



BEEYONDERS

Learning Activities Resources

D5.3: Active user-centric learning resources for H&S and attraction of the next generation workforce

WP5, T5.3

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Technical references

PROJECT ACRONYM	BEEYONDERS
PROJECT TITLE	Breakthrough European tEchnologies Yielding cOnstruction sOvereignty, Diversity & Efficiency of ResourceS
PROJECT COORDINATOR	Antonio Alonso Cepeda antonio.alonso.cepeda@acciona.com
PROJECT DURATION	June 2022 – November 2025 (42 months)

DELIVERABLE NO.	D5.3
DISSEMINATION LEVEL*	PU
WORK PACKAGE	WP5 – Worker-centric technologies to improve health, safety, and well-being
TASK	T5.3 – Active user-centric learning resources for H&S and attraction of the next generation workforce
LEAD BENEFICIARY	DTU
CONTRIBUTING BENEFICIARY/IES	ACC, TEC, STAM, EBC
DUE DATE OF DELIVERABLE	31/05/2025
ACTUAL SUBMISSION DATE	29/08/2025

* PU = PUBLIC

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0.2	12/02/2025	DTU	Kilian Speiser, Jochen Teizer
0.3	27/05/2025	DTU	Kilian Speiser, Jochen Teizer
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1.0	30/05/2025	DTU	Kilian Speiser, Jochen Teizer
1.1	23/07/2025	DTU	Kilian Speiser, Jochen Teizer



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Acronym list

	DESCRIPTION
3DPC	3D Printing concrete
API	Application Programming Interface
AWL	Autonomous Wheel Loader
BIM	Building Information Modeling
BT	Breakthrough technologies
CAD	Computer-Aided Design
DB	Database
DT	Digital Twin
DTSI	Digital Twin Services Input
HSA	Human Safety Analysis
EM	Emissions Monitoring
SCC	Safety and Compliance Checking
SWD	Smart Wearable Device
VR	Virtual Reality
VTE	Virtual Training Environment



Executive Summary

This report investigates how a Digital-Twin-driven virtual reality (VR) platform can raise construction-site safety and LEAN productivity by turning real project data into immersive, multiplayer training experiences. Two case studies, a high-rise crane-hoisting scenario and a road-works human-robot interaction scenario, serve to test the framework, its new behavior-based performance metrics, and its capacity to deliver personalized feedback.

Section 2 of this report identifies the relevant background and presents context for active training, real-world hazards in VR training, performance assessments in such training, and human-robot interaction. The section highlights the relevant literature and identifies several concepts that are relevant to the objectives of the work presented in this report. Based on existing literature, Section 3 identifies the objectives of the VR training environment.

Section 4 overviews the training platform that is implemented in two case studies. The platform itself is described in detail in the deliverable D3.7 of the BEEYONDERS project. This report focuses on the instantiation of the framework presented in deliverable D3.7. The case studies are then presented in Section 5 and Section 6. The two case studies involve a Building Use case and a Road construction use case. In a BIM-based high-rise scene, three trainees (operator, two riggers) use VR headsets and a gesture-recognition glove. In the Road construction use case, RTK-GNSS recordings of an autonomous wheel loader and worker are replayed. A time-expanded Safety-Graph algorithm assigns energy-based costs to every 1 m grid move, guiding the safest paths and tallying exposure.

The report concludes with Section 7 confirming that the framework can rapidly generate realistic scenes from project data, capture rich behavior analytics, and spotlight actionable gaps in communication, hazard awareness, and waste. Limitations set the agenda for larger trials and deeper AI integration, but the evidence already points to a scalable route toward safer, leaner construction sites.



1. Introduction

Construction remains one of the most hazardous industries [1]. Workers receive training to act safely and increase hazard awareness while still being productive. Different training methods exist to prepare workers. On-the-job training is a common method for developing skills but has the disadvantage of exposing trainees to hazards. Other traditional methods, such as classroom lectures or video-based training, do not expose trainees to conveying relevant knowledge but fail to train behavioral skills [2]. These approaches primarily address the trainees' intentions, a potential reason for the lack of transfer of learning [3]. In response, virtual training methods merge these advantages by allowing workers to train in a simulated world where hazards are recreated and mistakes are forgiven. At the same time, virtual training not only develops intention but actually trains behavior since workers complete tasks in action [3]. Such active methods have also proven to be more engaging [4]. Several studies have demonstrated their high efficiency [5,6]. For this reason, the report presents two virtual training scenarios for construction workers that train safe behavior and LEAN principles, combining effective work completion with adherence to safety rules. It evaluates a framework that defines the concepts and entities necessary to develop specialized training scenarios for various use cases.

The training scenarios are based on a virtual training framework that was developed during the BEEYONDERS project. While the platform has been described in Deliverable D3.7 of the BEEYONDERS project, the following report will demonstrate the functionality of the platform and demonstrate its efficiency in two case studies:

- Building use case: a multi-user training environment on a high-rise construction site
- Road construction use case: human-robot interaction scenario



2. Background

2.1. Active Training

Traditional safety education and training in construction have primarily relied on classroom lectures, video tutorials, and on-site field instructions. These methods are often designed to convey specific knowledge, such as safety rules related to hazardous equipment, materials, or restricted work areas. However, such approaches are passive, positioning participants as observers rather than active learners. This passive role fails to address the dynamic characteristics of real construction sites, where hazards can be unpredictable and require immediate, behavior-based responses.

VR offers a promising alternative by actively immersing trainees in lifelike hazard scenarios, providing a more engaging and impactful learning experience. Unlike traditional methods, VR enables participants to interact with realistic construction environments, confront hazards, and receive real-time feedback without exposure to actual risk. VR-based training has been widely adopted in professional fields like military, aviation, and medicine, and its application in construction is gaining traction. Several studies have reviewed the benefits of VR for construction safety training [6–8]. According to Golovina et al. [9], VR offers the following advantages. Users can be confronted by hazards without being at risk. VR training increases engagement and empowers them to explore scenarios that have not been anticipated. VR training can be personalized and can provide data-driven feedback due to its capability to collect performance data reliably.

On the other hand, VR-based learning environments were criticized in research for being unrealistic compared to participants making real-world experiences [10]. Recent research proposed a data model to include more realism from BIM and IoT [11,12], and Speiser & and Teizer included these data sources into a digital twin context to enhance realism and include real-world hazards [13]. Such integrations may reduce the time required to create VR training, which has been outlined as the main reason for preventing details and real-world context [14]. Similarly, Zhao & and Lucas emphasize using geometric data from BIM to increase the visual and contextual accuracy of VR construction scenes. However, implementing VR-based training faces practical challenges [15]. Up to 25% of participants in VR experience motion sickness [4] in multi-user environments (needed when training larger groups) [16]. Finally, some studies have reported that safety knowledge gains achieved through VR training are comparable to those obtained through traditional learning approaches [17,18]. This finding suggests that while VR excels in engagement and hazard simulation, its ability to achieve superior learning outcomes may depend on the design and application of the training scenarios.

These studies commonly use pre- and post-training interviews or tests to assess the effectiveness of the training. Such assessments, however, do not address the behavior of the user but only the intention of such users [19]. Workers may demonstrate an intention to follow safety practices during assessments but fail to translate these intentions into real-world behaviors. This intention-behavior gap represents a critical limitation of conventional training methods, especially in dynamic and high-risk construction environments where the ability to respond to hazards is essential for safety.



2.2. Digital Twin Integration for Enhanced Context Relevance

Such behavioral assessment, however, can only be meaningful if the hazards and the environment in the training scene reflect real-world scenarios. Several studies have included BIM models to include such real-world data [20,21]. Another approach is the utilization of a digital twin [22,23]. Nevertheless, integrating construction training into the context of digital twins has not been fully explored. [24] utilized a digital twin for safety training in an industrial environment, and [25] integrated a digital twin for training crane lifting operations. Another study proposed a framework for integrating construction safety training into a digital twin [26]. However, this framework has not been implemented; it has only been discussed on a conceptual level. The concept has been refined and applied in several case studies [12,27]. In these works, the authors use the definition of the Digital Twin for Construction (DTC) introduced by Sacks et al. (2020) and utilize the as-planned and as-performed information to recreate a training scene using real-world knowledge. The only existing approach to include IoT data in VCST utilizes Real-Time Location Systems (RTLS) for simulating construction workers and machinery [2].

When integrating real-world data, behavioral safety performance can be relevant, but existing approaches merely assess VCST using subjective methods or based on surveys. Many studies evaluate the performance of the trainees using interviews [28,29] and questionnaires [14,18,30]. A disadvantage of this approach is that they are subjective and quantify intention rather than behavior. Other studies assess the performance based on the number of identified hazards [31,32]. Other approaches involve collected data, such as the time for completing a task [28,33] or the time until a hazard is recognized [34,35]. It is crucial to quantify the behavior, and in VCST, it is simple to collect data capturing the behavior of the trainees. Nevertheless, most studies do not utilize this feature [7]. Studies addressing the worker's behavior analyze the position of the trainees [36] and [27] integrate methods to detect and quantify proximity between hazards and trainees based on previous efforts [9]. For integrating behavioral safety performance, it is essential to include the spatial-temporal context.

The benefits of VR training are evident in psychomotor performance, knowledge acquisition, and spatial ability improvement [6]. Several studies highlight the improved effectiveness of virtual training compared to traditional lecture-based approaches [4,5]. However, [17] emphasizes the need for further investigation, particularly regarding the applicability of these findings to construction workers. Other studies find that extensive resources are required to create virtual training scenarios [21].

A reusable framework connecting to existing knowledge from the safety domain and other domains and use cases could improve CR safety training in construction in two aspects. First, it can reduce the resource demand in training creation by reusing existing knowledge from real-world data [11,13,37]. Second, the framework could measure behavioral shifts instead of intention by reproducing real-world hazards in VR. For such a framework, the knowledge from the construction safety domain must be captured. Hence, the following section describes the different approaches to formalizing safety knowledge in construction.



2.3. Human-robot interaction

The construction industry faces persistent challenges with high incident rates and low productivity. While industries like manufacturing have significantly enhanced productivity through robotics and automation, construction lags behind [38]. This discrepancy stems from several inherent reasons, such as the uniqueness of construction projects, the constant change in the construction sites, and the large scale of components compared to industrial manufacturing. On top of that, Human-Robot Interaction (HRI) in construction remains underexplored and represents a knowledge gap [39]. These factors make the integration of robotics in construction complex.

Construction sites are dynamic environments where workers from diverse trades perform concurrent tasks. Introducing robots adds complexity, as workers require specific knowledge to interact with them. Such HRI can range from direct collaboration on shared tasks to concurrent activities where humans and robots operate independently [39]. While HRI has focused on robotic arms, autonomous ground vehicles (AGV) as a specification of robots are seldom in focus, despite AGV being developed for construction purposes.

A critical factor in HRI is occupational health and safety (OHS) in such environments. Several components of OHS have been investigated, collisions and interference being the predominant research focus, but other human factors like trust are also relevant [40]. A key challenge for robots avoiding collisions lies in the limited predictability and variability of human behavior in construction [41]. Collisions are particularly relevant for AGV, where humans and robots share workspaces. While a designated workspace for each human and robot most effectively avoids collisions, the character of construction may not allow such separation, especially when humans collaborate with the AGV. To avoid collisions, several approaches have been studied, such as trajectory planning, safety zone monitoring, and distance monitoring. These approaches share the robot's perspective when addressing safety enhancements. For instance, [42] proposes a model for recognizing spatiotemporal human activities to improve robot safety, and [43] introduces a deep learning model for predicting human movement to prevent collisions. Yet, the key challenge for robots avoiding collisions lies in the limited predictability and variability of human behavior in construction [41]. Limited research approaches the issues relating to HRI from the human perspective. If we had less variance in human behavior, the construction site would be more predictable, and the robots would be more reliable. Reducing the variability in human behavior and increasing its predictability could provide a pathway to addressing this challenge, shifting the focus from solely enhancing robots' abilities.

