



Digital construction site layout planning and real-time trajectory analysis for proactive safety monitoring and control of struck-by hazards

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ABSTRACT

Poor construction worksite conditions cause many Serious Injuries and Fatalities (SIF). This paper introduces the Right-time Analysis and Mitigation (RAM) module as part of the Digital Twin for Construction Safety (DTCS) concept. RAM (a) leverages safety rule-based compliance checking of construction layout plans in Building Information Modeling (called safeBIM) and (b) records and analyzes resource trajectory data involved in potential struck-by incidents using wearable and mobile Real-Time Kinematic Global Navigation Satellite Systems (RTK-GNSS) technology. RAM further (c) provides new access to unprecedented information and gives detailed insights into human-machine interactions that (d) permit rapid implementation of change by targeted control. Results from real-life validations create an in-depth understanding of the potential root causes that often lead to harmful struck-by incidents. While the proposed DTCS technology contributes data input and information output, the change in safety management processes leads to safer work practices. Both prevent SIF that plague the construction sector.

1. Introduction

Construction sites are widely recognized as some of the most hazardous workplaces, with higher rates of fatalities and injuries compared to any other industrial sector. In the European Union, for example, construction is responsible for over one-fifth of all workplace fatalities, with up to 15 % resulting from incidents where workers are struck by equipment or other objects [1]. Similarly, in the United States, the close proximity of pedestrian workers—those who are on foot at off-road worksites working alongside vehicles and equipment—to equipment or its components increases the risk of struck-by injuries, accounting for 48 % fatal and 20 % nonfatal injuries in construction sites [2,3]. The inherent safety risks on construction sites arise from the simultaneous execution of multiple tasks and the presence of essential resources within the constrained workspaces, such as partially completed structures, temporary installations of supportive equipment, and cluttered areas filled with building materials. In tasks involving heavy equipment, workers are particularly at risk of being run over, crushed, or struck by moving equipment or falling objects. Unless controlled, many of these risks can evolve into serious injuries and fatalities (SIF).

The potential root causes and control methods of many SIF are well studied. Consequentially, as one of many examples around the world,

the German Workplace Ordinance [4] sets (minimum) requirements for employee safety and health protection. Such a law primarily intends to establish and operate safe workplaces in the construction sector. It requires employers to identify and assess the risks associated with work tasks and design hazards out before work starts. While various measures exist to mitigate risks upon detection, such as installing barricades that clearly separate pedestrian workers from onsite vehicle traffic, safety plans are still predominantly generated manually and are rarely updated along dynamic construction schedules. Likewise, safety responsibilities are often outsourced to consultants managing multiple projects, making it difficult to frequently update safety plans. Often, construction site safety supervision is left to site managers and superintendents. Unless a construction site reaches a decent size to warrant dedicated safety personnel on site, safety tasks stay within broad field monitoring. Furthermore, unplanned work or changes in activities often lead to non-compliant safety practices, necessitating continuous monitoring.

Traditional safety management tools rely heavily on manual methods, such as identifying hazard zones on printed layouts and conducting manual site observations [5]. Nevertheless, labor-intensive methods often lack sufficient frequency and accuracy to keep up with the actual site condition. Relying yet on safety managers' experience and subjective judgment can result in overlooking hazards that can result in

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notable incidents. All these observed challenges highlight the need for improved tools that integrate safety planning and continuous monitoring of workforce safety status, enabling the automation of hazard assessment and dynamic modification of worksite layout plans.

The emergence of advanced technologies as part of digitalizing construction safety processes has significantly transformed safety management tools. For instance, Building Information Modeling (BIM) method has enhanced the geometric and semantic representation of construction schedules, enabling more precise planning. BIM has facilitated the adoption of the Prevention through Design and Planning (PtD/P) concept by enabling the proactive identification and elimination of hazards during the early stages of construction planning. Recent advancements include preemptive hazard zone identification algorithms that automate the creation of a digital construction safety plan [6–9]. Sensing technology has also advanced, enabling continuous and accurate monitoring of safety status. Despite varying location errors, Real-Time Location Tracking Systems (RTLS), such as Ultra-Wideband (UWB) and Global Navigation Satellite System (GNSS), allow resource trajectory monitoring in outdoor construction environments in runtime [10,11]. The integration of magnetic-field technology on construction equipment and wearable radio-frequency tags on pedestrian workers enhances situational awareness around construction equipment [12]. Such advancement in technologies can enable the detection of incidents where workers enter hazard zones, providing the involved operator and worker/s with critical real-time alerts. These alerts help prevent injuries or equipment damage. Additionally, incident data logging and analysis have demonstrated value for safety managers and trainers, supporting the development of virtual training environments as part of serious gaming [13–18].

However, a research gap remains in the method of holistically integrating the output from these technologies, resulting in incomplete hazard identification and incident detection. (Semi-)Static hazard zones—temporary zones with hazards that are not mitigated effectively or immediately and are often pre-identified on the site layout plan—and dynamic hazard zones - areas surrounding moving and operating equipment that constantly change in location and size along with construction activities - cannot be effectively merged for incident detection. This limitation significantly impedes the ability of safety personnel to accurately assess the on-site safety situation. Even with the availability of digital safe site layout plans, merely visualizing RTLS data on a simplified or outdated site layout model in BIM would still require significant human effort to detect or monitor deviations over time before a safety responsible person could react upon worthwhile findings [5,19].

Recent studies towards this direction have proposed a Digital Twin for Construction Safety (DFCS) as a method to enhance safety engineering and management processes throughout the planning and execution phases [7]. DTCS not only automates data flows between physical construction sites and their digital counterparts but also enables the analysis, prediction, and prevention of next or future hazardous incidents. Additionally, DTCS serves as a comprehensive platform and user interface for exchanging data, information, and knowledge related to safe site layout planning, monitoring, and control [7]. As such, a digital twin that integrates models and resource trajectories has the great potential to make construction safety more efficient, proactive, and adaptive.

This paper focuses on the process of the automation and integration of incident detection, assessment, and proactive mitigation within the DTCS framework. The process is achieved by connecting the modules of safety layout planning and sensor-based tracking, utilizing statistical methods to analyze the spatiotemporal distribution of hazards and incidents, and providing site layout adaption recommendations, which are eventually integrated into the site model. Additionally, this study evaluates the applicability and performance of Real-Time Kinematic-Global Navigation Satellite System (RTK-GNSS), a GNSS-based tracking solution with improved accuracy and reliability [20,21], for construction resource location tracking in live outdoor construction work

environments. In summary, this study aims to address the following research questions (RQ):

- RQ1: Is RTK-GNSS a viable and accurate location tracking technology for resource tracking in live outdoor construction work environments?
- RQ2: How can digital worksite layout plans and location tracking technologies be integrated to enhance safety planning, monitoring, and incident prevention?
- RQ3: What level of detail is required to identify and understand the root causes contributing to too-close proximity or struck-by equipment incidents?
- RQ4: Accordingly, what are suitable mitigative measures for the different types of incidents, and how can these measures be effectively communicated and implemented in the DTCS?

This paper is organized as follows. Section 2 reviews the related work in BIM-based safety planning, sensing technologies for resource location tracking, and the most recent works on digital twins with respect to construction safety. Section 3 presents the proposed framework and the developed computational methods. Section 4 details the field experimental setups and presents results from two realistic case study implementations. Lastly, the method's strengths and limitations are reviewed and discussed, followed by future research directions.

2. Related work

This section presents an overview of existing researches that focus on digital site layout planning, real-time location sensing, and digital twin applications for construction safety.

2.1. From manual to digital safety site layout planning

BIM has made significant contributions to the digitalization of construction management processes, incorporating multiple domains critical to construction projects, such as design, cost, and scheduling. However, the integration of safety into BIM in the project design and planning phases, which would enable Health, Safety, and Environment (HSE) professionals to eliminate or reduce hazards at the earliest possible moment or more frequently, has only recently begun to gain recognition [9].

