because they calculate the potential benefits or costs of the behaviors [5,12]. Giving people positive reinforcement improves their self-management abilities and encourages them to reproduce appropriate behaviors [34]. Alternatively, individuals may acquire behaviors through negative consequences that prevent them from reproducing similar behaviors [35,51]. Amid this theoretical disagreement in social learning theory, it remains unclear in the construction safety literature how the social learning process is formed at the individual level and how the two reinforced learning methods (positive reinforcement or negative reinforcement) affect construction workers in safety training. The absence of such knowledge prevents safety managers from developing effective fall accident prevention measures for workers on construction job sites.

To fill this knowledge gap, this study investigates how different types of safety instruction – positive reinforcement (showing correct demonstrations) and negative reinforcement (showing fatal consequences) – affect safety behaviors in a hazardous situation. Owing to the difficulty of simulating hazardous situations in the real world, a multi-user Virtual Reality (VR) system [24–26,87] with a full body tracking feature was developed. Numerous VR studies indicate that realistic virtual environment can provide a strong sense of presence and cause people to respond realistically [28,67,90]. In our developed VR model, a walking scenario between two high-rise buildings was selected as the hazardous situation. The results of this study indicate that the two social learning methods systematically change safety behaviors at the individual level. The findings are expected to help safety managers select an appropriate safety training strategy for workers in hazardous situations.

2. Literature review

2.1. Social learning in construction field

Construction workers usually work collaboratively. The interpersonal connection not only influences workers' productivity but also their safety behaviors. Thus, exploring social learning has drawn considerable interest in the construction literature. Social Learning Theory (SLT) was originally proposed by Albert Bandura [8] to provide a theoretical framework about how interpersonal influences form a learning process. Bandura and Walters [7] defined social learning as a cognitive learning process where people learn behaviors through the observation of other people's behaviors. Specifically, there are two ways of learning: rewards and punishments [6]. Bandura conducted a famous human subject experiment (the bobo doll experiment) to investigate how the processes of reward and punishment affected children's aggressive behaviors through the social learning process. He randomly assigned children to one of the following groups: a control group with a nonaggressive demonstration model, another control group with no demonstration model, a reward group with an aggressive demonstration model with reward consequences, and finally, a punishment group with an aggressive demonstration model with punishment consequences. It was found that children in the punishment group behaved less aggressively, while children in the reward group tended to reproduce the aggressive behaviors. The results indicate that demonstrating information with negative consequences could prevent children from reproducing inappropriate behaviors. Yet it is still unclear if a similar conclusion is applicable in the construction field. In general, construction safety scholars agreed that social learning can help form a better safety climate [110], which reduces unsafe behaviors [31,37]. Choi, et al. [17] studied the impact of social influence on construction workers' safety behaviors based on empirical data collected from 284 construction workers in the United States. The results prove the role of social influence and social norms in fostering a safety climate. However, in real-world practice, safety managers always demonstrate negative consequences of unsafe behaviors to prevent workers from reproducing the unsafe behaviors. Fig. 1 shows a safety training module in a real project. It remains unclear how the two opposing reinforced learning methods (positive or negative) affect workers' safety behaviors in safety training. Because the fall accident is a major problem in construction safety, this study uses fall accident as the simulation scenario used to investigate this problem.

2.2. Studies of fall accidents in construction field

Based on statistical data from the U.S. Department of Occupational Safety and Health Administration (OSHA), falling accident was the leading cause of worker deaths in the construction industry in 2016 [72]. Previous research has investigated the root causes of falling accidents and utilized different approaches to detect fall risk behaviors and improve workers' safety on construction sites. Huang and Hinze [48] studied fall accident records from 1990 to 2001 in the OSHA database and summarized the root causes of fall accidents. They identified several factors related to fall accidents, such as construction building type, fall height, working experience, work location, and human errors. Meanwhile, Chi et al. [16] investigated 621 fall accidents and identified accident patterns in the construction industry. They also provided fall prevention measures for each fall accident pattern. In order to prevent fall accidents and improve workers' safety, many studies have utilized different techniques for early detection of workers' fall risk behaviors to prevent fall accidents. Lee et al. [60] established a mobile safety monitoring system to reduce the rate of fall accidents on construction sites. The system integrated a mobile location sensor, transmitter, and exclusive software. The proposed system was implemented on a real construction site to test the system's usability and feasibility. The results revealed that the system can successfully monitor workers' safety performance in real time on a construction site. Zhang, et al. [107]

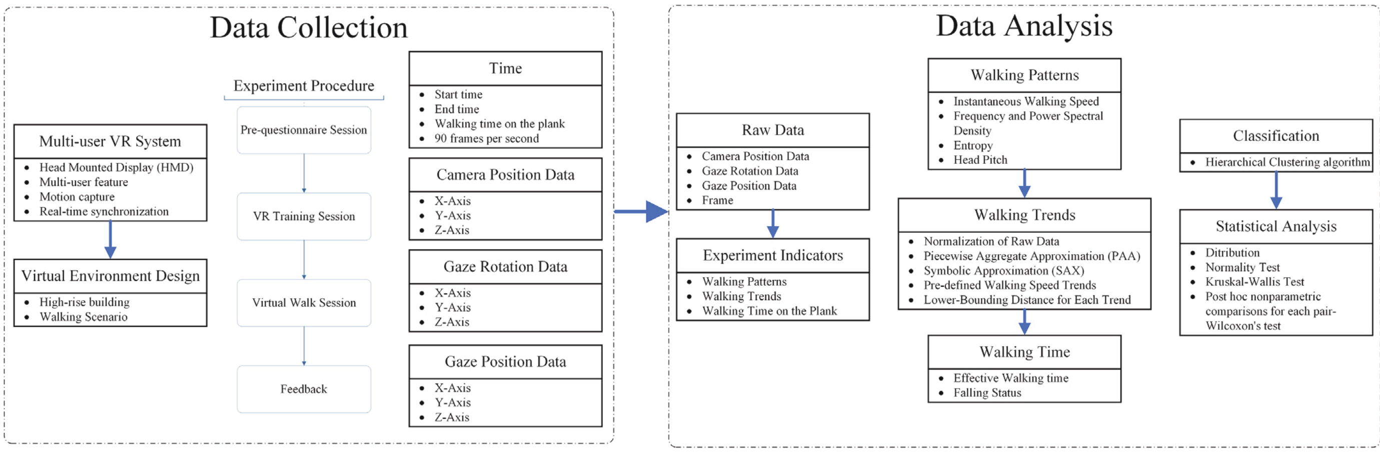

Fig. 2. Research framework.

developed an automated rule-based checking system for Building Information Models (BIM) to prevent fall accidents in the safety planning phase. This system can automatically detect fall hazards and provide preventive measures for users in the building models. Yang, et al. [105] introduced a near-miss fall detection system by using a Wearable Inertial Measurement Unit (WIMU). WIMU can be easily attached to a worker's body and collect kinematic data through wireless communication. The researchers utilized a semi-supervised pattern-recognition algorithm to process the kinematic data collected from the ironworkers in the experiments. The results indicated that this system can successfully identify near-miss falls of ironworkers.

Although different techniques have been implemented to detect fall risk behaviors on construction sites, most studies have so far focused on identifying individual level fall risk behaviors. The interpersonal influences of workers in fall accidents have not been well explored. On the other hand, some studies investigated this problem as a safety climate issue [65,110,111], but these studies only investigated this issue at the group and organizational levels. The effects of demonstrating different consequences to workers remain unclear. Due to the difficulty of simulating fall accidents in the real world, this study utilized a VR approach to investigate people's fall risk behaviors affected by observing different consequences in a hazardous situation.

2.3. The implementations of VR and AR techniques in AEC industry

With proven effectiveness and increasing industry awareness, VR has gained popularity in the construction field in recent years. VR is an interactive and immersive three-dimensional (3D) virtual environment in which users can dynamically control the viewpoint and realistically interact with various components [11,55]. The advantage of using a VR system is that it can realistically simulate scenarios that are difficult to simulate in the real world such as acrophobia [28,83], disability [19], social psychology [10], and emergency evacuation [86]. At the same time, VR can also provide a strong sense of presence [89], train specific behaviors [78], and trigger user behaviors similar to those in the real world [42]. With these promising benefits, researchers have started to use VR techniques to investigate a variety of research problems in the architecture, engineering, and construction (AEC) industry. VR has been widely used in architecture design review and coordination [27,102], lighting design [43], construction planning [99], construction operation [61,81], construction education [4,56], operation and maintenance [47,100], facility management [87], and safety training [85].

In the construction safety field, VR is used as a safety training tool. Compared to traditional safety training methods, VR safety training is more effective in maintaining trainees' attention and concentration [85]. Due to the difficulty of simulating dangerous construction scenarios in the real world, VR is an effective approach for safety training. For instance, Sacks et al. [85] investigated the effectiveness of using VR on construction safety training. The researchers compared the performance of safety training by using traditional classroom training with visual aids and using a 3D immersive environment on a large wall display. They found significant advantages to using VR training for stone cladding work and cast-in-situ concrete work. The VR safety training helped participants maintain attention and concentration during the safety training process. Meanwhile, the effectiveness of VR training has also been illustrated for promoting construction safety. Zhao et al. [108] developed a VR-based safety training system to improve construction workers' electrical hazard awareness and intervention knowledge. Their system effectively helps users rehearse electrical hazard tasks. Teizer et al. [94] proposed a framework that integrates a real-time location tracking technique and a3D virtual environment to improve ironworkers' safety and productivity performance. The results revealed that this system can help workers identify safety issues about which they may be unaware in their work environment. All these studies have provided valuable insights for implementing VR techniques in the AEC industry.

3. Research methodology

This study aims to investigate the effects of two different reinforced learning techniques, i.e., demonstrating safety instructions with positive consequences and with negative consequences, on construction workers' fall risk behaviors. VR was used in our human-subject experiments to create an immersive virtual environment that realistically simulates a high-rise walking scenario. As illustrated in Fig. 2, this study consists of two main steps: data collection and data analysis.

For the data collection, due to the difficulty of simulating the hazardous situations existing in the real world, a multi-user VR system with full body tracking function [88] was developed to simulate workers' behaviors. A walking scenario with a plank placed between two high-rise buildings was selected as the hazardous situation in this study. A human-subject experiment was conducted to investigate people's walking behaviors. In the experiment, participants were asked to walk across a plank that was placed between two virtual high-rise buildings. To test the impact of the two reinforced learning methods, participants were required to witness one of three conditions before walking across the plank: 1) no one walking before they walk across the plank (control group); 2) an avatar slowly walking across the plank without falling (not-falling group); and 3) an avatar quickly walking across the plank and falling off (falling group). Participants' walking time, instantaneous walking speed, XYZ position data, and gaze movement data were recorded during the experiment.