2.4. Performance assessment

Traditional training methods, such as video tutorials, classroom lectures, and toolbox talks, are decoupled from lean construction concepts. They mostly focus on raising hazard awareness and improving knowledge. These methods focus on training intentions - what workers plan to do in theory - rather than their behavioral safety and lean performance - what they do in practice [13]. This intention-behavior gap [3] poses a significant challenge, as effective, safe practices require workers to transfer intentions into real-world actions. Workers may demonstrate an understanding of safety practices in assessments but struggle to translate these intentions into safe behaviors on-site, creating an intention-behavior gap that remains a critical challenge in construction safety training [44].



The inability to measure behavioral safety performance becomes especially problematic when evaluating the effectiveness of different training methods [44]. In particular, safety performance relies on workers' ability to recognize and respond to hazards. Several efforts compare the effectiveness of different training methods, often suggesting that active training is more effective [45]. Recently, a study showed that active training is more engaging but not more effective when it comes to skills [44]. However, such studies often rely on intention-based measures, such as tests or interviews [7,17,44]. For instance, a worker may correctly state in a test that they would use protective equipment, but intention-based assessments cannot verify if the same worker adheres to this practice during actual tasks. Without directly observing and quantifying behavior, the true impact of training methods on safety and LEAN behavior remains unclear. To overcome this issue, training should be evaluated, addressing the behavior instead of the intention.

Simulated environments like in VR offer a promising solution. While VR has been studied for safety [6–8], and LEAN training [14,16], the inherent characteristics that enable it for training may also make it suitable for behavior-based performance assessment. Such VR environments enable the creation of lifelike construction environments where workers can interact in suboptimal construction workplaces with hazards without real-world risks. Compared to on-the-job assessments, VR environments collect objective data that could be used to quantify safety and lean performance. Such a direct measurement of performance can overcome the intention-behavior gap.

2.4.1. Safety performance

OHS performance relates to “the effectiveness of the prevention of injury and ill health of workers” [46]. Measuring the performance in training is essential to finding objective and measurable behavior and interaction with hazards. With the quantified performance indicator, workers can be compared, and progress between sessions can show improvements over time. Additionally, the efficiency of training can also be monitored using performance indicators. While previous studies in virtual training primarily rely on measured time or the number of close calls [7,47], a standardized indicator is still missing [48]. To find an indicator, the following sections present common KPIs in the industry to quantify safety performance.

Over the years, several indicators have been proposed to provide measurable results expressing the OHS performance. Some of the most common indicators are the total recordable incident rate (TRIR) or the day away, restricted work, or transfer (DART) injury rate. The purpose of these indicators is to provide information by which contractors could assess their safety performance compared to the industry average or compared to other firms [49]. These indicators, however, have two major shortcomings. First, organizations may be prone to not reporting all incidents just to keep the numbers low. Second, they are lagging indicators, meaning that they express historic safety performances and are linked to the outcome of already occurred incidents [49,50]. Lagging indicators cannot predict future performance once circumstances have changed. Especially in construction safety, this is problematic because you can only assess changes in performance after accidents occur when using lagging indicators. In comparison to lagging indicators, leading indicators also predict future performance.

Leading indicators can be used as predictors of future levels of safety performance. As [49] outlines, leading indicators are predictive, heading, and positive indicators, while lagging indicators are historic, trailing, and negative. Examples of leading indicators are the percentage of certified workers in a team or project or the number of training sessions. The number of reported close calls is also considered a leading indicator. More



recently, [51] introduced the high energy control assessment (HECA) as a leading indicator. The HECA score expresses the percentage of controlled high-energy hazards compared to the total number of high-energy hazards, referring to the findings that the severity of incidents correlates with the hazardous energy potential. The underlying theory of HECA is that the severity of an accident correlates with the hazardous energy released during the accident [52]. The hazardous energy can, therefore, also be considered a leading indicator of safety performance on a much smaller level. [48] showed that a construction site could be described through a graph of energy levels where each possible motion in a site has an energy defined. In this presented framework, safety performance is described as exposure to hazardous energy.

Based on the existing approaches in the literature, a new indicator based on existing indicators in the industry will be presented and integrated into the framework. With this indicator, safety performance is expressed using the exposure to hazardous energy.

2.4.2. LEAN performance

Empirical studies have shown that safe and lean construction go hand-in-hand, and respective concepts are mutually beneficial to each field [53]. A central aspect of lean construction is the reduction of waste. Originally defined in seven types [54], recent literature identifies the following eight types of waste: defects, overproduction, idleness, lack of utilized talent, transportation, inventory, motion, and extra processing. Construction safety management can contribute to reducing some of these waste types. Adequate safety plans and safe construction site layouts can decrease unnecessary motion and transport of workers. Reduced incidents as a consequence of effective safety training decrease the waste of unutilized talent. Moreover, effective safety training can enhance understanding of lean principles and reduce waste as a consequence of more awareness among the workforce. However, different training methods often do not result in a transfer of learning [55].

In virtual training, LEAN performance can be evaluated through data collection of waste-related information. The simulated environments enable us to collect data about workers when they are idle or perform work multiple times. In contrast, on-the-job training would require sophisticated sensor technologies of computer vision algorithms or manual observation and measuring of such occurring waste. Similarly, the quality of work can also be measured. Lastly, another principle of LEAN, the continuous improvement principle, is considered through the training framework by tracking training performance over time. The users can follow their progress and shortcomings over time.

The framework presented in this report implements functionalities to monitor different waste types for individual workers and working crews. We, therefore, identify specific wastes for each role that they produce individually and that are produced through ineffective collaboration or cooperation. The aggregated waste results in a LEAN performance indicator that enables us to compare the LEAN performance of individuals and working crews for each training session. Hence, this enables a comparison of different workers and crews, as well as a comparison over time or comparison between different site layouts where safety plans are designed differently.



3. Objectives

This report presents multiplayer user-centric learning environments using VR and real-world data from the Digital Twin. It presents two case studies utilizing the training and learning platform that has been developed in the BEEYODNERS project. The platform itself has been described in deliverable D3.7 of the Beeyonders project. The platform specified four main objectives.

The platform's objectives are to improve the safety and LEAN behavior of trainees. This behavioral shift is targeted through the game-based VR aspect of the platform. Trainees engage in a virtual environment that closely replicates real-world construction sites, allowing them to experience scenarios similar to on-the-job training. The platform uses real-world data from various sources, including BIM models, point clouds, and RTLS data, to accurately recreate construction sites. This close resemblance between virtual and real environments enhances training effectiveness by enabling trial-and-error learning without real-world consequences. A focus of the training environment lies in human-machine interaction.

Second, the platform offers flexibility, allowing it to adapt to different projects. Trainers can easily create various training scenarios using standardized real-world data from BIM models, point clouds, and RTLS. This standardization is crucial for integrating diverse projects. It is also important to note that trainees' tasks may vary depending on the construction schedule, making flexibility essential.

The VTE furthermore aims to assess the performance of workers based on quantitative and objective data-driven methods. Its advanced data collection capabilities allow for the evaluation of waste and productivity (LEAN assessment) and hazardous energy exposure (safety assessment) during human-machine interaction. Beyond simple time tracking, the platform detects interactions with hazards, monitors task progress, and identifies waste. This ensures that performance assessment is meaningful and closely aligned with real-world conditions. The training environment, based on BIM models, point clouds, and RTLS data, accurately replicates hazards, building elements, and surroundings from the physical site. Such data collection capabilities also support personalized training scenarios and long-term progress tracking.

Fourth, the platform provides accessible feedback that tracks long-term progress. Trainees can engage in training activities over extended periods, with their progress continuously monitored. This data helps trainers and construction managers identify trends in safety and LEAN behavior. It also assists decision-makers in recognizing knowledge gaps or inappropriate behavior within training scenarios. Based on this information, decision-makers can recommend personalized training methods. For instance, if a crane operator consistently scores low in minimizing wasted time during hoisting operations, targeted training can be suggested. Similarly, if an electrician frequently encounters falling hazards, a focused training module can be developed to address this issue.

These four objectives form the foundation of the training environment. While the previous report, D3.7, presented the technical concepts and foundations of the platform, this report evaluates the platform in two case studies. The first case study presents a multi-user training environment for the Building Use Case where several trainees perform crane lifting operations simultaneously. The scene includes hand-tracking technology and VR and assesses the trainee's collaboration regarding safe and lean performance. The second case study represents the Road Construction Use Case, where the system is evaluated with respect to its human-robot interaction capabilities. The scene includes recordings from the AWL and exposes the trainees



to a scenario where the AWL follows trajectories from a real-world study. In this environment, trainees can engage with the AWL to learn how to interact with such machinery.



4. Framework Architecture

The training framework integrates with the DT. While deliverable D3.7 gives a detailed overview, this section briefly overviews the core concepts and components. The Digital Twin for Construction Safety (DTCS) maintains two knowledge bases. The Project Intent Information (PII) holds as-designed products and as-planned processes, including structural models, schedules, and a safety plan from the Prevention through Design and Planning module. The Project Status Knowledge (PSK) captures as-built products, as-performed processes, and applicable regulations through on-site monitoring. A conformance-checking component compares the PSK to the PII, flags deviations such as missing guardrails or unexpected crane paths as hazard zones, and feeds those back into the PSK for continuous updating.

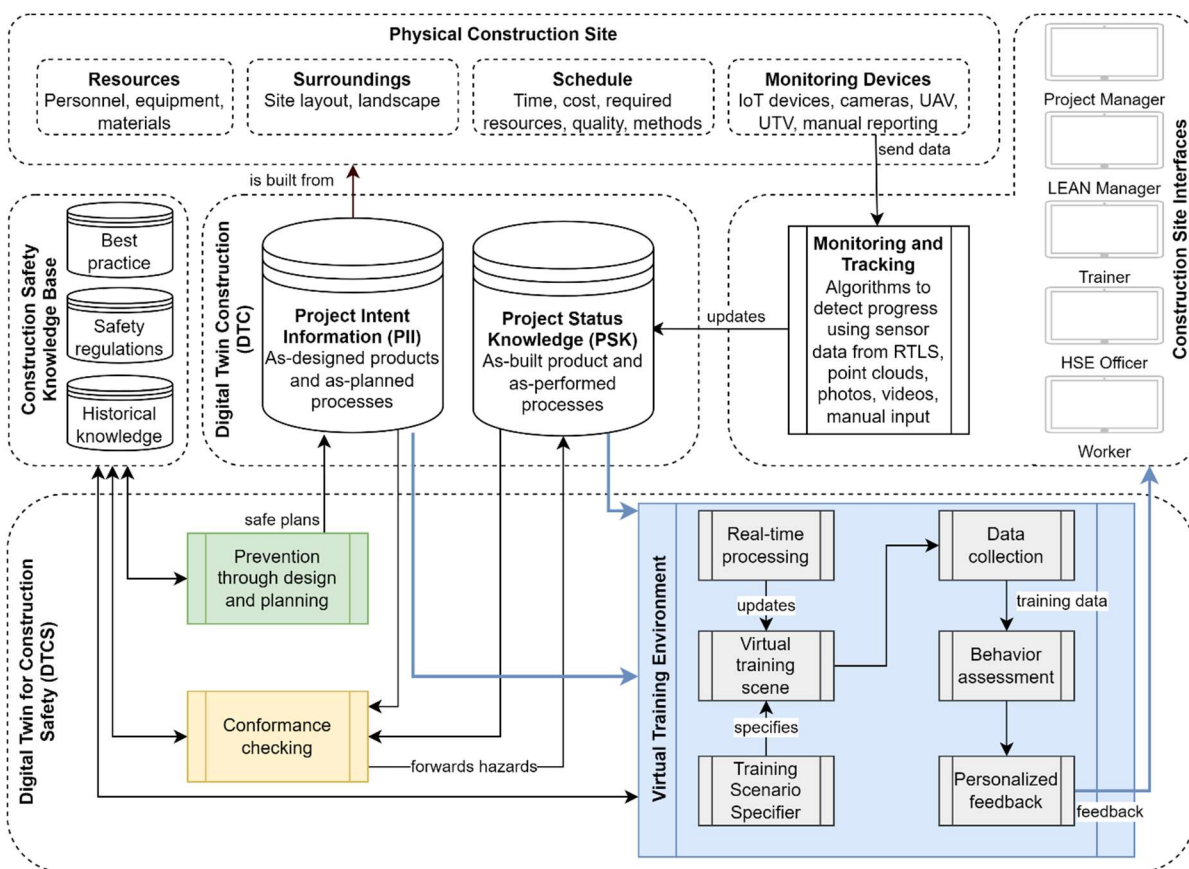


Figure 1: Virtual construction safety and lean training as part of the digital twin for construction safety (DTCS).