So far, digital safety planning using BIM methods aligns with the existing PtD/P strategy, which proactively identifies and eliminates hazards during the early design stages of a project, continuing up until the start of execution [8]. While PtD/P is still applied iteratively in the operations phase, it primarily involves the identification and mitigation of known yet uncontrolled hazards before they escalate active risks [22]. In the context of safe construction equipment operations, Teizer and Cheng [23] classified the hazard types, while Johansen et al. [9] further expanded this classification, distinguishing between semi-static and dynamic hazard zones.

Traditionally, PtD/P requires substantial manual effort from the architectural and engineering disciplines [24]. For instance, in conventional risk assessment, the safety responsible must manually identify unprotected leading edges and floor openings on printed construction drawings to determine where fall protection equipment is required. As project sizes grow, this task becomes increasingly labor-intensive and prone to errors [25]. Even with the adoption of BIM models, a safety responsible knowledgeable in BIM must examine three-dimensional (3D) building information models and schedules to identify hazards embedded in the spatial-temporal context of the design intent. To assist this process, automated hazard identification has been proposed, utilizing BIM object information (e.g., geometry, spatial-temporal relationships, and associated work tasks) to reduce manual efforts and detect hazard zones that might otherwise be overlooked [6,26].

Zhang et al. [6] first came up with a rule-checking algorithm to

Table 1

Previous research on sensor technologies and their safety monitoring applications.

Technology	Key feature(s)	Advantages	Accuracy	Implementation	Reference
Vision-based Tracking	Utilizes cameras for monitoring	Multi-object tracking within the environmental context	Medium (m-level)	Cameras and image processing software	[19,35]
Radio-Frequency Identification (RFID)	Passive to active tracking	Tracking multiple tags in large areas	Low	Passive RFID readers and tags	[31]
Ultra-wideband (UWB)	High precision, effective in obstacles	High-precision tracking in dense areas	High (dm-level)	UWB transmitters and receivers	[30]
Bluetooth Low Energy (BLE)	Low power consumption	Long-term, low-maintenance tracking	Medium (m-level)	BLE beacons and compatible devices	[5]
Global Navigation Satellite System (GNSS)	Global coverage, large outdoor areas	Large-scale outdoor monitoring	Medium (m-level)	Satellite receivers	[32,33]
Real-time Kinematic (RTK)	Easy setup	Monitoring subtle changes with high accuracy	Very high (cm-level)	RTK rovers and base stations	[34]

identify fall hazards, such as unprotected edges and openings, within BIM models. Building on this, Kim et al. [27] enhanced this approach by developing a rule-checking engine capable of detecting hazards related to temporary construction elements, such as scaffolding. Further advancements were made by Johansen et al. [28], who developed a 4D BIM-based tool for detecting fall hazards and struck-by incidents caused by falling objects, inserting protective equipment (e.g., guardrails and safety nets) directly into BIM models. With the creation of PtD/P knowledge bases and safety ontologies, which encapsulate safety requirements and best practices, rule-based algorithms have demonstrated significant adaptability to various hazard types and safety regulations [29]. These safety rule-checking algorithms evaluate construction schedules against safety regulations and recommend mitigation measures, enhancing the efficiency and accuracy of safety planning.

2.2. Real-time resource location tracking

Real-time location tracking using sensor-based systems is an essential method for monitoring the locations of workers, equipment, and other resources on construction sites.

The research community has extensively tested various location tracking systems to evaluate their effectiveness on construction sites. Cheng et al. [30] assessed UWB systems for real-time tracking of mobile resources in challenging construction environments and performed analyses of worksite operations through case studies. Their findings demonstrated UWB's applicability for the design of construction management tools. Costin and Teizer [31] used Radio Frequency Identification (RFID) to monitor worker locations in indoor environments, visualizing these locations within BIM models. Park et al. [5] presented a safety monitoring framework that integrates Bluetooth Low Energy (BLE)-based location tracking technology with BIM.

For outdoor tracking in construction sites, Global Positioning Systems (GPS) have been widely applied due to their simplicity and wide coverage [32]. Zhang et al. [33] utilized GPS data loggers attached to workers' hardhats to monitor their movements during the construction of cast-in-place concrete columns. RTK-GNSS, an enhanced GPS solution, improves accuracy by receiving signals from more satellites and incorporating corrections from static sensors, thereby delivering centimeter-level accuracy [34]. Compared with standard GNSS, RTK-GNSS provides significantly higher accuracy and reliability, making it especially valuable for safety monitoring applications. Beyond sensor-based tracking, computer vision has become a prominent alternative for detecting and monitoring construction resource detection and monitoring on construction sites. For instance, Kulinan et al. [19] highlighted the application of vision-based tracking, while Pfizner et al. [35] used vision data to track workers' locations and map them onto floor plans for productivity analysis.

Collected location data often requires further filtering to remove offsets. Various filters, such as the speed filter, Kalman filter, and Savitzky-Golay filter, have been implemented to preprocess collected

location data for productivity monitoring and analysis [31,36]. However, these low-accuracy techniques are not suitable for immediate incident detection, as they may trigger false alarms or, more critically, fail to detect critical incidents. To sum up, Table 1 summarizes the features, benefits, and application scenarios of various location tracking technologies referenced for construction safety monitoring.

2.3. Digital twin for construction safety

A digital twin is a data-driven model that mirrors real-time conditions of physical systems, enabling autonomous control and management based on accumulated insights [37]. Originally adopted from the manufacturing sector, this concept has been adapted in construction research to enhance real-time monitoring, decision-making, and process optimization. Sacks et al. [38] introduced the term *Digital Twin Construction* (DTC) as a data-driven management and control model, leveraging various site monitoring technologies and data sources to provide accurate real-time status updates and enable proactive process optimization. Similarly, other studies [39,40] suggest digital twins as a comprehensive approach for real-time management and control over construction processes, equipment, materials, workforce, quality, and safety.

Teizer et al. [7] first introduced the concept of *Digital Twin for Construction Safety* (DTCS), integrating safety assessment and control within the DTC framework. DTCS comprises four key steps: (a) hazard prevention, (b) conformance checking, (c) right-time alerts and analysis, and (d) continuous performance improvement via proactive learning and feedback. DTCS enhances the utility of real-time site data (e.g., building progress, schedules) by integrating on-site sensor data, enabling continuous safety monitoring, incident detection, proactive avoidance, and learning.

In digital twins, the integration of Internet of Things (IoT) devices enables the collection and transmission of real-time data for processing in the digital twin environment. Zhao et al. [41] introduced a BLE sensor-based digital twin framework for safety management, demonstrating its effectiveness in tracking motion and identifying stationary behavior through accelerometer data in residential building construction projects. Similarly, Ye et al. [42] developed a digital twin-enabled platform for safety management and early warning systems in dynamic tunnel construction, analyzing sensor data to provide real-time alerts to potential incidents.