For the data analysis, three indicators were selected to represent

Table 1
Summary of indicators in the experiment.

Indicator	Feature	Description
Walking patterns	Frequency	The changing rate of instantaneous walking speed in the certain time period. Represents walking speed patterns in a short-time period.
	Entropy	Measures the irregularity of the time-series data. Represents the walking speed pattern in a long-term period.
	Head pitch	An individual's vertical head rotation. Represents the changes of attention during the walk.
Walking trends	N/A	The overall change trend of instantaneous walking speed.
Walking time	Time	The difference between start-time and end-time on the plank.

participants' walking behaviors in the virtual environment, including walking patterns, walking speed trends, and walking time on the plank, as listed in Table 1. To represent walking patterns, three features were selected: frequency, entropy, and head pitch. Analyzing human gait is complicated, and various metrics related to gait variability and gait stability are used in gait analysis. Any single metric cannot sufficiently represent the gait pattern. Walking pattern is a widely accepted indicator to represent people' gait in previous gait studies [14,57]. Yang et al. [106] indicated different gait features, such as stride time, stride distance, and average velocity, that can be used as experimental features to represent workers' walking patterns based on wearable inertial measurement unit (WIMU). The reason we selected frequency is that the raw data that we collected from the sensor is time-series data. A popular and effective way to analyze time-series data is to convert the data from time-domain to frequency domain. This approach is widely used in activity recognition studies using an IMU sensor [9]. Meanwhile, entropy is often selected to represent the irregularity of time-series data. The reason we selected head pitch to represent walking pattern is that it is an important reflection of walking speed [50]. More importantly, head pitch is related to the attention or cautiousness of walkers [3]. While frequency and entropy both relate to gait variability/regularity, frequency focuses on the polarization of walking speeds over the entire course of a walk and entropy measures dissimilarity between consecutive steps. Thus, these three features (frequency, entropy, and head pitch) were selected to represent participants' walking patterns. The second indicator, walking speed trend, was discovered in the preliminary data analysis, which found a significant difference in walking speed trends. For example, some subjects kept increasing the walking speed while some others decreased. This inspires a new dimension of understanding gait patterns. Fig. 6 shows the different walking speed trends of participants. Because participants' instantaneous walking speed data is time-series data, a symbolic approximation (SAX) approach was applied to reduce the dimension of the data and extract the trend features. A classification workflow was also introduced to classify participants' walking trends into different categories. Each category of walking trends was then analyzed separately. The third indicator, walking time on the plank, was used as the task performance indicator in this study.

4. Experiment design

4.1. Multi-user VR system and virtual environment design

A multi-user VR system [25] integrated with motion sensors was used in the experiment. To achieve multi-user functionality, a third-party cloud server Photon Unity Networking (PUN) [98] was used to enable different users to interact in the same virtual environment [24]. With PUN, users frequently broadcast their moving positions, body rotations, and body motion transforms to the other users in the virtual environment. On the avatar receiver side, the avatars update this information in real-time through the PUN cloud server. Thus, participants can see other avatars' motions and movements in the virtual environment. Oculus Rift Consumer Version 1 (CV1) Head-Mounted Display (HMD) was used as the headset [70]. This device features dual displays with one display per eye with a resolution of 2160×1200 pixels. The horizontal Field of View (FOV) of this HMD is 80° and the vertical FOV is 90° when the eyes are 10 mm away from the lenses [49]. For this experiment, the HMD worked with about 120 diagonal degrees. The participants could freely turn their heads and bodies when they used the device in the experiment. This inertial sensor-embedded HMD device is widely used in the Human Computer Interaction (HCI) area to track head movement and rotations. According to Niehorster et al.'s [69] study, the end-to-end VR system latency is 22 milliseconds. The tracker jitters of the VR headset are below 0.02 cm in XYZ directions and below 0.02° for head yaw, pitch, and roll. Meanwhile, Xu et al. [104] studied the accuracy of a VR headset to investigate cervical spine mobility. They compared measurement accuracy between the VR headset and a reference motion tracking system. They found that the absolute error of the VR headset-based method (move from one side to the other side) was 5.4° for lateral bending, 3.7° for axial rotation, and 2.3° for flexion or extension compared to the motion tracking system. The results indicated that a VR headset can provide good estimates of full range of motion.

A Microsoft Kinect was used as the sensor for real-time body and movement tracking so that participants' physical motions could be mapped to their virtual avatars. Being inexpensive and carrying good performance, this tool has been chosen by many researchers to carry out studies related to motion tracking on construction job sites [40,59,79]. It was also widely used in the field of HCI. It can be used for either detecting a user's motions or navigating in a virtual environment [22,39]. In this study, participants navigated in the virtual environment by using an actual physical walking technique. Previous research has shown that navigation via real walking can allow a high sense of presence in the virtual environment [97]. The measurement range of Kinect is 0.5 m to 4.5 m and the number of artificial anatomical landmarks (the “Kinect joints”) is 25. The 3D Euclidean distance differences between Kinect and Vicon (high precision tracking system) is 1 and 2 cm [73]. The Kinect sensor can be used as a reliable and valid clinical measurement tool compared to a marker or wearable sensor-based system such as Vicon [73]. In order to ensure position accuracy, the starting point of the real plank is a fixed position in the room. The virtual plank and real plank are carefully calibrated before each experiment trial. Fig. 3 shows the captured Kinect user motions and the synchronized user motions for the virtual avatar. To achieve these features, the API provided by Microsoft Kinect SDK [66], the skeleton tracking libraries in Unity [32], and several C# scripts were used to control the virtual avatar based on the motion data captured, including Kinect Manager, avatar controller, user rotation, and network character. The Kinect manager script, the main Kinect-related component, was used for transferring the data between the Kinect sensor and the Unity application. The user can define the height and tracking angle of the Kinect sensor, the maximum number of tracked users, tracking distances, and so on. The avatar controller script was used for transferring the captured user motion data to a humanoid avatar. The user can define the avatar's moving speed related to real movement speed, vertical and horizontal offset of the avatar, and the smoothness of the avatar' motions. The user rotation was used for controlling the avatar's body rotation related to the camera in the vertical direction. The network character script was used for broadcasting avatar transform and rotation information, avatar joints' transform and rotation information, and animation information to the other avatars in the virtual environment through the PUN cloud server.

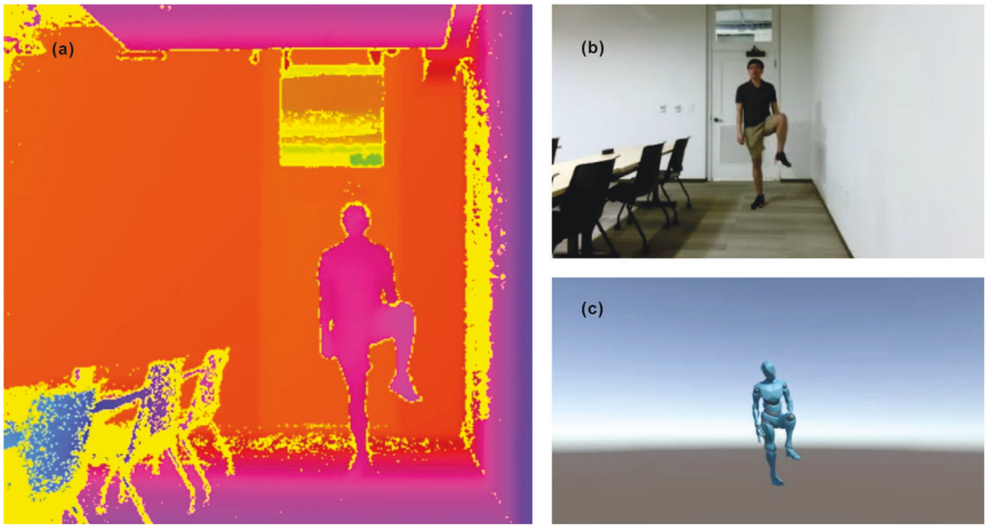

Fig. 3. Views of the motion tracking. (a) view captured by Kinect, (b) view in real-world, and (c) view in the virtual environment.

Fig. 4. Views in the virtual environment. (a) the perspective view of the overall virtual environment, (b) the real-world setup, (c) the first-person view in the virtual environment, and (d) a perspective view of the avatar.

The application for the experiment was written with C# in Unity 3D-5.6.5 version. The virtual scenario was developed in Unity. The application ran on a Microsoft Windows 10 workstation with an Intel Xeon CPU at 2.60GHz and 64GB of RAM. The graphic card of the workstation is NVIDIA GTX 1080. The frame rate was approximately 100 frames per second for all conditions in the virtual environment. Fig. 4 shows the views of the virtual environment along with the physical setup and real wooden plank.

The high-rise building walk scenario was selected as the hazardous scenario in this experiment, even though it is unlikely to occur in reality given the stricter safety requirements nowadays. The main focus of this study relies on understanding the behavioral reactions of participants to the two reinforced learning methods in hazardous situations, so the reflections themselves can inspire real-world applications. If a less hazardous simulation were used, the reactions of interest could be very subtle or even undetectable. In order to trigger a stronger behavioral response for the theoretical discoveries, we chose to create a less likely but more intense stimulus (i.e., unprotected high-rise work) to amplify participants' physiological and psychological reactions in the simulated hazardous environment. It is worth noting that this practice (creating atypical but stronger stimuli to trigger reactions of test subjects) has been very popular in HCI and psychology literature, such as the virtual reality exposure therapy (VRET) approach [82]. For example, VRET has been found to be more helpful in studying post-traumatic stress disorder (PTSD) [23,84], anxiety [75], social anxiety [1], acrophobia [71], and other cognitive and psychological questions. In the meantime, we recognize the importance of not delivering a misleading message to either the participants or the public. Therefore, prior to the experiments, we made it very clear to the participants that the simulated environment would be used only for scientific research purposes and did not imply any real-world practices.