The Virtual Training Environment (VTE) delivers personalized safety and lean-construction training. Trainers define tasks and roles via a scenario-specifier interface. Trainees work through scenarios in a virtual training scene rendered in VR. A real-time processing module ingests sensor and IoT data to update the environment as the session proceeds. A behavior analyzer evaluates trainee actions, and a feedback provider issues targeted coaching to individuals and teams. The framework integrates static and dynamic site data. It imports BIM models as IFC files or loads point-cloud meshes, all geo-referenced to real-world coordinates. It tracks



materials, tools, equipment, and workers via RTLS, telematics, inertial sensors, and motion trackers. A detailed construction schedule links each task to start and end times, required resources, and expected or recorded resource states, ensuring the virtual scene matches either planned or actual site conditions.

The system defines each hazard zone by its geometry and severity. It identifies hazards from BIM models, task schedules, conformance checks against safety rules, laser scans, and drone surveys. A mitigation library maps each hazard to the required controls, for example, guardrails, nets, or signage. Scenarios automatically include both the hazards and their countermeasures. Figure 2 illustrates a scenario where several hazard types and roles are present.

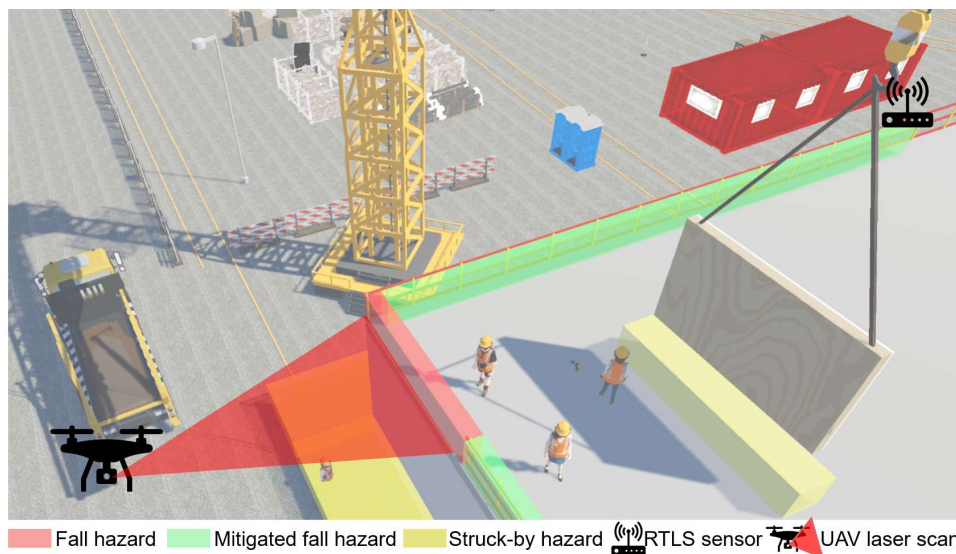


Figure 2: Several hazard zones are present during the assembly of the wall element: (1) a fall hazard due to a missing guardrail, (2) a struck-by hazard under the working crew as the guardrails do not have a safety net, (3) a struck-by hazard under the prefabricated wall element.

An AI-assisted risk assessment pipeline generates draft safety plans. The system builds a Construction Safety Information Base from OSHA and Safe Work Australia texts. It splits documents into overlapping chunks, embeds them, and indexes them in a vector search engine. A hybrid semantic retrieval combines multiple LLM-generated queries with keyword searches, fuses rankings, and applies a semantic re-ranker. Agentic AI components then create work sequences, identify hazards and risk scores, select ISO-standard PPE, and convert the results into SPARQL inserts against a digital-twin ontology. Safety experts review and refine the draft before finalization.

Trainers specify each scenario by project, start time, and participant roles. If the start falls in the past, the system uses historical data; if it lies in the future, it uses planned data. Roles may include human trainees, virtual agents, or robots to support solo, cooperative, and collaborative exercises. The platform stores all scenario definitions in its data layer for seamless deployment.

During each session, the system logs trainee interactions with hazard zones using collider-based proximity detection. It records location, duration, and energy exposure to compute a Safety Performance metric. It also tracks lean construction waste in four categories: waiting, defects, unnecessary motion, and extra processing.



D5.3: Active user-centric learning resources for H&S and attraction of the next generation workforce

A web-based dashboard presents the safety and lean KPIs alongside a task timeline, giving trainers and trainees clear insights into performance.



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5. Building Use Case

The first case study presents a multi-user training environment for the Building Use Case where several trainees perform crane lifting operations simultaneously. The scene is created using the game engine Unity. Unity has been demonstrated as a successful tool in construction research for safety training [2,56], monitoring [57], or simulations [48]. The virtual environment represents a situation where a crew performs hoisting of prefabricated elements. The following sections first present the motivation and background for choosing this scenario for the training activities, followed by the description of the scene creation and a case study.

5.1. Background

5.1.1. Crane operations and safety

Struck-by incidents stand as one of the foremost causes of fatalities in the construction industry. Between 2011 and 2021, struck-by hazards comprised 17% of all construction fatalities in the United States [57], also emerging as the largest contributor to nonfatal injuries, accounting for 21.5% in the same years [57]. These accidents encompass a variety of risks, including being struck by heavy equipment and other vehicles like excavators, dump trucks, and various types of cranes.

Among the most common accidents associated with struck-by incidents are those occurring during lifting operations, where workers find themselves within the hazardous workspace where harmful contact with the equipment or its parts can occur [58]. Hoisting operations are indispensable in construction projects, with cranes frequently maneuvering loads near and above workers in crowded areas that may overlap with multiple ground crews [59]. Between 2011 and 2017, the US Bureau of Labor Statistics recorded 297 crane-related fatalities, with more than half involving pedestrian workers struck by moving crane parts or falling objects [60]. In recent years, there has been a steady rise in lifting operations both on construction sites and off-site, driven partly by the construction industry's increasing use of prefabricated elements and modular building components. Given the weights and sizes of such elements, lifting becomes necessary at various stages of the construction supply chain and assembly process.

Considering this, Fard et al. delved into 125 accidents related to modular and prefabricated building components, finding that 62% of these accidents occurred on construction sites, primarily during installation tasks [61]. Similarly, the Norwegian Labor Inspection Authority analyzed accidents related to prefabricated elements, examining 21 cases and identifying that in over 50% of these incidents, workers were situated within hazard zones [62].

The complexity of conducting safe crane operations underscores the importance of clear and comprehensive communication between the crane operator and the pedestrian workers. Pedestrian workers must remain vigilant about their surroundings, including the presence of loads, and must ensure they stay clear of danger zones to avoid potential accidents involving falling loads or crane components.



5.1.2. Challenges in crane operations communication

Effective communication is crucial for safe crane operations. As mentioned before, Human error accounts for a significant share of crane accidents, implying that proper training of crane operators and signalers is essential [63]. Typically, hoisting involves a crew where a signaler communicates with the crane operator, who executes commands using a remote control or controls on the crane itself. Depending on the crane type, the operator may be situated in a cabin or on the ground, facing limited visibility and relying on communication with the pedestrian workers so that successful hoisting operations are possible.

Typically, the rigger or signaler would use hand gestures to share commands with the crane operator, but limitations exist. Figure 3 shows a selection of commonly used signals. They enable effective communication irrespective of the construction noises and language barrier between the workers [64]. There are standard hand signals for operations such as crane rigging. However, misinterpretation of these predefined hand signals by the operator of the cranes may cause severe accidents [65]. Additionally, these hand gestures require a direct line of sight between the crane operator and the riggers. However, in highly dynamic environments like construction sites, occlusion occurs frequently, hindering effective communication. Automatic recognition and interpretation of hand gestures may potentially assist in effective communication between the signaler and the operator.

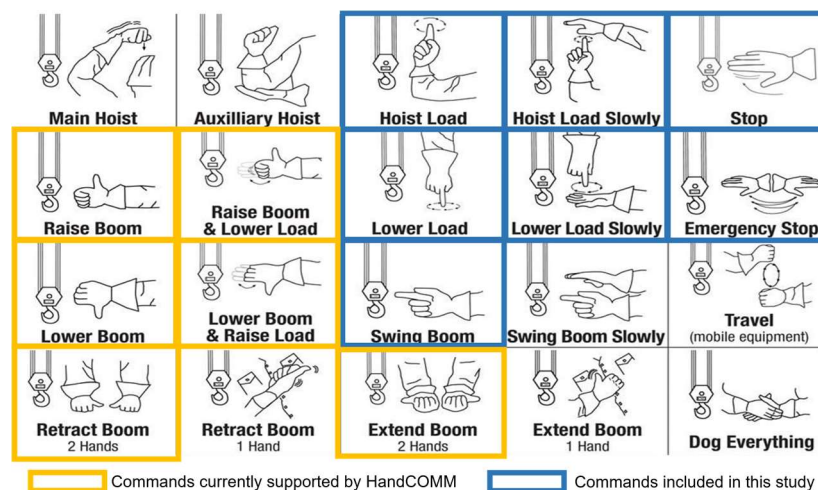


Figure 3: Hand gestures commonly used in tower and mobile crane operations.

Several technologies support automated hand gesture recognition, which can be categorized into wearable devices and computer vision-based devices. Computer vision-based gesture recognition methods involve data collection using cameras, offering the advantage of not requiring the worker to wear a glove; however, they are sensitive to occlusion and environmental conditions [66]. Wearable devices include data gloves, inertial sensors, and myoelectric sensors [67]. Data gloves are widely used in virtual environments for gesture recognition, involving processes such as data collection, parameter extraction, and selection [68]. Despite their high recognition accuracy, data gloves are costly, unsuitable for construction sites, and may impede workers from performing manual tasks.



5.2. Objectives and research methods

Crane operations contribute significantly to construction site accidents, and hand gestures are relevant. However, in environments like high-rise construction sites where visibility is often limited, hand signals are not always feasible. Despite this, hand signals remain effective due to workers' familiarity with them, and their standardization facilitates collaboration. For these reasons, this case study presents a training environment for rigging operations. The training follows three objectives. First, the trainees should improve their collaboration skills through hand signals, even in low-visibility environments. Second, the trainees should familiarize themselves with the present hazards and improve their safety performance while such hazards are present. Specifically, they should learn not to be exposed to the crane loads. Third, while following safe working procedures, the trainees should at the same time learn LEAN principles and how to reduce waste during lifting operations.