Digital twin platforms enable the implementation of sensor-based spatiotemporal analysis, allowing for immediate responses to monitor safety conditions, detect incidents, and issue timely warnings. This analysis primarily evaluates the proximity of workers to hazard zones, facilitating targeted safety interventions. For instance, Li et al. [43] explored the use of crowd-sourced density maps to infer safety conditions across multiple site areas, demonstrating how collective data can enhance situational awareness. Golovina et al. [12] proposed a framework for assessing the severity of close-call incidents based on worker

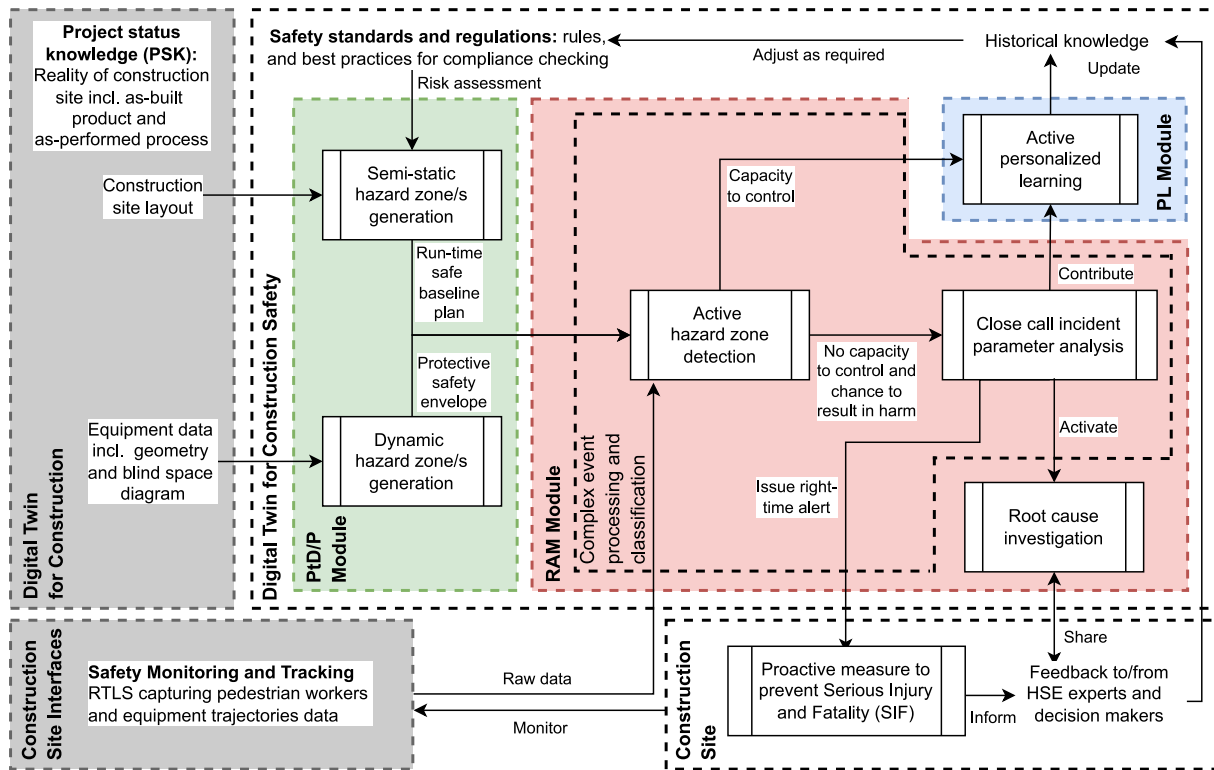


Fig. 1. Framework of hazard identification, incident detection, and safety plan refinement (extended from Digital Twin for Construction Safety (DTCS) [44]).

proximity, enabling personalized feedback for safety improvement. However, their work did not explicitly incorporate the digital twin concept.

In summary, this study aims to extend the DTCS workflow by incorporating incident and hazard analysis of collected location data to inform and guide modifications to the construction site layout plan. The implementation of RTK-GNSS enables precise tracking of pedestrian workers and equipment, accurately reflecting their spatial relationships and laying a foundation for further integrating their trajectories into site layout planning.

3. Framework and methods

This section expands upon and elaborates on the DTCS framework, providing additional details on the methods employed in this study, which are subsequently applied in a case study for validation.

3.1. Framework

Building upon the DTCS framework [44], an enhanced framework was developed to integrate RTK-GNSS with BIM for hazard detection, incident management, and layout modification recommendations. As shown in Fig. 1, this framework focuses on the *Right-time Analysis and Mitigation* (RAM) module, which interfaces with other modules to enable timely and effective safety interventions.

As defined in prior research, hazard zones are classified as semi-static and dynamic [9]. *Semi-static hazard zones* arise from operational constraints or planned activities and maintain consistent geometry and location over a time period. In contrast, *dynamic hazard zones* are associated with moving and operating equipment and are characterized by variable geometry and location.

To identify hazard zones, the *PtD/P module* accesses the site layout and equipment models from the Project Status Knowledge within a DTC [38]. Semi-static hazard zones are determined through a risk assessment process based on established safety standards and regulations. Dynamic

hazard zones are defined initially by delineating a 1-m boundary (according to [45]) and identifying equipment operator blind spaces from the equipment models (like previous research [46–50]).

Since the location of dynamic hazard zones shifts as equipment moves, location and orientation data are continuously collected from sensors mounted on the equipment to accurately track these changes in real time. The *Construction Site Interface* module gathers real-time site data, including the locations of equipment and pedestrian workers. The identified hazard zones, along with the location data, are then transmitted to the RAM module for incident detection. A hazard zone becomes active when an incident is detected within it. If the pedestrian worker within this active hazard zone lacks the capacity to control the incident, it escalates to a close call (def. in [51]), triggering an immediate alert. This alert is sent to the *Construction Site* to enable proactive measures to prevent events that otherwise could result in an injury, fatality, and/or collateral damage.

Each close call initiates a root cause analysis, with the results communicated to the safety responsible (incl. HSE manager) assigned to the worksite. Regardless of whether an incident escalates to a close call, all events are systematically documented to facilitate active, personalized learning in the *Personalized Learning* module. This process involves analyzing incident density maps—areas of concentrated activity that warrant further attention—alongside movement patterns, hazardous activities, and active work zones. These insights are then used to update safety protocols and recommend mitigation strategies, such as generating designated zones or temporary controlled walkways, by revising the safety plan.

3.2. Integrating RTK-GNSS with digital safety plan

Before construction starts, a safety plan is generated from as-planned building models, and a first baseline safety plan is selected. As construction progresses, the plan is continuously updated to reflect the current construction status and accommodates the results of conformance checks (as shown by [52]).

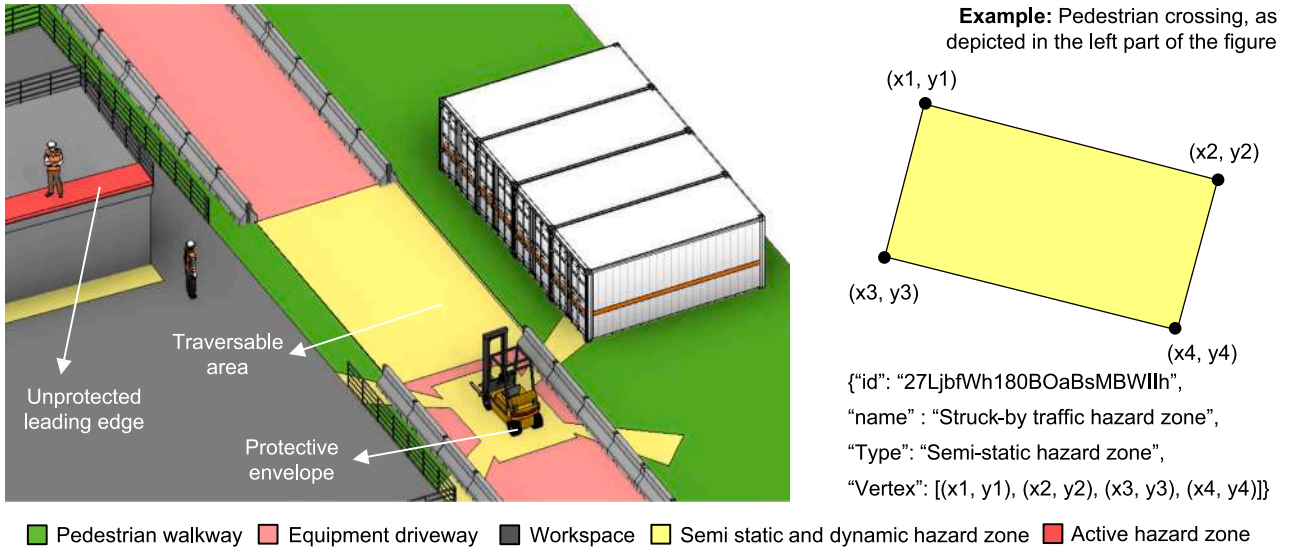


Fig. 2. Example of hazard zone identification and geometry extraction in a BIM model.