The high-rise building scenario was built with two virtual planks placed between two high-rise buildings. The virtual plank on the right-hand side was carefully calibrated to match the real size and position of a wood plank in the real world. By matching the physical and virtual objects, participants could feel the edge of the plank with their feet, which provided greater tactile realism and sense of height for the high-rise scenario. The length of the plank in the real world is 12 ft. The height of the plank is 2 in. The width of the plank is 12 in. The selection of the plank length depended on two factors: 1) its ability to reflect a typical scene on a job site, and 2) its feasibility in our designed VR experiment. For high-rise building construction workers, a scaffolding system or steel beams are usually used. The spacing and structure are very similar to the selection of 12 ft. In addition, 12 ft is an effective tracking distance in the Kinect system. For the width of the plank, according to the American Society for Testing and Materials (ASTM), A6 standard [2], the flange width of the steel wide flange beam ranges from 3.94 in. to 14.725 in. Thus, the width of the plank was selected as 12 in. The plank height in the real world was not duplicated in the VR environment. The only purpose of having a suspended plank in the real world was to simulate the edge of the virtual plank. So, the height is not as critical as the dimensions of the virtual plank in the VR environment. With that said, IRB has a very strict requirement about the height of the plank as part of a human subject experiment. Since participants were wearing a VR headset when they walked on the real plank, a higher height of the real plank could hurt an ankle, if they stepped off the side of it. Thus, the final height of the real plank was decided after consulting with TAMU's IRB office. A wall was used to protect the test subjects, an arrangement that also resulted from the IRB consultancy. In our experiment, subjects would not notice the existence of a real wall when wearing a VR headset. However, if a subject was leaning to fall, and if he/she contacted the wall, we considered that to be a failed data point. Our effective sample size ($n = 126$) did not include failed data points. The other virtual plank on the left-hand side was used to demonstrate walking instructions. An avatar controlled by us walked on this virtual plank. Fig. 5 shows a first-person view of the walking instruction before participants walked across the plank in the virtual environment. Fig. 5 (a) shows an avatar carefully walking across the plank without falling. It is the demonstration scenario that participants in the not-falling group observed before they walked. Fig. 5 (b) shows an avatar walking across the plank with the falling condition. It is the demonstration scenario that participants in the falling group observed before they walked. Compared to playing a prerecorded animation, it seemed more natural and acceptable to the subjects when another lab staff member controlled the avatar in real time. In order to control the variables in the experiment, the demonstration avatar's moving speed was set to be constant based on the lab staff's walking speed. Unity 3D was used to create the virtual environment. The building models and planks were modified with physical features that allowed participants to freely walk on the top of the buildings and planks. Participants viewed the virtual environment through the first-person perspective and had character avatars for their bodies. The avatars were also created with physical features, so they could realistically fall from the plank in the virtual scene. The avatar model was developed based on a humanoid model on Mixamo.com. We added several textures and shaders to model the avatar as a construction worker with a lab logo.

4.2. Experiment procedure

The experiment consisted of three sessions: pre-questionnaire session, VR training session, and the virtual walk session. The pre-questionnaire session lasted 5–10 min. After participants signed a consent form describing the experiment, participants were asked to provide their basic demographic information such as age, gender, and other background information. Since people's previous video game experience or VR experience could influence their VR task performance [30], participants were also asked if they had any video game experience or VR experience. The VR training session lasted 5 min, during which participants were introduced to the HMD device and the virtual environment. The purpose of this VR training session was to let participants familiarize themselves with the tracked movement, the field of view control, and synchronization between physical and virtual bodies. The virtual avatar was designed to stand away from the edge of the building so that the plank was visible but not accessible. This way, participants could see and understand the plank-walk scenario without feeling the stress of being close to the edge of the high-rise building. Participants were given instructions about the scenario and they were asked to walk across the plank as safely as possible. The virtual walk session had no time limit. After the VR training session, the participants were instructed to step onto the plank with the physical plank that matched the virtual plank. For the falling and not-falling groups, participants then watched the other avatar walking across the plank. Participants were then asked to walk across the plank. At the end of the experiment, their comments and feedbacks were solicited. Each participant was randomly assigned to one of the three groups (control, not-falling, or falling) before the experiment. The experiment procedure took approximately 20 to 30 min for each participant.

5. Data analysis and results

5.1. Overview

A total of 126 participants (90 males, 36 females) took part in the study, including 115 students and 11 university staff. All participants

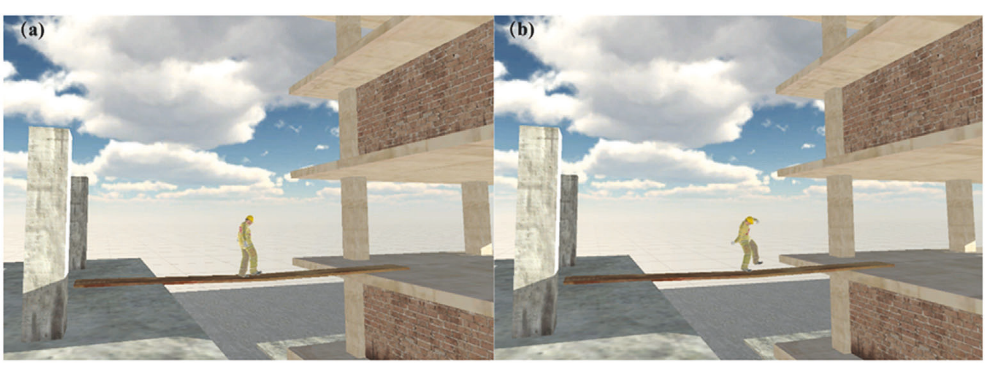

Fig. 5. Walking demonstration for not-falling group and falling group. (a) shows an avatar carefully walking across the plank without falling; (b) shows an avatar walking across the plank with the falling condition.

Table 2
Demographics of participants.

Demographic factors	Response range	Mean or percentage	Median
Gender	Male/female	71.4% male	–
Age	18–66	24.6	23
Occupant	Student/staff	91.3% student	–
Did participant have any video game experience	Yes or no	54.8% yes	–
Did participant have any VR experience	Yes or no	38.9% yes	–

were recruited by university email. Participants were from a variety of disciplines, and most of them were construction science students and architecture students. Participants' ages ranged from 18 to 66, and the median age was 23. The extent of video game experience and VR experience were also collected in the background questionnaire. A total of 69 participants reported having video game experience and the average video game time was 7.2 h. A total of 49 participants reported that they had VR experience before the experiment. Each participant was randomly assigned to one of three groups (control, not-falling, or falling) before the experiment. Table 2 summarizes the demographic information of the participants. Fig. 6 shows examples of participants who walked across the plank in the experiment.

5.2. Walking patterns

Our first test focused on understanding how two reinforced learning methods would affect participants' walking patterns measured by changes to the instantaneous walking speed. The instantaneous walking speed is a critical component of people's walking behaviors. It does not only represent the stability of their physical body [29] and age [91], but also reveals their emotion and behaviors [38,92]. Literature indicates that people tend to walk faster when they feel joy or anger and walk slower for sadness [38]. Meanwhile, Maki [64] also found that people decrease their walking speed to stabilize the body when they feel a fear of falling. Based on the studies mentioned above, instantaneous walking speed was selected as an important indicator to represent participants' walking behaviors.

Subjects' positions were collected by the location tracking sensor in HMD. According to existing gait research, there is little head movement in space when the walking speed is up to 1.2 m/s [44]. Thus, the three-axis camera positions in the horizontal direction were used to represent the subjects' positions in this experiment. These three-axis positions are accurate to centimeter and the HMD system end-to-end latency is about 22 ms [69]. The sampling rate of the subjects' position was 90 Hz (90 frames per second). All the instantaneous walking speeds were calculated by Eq. (1).

$$\bar{v}_t = \frac{S_{t+h} - S_t}{h} \tag{1}$$

where S_t is the current state position and h is the recording timestep. Fig. 7 shows examples of instantaneous walking speeds based on the raw data. The vertical lines were caused by the lost track of the system. Since the sampling frequency of the system is 90 Hz (90 frames per second), the lost track issues happened within 2 to 3 frames in the raw data. To avoid these issues, all the raw data were processed before the data analysis by using the interpolation method to calculate these missing frames. Three features were selected to indicate participants' walking patterns: frequency, entropy, and head pitch. Frequency is the changing rate of instantaneous walking speed in a certain time period. It represents the walking speed patterns in a short-time period. Entropy measures the irregularity of the time-series data. It represents the walking speed pattern in a long-term period. Finally, head pitch is the vertical head rotation of a human being. It represents the changes of attention during the walk. The literature indicates that head pitch is strongly related to people's walking patterns [3,44].

5.2.1. Frequency and Power Spectral Density (PSD)

Based on previous gait studies [106], when an individual's foot is on the ground during the stance phase, there is a short period velocity drop of instantaneous walking speed. Thus, a human's normal instantaneous walking speed should be time-domain data with regular speed circles. However, in this study, the participants encountered a hazardous situation when they walked across the plank in the virtual environment. It was hard for them to maintain their normal walk patterns. It was also difficult to analyze the instantaneous walking speed data since each participant spent different time to finish their walking task. Therefore, the spectral analysis method was applied to analyze participants' instantaneous speed data. All the time-domain instantaneous walking speed data was converted into frequency-domain data using Fast Fourier Transform (FFT). FFT is an algorithm that divides a signal over a period of time into different combinations of frequency components [20]. FFT is widely used in activity recognition [9], speech recognition [74], and image processing [80]. In our study, frequency represents the changing frequency of instantaneous walking speed in a certain time period and the PSD means the power spectral density in that certain bandwidth. Fig. 8 (a) illustrates an example of the instantaneous walking speed data in the time domain. Fig. 8 (b) shows the same example of instantaneous walking speed data in the frequency domain.

For the results of frequency and PSD, since human normal walking speed frequency is always between 1.5 Hz and 2.5 Hz [52], we mainly investigated bandwidths between 1 Hz and 3 Hz. Since the purpose of this study is to investigate differences among the three groups, the aggregated PSD of each experimental group was calculated. The higher value of aggregated PSD indicates more energy in that frequency bandwidth. Most of the participants' walking speed frequencies are in that frequency bandwidth. On the other hand, a lower value of

Fig. 6. Example of participants walking across the plank in the experiment.