In order to reach these learning objectives, a training environment in VR is established, given the advantages of virtual training compared to on-the-job training. In response to the limitations in existing literature, an exploratory system that incorporates a signaling glove into crane lifting operations has been designed (see Figure 4). To further explore potential valuable data, the study also tracks the hazard exposure of pedestrian workers to crane loads. The system was implemented in an experimental, controlled environment using the Unity game engine in a virtual multiuser setting. This environment allows for the assessment of the safety and lean behavior of the trainees when analyzing the data.

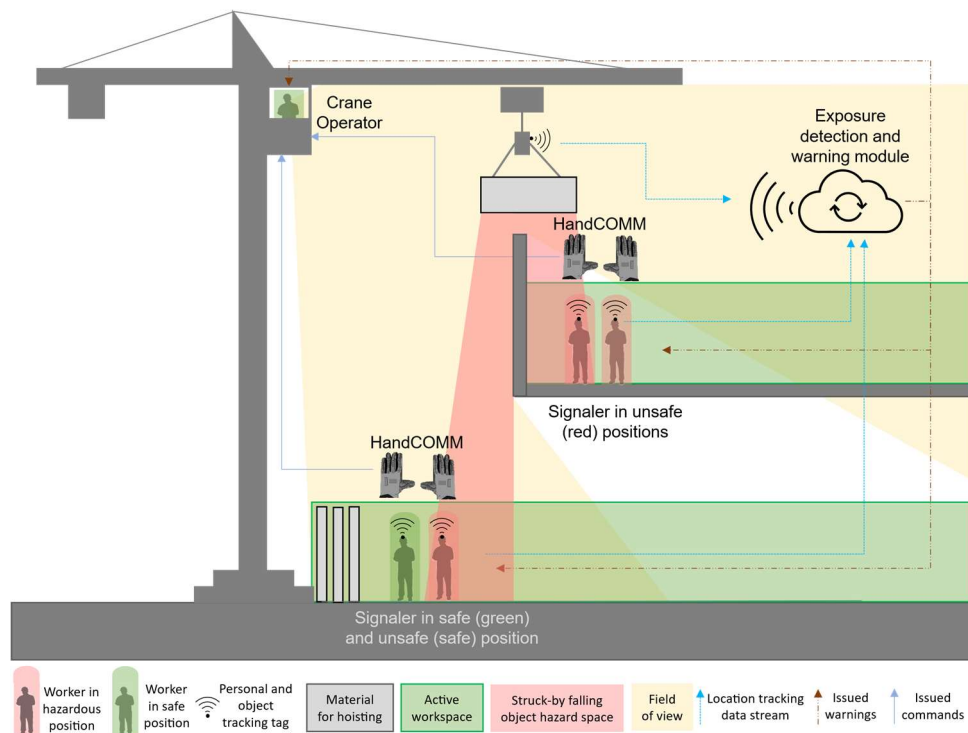


Figure 4: The proposed system in the context of one potential use case.



5.3. Scene generation

5.3.1. BIM model integration

A BIM model is integrated from the DT. The BIM model is from a residential housing project. It includes several apartment units where modular bathroom pods are installed. The installation of these bathroom pods involves crane lifting operations and is, therefore, ideally suited for the training objectives. Besides, the VTE is intended to include further trades in the next steps. Installing such bathroom pods and completing apartment units with similar characteristics is well-suited for training LEAN principles. The remaining trades, however, are not part of this case study. Figure MM shows the BIM model in the Unity scene. The BIM model has eight units with similar characteristics, and the hoisting crew must install a total of 4 bathroom pods. The bathroom pods are in the BIM model but will be removed in the training scene and placed on the trucks that bring the modules to the site (see hoisting process in the next section).



Figure 5: Example BIM model for the building use case in Unity for generating the unity scene.

The BIM model includes several hazard zones. For instance, the leading edges where windows will be installed are not present in the training scene. Hence, guardrails must be installed. These guardrails are removed in some places, and hazard zones are placed. Now, when a worker gets close to these zones, a hazardous event is logged.

5.3.2. Hoisting process

A truck arrives at the construction site, delivering three prefabricated bathroom pod elements. At this point, the process illustrated in Figure 6 starts. The crane operator moves the hoist to the truck so that the pedestrian worker on the ground (Rigger X) can connect the first element to the crane. During this step, the riggers indicate the motions to the crane operator. Once the hoist is in the right position, Rigger X connects the first element to the hoist. Then, the crane operator moves the object to the designated position. During this process, the pedestrian worker on the building (Rigger Y) communicates with the crane operator. The



rigger is equipped with a glove to detect signals. Once the final position is reached, Rigger Y gives the signal to stop the hoisting. Once they are sure the crane operator understood, they can detach the element. In the last step, Rigger Y indicates that the hoist is detached so that the crane operator can continue with the next element. The complete process is repeated three times until all four elements are moved.

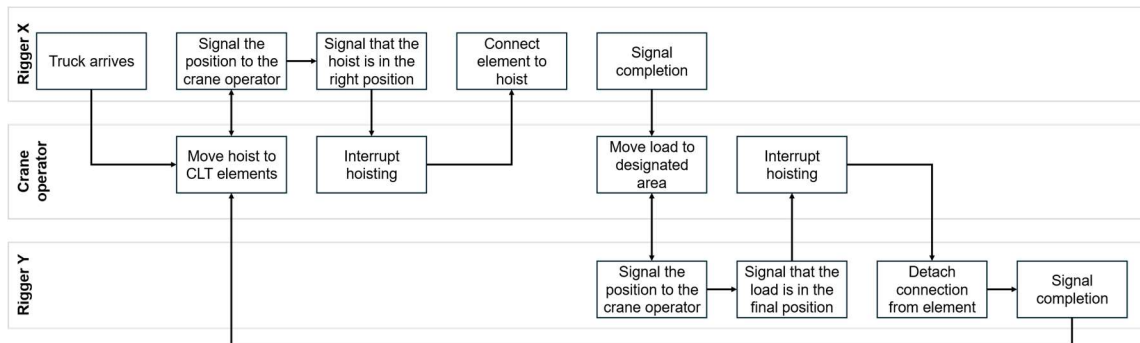


Figure 6: Hoisting process.

5.3.3. Technical implementation of the multiuser features

The virtual environment includes three workers: A crane operator and two riggers. While the previous paragraphs overviewed the tasks and process of the hoist operations, the following paragraphs describe the technical implementation of facilitating these features in Unity.

Figure 6 illustrates the technical setup. Each role is controlled by humans using computers and represented by avatars in virtuality. For each role, a separate computer is used to visualize the virtual environment from their viewpoint. The three computers communicate through the Unity system Photon. Each object in the training scene has a *PhotonView* assigned so that possible changes in their states are shared with all other computers.

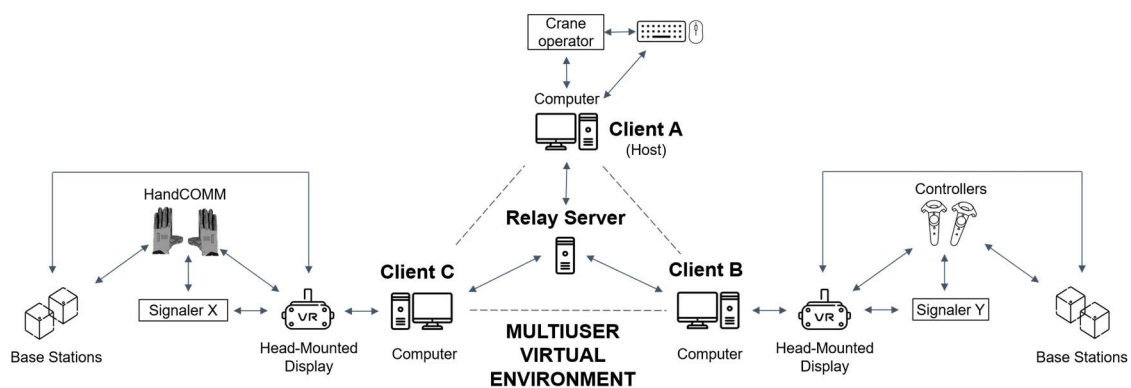


Figure 7: Experimental setup of the augmented virtual reality hardware and communication.

The crane operator observes the scene from the perspective of the operator's cabin, which is visualized on a monitor. Commands can be entered using a keyboard, and the view angle can be adjusted using a mouse. The operator sees the highlighted hazard zone and the protective envelopes of the workers to estimate their



safety (see Fig. 4b). Moreover, the operator visually processes the commands detected from a signaling detection glove.

The riggers wear a Head-Mounted Display (HMD) and use controllers to navigate the scene. The riggers send their signals using the controllers and making the gestures. Once a gesture is detected, the crane operator is visually informed.

5.4. Hazard interaction detection

The pedestrian workers often do not realize that they are under suspended loads. Incidents relating to crane operations occur frequently, as mentioned before. The Exposure Detection and Warning (EDW) module of the proposed framework detects workers who are exposed to suspended crane loads. The workers can either be workers involved in the hoisting process (riggers, signalers, crane operators) or pedestrian workers performing independent tasks. To facilitate this functionality, two variables are required: The location of the workers and the spatial description of the hazardous area.

Safety monitoring in construction involves tracking the status and movement of workers, materials, and equipment to detect safety incidents in both static and dynamic environments before they turn into accidents [69]. Real-time location tracking is crucial for monitoring safety, allowing for spatial and temporal analysis to identify violations of safety rules or conflicts between resources. Various tracking systems, both active and passive, have been utilized in different construction scenarios. For instance, Costin and Teizer employed passive Radio Frequency Identification (RFID) to locate workers indoors [70], while Cheng et al. utilized ultra-wideband tracking to visualize worker positions in construction models [71]. Global Positioning Systems (GPS) are commonly used for outdoor tracking on construction sites [72,73]. Real-Time Kinematic Global Navigation Satellite System (RTK-GNSS), an advancement of GPS, offers higher accuracy by correcting the signal using static sensors [74]. Another approach represents the use of computer vision, where locations can be determined using camera footage [75].

In our proposed system, location tracking occurs directly in the virtual environment. There is no need for a sensor system. The advantage is that no noise or signal issues occur. On the other hand, it represents a limitation of this study as the feasibility of the system in a real-world scenario is not assessed. Nevertheless, the above-mentioned research demonstrates several applicable pathways.

The hazardous area can be described as a cone-shaped spatial object. Similarly to the tracking technologies described for tracking the workers, a sensor attached to the crane loads or computer vision algorithms can determine the position of the hook. Then, the hazardous space can be described as a space under the crane load. Figure 8 illustrates an example of such a scenario. The transporter material creates a hazardous space below the load. Determining the geometry in a real-world scenario may require the dimensions of the load. Additionally, the swing motions would influence the exact shape of this space. In this study, the shape is considered to be constant.

Once the exposure has been detected, a warning must be forwarded to the workers. Research shows different results about sending warnings. Besides runtime issues due to latency, there are concerns that sending warnings may lead to undesired behavior, which could cause incidents where no incidents happened without the alert. Another issue with alerts is so-called alert fatigue, where workers no longer react to alerts



as they occur too frequently. Despite the known issues, our system includes a warning module. Further research must investigate how this feedback is transferred most effectively, and filtering should occur based on other indicators. In this research, however, the warning is always forwarded to the pedestrian worker and crane operator once an exposure is detected. This warning is forwarded visually as research shows that workers react faster to visual feedback. In practice, however, this would imply that the workers must wear smart glasses. In the virtual environment, issuing this warning is facilitated through a warning on the screens.