Designated zones and protective equipment play a critical role in preventing workers from being exposed to hazards. A safety plan defines work and support areas—including work zones, pedestrian walkways, and equipment movement zones—and specifies the locations of protective equipment. It also identifies built-in hazard zones arising from unavoidable risks inherent in the design and planning phases, such as traversable intersections.

SafeBIM, a BIM-based safety layout, integrates safety details into as-built and as-performed BIM models. It is created manually or through automated methods, such as the SafeCon framework [30], to incorporate safety equipment and highlight hazard zones. This study focuses on integrating location-based hazard analysis into SafeBIM. The use of Industry Foundation Class (IFC)-formatted BIM ensures interoperability across different BIM tools [53].

The PtD/P module identifies hazard zones within the construction models and utilizes Ifcopenshell, an open-source Python library, to extract their locations and geometries [54]. For example, unprotected crossings are classified as semi-static struck-by hazard zones, while unprotected leading edges in active elevated workspaces are categorized as semi-static fall hazard zones. Fig. 2 presents an example of how a struck-by traffic hazard zone is identified and extracted.

Commercially available components were configured to an RTK-GNSS system that provides high-precision, real-time tracking of pedestrian workers and construction equipment. The developed system consists of one base station and multiple rovers. The base station broadcasts correction signals to nearby rovers, enabling them to correct measurement errors. Although public or subscription-based base station services are available, using a 'private' base station enables centimeter-level precision within the coverage area without requiring extensive infrastructure or incurring high implementation costs. For this study, a base

station was installed on the construction site, placed statically in an open space with an unobstructed view of the sky. The rovers were attached to construction resources—embedded as wearables in safety vests (on the back or shoulder) for pedestrian workers and mounted on top of equipment cabins for construction equipment.

Hazard monitoring and incident detection require the integration of hazard zone data with real-time location data. Hazard zones are extracted from SafeBIM, which must first be georeferenced to ensure alignment with the location data. The integration begins by unifying the coordinate systems, which differ in dimensions, scales, and datums. SafeBIM typically operates in a local Cartesian coordinate system optimized for site-specific precision and efficient data handling. In contrast, RTK-GNSS uses the World Geodetic System 1984 (WGS84), represented by latitude, longitude, and altitude.

To align the two, WGS84 coordinates are first converted to the Universal Transverse Mercator (UTM) system, a Cartesian coordinate system compatible with BIM. The final step involves applying a transformation matrix to translate and rotate the UTM system so it matches the local BIM coordinate system. This procedure is detailed in the pseudo-code in Algorithm 1.

Location data is streamed to the DTCS in real time and stored locally. This way complies with the required General Data Protection Regulations (GDPR). A data preprocessing module filters the incoming data to remove noise, converts it to the BIM coordinate system, and reformats it as (id, x, y, z, t) before passing it to the run-time incident detector. The RAM module detects incidents during real-time site monitoring and creates valuable output information for the safety responsible in the Digital Twin user interface. If necessary, it sends immediate alerts to the affected pedestrian workers and equipment operators.

Input: utmEasting, utmNorthing, localOriginUTM, rotationAngle

Output: localBIMX, localBIMY

- 1: Initialize an output list for BIM coordinates
- 2: For each coordinate point:
 - 3: $offsetX := utmEasting - localOriginUTM.easting$
 - 4: $offsetY := utmNorthing - localOriginUTM.northing$
 - 5: Rotate coordinates to align with BIM axes:
 - 6: $localBIMX = offsetX * \cos(radianAngle) - offsetY * \sin(radianAngle)$
 - 7: $localBIMY = scaledX * \sin(radianAngle) + scaledY * \cos(radianAngle)$
- 8: Return the list of local BIM coordinates

Algorithm 1. Convert RTK-GNSS to Local BIM Coordinates

Additionally, a precision test on the RTK-GNSS was conducted by analyzing the 50th and 95th percentile error of the location data collected from a static rover. The calculation follows a two-step process: first, the center point of the dataset is determined by computing the mean x and y coordinates of all recorded positions. Then, the distance d_i of each data point from this center is calculated as:

$$d_i = \sqrt{\left(x_i - \frac{1}{N} \sum_{i=1}^N x_i\right)^2 + \left(y_i - \frac{1}{N} \sum_{i=1}^N y_i\right)^2}$$

The 50th and 95th percentiles of these distance values represent the corresponding percentile errors of the RTK-GNSS data.

3.3. Assessing safety performance and site conditions

Construction sites present unique challenges due to the presence of both semi-static and dynamic hazard zones, each requiring distinct approaches for effective incident detection and assessment.

3.3.1. Detecting unauthorized entry and too-close proximity

Every construction resource is surrounded by a (virtual) protective envelope (aka. Safety envelope) designed to restrict intrusion by other resources (e.g., vehicles or parts). For dynamic hazards, the safety envelope aligns (at minimum) with the associated hazard zones. Three levels of detail in safety envelope models are considered:

- **Simplified model:** Represents the boundary of construction resources as polygons or circles with a 2-m boundary as a safety envelope for general safety requirements, adjusted per standard. The safety envelope for a pedestrian worker is modeled as a circle with a 1.5-m radius, adjusted according to standard guidelines.
- **Detailed model:** Incorporates detailed measurement of risky areas surrounding the construction resources. For example, construction equipment involves operation range, blind spaces, and a 1-m boundary. The blind spaces are based on operational visibility guidelines defined in ISO 5006:2017 [45]. These parameters are further derived from on-site observations or manufacturer specifications when available.
- **Statistical model:** Utilizes spatial data distributions and movement patterns around construction equipment, necessitating substantial sampling to map the areas where each construction resource can operate safely and without interruption.

Incidents are primarily categorized into two types: unauthorized workspace entries and too-close proximity to moving equipment.

- **Unauthorized entry:** Pedestrian workers or mobile equipment deviate from designated work zones and enter semi-static hazard zones, such as equipment driveways.
- **Too-close proximity:** Pedestrian workers enter the dynamic hazard zones around the moving and operating equipment, including blind space.

Incident detection is modeled as the overlap between the safety envelopes of two or more construction resources. For unauthorized entries, detection checks whether the worker's safety envelope intersects with an unauthorized zone. For too-close proximity, detection checks whether a pedestrian worker's envelope collides with that of equipment. Once detected, incidents are systematically documented as a time series of location data (id, x, y, z, t) of the involved resources.

Previous studies have proposed various indicators and criteria for assessing individual incidents. In this study, we adopted the hazard weights outlined in [51], which evaluate each incident across five

dimensions: duration, deviation, distance, orientation, and velocity, each rated on a 1 to 5 scale (with 0 indicating no hazard and 5 indicating highest severity). The complete formula for calculating the overall hazard score is provided in the referenced work.

Each incident is linked to the corresponding construction resource (e.g., worker or equipment), and incident statistics are used to evaluate individual safety performance. The integrated hazard weights ($w_{h,i}$) for a worker i is calculated as:

$$\hat{w}_{h,i} = \frac{N_i}{\sum_i N_i} \times \frac{\bar{w}_i}{5} \times \max(w_i)$$

Where:

- $\hat{w}_{h,i}$ is the integrated hazard weight for worker i .
- N_i is the number of incidents associated with worker i .
- $\bar{w}_i$ is the average weight of all incidents in which worker i was involved.
- $\max(w_i)$ is the max weight of all incidents in which worker i was involved.

This formula integrates the frequency, average severity, and peak severity of incidents to derive a comprehensive risk score. A higher value of $w_{h,i}$ indicate greater risk, reflecting both how often incidents occur and how severe they are.