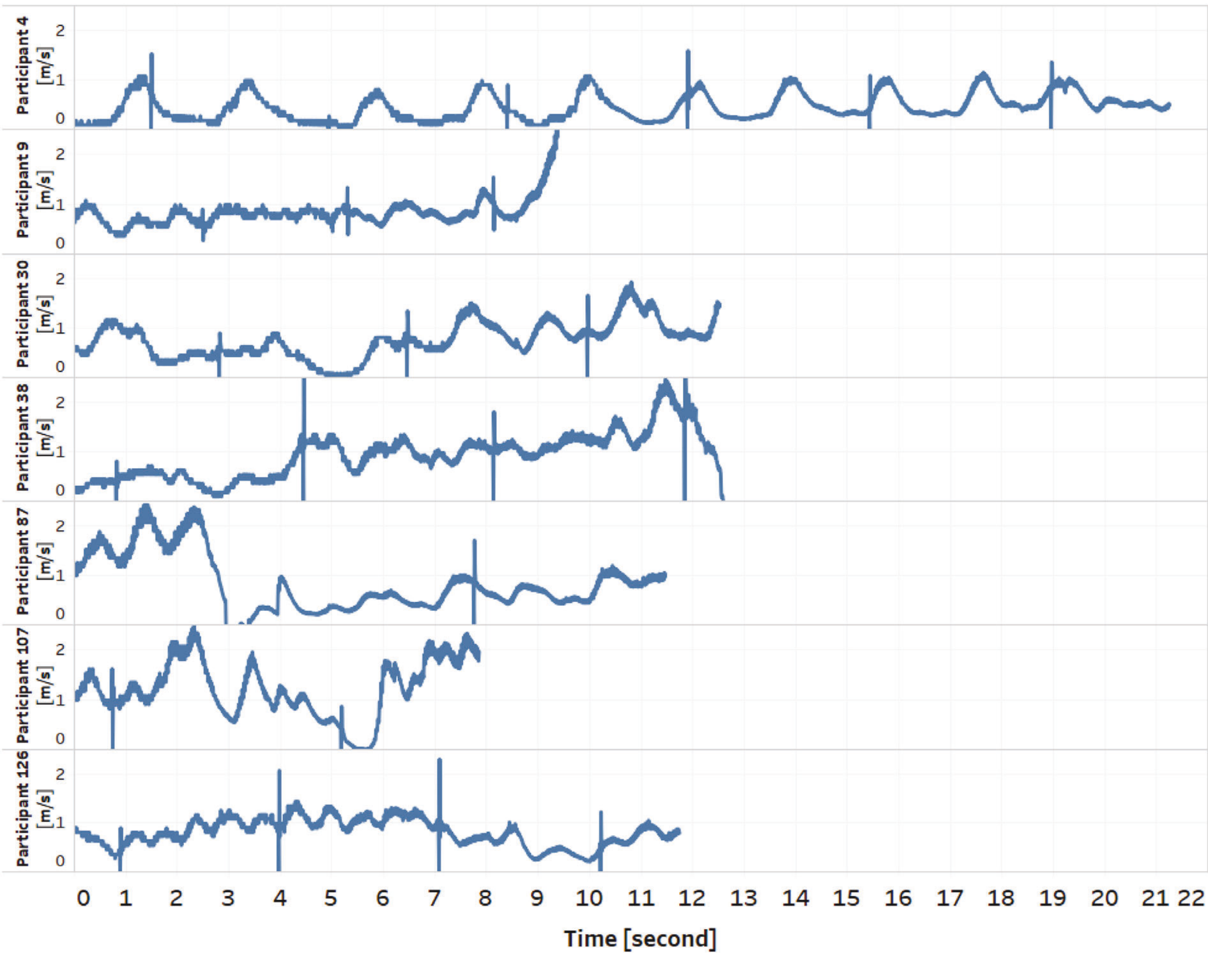

Fig. 7. Results of participants' instantaneous walking speeds.

aggregated PSD indicates less energy in that frequency bandwidth. Few participants' walking speed frequencies are in that frequency bandwidth. Fig. 9 illustrates the aggregated PSD for the control group, not-falling group, and falling group. The aggregated PSD of the control group are normally distributed in different bandwidths and mainly located between the bandwidths of 1.8 Hz and 2.1 Hz. This suggests that since there was no walking model shown to them before they walked, participants freely choose their walking strategies and most participants kept walking at normal speed when they were in the virtual environment. On the other hand, the aggregated PSD of the not-falling group were mainly located in the slow walk bandwidth [95] (1.1 Hz to 1.6 Hz) and the fast walk bandwidth (2.3 Hz to 2.8 Hz). Previous literature found that there is a linear relationship between frequency and walking speed [52]. It indicates that after observing an avatar safely walk across the plank, participants' walking frequencies tend to polarize to either walking slower or walking faster. Moreover, the aggregated PSD in the falling group indicates the polarization was significantly different based on the frequency domain data. The dominant frequencies of the falling group were located at 1.4 Hz and 2.6 Hz. The aggregated PSD values in slow walking bandwidth and fast walking bandwidth of the falling group are much higher than in the other two groups, indicating that most participants in the falling group either walked slowly or walked fast. It was revealed that the falling information strengthened the polarization of walking frequency. One reasonable explanation of the polarization is that because the negative consequence shown to the falling group was fairly strong (a person falling), it may trigger other complex psychological processes, such as the fight-or-flight response, which overrides the reinforced learning process. The fight-or-flight response, first discovered by Walter Cannon in 1932 [13], refers to a psychological reaction that occurs in response to perceived harmful events. This response is triggered as a human behavioral response to intense stresses [93]. When facing a major stress, people tend to split into two groups in terms of reactions: fight or escape the harmful event. In our experiments, the falling demonstration could be a stronger stressor, and perceived as a harmful event by the participants in the falling group. Thus, the fight-or-flight response may have occurred and overridden the results of reinforced learning during the experiment, resulting in the polarization of walking frequency. This theoretical finding is expected to inspire safety managers to institute an appropriate reinforced learning technique for construction workers during safety training, since overly negative demonstrations like death, falling, or injuries may cause a series of less understood psychological processes and complicate the training results. Table 3 shows the summary of aggregated PSD in each speed frequency bandwidth. The figures in the table represent the sum of Power Spectral Density (PSD) for different walk bandwidths (slow, normal, and fast) in each experimental group. The higher value of aggregated PSD indicates more energy in that frequency bandwidth. Most of the participants' walking speed frequencies are in that frequency bandwidth. On the other hand, the lower value of aggregated PSD indicates less energy in that frequency bandwidth. Few participants' walking speed frequencies are in that frequency bandwidth.

5.2.2. Entropy

Entropy quantifies the level of irregularity in time-series data [77]. As mentioned above, it is very difficult for participants to maintain regular walking patterns when encountering a hazardous situation in a virtual environment. In the study, participants utilized different

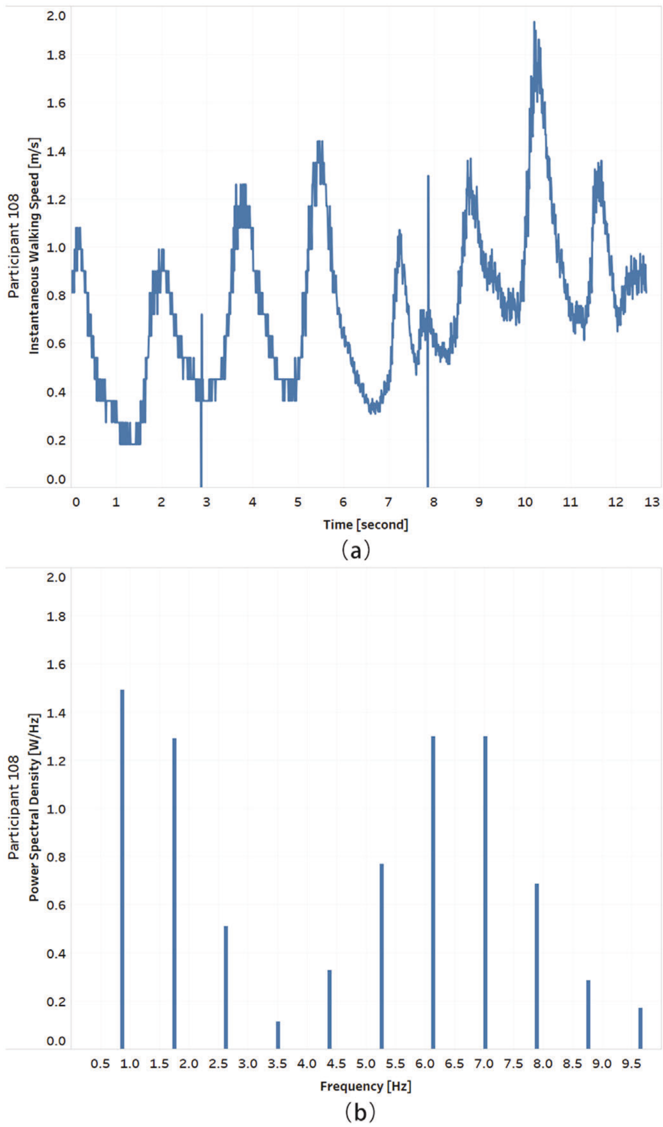

Fig. 8. Results of the FFT algorithm. (a) the instantaneous walking speed data in time domain, (b) the instantaneous walking speed data in frequency domain.

walking strategies to overcome this problem. Some unpredictability fluctuations of walking speed were detected in participants' instantaneous walking speed data. The higher value of entropy indicates more irregularity and unpredictability of instantaneous walking speed of participants. The lower value of entropy, on the other hand, indicates that participants' walk was relatively stable and regular. For instance, Fig. 10 illustrates two participants with different walking patterns. Participant 4 presented a stable and regular walking pattern during the walk. The entropy value of his/her walk was 5.75. On the other hand, participant 75 presented an irregular and unpredicted walk; there was a significant speed fluctuation between 4.5 and 7.5 s. The entropy value of his/her walk was 6.33. Entropy was found to be an effective feature to represent participants' walking patterns in our study. Participants' entropy of instantaneous walking speed was calculated by Eq. (2).

$$entropy\ (x) = -\sum_{i=1}^{\infty} P\{x = x_i\} \ln(P\{x = x_i\}) \tag{2}$$

In the results for each group, the entropies were found to not be normally distributed based on the results of Shapiro-Wilk tests of normality, so the data did not meet the assumptions required for parametric statistical testing. Since the data was nonparametric, a Kruskal-Wallis test was used to compare the entropies across conditions, and we used $\alpha = 0.05$ as the threshold for significance. We found a significant difference ($p = 0.0154$) in the entropy of participants' walking speed among the control group, not-falling group, and falling group. A post hoc nonparametric comparisons for each pair-Wilcoxon's test found differences between the control group and falling group ($p = 0.007$), and between the falling group and not-falling group ($p = 0.0313$). We did not find significant differences between the control group and not-falling group ($p = 0.4176$). The results reveal that the participants in the falling group had more unstable and unpredictable walking patterns than did the other groups. The falling information strongly affected participants' walking behaviors in the experiment. Fig. 11 shows the results of entropy for each group.