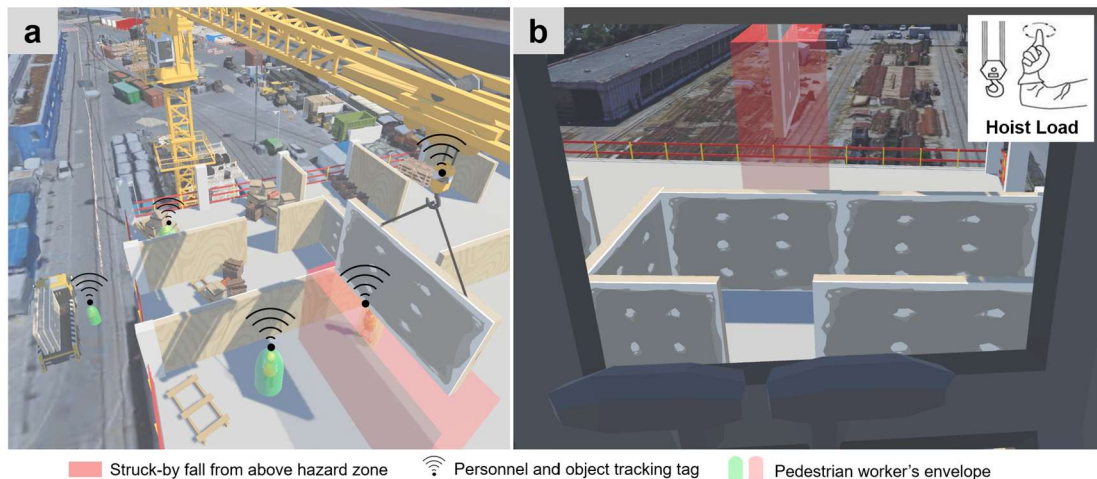


Figure 8: The virtual learning environment for hoisting tasks.

The virtual environment in Unity detects workers' exposure to suspended loads. Facilitating this feature includes an extension to an existing approach by the authors where hazardous zones are represented as geometric representations in virtual environments [12,27]. In this particular case, a hazard zone in the shape of a trapezoidal prism is added to the crane hook (see Figure 9). While the angle of the cone should consider parameters such as velocity and dynamically adjust the size, we assume a constant angle of five degrees, as proposed in previous research [76].

The VTE also adds protective envelopes to the endangered workers. Both elements, the protective zone of the worker and the hazardous zone connected to the hook, are hidden from the agents in the training scene (see Figure 9b). And yet, the protective envelope and the hazardous zones exist as objects in the background to facilitate collision detection. Unity provides this functionality with the *OnTriggerEnter* and *OnTriggerExit* methods. These functions represent events that are triggered once the objects collide. Upon collision, the pedestrian worker receives a visual warning, as shown in Figure 9b. While further research is required on who and how such feedback should be communicated, this approach uses visual alerting as research indicates a quicker response to such feedback compared to audio alerts. The authors are aware that forwarding visual alerts in practice requires overcoming constraints; however, smart glasses or augmented reality-enabled displays could facilitate these warnings.



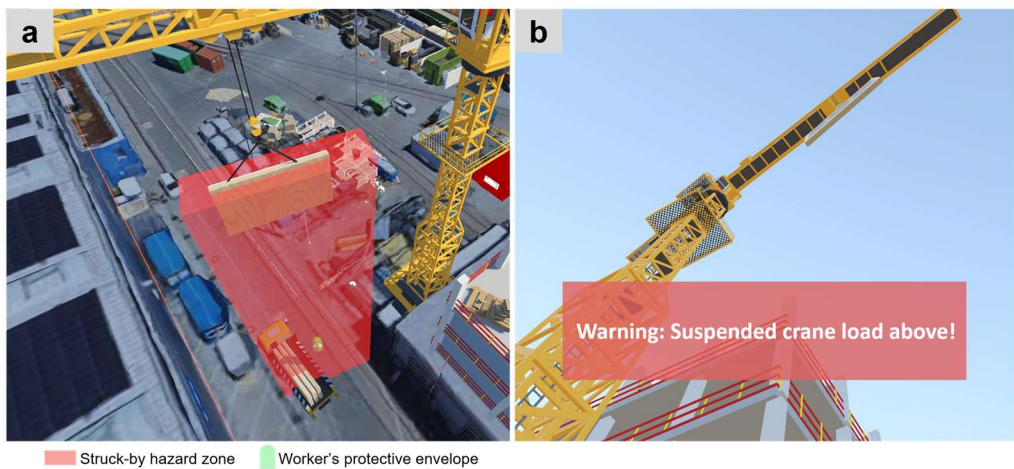


Figure 9: (a) The pedestrian worker is exposed to a crane load and detected using the collision detection method, and (b) the worker is visually informed.

The virtual environment supports additional data collection functionalities. Throughout the virtual experience, the environment constantly tracks the distance of each worker from the hazardous zone. Unity provides a built-in method to determine the shortest distance between a point and a trapezoidal prism. The distance is logged with a frequency of 1Hz and then stored in a *.json file for further processing. Besides, the environment also logs the timestamps and type of each command that was detected by the glove. Last, the commands performed by the crane operators are logged. Having this information available allows us to assess the efficiency of the communication based on two indicators: (1) the total number of correct and wrong operations directly after receiving the command and (2) the time elapsed between sending the signal and the crane operator to react.

5.5. Waste detection

Each role can cause waste during their task. The waste is detected in the scene using collider objects and resource tracking. For instance, if the bathroom pods collide with other elements, they could damage these elements. Hence, they are defined as waste.

Table 1: The different waste types and how each role can cause waste.

	Waiting	Defects	Motion	Inventory
Crane operator	All times when the crane operator is waiting for the rigger, including the time waiting for the riggers, or waiting as the next element	Uncareful placement can cause defects. If the bathroom pods collide with any objects like walls, damage is caused.	Deviation from the shortest path	



	cannot be placed as the room is still occupied.	Collider objects will detect the collisions.		
Rigger Ground	Time in between tasks. The time when the rigger is neither transporting elements, moving, or connecting the rigging equipment to the hoist	Inadequate connection of the rigging equipment can cause defects. If the rigger indicates a successful connection but is not correctly connected, an event will be logged, and the bathroom pod will fall over, requiring another truck to arrive at the site.	Unnecessary walking around. Determine the shortest path for all tasks and detect the deviation from it. This will identify the waste due to motion.	The rigger on the ground will have clear instructions on how to prepare pallets with certain materials. Too much or too little will result in the wrong inventory. The deviation is determined with a standard deviation.
Rigger Top	Time is spent waiting for the crane operator between tasks. This is the time from the moment all preparations for the bathroom placements are made and the moment the bathroom arrives at the location once the rigger needs to signal the location to the crane operator.	If the rigger did not place the plastic heels in the site, rework is needed. Track if they were placed.	Unnecessary walking around. Determine the shortest path for all tasks and detect the deviation from it. This will identify the waste due to motion.	

5.6. Preliminary case study

The objective of this research was to explore the possibilities of integrating a smart signaling system into crane operations. For that reason, the capabilities of a hand gesture recognition system were investigated. In the second step, the potential of collecting data to provide nuanced insight into communication skills and



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hazard exposure was investigated. Both approaches apply a qualitative approach to discuss the proposed system. The following results must be considered preliminary as further tests with more participants are needed.

The VTE can provide valuable insight into the communication skills of a work crew. Figure 10 visualizes the collected data from the system in the virtual setting. The system constantly tracks the trainees, from sending signals to executing a task. Using this data, we can assess how effectively the workers communicate if the crane operator follows the indicated signals by the workers on the ground. Looking at the recorded graph in Figure 10b, we can see that the crane operator was not always following the signals sent by the signaler. Figure 10b also allows us to quantify the response time. In fact, three times, they chose to do other things. The second insight from this is that we can see the response time. On average, the crane operator lost 4.5 seconds from receiving the signal to performing the action. The system effectively detects the workers under the crane load. In the case study, the signalers were exposed to the crane load, as indicated in Figure 10a. Signaler X was exposed five times, and Signaler Y was exposed nine times. This information can be valuable in estimating workers' hazard awareness. The feedback has been forwarded visually (as illustrated in above) to the workers.

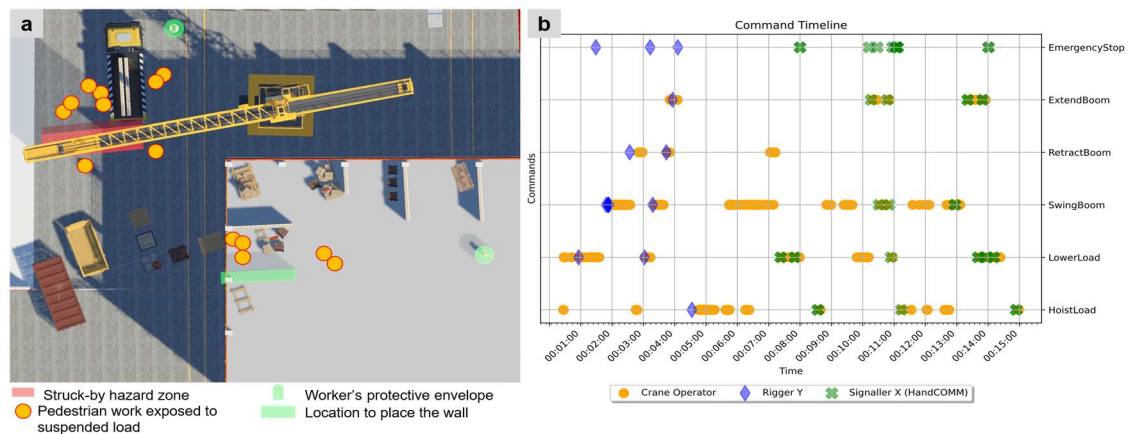


Figure 10: (a) The EDW module detects when workers are exposed to the crane load and stores the location of such events during the training, while (b) the signalers share hand signals with the crane operator. The chart indicates when the crane operator follows the shared signals.

To sum up, the explorative study indicates that the system can provide valuable insights that have not been available before. The quantification of communication skills can indicate workers' collaboration skills. The exposure detection tracking can help to identify which workers require further training in hazard awareness or which crane operators may risk too many operations over the workers. Lastly, the virtual framework also allows us to determine the distance between the crane load and the workers. Yet, all these parameters need to be tested in specific scenarios in virtual and real-world settings.