3.3.2. Creating density maps and identifying hazardous activities

An incident or risk density map visualizes work zones based on observed incident frequencies, using heatmaps to present the data in an intuitive and easily interpretable format. Areas with higher incident frequencies can inform predictive analysis and support the proactive elimination of future risks. In addition to incident counts, equipment behavior data, such as frequent speeding or reverse motion, also contribute to classifying hazardous activities in work zones. For example, backward driving presents an elevated hazard level due to limited rear visibility. Although construction equipment typically drives at slower speeds than road vehicles, any increase in speed can significantly increase the hazard level. Therefore, construction site speed limits are typically set by a traffic engineer and range anywhere from 5 to 15 km/h [55]; in this study, a 10 km/h speed limit was applied.

To visualize the spatial distribution of incidents and hazardous activities, density maps are generated using 2D histograms of location data points. Each histogram maps the number of events within a grid of 1×1 meter cells over a specified time period. Since data are collected at a fixed frequency, the number of location data points in each cell directly reflects the duration of events within that cell. The 1-m grid resolution was chosen to align with the average worker's body dimensions (approximately 0.5 m in width) and movement characteristics (1.3–1.5 m/s), ensuring a practical and human-scale level of detail. Once the heatmap is created, dense areas are identified through a thresholding process. In this study, the median value was used as the threshold to filter out outliers, such as areas where equipment may have been idling for extended periods.

The identified cells are then combined into polygons, representing areas where event occurrences exceed the median value. To facilitate spatial data extraction and integration into the updated safety plan, polygons are further simplified using the Ramer-Douglas-Peucker algorithm [56]. It reduces the complexity of the polygons by removing vertices while preserving the overall shape and key features. By minimizing the number of points in the polygons, computational load is reduced, enabling faster processing for real-time hazard detection or spatial mapping. The process for identifying dense areas is summarized in Algorithm 2.

Input: LocationList (List of (x, y)), CellSize, GridBounds (xmin, xmax, ymin, ymax)
Output: DenseArea (Polygon)

1. Define a 2D grid covering the spatial extent (**GridBounds**) with uniform cells of size **CellSize**
2. Count the number of location points in each grid cell to generate a 2D histogram of spatial density
3. Extract all non-zero cell values and calculate the median occurrence value
4. Identify all cells whose values exceed the median threshold
6. Initialize list for cell polygons
7. FOR each identified cell
 CREATE polygon for grid cell at index
 ADD polygon to list
8. END FOR
9. Combine all polygons into one unified polygon
10. Simplify the combined polygon with Ramer-Douglas-Peucker Algorithm
11. Return the final unified and simplified polygon **DenseArea**

Algorithm 2. Identify dense areas using histogram-based heatmap

Additionally, to analyze incidents and worker presence within dynamic hazard zones, the spatial distribution of workers relative to moving zones is examined. Worker locations are rotated and translated to align with a coordinate system centered on the hazard zone, with its heading direction aligned to the positive x-axis. This mapping approach supports both quantitative and qualitative analysis of worker presence and movement patterns within specific dynamic hazard zones. When data are limited - for instance, in incidents involving brief worker presence within equipment-generated hazard zones - Gaussian Kernel Density Estimate (KDE) method is applied for heatmap generation. Kernel density estimation method spreads each data point's influence over space, enabling visualization of sparse data [43,57]. The 2D Gaussian kernel function is defined as:

$$K(x, y) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{x^2+y^2}{2\sigma^2}\right)}$$

where x and y represent the horizontal and vertical distances from the center of the data point (kernel), and σ is the bandwidth parameter controlling the spread of the kernel.

In this study, Gaussian KDE was applied using *gaussian_kde* defined in SciPy, which selects bandwidth automatically based on Scott's Rule:

$$\sigma = n^{-\frac{1}{d+4}}$$

where n is the number of data points and d is the number of dimensions. For each cell in the grid, KDE aggregates the contributions from all data points, which gives a smoothed density estimate representing how dense the event is at that location.

While bandwidth significantly affects the smoothness of the heatmap—balancing noise reduction and pattern clarity—the fine-tuning of statistical parameters is not the focus of this study.

3.4. Revising and updating the safety plan

To enhance safety plans, a quantitative analysis is conducted to identify the dense areas of incidents and hazardous activities, focusing on incident frequency and their spatial distribution. Based on the analysis results, revisions to the safety plan are proposed. The primary strategy is to improve the spatial separation between workers and equipment, thereby significantly reducing the risk of future conflicts and safety incidents.

3.4.1. Separating worker and equipment areas

As described previously, a dense area of incidents is defined as a cluster of cells with an above-median incident occurrence. These areas require additional localized attention and targeted safety interventions. One of the key factors influencing hazard levels is the spatial overlap between pedestrian workers and mobile equipment in the highly frequented movement areas. To quantify the risk in these areas, we

calculate the overlap ratio, as calculated using the formula:

$$\text{Overlap ratio} = \frac{\text{Area}_{\text{worker}} \cap \text{Area}_{\text{equipment}}}{\text{Area}_{\text{worker}}}$$

This metric measures the proportion of the worker movement area that intersects with the equipment movement area. A higher overlap ratio suggests increased risk and the need for immediate mitigation.

When high overlap ratios were observed, targeted measures were implemented. In line with OSHA and NIOSH recommendations [58], the primary strategy is designating specific zones, such as waiting zones and human-equipment collaboration zones, for different construction resources to minimize interaction. Protective equipment is installed to clearly separate pedestrian workers from equipment moving and operating zones, reducing the potential for too-close incidents or even contacts.

3.4.2. Generating temporary pedestrian walkway

Temporary controlled walkways serve as an effective mitigation strategy for resolving movement zone conflicts between workers and equipment, particularly when predefined pedestrian paths are insufficient. The temporary walkways are designed to follow optimal routes that minimize pedestrian workers' exposure to equipment movement while maintaining travel efficiency.

A graph-based route optimization approach is utilized, combining Dijkstra's algorithm with a visibility graph [59]. Unlike cell-based methods, which divide walkable space into uniform grids and often produce inefficient or indirect paths, visibility line analysis connects the vertices of the polygonal obstacles and walkable areas via direct lines, allowing for a smoother and more realistic path [60].

Dijkstra's algorithm, a well-established method for finding the shortest path in a weighted graph, iteratively selects the node with the lowest cumulative cost and explores its adjacent nodes until the target is reached [61]. In this approach, polygon vertices are recognized as nodes in the Dijkstra's algorithm, and edges are evaluated for line-of-sight visibility. Any edge intersecting with non-walkable areas is discarded, ensuring that only feasible paths are considered.

To incorporate safety factors, this cost function accounts for both travel distance and hazard level. As illustrated in Fig. 3, the process begins by identifying start and end points based on workers' frequently visited areas and active work areas. Walkable zones are then defined, and paths intersecting hazardous regions are penalized with higher travel costs to prioritize safer alternatives. The cost of intersections between pedestrian walkways and hazardous areas is factored into the analysis, increasing the travel cost of routes by traversing hazardous zones to prioritize safer paths. Notably, this approach simplified the dimensions and trajectories of workers into an idealized point and straight line, ensuring computational simplicity and compatibility with Dijkstra's algorithm.