5.2.3. Head pitch

Head pitch is defined as head movement in the vertical direction. It is an important factor to represent people's walking speed [50] and risk perception [3]. Hirasaki et al. [44] found that an individual's walking speed is strongly related to head pitch. As walking speed increases, a person's head tends to point at a fixed point in front of his/her body and reduce the angle between head and trunk. Avineri et al. [3] found that people's risk perception has a significant effect on head pitch. People usually look down when they fear falling during walking. In our study, participants' head pitches were calculated by Eq. 3 based on camera positions and gaze positions. Gaze positions were recorded using the Raycast technique [96]. An invisible ray shoots from the center of the camera and returns a three-axis position value when it collides with other objects in the virtual environment [21]. This technique is widely used in the computer graphic and HCI fields for recording camera directions or people's attention. The sampling rate of the camera position and gaze position was 90 Hz (90 frames per second). At the end of each experiment trial, the system automatically generated a CSV file with all these raw data in the folder. Fig. 12 illustrates the calculation process in the virtual environment.

$$\tan\alpha = \frac{z - z'}{y' - y} \tag{3}$$

The distributions of participants' head pitches in different groups were found to be 2-mixture normal distributions and we were only interested in analyzing head pitch angles between 0 and 90°. Fig. 13 illustrates the distributions of head pitches for each group. It suggests that there were two head pitch patterns in each group. One pattern was looking down ($0° < \alpha < 45°$) when participants walked across the plank. The other head pitch pattern was looking forward ($45° < \alpha < 90°$) when they walked. For the control group, the mean of the distribution was 54.03° and the standard deviation was 16.97°. The two peaks of the distribution were $\mu1 = 37.44°$ and $\mu2 = 65.65°$ with $\Delta1 = 28.21°$. The head pitch pattern of looking forward was dominant in the control group. For the not-falling group, the mean of the distribution was 53.5° and the standard deviation was 17.31°. The two peaks of the distribution were $\mu1 = 40.27°$ and $\mu2 = 65.39°$ with $\Delta2 = 25.11°$. This indicates that after observing a walking example before participants walked, the head pitch patterns tended to be centralized and the distance between two peaks was smaller than in the other groups. For the falling group, the mean of the distribution was 51.23° and the standard deviation was 18.09°. The two peaks of the distribution were $\mu1 = 38.5°$ and $\mu2 = 70.12°$ with $\Delta3 = 31.62°$. It suggests that after seeing the falling scenario of the other avatar, the head pitch pattern of looking down was dominant in the falling group and the distance between the two peaks was larger than in the other groups. This result indicates that most participants in the falling group tended to look lower when they walked across the plank. According to Avineri et al.'s [3] research, people's risk perception had a significant effect on head pitches; they look down when they feel a fear of falling during walking. Meanwhile, the wider distance between two head pitch peaks indicates a split of behaviors in the falling group. A possible cause

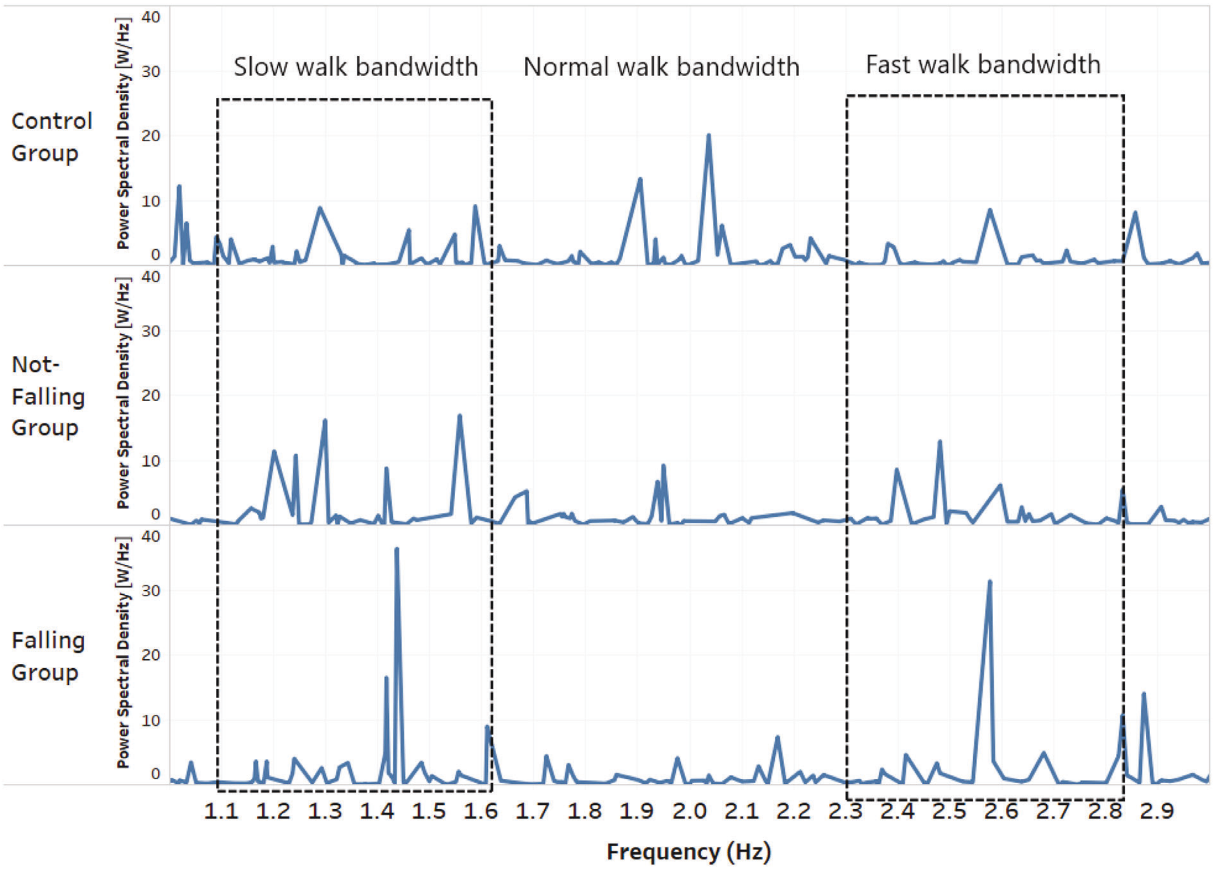

Fig. 9. Aggregated PSD for each group in frequency-domain.

Table 3
Summary of aggregated PSD in each speed frequency bandwidth.

Group	Sum of PSD (W/Hz)		
	Slow walk bandwidth (1.1 Hz to 1.6 Hz)	Normal walk bandwidth (1.6 Hz to 2.3 Hz)	Fast walk bandwidth (2.3 Hz to 2.8 Hz)
Control group	60.70	85.91	31.30
Not-falling group	86.17	53.65	52.1
Falling group	100.49	57.62	60.68

is the participants' fight-or-flight responses due to the strong stimulus (a falling person). Like we discussed earlier, strong stimuli such as intense stress or harmful events could result in completely opposite reactions among people, which is shown as the polarization of head pitch in our experiment. This finding further supports our argument that the effect of negative reinforced learning may greatly vary by subject. Negative reinforced learning can complicate safety training results. The experiment also indicates that head pitch of construction workers can be used as an effective indicator of risk perception in hazardous situations.

5.3. Walking trends

Based on the preliminary results, it was found that different categories of walking trends (i.e., overall change trend of instantaneous walking speed) existed when participants walked across the plank. For instance, some participants walked across the plank at a constant speed. Others walked slowly at the beginning and gradually increased their speed at the end. Several participants had some short-period breaks in the interim. All these walking speed trends can be seen as participants' different strategies when they encountered the hazardous situation.

Since the walking duration was different for each participant, it was important to standardize raw data into the same time length. In this study, Symbolic Approximation (SAX) [63] was applied to analyze participants' walking trends. Based on Piecewise Aggregate Approximation (PAA), SAX is used for converting continuous large-scale time-serious data into discrete symbolic representations that keep the original trends of the dataset [58]. SAX can greatly reduce the dimension of time-series data and index with a lower-bounding distance measure. Each participant's walking speed data was converted into a 10-digit string with five alphabet symbols (a,b,c,d,e) using SAX approach [101]. Five walking speed trends were used to represent participants' walking behaviors depending on how the instantaneous speed changes over the course, including slow to fast, fast to slow, slow to fast then slow, fast to slow then fast, and regular-paced walking speed. We also indexed these five walking speed trends with 10-digit strings such as (aabbccddee), (eeddccbbaa). For each participant, five lower bounding distances were calculated by comparing the subject's string to these walking trends strings. After the calculation, these five lower bounding distances were treated as the clustering features for the hierarchical clustering algorithm. Fig. 14 shows the workflow of the walking speed trends classification.

There were 42 participants in each of the control, not-falling, and falling groups. Based on the Mahalanobis distance rule for outlier analysis [45], eight outliers were removed from the results. Outlier analysis was performed in this study because we found that the data of several subjects were off the expected range possibly due to unfamiliarity with the VR environment. For example, some subjects stopped for a long time in the middle of the experiment as they were disoriented in VR. In addition, in different analyses certain subjects were beyond a reasonable range, which could be attributed to tracking errors. Leaving these data points in our analyses could distorted the findings. As a result, outlier analysis was performed prior to each of the