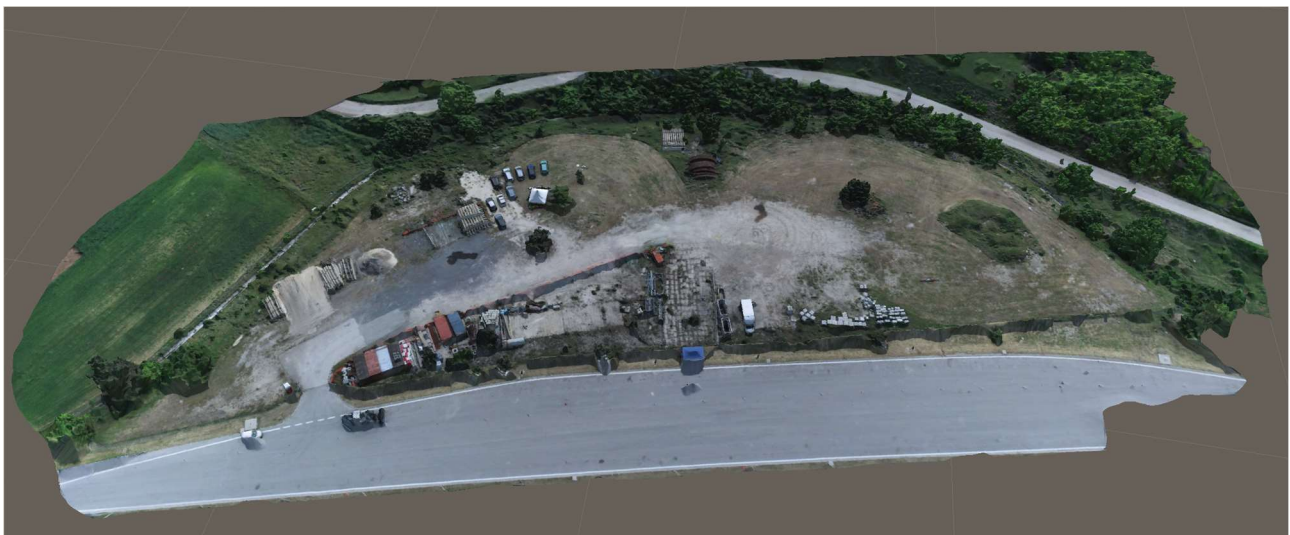


6. Road Construction Use Case

Road use is deployed to train human-machine interaction. The human-machine interaction is addressed using the autonomous wheel loader. In the absence of project-related data from BEEYONDERS, the training environment is presented using data from a sample test. The framework is also expected to function with the data from the road construction.

6.1. Scene overview

A mesh in the form of a .obj file is queried from the DT storage and loaded into the Unity scene. The mesh was generated based on a point cloud recording. The quality of the point determines the general quality of the scene.



6.2. Hazard zone inclusions

6.2.1. Generative AI framework

The Agent AI framework contributes to detecting relevant hazards and mitigations. For this reason, the ongoing task at the construction site is first sent to the AI framework, where relevant hazards and mitigations are identified. These hazards and mitigations are then translated into an ontology and added to the training scene by linking them to the relevant objects. As this report was written while the data collection efforts were still ongoing, the following sections partly refer to a test data set.



6.2.2. Autonomous wheel loader

The wheel loader poses risks in the virtual training. The resource location tracking data is retrieved from the DT and simulated in the VTE as described in D3.7. The AWL follows the trajectory of the recording and, therefore, creates hazards based on real-world data. Once the telematics data, including the estimated boom and bucket position, are streamed to the DT, these objects can also be visualized, and hazard analysis can occur on a more detailed level.

6.3. Performance evaluation

6.3.1. Safety performance assessment using safest path simulations

Assessing the safety performance in this scenario is based on the trainees' exposure to hazardous energy during the task. Determining the hazardous energy exposure is based on simulating the hazardous energy in the construction site. The simulation generates a graph, the Safety Graph, that can provide the safest paths in a construction site, as outlined in the following sections.

The Safety Graph assesses the potential hazards faced by human workers while navigating a construction site. This paper presents an algorithm embedded in a simulation framework designed to create such a graph. The following section first overviews the Safety Graph before describing the algorithm for creating the graph.

6.3.1.1. Algorithm Creating the Safety Graph

As described before, a graph consists of nodes and edges. To generate the nodes, we distributed the construction site into one-meter squares. Each square represents one node in the Safety Graph, and adjacent nodes, which a worker can reach, are connected by edges (see Figure 11a). Each edge has a cost, representing the hazardous energy a worker faces when traveling from one node to another. While this cost should encompass all potential hazards like falling, tripping, being struck by objects, or electrocution, this work only integrates falls and trips as they account for more than 40 percent of accidents in construction [1]. Wang and Qin have considered fall hazards in path planning [17], but no previous work included trip hazards in path planning for workers. The novelty of this work lies in generating the *Safety Graph* by simulating the hazardous energy impact on the worker for each possible movement in the construction site. The resulting graph can then function as the base for finding the safest route in the graph (see the blue graph in Figure 11 using search algorithms like Dijkstra [19]). While Figure 11 depicts the shortest path between a particular start and end node, it is crucial to note that graphs enable finding the shortest path for any combination of start and end nodes [10].



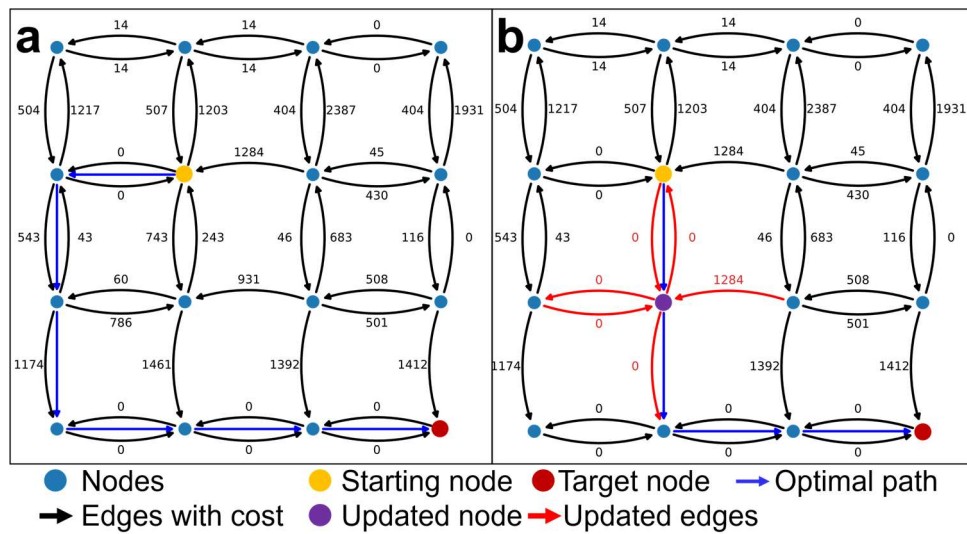


Figure 11: (a) Brief example of a Safety Graph and (b) updating after changes in the construction site.

The benefits of having such a graph are twofold. First, in a static environment, the algorithm runs once. After that, path planning algorithms can efficiently use the graph to identify optimal routes and do not require continuously re-evaluating the site layout. Second, in dynamic environments like construction sites, our graph-based approach allows for updating specific areas of the map without repeating the entire simulation. Figure 11b illustrates the concept: The construction site has changed as, for instance, an object was moved by machinery. Now, the simulations must only update edges connected to this node (highlighted in red in Figure 11b). The update of the node and connecting edges also changes the optimal path from the starting node to the target (see blue edges in Figure 11b).

6.3.1.2. Simulation Development in Unity

The described *Safety Graph* is generated using the algorithm implemented in a Unity simulation. The developed algorithm simulates each possible motion of a worker from one node to an adjacent node and measures the hazardous energy impact on the worker during this motion. For instance, if a worker jumps one meter down during this motion, the hazardous energy of this jump will be considered the cost of this particular movement. Similarly, the energy can be determined for other kinds of hazards such as trips, electrocution, struck-by, or caught-in-between.

The underlying idea of utilizing hazard energy as the edge cost goes back to the findings that the energy of a hazard correlates with the result of an accident [77]. According to Hallowell et al., hazards between 500 Joule and 1,500 Joule are likely to result in medical treatment, while hazards with more than 1,500 Joule most likely cause a severe injury or fatality [51]. The energy intensity would provide more insight, but it would be more challenging to obtain [51]. Thus, in this work, we compute the hazardous energy that a human worker is exposed to when traveling from one location in the construction site to adjacent locations.

To determine the hazardous energy, we developed a simulation framework in the game engine Unity. As Unity facilitates real-world physics, the hazardous energy can be calculated. While the authors expect this algorithm to be generally feasible, obtaining the hazardous energy through the game engine is only one



proposed approach. Other methods may utilize camera footage from a site to detect hazards and corresponding safety potential. Nevertheless, this approach has several advantages: It not only includes the safety aspect but also allows for the determination of other parameters, such as accessibility for agents or expected time of traveling.

Table 2 shows the algorithm to create the *Safety Graph*. The algorithm first distributes the construction site in nodes, adds the agent, and instantiates an empty set of edges (lines 1-3). Then, for each of the nodes, the agent is moved to the neighboring squares. If the motion is possible (no obstacles), the energy potential is calculated, and an edge is added to the graph (lines 5-13). Eventually, the algorithm returns the completed graph in line 14. The following section will first describe the setup of the Unity scene before illustrating the underlying concept of calculating the hazardous energy.

Table 2: Algorithm generating the *Safety Graph*.

1	Function CreateSafetyGraph
2	<i>nodes</i> = SegrateSite()
3	<i>edges</i> = empty collection
4	<i>agent</i> = CreateAgent()
5	For each <i>node</i> in <i>nodes</i> :
6	If <i>edge</i> = SimMotion(<i>agent</i> , <i>node</i> , 1, 0) is not null
7	Then add <i>edge</i> to <i>edges</i>
8	If <i>edge</i> = SimMotion(<i>agent</i> , <i>node</i> , -1, 0) is not null
9	Then add <i>edge</i> to <i>edges</i>
10	If <i>edge</i> = SimMotion(<i>agent</i> , <i>node</i> , 0, 1) is not null
11	Then add <i>edge</i> to <i>edges</i>
12	If <i>edge</i> = SimMotion(<i>agent</i> , <i>node</i> , 0, -1) is not null
13	Then add <i>edge</i> to <i>edges</i>
14	Return Graph <i>G</i> with <i>nodes</i> and <i>edges</i>

6.3.1.3. Hazardous Energy Simulation

The proposed algorithm initializes the Graph *G*, utilizes the geometry of the environment, segregates it into one-meter squares, places a node at each center point (see blue dots in Figure 11b), and adds the nodes to *G*. After generating the nodes, the algorithm iterates through the nodes and assesses the hazardous energy associated with traveling from each node to its adjacent tiles. As indicated in Table 2, the simulation of the motions occurs four times for each node. Figure 12 illustrates the process for simulating one motion, and the following paragraphs will describe each of the steps.



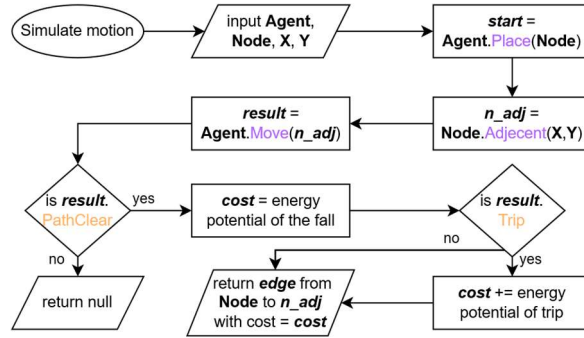


Figure 12: Flow chart for risk assessment of one individual movement of the agent.

The simulation of an individual motion to a neighboring node begins with placing the avatar on the current node n . To ensure the correct vertical placement, we cast a ray downwards from a 100m offset using Unity's *RayCastHit* structure. Then, we place the agent in the position of the first hit.

After placing the avatar, the simulation waits for 100 milliseconds to ensure that the avatar is placed correctly. Then, the algorithm queries the neighboring node n_{adj} from G , and moves the agent towards n_{adj} using the method *Rigidbody.MovePosition* in Unity. This method moves the agent, but only if the path is free. After moving the agent, the simulation stops for 200ms to evaluate the impact of the motions. For instance, if the worker moves from an unprotected leading edge, the simulation needs to wait until the agent touches the ground. The vertical gravity in Unity is set to -300 to accelerate the simulation.