To quantify and differentiate the hazardous zones identified on-site, a three-step hazard level is assigned to each zone. Each hazard level is

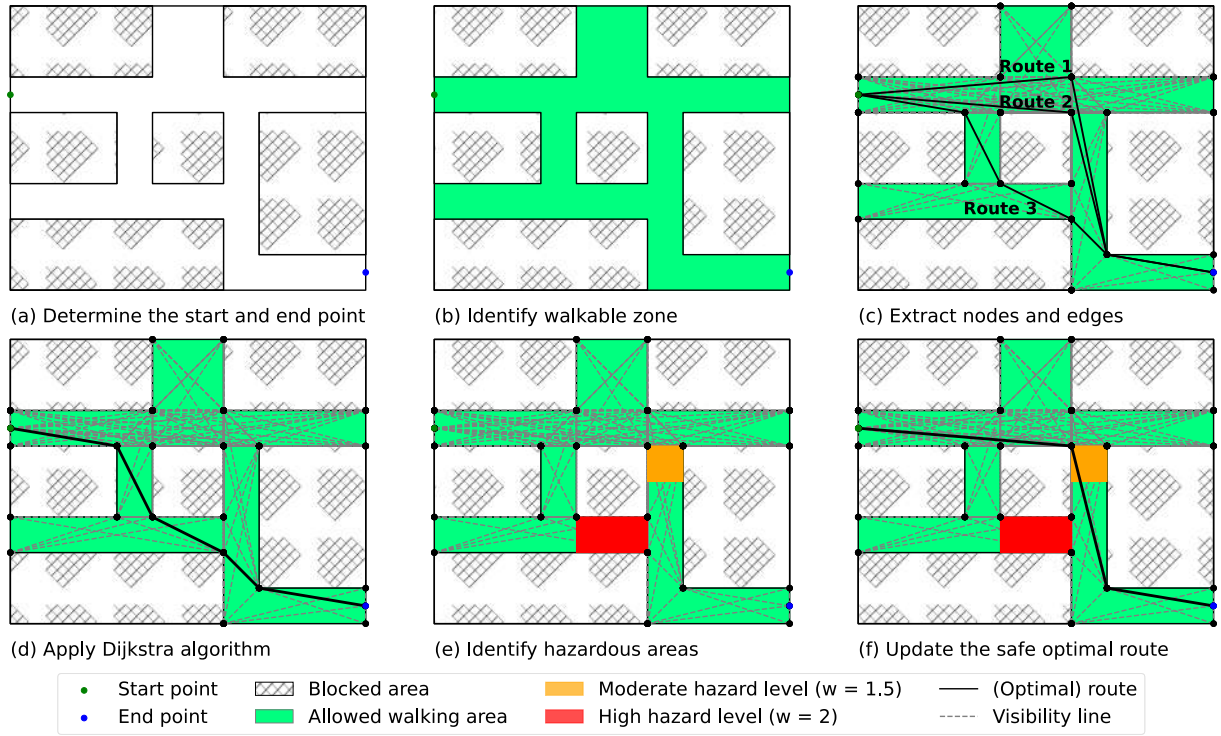


Fig. 3. Procedure for safety-weighted route optimization in construction site navigation.

associated with a weight factor, w , which adjusts the travel cost of routes traversing these areas. Hazard levels are assigned based on the potential risk to pedestrian workers, as follows:

- Low hazard level ($w = 1$): Safe zones with minimal or no mobile equipment activity, such as predefined pedestrian walkways that do not intersect with equipment driveways.
- Moderate hazard level ($w = 1.5$): Areas with slow-moving equipment or where equipment movements are predictable, such as zones of controlled human-equipment interaction.
- High hazard level ($w = 2$): Dynamic hazard zones involving fast-moving equipment or complex maneuvers, such as reverse driving or high-speed travel.

Travel is calculated as the Euclidean distance, while travel cost reflects the adjusted distance based on safety risk. The total cost of a route is defined as:

$$C_{route} = \sum_e \sum_i w_i d_{i,e}$$

where:

- w_i is the safety weight of zone i , (and)
- $d_{i,e}$ is the intersection distance between the edge e and zone i .

For example, areas where equipment exceeds speed limits are classified as high hazard levels ($w = 2$). Conversely, controlled or safe areas such as walkways with no equipment traffic are assigned a low weight ($w = 1$). The final walking path is selected by identifying the route with the lowest cost, balancing both travel distance and safety considerations. Once the optimal path is selected, the temporary controlled walkway is integrated into the SafeBIM model for on-site implementation.

4. Experiments and results

Experiments were conducted to evaluate the effectiveness of the proposed framework and methods. These experiments were carried out in the staging area of a subway rail infrastructure maintenance project in Munich, Germany. The project involved pedestrian workers, ground-

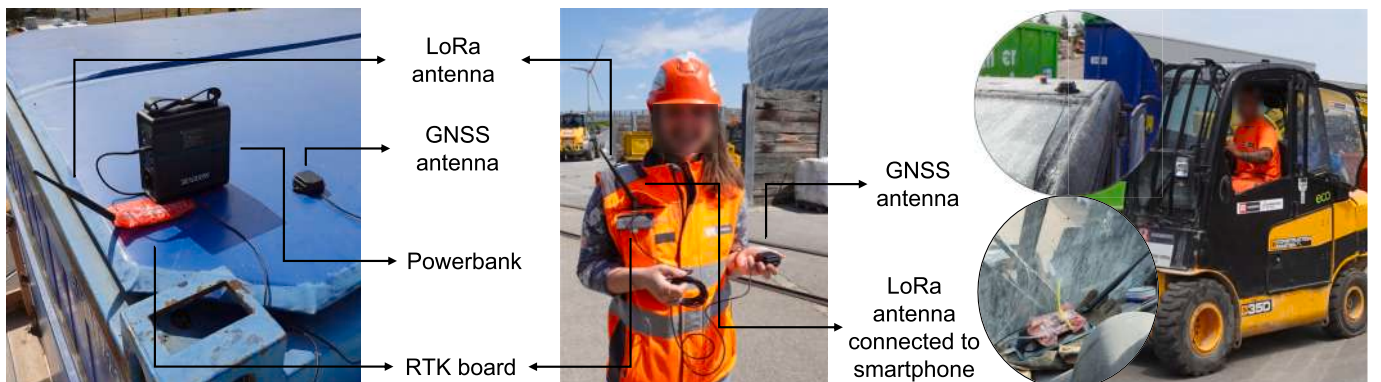


Fig. 4. Setup of the LoRa network and RTK-GNSS system for pedestrian workers and heavy construction equipment.

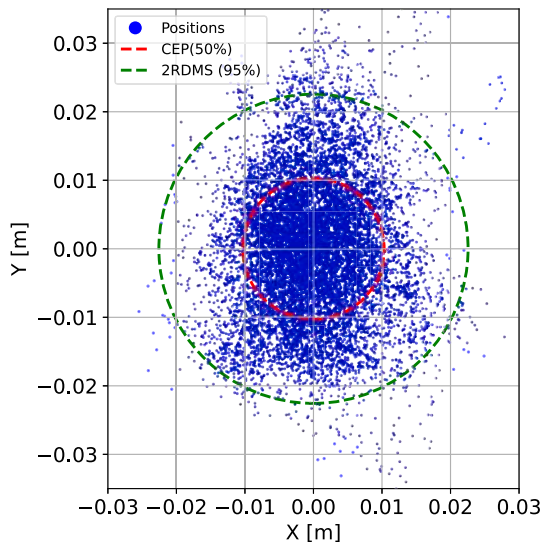


Fig. 5. 50th and 95th percentile error test results for the RTK-GNSS system used in the study.

moving equipment, and railcars performing tasks such as loading, unloading, and recycling railway materials. The primary hazard identified during these activities was the risk of workers being struck by mobile equipment.

4.1. RTK-GNSS implementation

An RTK-GNSS system [62], based on a Long Range (LoRa) network

[63], was deployed to monitor the movement of workers and equipment throughout a three-day-long field experimental period. The system, sourced from simpleRTK2B, consisted of a base station and multiple rovers. As shown in Fig. 4, the base station was positioned on top of a two-story office container, while rovers were embedded into existing pockets on pedestrian workers' safety vests. For mobile equipment, rover antennas were mounted through existing strong magnets outside and on top of the equipment cabin, centered close to the equipment operator's seat. All relevant dimensions and equipment specifications were recorded.

Location data collection and streaming began once the base station was fully operational and the rovers started receiving correction signals. Workers' locations were recorded at a frequency of 1 Hz, the system's default setting, while equipment locations were recorded at 5 Hz to better capture motion. All data were stored locally on smartphones connected to the rovers.