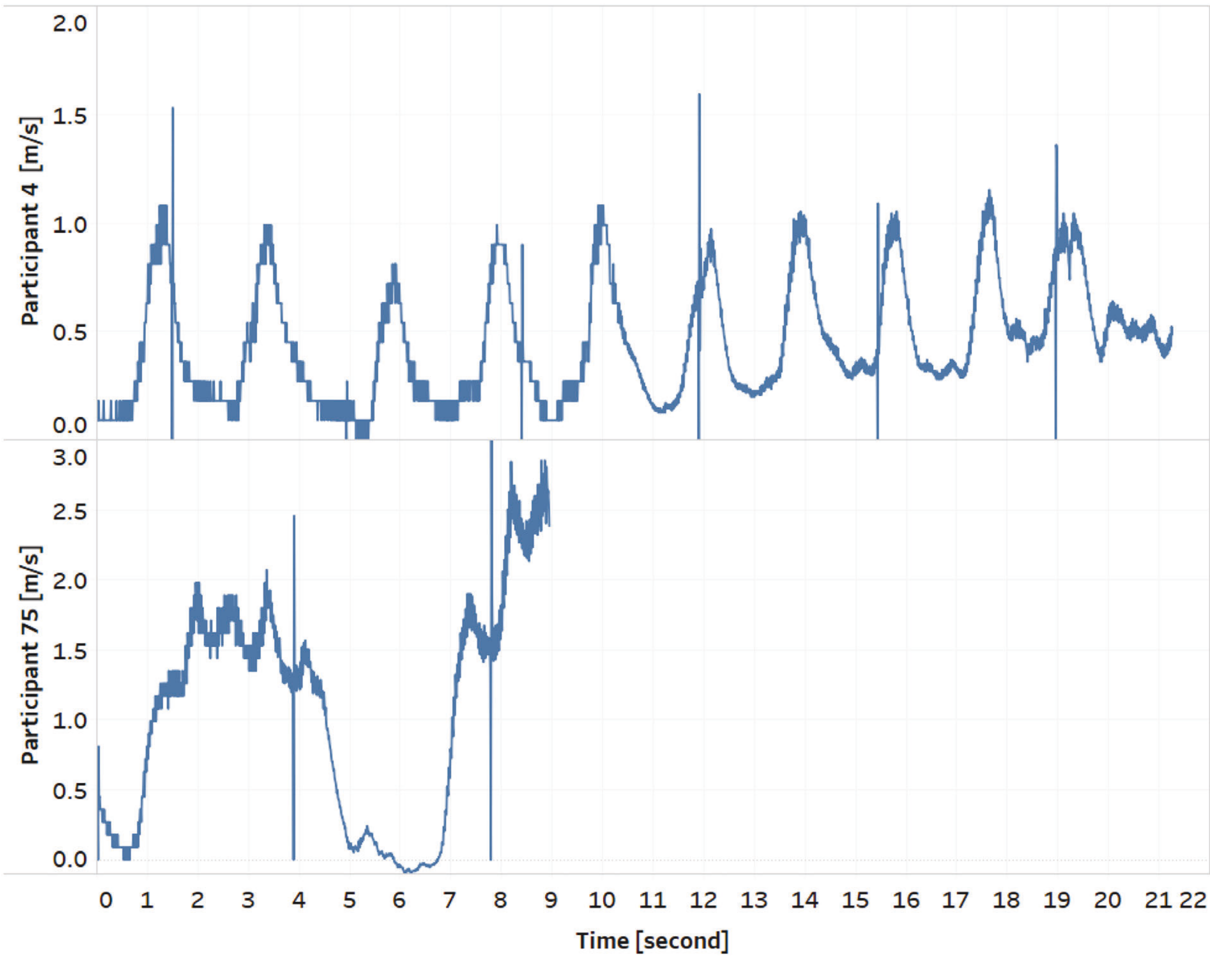

Fig. 10. Results of two walking patterns: (a) the regular walking pattern in time-domain; (b) irregular walking pattern in time-domain.

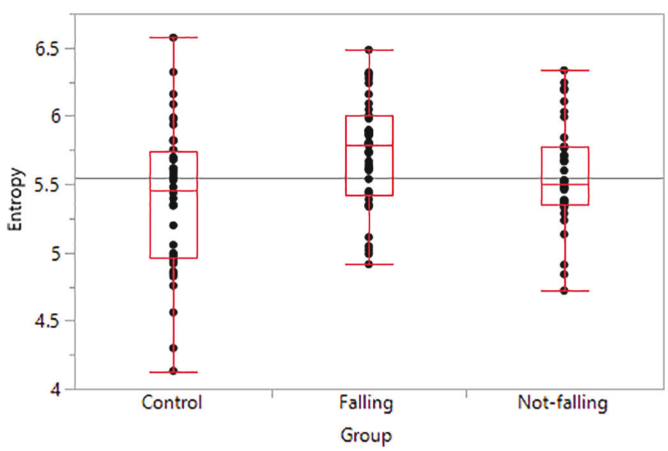

Fig. 11. Results of entropy for each group.

data analyses. Following the common practice [45], in our outlier analysis the Mahalanobis method was used to standardize the distance between a data point to the mean value. Data points beyond two standard deviations from the mean values were removed as outliers. This ensures that the preserved data points represent 95% of the population. After removing the outliers, there were 38 participants in the control group, 42 participants in the not-falling group, and 38 participants in the falling group. Based on SAX results, the hierarchical clustering algorithm found two categories of walking speed trends: regular walkers who presented relatively stable walking speed over the course and irregular walkers whose walking speed changed dramatically over the course. Fig. 15 shows the dendrograms of clustering for each group based on SAX results. The numbers on the bottom indicate the ID of the participants. We used the ward method to generate the sequence of clusters in the hierarchical clustering algorithm. The hierarchical clustering is also called agglomerative clustering, and is a bottom-up clustering approach. Each observation finds its nearest data point to form its own cluster. For each step, the clustering process calculates the distance between all pairs of clusters and combines two cluster that are closest together. The clustering process continues until all the data points are combined into one cluster [54]. The agglomerative process shown in Fig. 15 is called a dendrogram. It clearly shows the number of clusters for each group. For the regular walking trend, the normal gait circle existed in this walking trend. The number of regular walkers were control group = 18, not-falling group = 26, and falling group = 9. For the irregular walking trend, the normal gait speed circle did not exist. The number of irregular walkers were control group = 20, not-falling group = 16, and falling group = 29. These results confirm the two categories of walking trends (regular walking trend and irregular walking trend) when participants encountered a hazardous situation. The portion of regular walking trend in the control group is 47.4% and the portion of the irregular walk is 52.6%. However, after witnessing a walking example before they walked, more participants were intent on walking normally (62%) like the walking example shown than were those walking irregularly (38%). Moreover, after observing an avatar falling from the plank, more participants were intent on walking irregularly (80.5%) than on walking normally (19.5%). The reasonable explanation of this result is that after observing a strong negative

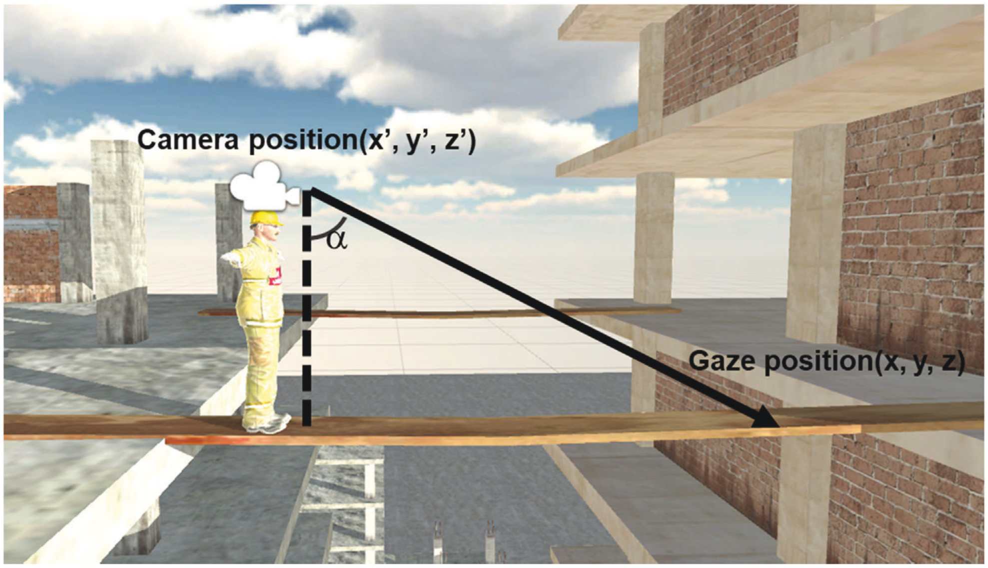

Fig. 12. Calculation process of head pitch in the virtual environment.

demonstration (falling) in the falling group, participants were made aware that they could also fall from the plank. Certain participants in the falling group may have become anxious or even scared to walk across the plank. Gait studies have found that when people feel fearful, the variance of their walking speed tends to be larger than in other emotional statuses such as happiness, sadness, anger, and neural [62]. As a result, the participants in the falling group tended to walk irregularly rather than regularly. Considering all the previous findings we discovered in the experiment, we conclude that the best technique for safety training is to demonstrate positive safety practices (positive reinforced learning) instead of demonstrating negative consequences (negative reinforced learning). Table 4 shows the number of participants in each group by walking trend.

5.4. Walking time

In order to accurately record participants' walking time on the plank, three invisible collision geometries were designed in the virtual environment. Fig. 16 shows the colliders that were used for recording the walking time on the plank. Colliders A and B were used for recording participants' waking time without falling condition and collider C was designed for recording participants' falling condition. Collider A recorded the start-time when the center of the virtual avatar exited collider A. Collider B recorded the end-time when the center of the virtual avatar entered collider B. Walking time is defined as the difference between start-time and end-time on the plank. Meanwhile, the system also recorded participants' falling status and general position changes in the virtual environment. At the end of each experiment trial, the system automatically generated a CSV file with participant ID.

Based on the Shapiro-Wilk tests of normality, walking time of the three groups was not normally distributed. The data did not meet the assumptions required for parametric statistical test such as Analysis of Variance or ANOVA. As a result, the nonparametric Kruskal-Wallis test was used to compare walking duration across the three groups. We used $\alpha = 0.05$ as the threshold for significance. We did not find any significant difference in participants' walking times across the three groups. We then analyzed walking time by different walking trends categories (regular and irregular walkers, as discussed in the last section). We found a significant impact ($p = 0.0221$) of the two reinforced learning methods on participants' walking times among those categorized as regular walkers. A post hoc nonparametric comparison for each pair-Wilcoxon's test found differences between the control group and falling group ($p = 0.0193$), and between the falling group and not-falling group ($p = 0.0087$). Fig. 17 shows the results of walking time by different walking trends.

For the irregular walkers, we reported the number of participants, mean (M), and standard deviation (SD) of walking time. The control group had M = 24.32 and SD = 2.39, the not-falling group had M = 18.95 and SD = 2.68, and the falling group had M = 17.29 and SD = 1.99. For the regular walking trend, the control group had

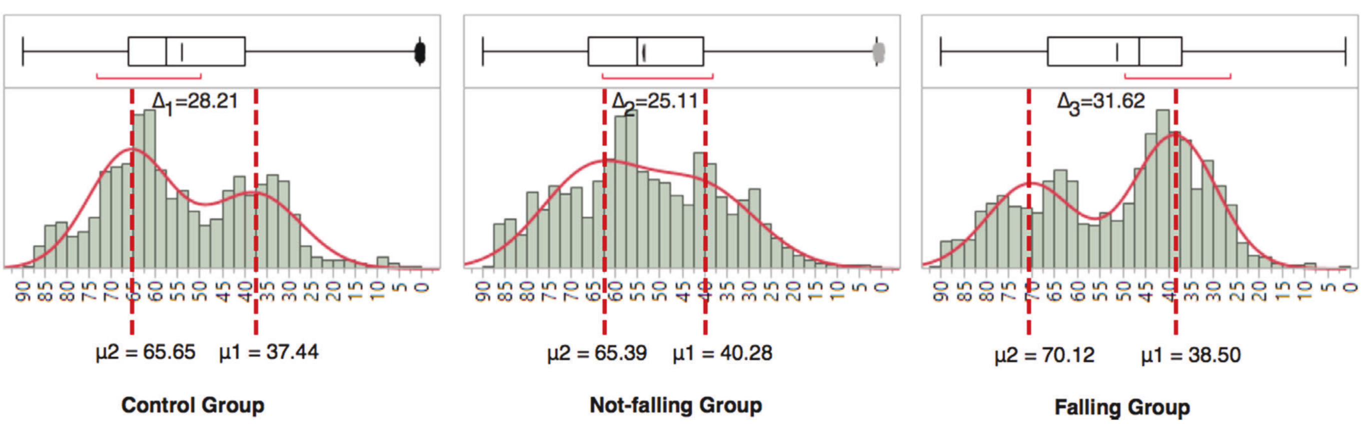

Fig. 13. 2-Mixture normal distributions of head pitches for each group.