In case of colliding objects during the movement from n to n_{adj} , the motion will fail, and the simulation continues with the next neighboring node. However, if the motion is successful, our algorithm adds an edge e to the G and calculates the hazardous energy $E_{Hazardous}$ during the motion as the cost of e .

The energy for the fall hazards is computed with Equation 1 where m corresponds to the mass of the worker, g represents the gravity, and Δh corresponds to the difference in height before and after moving the agent.

$$E_{Fall} = m \times g \times \Delta h \quad (1)$$

$$E_{Trip} = \frac{1}{2}mv^2 = \frac{78kg \times 10km^2}{2h^2} \approx 300J \quad (2)$$

$$E_{Hazardous} = E_{Fall} + E_{Trip} \quad (3)$$

Equation 2 regulates the hazardous energy for trips, assuming a constant value of 300 Joule. This value corresponds to the kinetic energy of an average human, assuming a mass of 78kg and a velocity of 10km/h. The velocity is selected rather high, integrating a safety factor. The trip hazard is detected using a collider object at the bottom of the worker (see Figure 13). When this object collides with any other object while moving the avatar, the trip hazard energy is added to the cost of e .



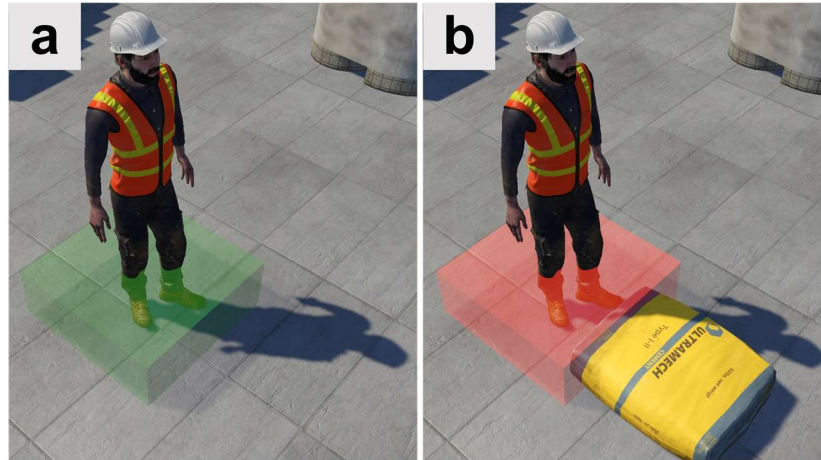


Figure 13: The concept for detecting tripping hazards with (a) a safe path without hazards and (b) a tripping hazard being present.

Figure 14 illustrates the simulation for one node, repeating the previously demonstrated simulation for each adjacent node. There is no edge between node A and B, as the avatar cannot reach B from A. Moving to D is associated with no risk as there are neither objects causing trips nor an elevation. When moving to C, a trip hazard is detected, and the cost of the motion is set to 300 Joule. Lastly, moving to E includes a potential fall of 0.6m (hazardous energy of 400 Joule).

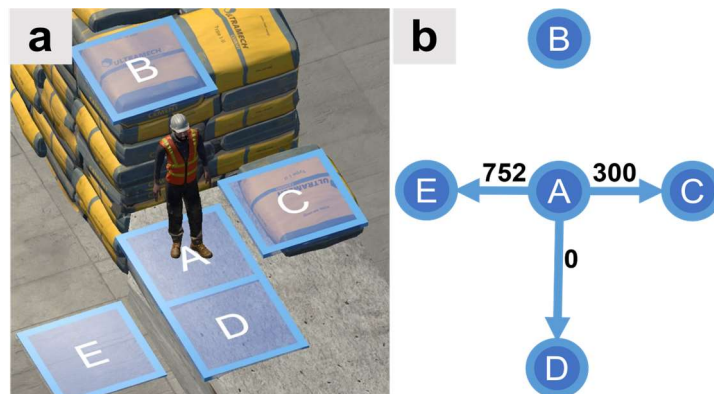


Figure 14: Generating the edges for one node (assuming no diagonal movement is possible).

6.3.1.4. Time-expanded graph generation

The graph is generated using a two-fold approach. First, a static graph G is generated with the simulation described in the previous section. The simulation illustrated in Figure 15 detects trip and fall hazards moving an agent in the Unity scene between every node while detecting the hazardous energy exposure. As the scene in this study comprises a grid of 80x90 nodes, the simulation has been changed to use 800 agents simultaneously, where each agent only explores nine nodes. Additionally, diagonal edges between adjacent nodes are added. Lastly, the environment includes traffic zones, where workers should also not enter. Figure



15 shows the graph generated in the simulation that creates the initial graph G for $t = 0$, which is stored in a JSON file for further processing. It includes the nodes and all edges, as well as the relevant costs for tripping and falling hazards in the environment. These hazards are considered static. In the second step, the time-expanded graph is constructed.

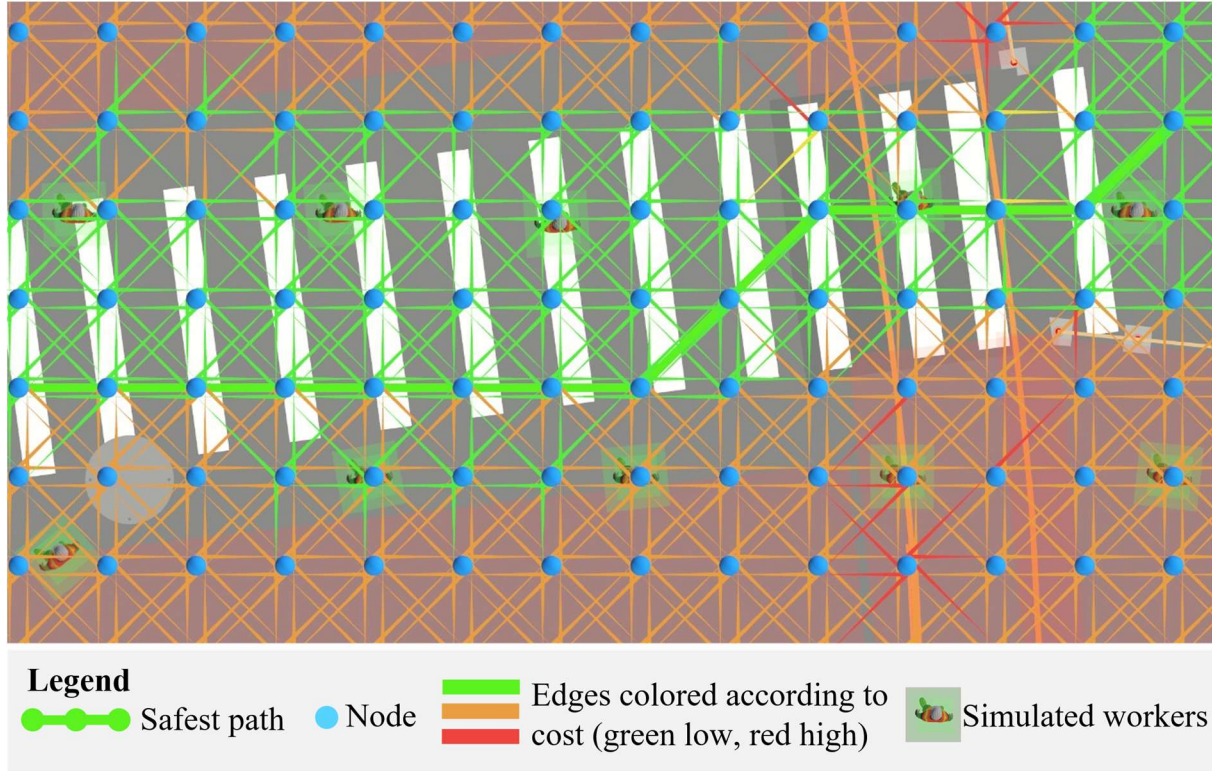


Figure 15: The simulation generates the static graph measuring hazardous energy while moving the agents to adjacent nodes.

Table 3 describes the creation of the graph. First, the static graph is copied for each timestep in T , comprising 300 seconds in our study. For each of the 300 time steps, the graph is first copied with all edges and associated, now time-dependent cost. With the assumption of a 6m-sphere around each equipment center, we can define the cost to all edges around the forklift. The cost of the edges around the forklift is replaced by infinite for each timestamp.

Table 3: Pseudo code to create the time-expanded graph.

Input: Static graph $G(V, E)$, equipment trajectory TR_{Eq} , Time horizon T , Hazardous extent H	
Output: Time-expanded Graph $G_T = (V_T, E_T)$	
1	Load H
2	Load TR_{Eq}
3	For each node $u \in V$:
4	For each timestep $t \in [0, T]$:



```

5   Add  $(u,t)$  to  $G_T$ 
6   For each edge  $(u,v) \in E$ :
7     For each timestep  $t \in [0, T-1]$ :
8       Add travel edge  $((u,t), (v, t+1))$  with cost  $c(u,v)$ 
9       Add waiting edge  $((u,t), (u, t+1))$  with cost 0
10  For each timestep  $t \in [0, T]$ :
11  For each piece of equipment:
12    Find equipment position  $(x_c, z_c) = TR_{Eq}[t]$ 
13    For each node  $(x, z, t)$  within the  $H$ :
14      Set costs of outgoing edges to  $\infty$ 
15  Save  $G_T$  as JSON.

```

Figure 16 and Figure 17 illustrate exemplary time expansion and pathfinding in a simplified example. With the set of graphs, we can now find the safest path in the construction site. While the previous research could run Dijkstra algorithms on the static graph, the inclusion of dynamic equipment entails more complexity, as we have a different graph for each timestamp. We assume a constant motion speed of the pedestrian worker when computing the graph and only calculate it once and do not update it continuously.

Based on these assumptions, we find the optimal path using the above-mentioned time-expanded graphs. Such graphs essentially duplicate each node for each timestamp. A default path search would now also require specifying a starting time and an end time, as the nodes are defined as (x, y, t) . We start at the node $t = 0$ but do not restrict the arrival time at the target node. For this reason, the optimal path search needs to identify the optimal path for each of the arrivals in the timeframe and then find the optimal (safest) one. The safest path can then be read in the virtual environment to visualize the path (see Figure 18). With the time-expanded graph and the trajectory of the user during the training scene, the hazardous energy exposure can be detected.

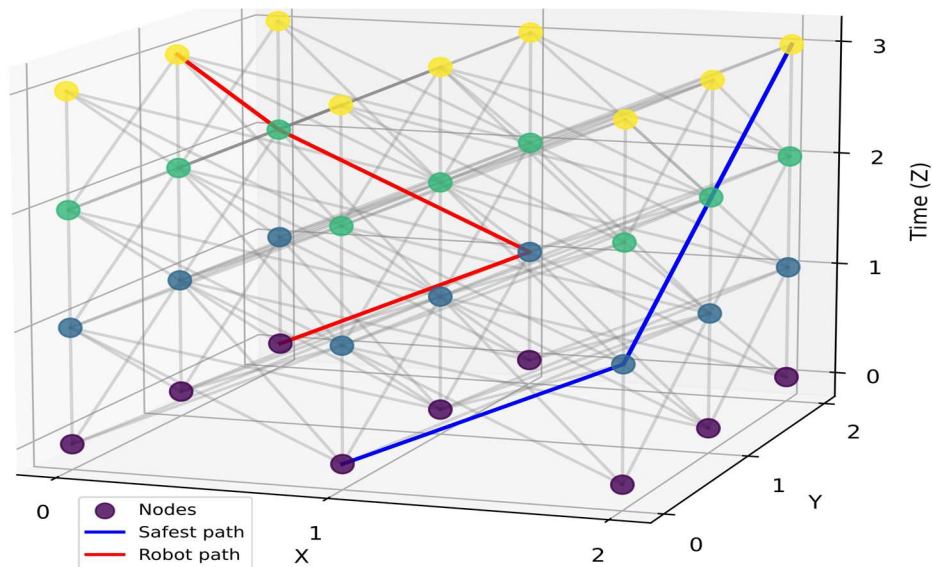


Figure 16: The time-expanded graph copies the nodes for t and updates the edges according to the dynamic hazards.