During data collection, a precision test was conducted for the RTK-GNSS system at the implementation site. According to the RTK board and device manufacturer's specifications, the system supports three tracking modes: RTK Fix, RTK Float, and Single [64]. RTK Fix offers centimeter-level precision, RTK Float provides accuracy within 0.5 to 1 m, and Single mode has the lowest precision, with accuracy ranging from 1 to 5 m.

To assess the system's precision, a rover was placed at a clear, unobstructed location in the staging area, and its position was recorded continuously for three hours. The system operated in RTK Fix mode, and the deviation from the mean position was used to evaluate precision. Approximately 10,800 location points were collected. The 50th percentile precision was 1.0 cm, and the precision at the 95th percentile reached 2.3 cm. Fig. 5 presents a visualization of the precision results, demonstrating the RTK-GNSS system's suitability for high-accuracy tracking in field applications.

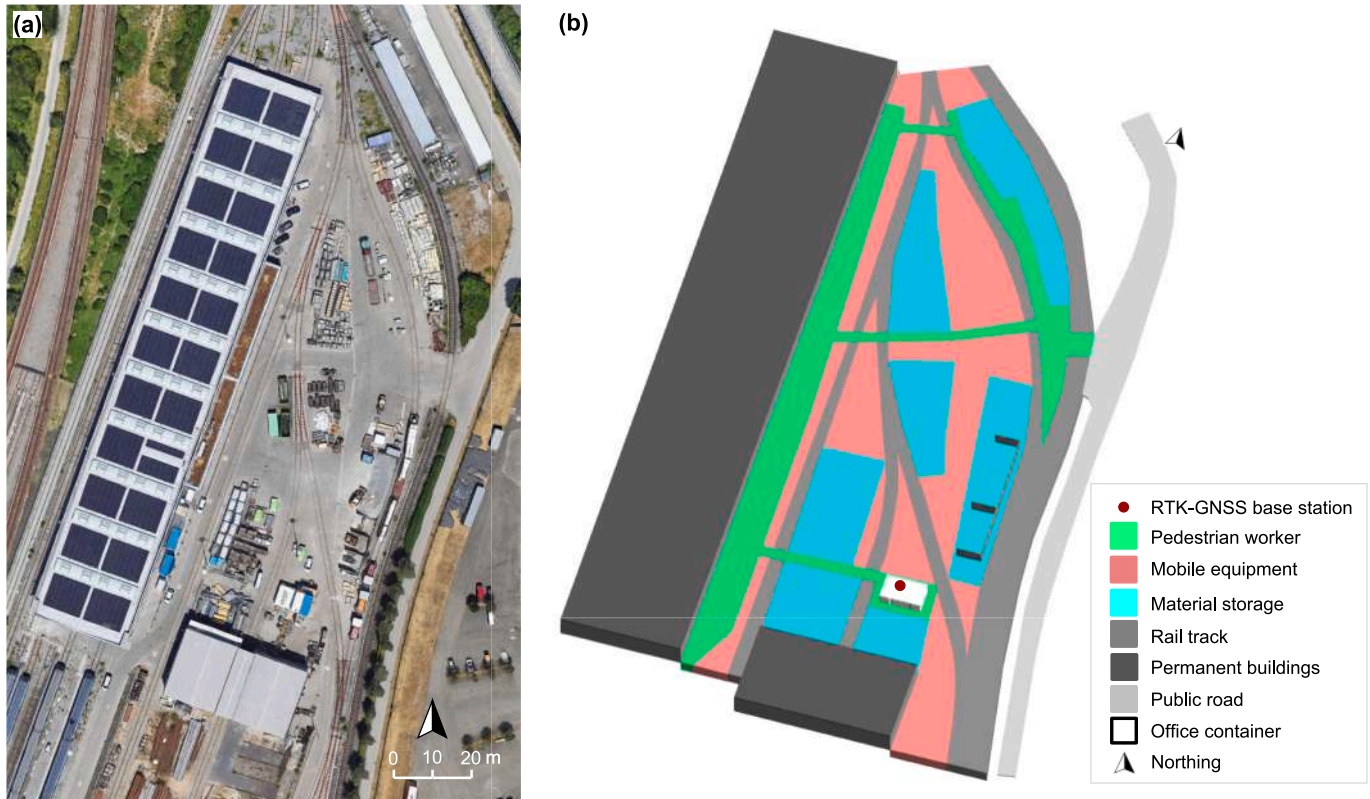


Fig. 6. (a) Satellite image of the remote construction site staging area and (b) isometric view of the safeBIM model highlighting the hazardous and designated work zones for pedestrian workers and equipment.



Fig. 7. (a) Railway ballast stored and waiting to be moved from the material staging zone to the railcars, (b) telehandler transporting ballast bags between the storage zone and designated waiting area for railcars, and (c) telehandler loading ballast bag onto the railcar for further transport, requiring pedestrian worker assistance in the loading and unloading process.

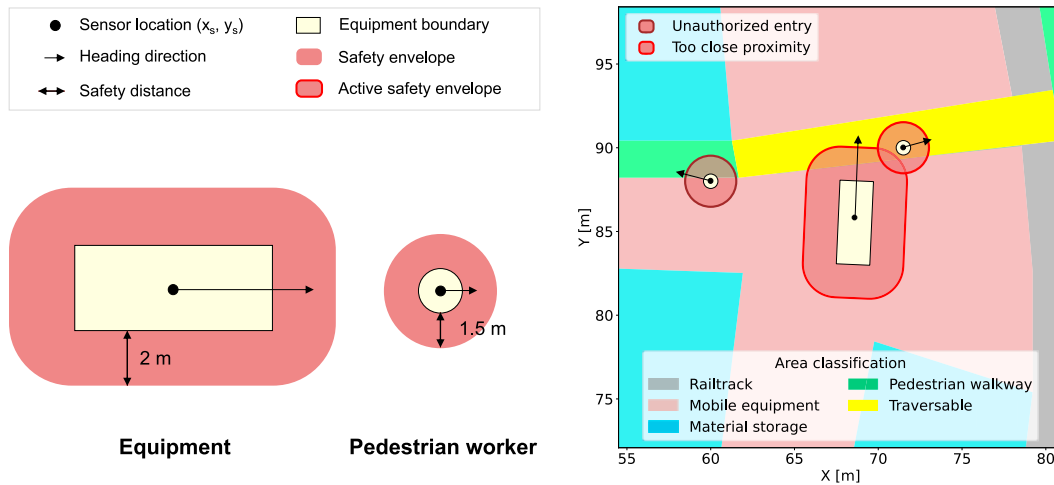


Fig. 8. Simplified version of the corresponding protective envelopes for a piece of heavy construction equipment (simplified by a bounding box) and pedestrian worker (left image) and illustrations of two types of incidents (right).

4.2. Hazard zone identification

A site layout model of the staging area was created using commercially available BIM software for manual modeling objects and geometries. Self-taken photographs and satellite images provided valuable input to designate zones for the identified work area, such as existing building structures, rail tracks, temporary material storage areas, and office containers. Based on this site layout model, the researchers, guided by responsible safety engineers, developed a safe baseline model to delineate distinct movement zones for the pedestrian workers and equipment. All of this work was done independently from the RTK-GNSS data collection and analysis to avoid potential bias.

As shown in Fig. 6, pedestrian worker walkways, mobile equipment driveways, and rail track zones were color-coded within the model. Given that the experimental site was confined to a single ground level, the coordinates were simplified to two dimensions (2D) for clarity and ease of use.

In the baseline model, concrete barriers were recommended for installation along the boundaries of the pedestrian walkways to protect them from nearby moving equipment. These barriers were intended to create a physical separation between workers and vehicles, ensuring that pedestrian workers remained within designated safe zones and reducing the likelihood of inadvertent entry into equipment driveways.