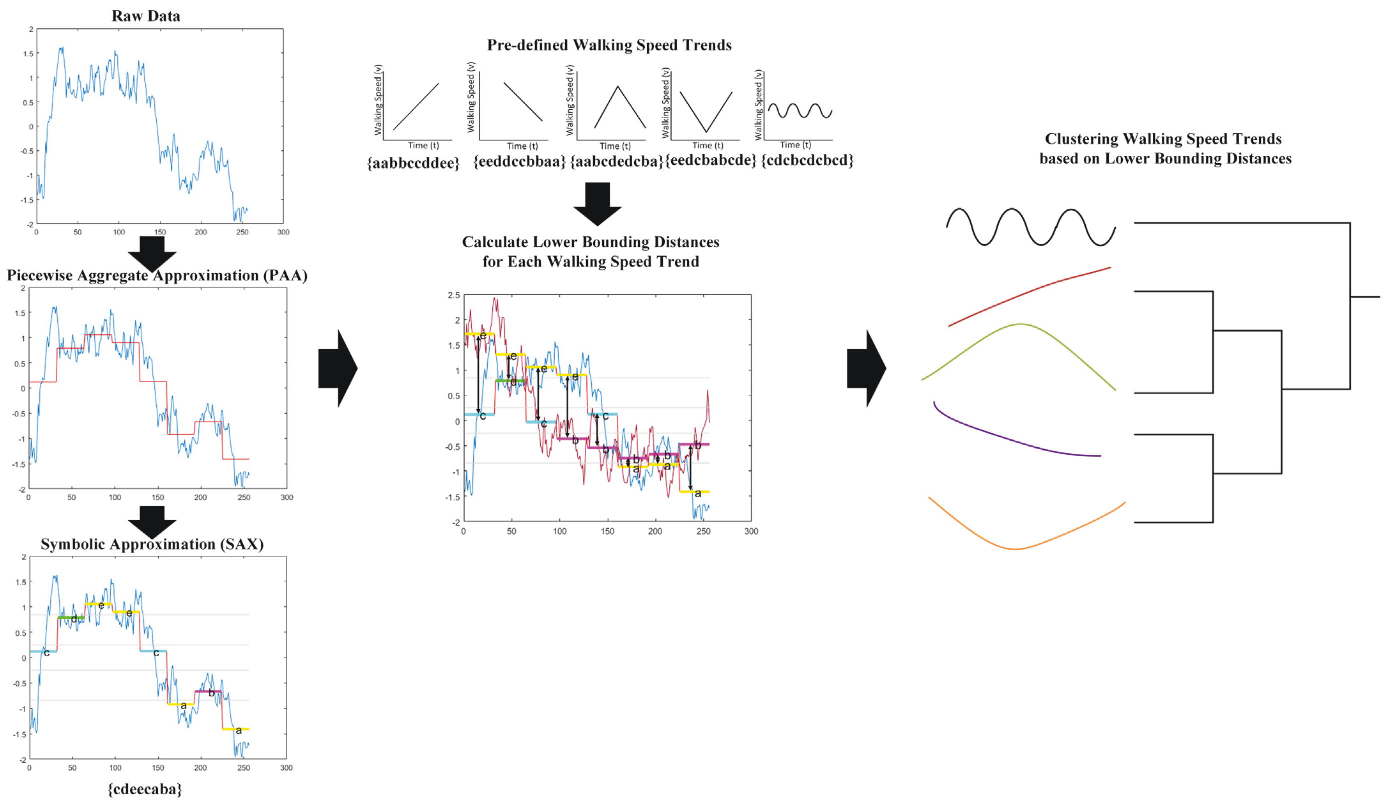

Fig. 14. Classification workflow of the walking speed trends.

M = 18.48 and SD = 11.27, the not-falling group had M = 19.66 and SD = 11.27, and the falling group had M = 9.5 and SD = 3.82. Table 5 shows the results of the classification based on lower bounding distances of participants.

6. Discussion

The results of this study confirm the impact of the two reinforced learning methods (showing positive behaviors and showing negative consequences due to inappropriate behaviors) on the three walking behavioral indicators: walking pattern, walking speed trend, and walking time. This indicates that participants who witnessed a positive walking example before they walked had a stable and slow walk and most of them followed the norms shown by the avatar. The participants who observed a negative falling scenario tended to walk in a more unstable and faster way, and most of them presented irregular walking trends. These walking behaviors could lead to more mistakes and unsafe behaviors in hazardous situations.

The main discovery in this study is that compared to positive reinforced learning, negative reinforced learning may trigger more complex psychological processes, making the results less predictable. This study contributes to learning theory in the construction literature in two ways. First, one finding indicates that the positive consequence information (not-falling group) encouraged participants to follow the walking demonstration and maintain a normal walking pattern in the hazardous situation. This finding supports most of the reinforced learning studies that positive reinforcement encourages good behaviors. The second finding of this study reveals that negative information, particularly the strong negative stimulus of showing a falling person, induced less desired behaviors (walking faster and more irregularly). This contradicts the reinforced learning theory that suggests negative reinforced learning is able to prohibit bad behavior. A possible explanation is that people's psychological responses to external stimuli is very complex. When the negative stimuli are too strong, such as showing participants a falling person in our experiment, it may trigger a series of unexpected psychological or physiological responses such as the fight-or-flight response, overriding the original reinforced learning results. The uncommon phenomenon we discovered in this experiment, such as the polarization of walking, head pitch split distribution, and the irregularity of walking patterns, all occurred in the falling group after the participants observed a virtual person falling off the plank. These could all be driven by the fight-or-flight reaction as discussed earlier, or other psychological processes that have not been well explored. The discrepancy with existing reinforced learning theory, as well as the rationales behind it, all suggest a further and deeper investigation is needed in this research area. As for the construction safety literature, the contribution of this study relies on evidence that the effect of the negative reinforced learning is less consistent compared to that of positive reinforced learning. Thus, while it could be more effective for some subjects, it could also augment fear for negative consequences and thus trigger undesired behaviors. Therefore, in practice, safety managers and trainers should be more prudent about using the negative reinforced learning method.

Meanwhile, the reinforcement learning process is a complex cognitive process and there are still numerous unknown factors affecting the reinforcement learning process. For example, according to Frank et al.'s [33] study, the neuromodulator dopamine plays a critical role in the reinforcement learning process. The results of their study indicated that Parkinson's patients without dopamine stimuli are better at learning from negative outcomes than learning from positive outcomes. The Parkinson's patients with dopamine stimuli are better at learning from positive outcomes than learning from negative outcomes. Several limitations still need to be addressed in the future. First, the calibration accuracy between the participants' actual movements and virtual animations still need to be improved. Some participants mentioned that there were slight movement mismatches in the virtual environment when they rotated their bodies. These mismatches affected participants' feelings of presence (that is, the sense of really “being there” in the

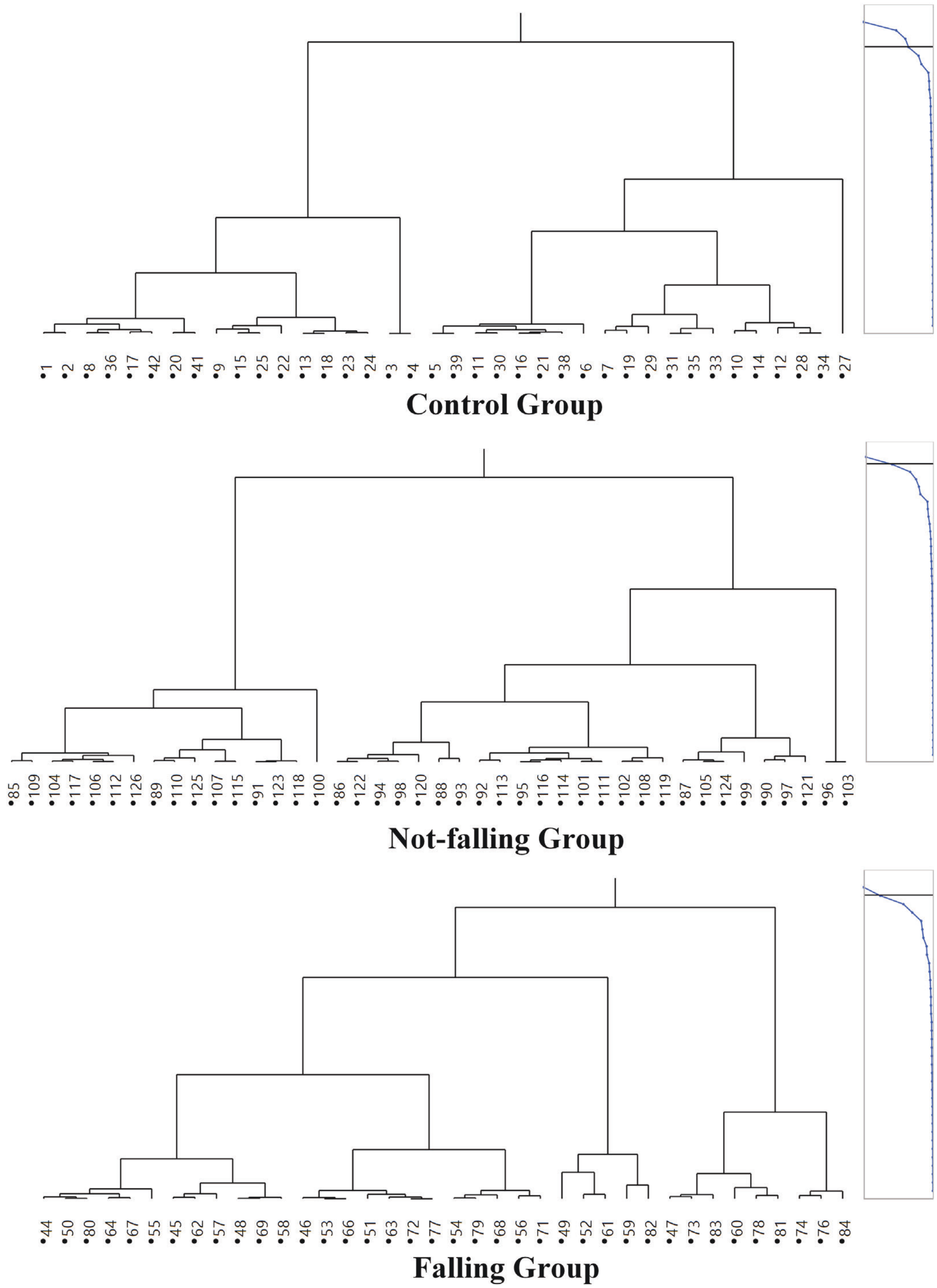

Fig. 15. Dendrograms of clustering for each group.