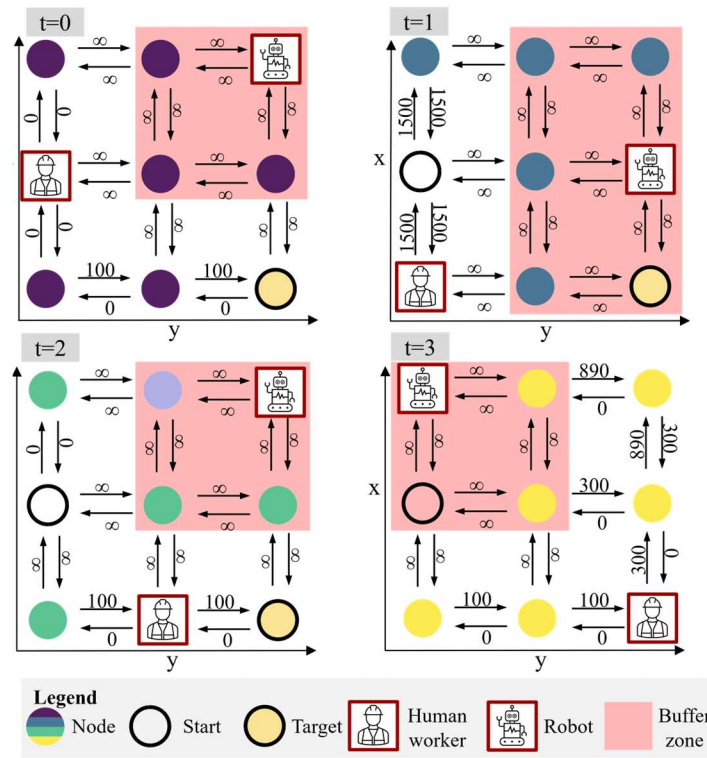


Figure 17: Plan view of pathfinding in the time-expanded graph (Note: the diagonal edges are not shown for simplification).

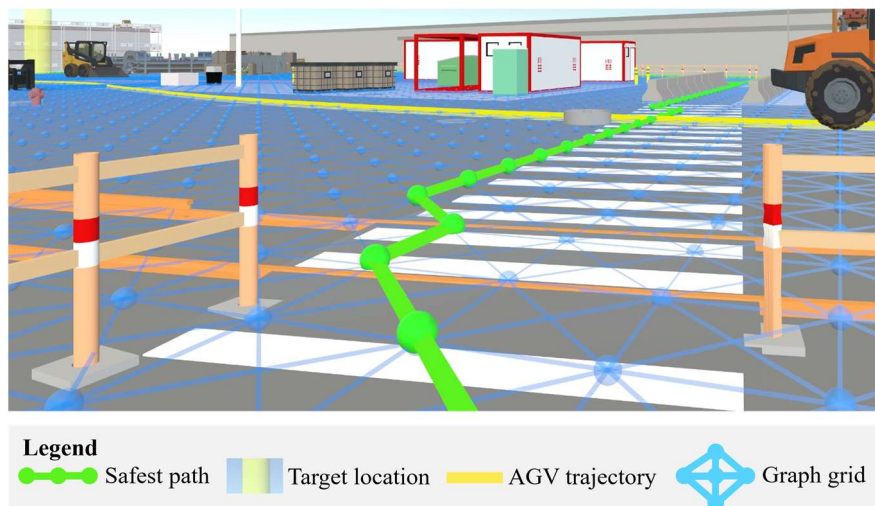


Figure 18: Example of a user's viewpoint (Note: the blue grid is not visible in the scene but is shown to indicate the graph).

6.4. Case study description

6.4.1. RTLS data integration

We collected the RTLS data at the staging area for a subway track replacement project. The collection lasted for three days during the early stage of the project. During the collection, we observed and tracked multiple tasks, such as unloading materials from the truck and arranging and loading materials onto rail cars. The tasks involved resources of both pedestrian workers and construction equipment.

The RTK-GNSS solution was used for the location data collection as it performs accurately in outdoor environments. The RTK-GNSS solution consists of two components: a base station and rovers. The base station is placed statically in open space, and workers and equipment carry the rovers. Compared to a single GNSS solution whose accuracy is affected by atmospheric delays or clock errors, the RTK-GNSS uses the base station to provide correction for rovers so that the workers and equipment are located with cm-level accuracy [78]. The accurate location information reduces the work of data processing and filtering when importing it into the training environment. In addition, it can cover a wider tracking area with a simple setup than other locating methods such as BLE or UWB.

Given that traffic from rail cars and construction equipment occurred within a limited area, the logistics at the staging area could be packed and complicated. Therefore, pedestrian workers must receive sufficient realistic safety training to train to work in such an environment. To test the proposed framework, we recorded a task where two construction workers moved materials from a storage area to a rail wagon. Figure 19 illustrates the scenario: One worker operates a forklift, and the other worker assists the equipment operator. The work lasted for 90 minutes. The pedestrian worker carries an RTK-GNSS module, and the forklift has a module mounted on the roof of the forklift, centrally placed on top of the operator's seat.



Figure 19: The forklift moves material from the loading area to a railway wagon while a pedestrian worker assists.

Figure 20 shows the trajectories of the two resources during the 90 minutes. The RTK-GNSS rovers streamed the location data to a database with a frequency of 5Hz for the machine and 1Hz for the worker. During that time, the worker supported the equipment operator by attaching the material bags to the forklift in the loading area and removing them in the unloading area. Figure 20 shows that frequent interactions between workers and equipment were inevitable when working simultaneously in a limited area.



As we mentioned previously, virtual construction safety training requires personalized feedback. Research has proposed methods for collecting such data, which can be visualized in a concise way for construction workers. In this research, we use the concept of safety parameters and collect data from the trainees when entering hazards using automatic data collection. In the same way as before with the worker in section 4.1, a proximity event is triggered once the trainee enters the bounding box around the forklift.

6.4.2. Training scenario 1: Simultaneous task

In the first training scenario, the trainee must collect various objects in the training scene and return them to a storage area. Meanwhile, the forklift and the pedestrian worker will follow the trajectories from the real-world data collection. During the training, the trainee needs to ensure that they will not trigger any hazards relating to the forklift. Figure 20a indicates such a situation: The trainee needs to cross while the forklift passes. Should the trainee get too close to the forklift, a close call will be triggered, and data will be collected and processed for personalized feedback. The training scenario that was created lasted 10 minutes, and the trainee needed to collect seven objects. Fig. Figure 20b shows the results. The trainee crossed the road six times while the forklift was nearby. The visual indicates that the worker always identified the forklift while heading east. However, returning, the trainee was very close to the forklift twice. This data allows us to conclude that either the equipment operator should have more distance to the pedestrian cross or that the trainee could not see the forklift. Figure 20b also depicts the three proximity events of the real-world worker during this 10-minute excerpt.



Figure 20: (a) Results of the first training scene, incl. the landscape, BIM model, resources, and trajectories from IoT devices, and (b) the trainee crossing the road while the forklift follows the real-world trajectory.

6.4.3. Training scenario 2: Collaborative task

In the second training scenario, the trainee takes over the role of the worker. Hence, the pedestrian worker is removed from the game, and the trainee is advised to support the equipment operator in loading the forklift. The trainee must wait for the forklift and assemble the boxes by pressing “C” on the keyboard. To ensure the worker is safe, the trainee is advised to wait in highlighted areas so as not to collide with the machine. Figure 21 illustrates the safe area, and Figure 21 shows the results from the 90-minute task. During the 90 minutes, the worker followed the forklift to assist in transporting the boxes. We collected the data about the proximity with the forklift using the 1m bounding box described before. When the worker collides



with the bounding box, a proximity event is triggered. Figure 21 shows the 37 collisions with the bounding box in yellow and highlights three actual hits in red. The figure indicates that the actual hits occurred not in the loading area but when the forklift was approaching the worker while the worker walked to the unloading area. The forklift was emitting sound, and the game engine increased the volume when coming closer to the sound source. Still, the worker did not avoid the equipment. However, it is likely that in real-world situations, the equipment operator would have stopped. These collisions are not realistic and reveal one major disadvantage of this approach: The machine is following the trajectory without reasoning. Hence, future work needs to investigate how to include such reasoning as the machine would most likely avoid the machine. Comparing the virtual performance of the trainee to the real-world worker, the trainee triggered more proximity events. There can be different reasons, but all yellow proximity events were triggered at the front. A reason could be that the forklift was stubbornly following the trajectory from the data collection and did not interact with the worker. There was no communication possible between the forklift operator and the construction worker. Hence, if the worker, for instance, did not finish, yet, mounting the box, the forklift will continue on the route and almost hit the worker. The authors propose two approaches to tackling this issue. First, the forklift may include intelligence, such as avoiding the worker while driving or waiting for the trainee to finish their task before moving. Second, a multi-player game where another trainee takes over the role of the equipment operator could enhance realism and improve collaboration between the workforce.



Figure 21: (a) the results from training scenario 2 indicating the trajectories and proximity events, and (b) the safe area where the trainee can wait for the forklift.



7. Conclusions

The work presented in this report demonstrates that a Digital-Twin-enabled, multiplayer VR training framework can close the long-standing “intention–behavior” gap in construction safety education. By fusing BIM, point clouds, and IoT/RTLS feeds with an AI-assisted risk-assessment pipeline, the platform automatically creates project-specific training scenes where hazards resemble real-world site conditions. Four design goals were tested in two case studies.

The two exploratory case studies confirm technical feasibility. In the high-rise crane-hoisting scenario, gesture-recognition gloves, proximity tracking, and waste detectors exposed concrete behavior gaps: the crane operator ignored 25 % of signals, and riggers entered suspended-load zones fourteen times, insights impossible to obtain from conventional training methods like on-the-job or classroom training. In the road-construction scenario, replaying cm-accurate RTK-GNSS trajectories of an autonomous wheel loader allowed trainees to practice simultaneous and collaborative tasks; the system captured 37 proximity alerts and three simulated “hits”, underscoring the need for better human-robot protocols.

Key to these insights are the new performance metrics layered into the framework. Safety is quantified through cumulative hazardous-energy exposure, while LEAN performance is logged as waiting, defects, motion, and extra-processing wastes per role. Because every movement, gesture, and collision is time-stamped at 1 Hz, trainers can now track behavioral trends session-to-session, compare crews, and empirically test which interventions yield safer, less wasteful practices.

The study is an early step. Sample sizes remain small, sensor noise was abstracted in the crane demo, robots followed pre-recorded paths, and the new KPIs have yet to be benchmarked against real incident data. Even with these limitations, the findings signal a meaningful advance for both research and industry. By turning rich project data into live, measurable training experiences, the framework offers a scalable route to safer, leaner worksites and a robust test bed for studying human-machine interaction. With continued refinement and validation, this approach can become a cornerstone of data-driven safety management and a template for broader construction-sector upskilling.



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