Table 4
Number of participants in each group by the classification of walking trends.

	Number of participants		
	Control group	Not-falling group	Falling group
Regular walker	18 (47.4%)	26 (62%)	9 (19.5%)
Irregular walker	20 (52.6%)	16 (38%)	29 (80.5%)

simulated world). More accurate motion tracking could be used for future systems. Second, this study has focused on studying how social learning affects people's walking behaviors in high-rise buildings and hazardous scenarios. Other hazardous scenarios should be identified and simulated in future studies. Third, the experiment tested the impact of reinforced learning on the participants immediately after they went through the learning process. Learning outcomes that persist over time were not considered in this study. In our future study, time will be considered as a critical variable to test. Fourth, the focus of this study was to investigate the impacts of reinforced learning on workers' walking behaviors in a high-rise hazardous situation; an ergonomics

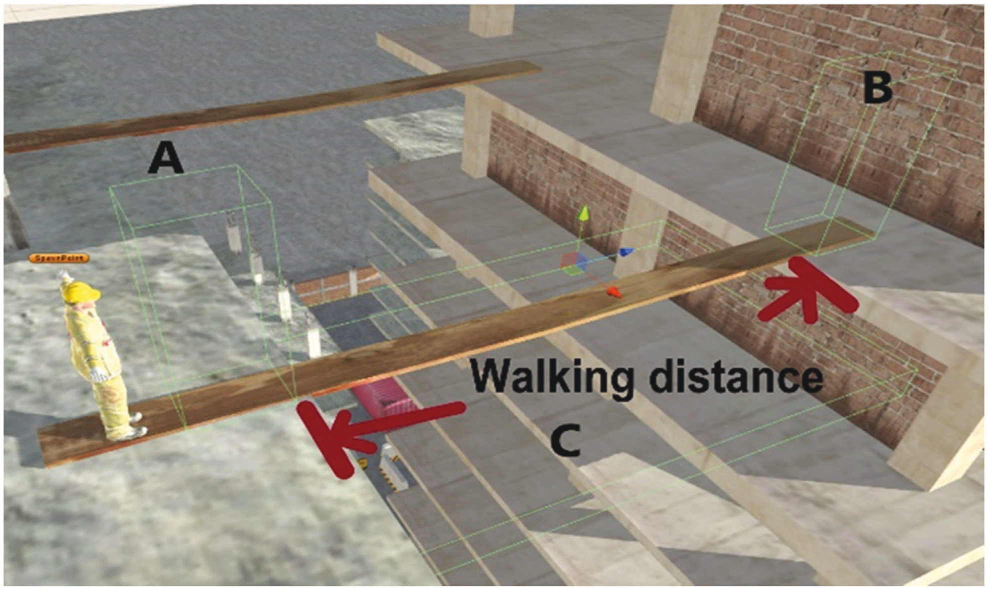

Fig. 16. Record-setting of walking time in the virtual environment.

analysis was not considered. Lastly, the animation realism of the experimenter-controlled avatar could still be improved, as some participants commented that the realism of the other avatar may have affected their responses and reactions in the virtual environment.

The developed multi-user VR system with motion tracking function was introduced in this study. Its potential for investigating human behaviors in hazardous situations was illustrated for real-world construction scenarios by conducting a human-subjects experiment. Based on participants' feedback, the virtual environment can provide a realistic experience of being in a hazardous situation on a construction project. Most participants (90%) stated that this VR system could realistically simulate real walking scenarios. The participants also mentioned that the real wood plank greatly enhanced the presence in the virtual environment, especially when they felt the edge of the real plank. Although VR system development is not the focus of this study, the developed VR system also represents several innovations, one of which was a data collection function. Instead of using the VR system only as a visualization tool, this study also used it as a data collection tool. Participants' body movements and gaze focus data were captured by the system using the RGB depth camera and embedded eye tracking sensors in the VR headset. The depth camera was also used to capture and reproduce participants' body motions in real time and allowed participants to navigate in the virtual environment in a natural way. It helped reduce cyber sickness due to the uncoordinated cyber and physical motors. According to the participants, only 11% of them felt sickness and 89% stated that this VR system realistically simulated the high-rise walking scenario in a comfortable way. The VR system also features a multiuser VR environment for team cognition studies in the construction field.

7. Conclusions

This study proposed a multi-user VR system integrated with a motion tracking function to investigate the impact of demonstrating different consequences (positive and negative) on people's fall risk behaviors in a hazardous situation. A walking scenario with a plank placed between two high-rise buildings was selected as the hazardous situation in this study. A human-subject experiment was conducted to investigate people's fall risk behaviors. Three walking performance indicators were selected to represent people's walking behaviors: walking pattern, walking speed trends, and walking time on the plank. The results of the experiment indicate that showing information with positive consequences to people could encourage them to follow the demonstration behaviors and maintain their normal walking behaviors in a hazardous situation. Alternatively, demonstrating information with negative consequences might induce people to walk fast and perform irregular

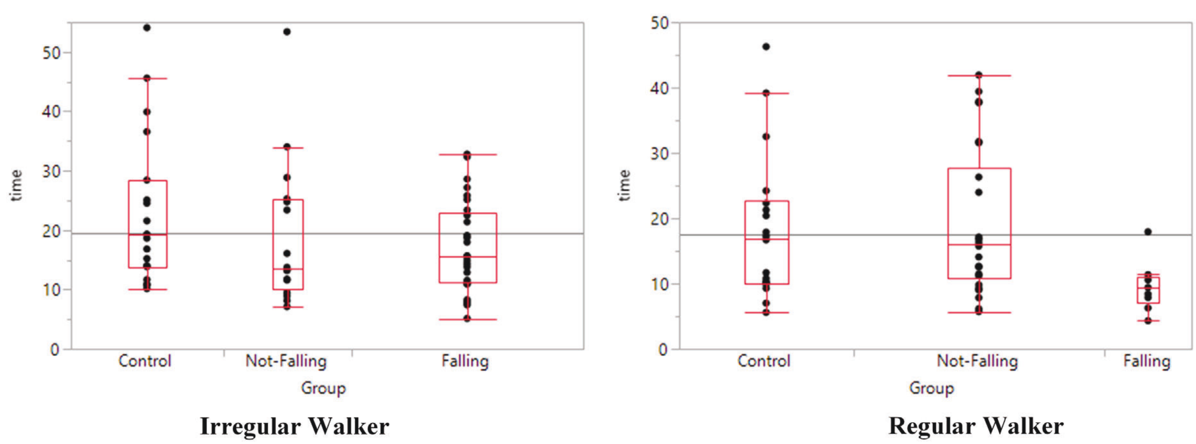

Fig. 17. Results of walk time by different walk trends.

Table 5
Summary of walking time in each group.

	Factor	Walking time (second)		
		Control group	Not-falling group	Falling group
Irregular walker	Number of participants	20	16	29
	Mean	24.32	18.95	17.29
	Standard deviation	2.39	2.68	1.99
Regular walker	Number of participants	18	26	9
	Mean	18.48	19.66	9.50
	Standard deviation	11.27	11.27	3.82

walking behaviors, which could lead to more mistakes and unsafe behaviors in a hazardous situation. Moreover, this study also validated the VR approach to investigating human behaviors in hazardous situations. The results of this study will enhance safety managers' knowledge of fall risk behaviors and help them provide suitable fall prevention measures to the construction workers who work in hazardous situations. The focus of this study does not only rely on a significant practical contribution such as improving safety training via VR. It also aims to make a theoretical contribution to the learning theories in the context of construction safety, i.e., exploring whether a certain reinforced learning process enhances safety perception and if so, why it happens. Meanwhile, we recognize the importance of VR applications for construction safety training. That being said, the findings of this study can also help the development of a better construction safety training program that is based on the learning processes of construction workers.

The two reinforced learning methods have clear definitions in the learning literature, with the arguable point being which method is more effective in learning outcomes in a variety of contexts. As for the definitions, procedures, and features, these two methods are distinctive. Yet it remains unclear which method yields a more effective result in the high-rise walking context, which is common to modern construction work. This represents learning in a stressful and hazardous situation and a specific case in construction. This study answers this critical question.

Walking at that height is quite common in many high-risk construction trades such as ironworks, and the VR scenario studied in this paper was developed to study walking behaviors at such a height. We chose walking between two high-rise buildings across a plank, in order to trigger risks perceived from the height. As for the main contribution of this study, the emphasis is to investigate the impacts of reinforced learning on workers' fall risk behaviors in a high-rise hazardous situation. The contribution relies on new discoveries about the relationship between training content and construction workers' perceptions in the context of learning theories. The findings are expected to help safety managers select an appropriate safety training strategy for workers in high-rise hazardous situations.

As a future research direction, more accurate motion tracking systems should be used for capturing users' body movements. By using the accurate motion tracking system, more complex and dynamic safety behaviors could be identified and investigated in the hazardous situation. Gesture monitoring and ergonomics analysis will be implemented in our future research agenda. Moreover, other hazardous scenarios need to be identified and simulated in future studies. In this study, we only investigated people's walking behaviors in a hazardous situation in a laboratory setting. In real-world practice, construction sites are more complex, and hazardous situations are always unpredictable. Thus, more complex and dynamic hazardous scenarios should be developed in future research. Lastly, physiological sensors will be applied to the proposed VR system in our future study. The physiological sensors will help us deeply explore people's cognitive processes and their behaviors in hazardous situations.

Acknowledgement

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