However, due to operational requirements, full separation of pedestrian walkways and equipment driveways could not be achieved. Specifically, vehicles moving across these (traversable) zones were necessary to allow equipment, such as telehandlers and wheeled loaders, to access key areas for material transportation to and from the railcars. These had to be loaded and unloaded with new or recyclable material, respectively. This inability to fully separate worker and equipment zones resulted in the declaration of one of the research objectives: the identification of these intersections as semi-static hazard zones.

Dynamic hazards were observed during the experiments, particularly due to the movement and operation of a telehandler tasked with transporting materials between storage zones and railcars. The telehandler's continuous operation created a hazardous environment for nearby pedestrian workers. Yet, they often needed to guide the telehandler during material handling tasks, such as positioning the forks into the handles of the ballast bags. This close coordination required workers to stand in very close proximity to the telehandler, often within its 1-m boundary and several blind spaces. The combination of workers standing near the equipment and the operator's limited visibility in these critical zones significantly increased the risk of struck-by incidents or close calls.

Additionally, the movement of the telehandler was a concern due to its frequent traversal of pedestrian walkways, creating overlaps between

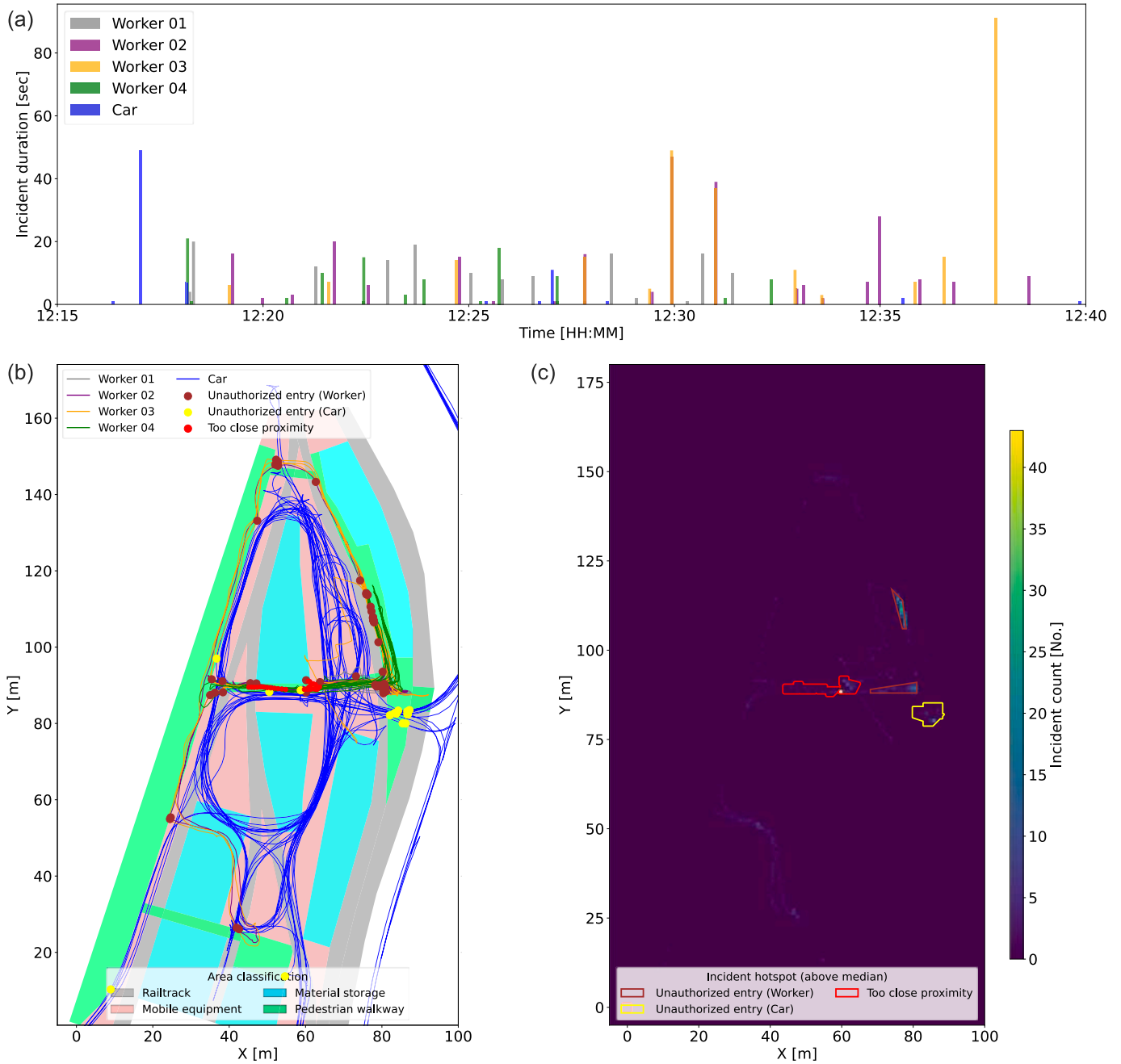


Fig. 9. Safety incidents of workers entering unauthorized zones in experiment 1: (a) safety incidents count and duration by workers, (b) locations of unauthorized entries and too-close proximity incidents, and (c) dense areas of incidents.

Table 2
Summary of the incident detection results related to workers.

Worker	Incident count [No.]	Max hazard weight of involved incidents ($w_{i,max}$)	Avg. hazard weight of involved incidents ($\bar{w}_i$)	Integrated hazard weight ($\bar{w}_{h,i}$)
01	20	2.5	1.4	0.14
02	28	1.8	1.2	0.12
03	27	4.2	3.0	0.68
04	24	3.1	2.5	0.37

worker and equipment movement zones. The risk was further increased by activities such as speeding and backward driving, which were observed during the experiment. These factors combined to significantly

heighten the risk of collisions between the telehandler and pedestrian workers. The photos in Fig. 7 illustrate some of these hazardous scenarios, depicting the telehandler moving material between the different zones.

4.3. Experiment 1: Monitoring hazards and incidents in a controlled test

The first 30-min long experiment was conducted in a controlled environment to simulate a scenario where one vehicle operated on-site at walking speeds while four workers performed regular work and inspection tasks. The selected vehicle was a 5-seat car from the construction management company.

During the observation period, incidents involving unauthorized entry and too-close proximity to mobile equipment were detected for both the vehicle and the workers. Although pedestrian walkways had

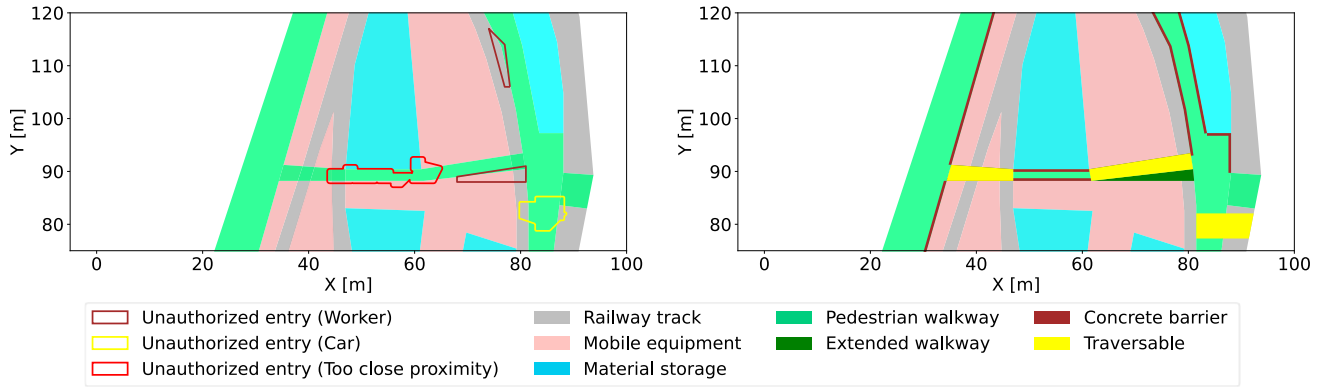


Fig. 10. Identified incidents by type, location, and size (left) and recommended measures (right).

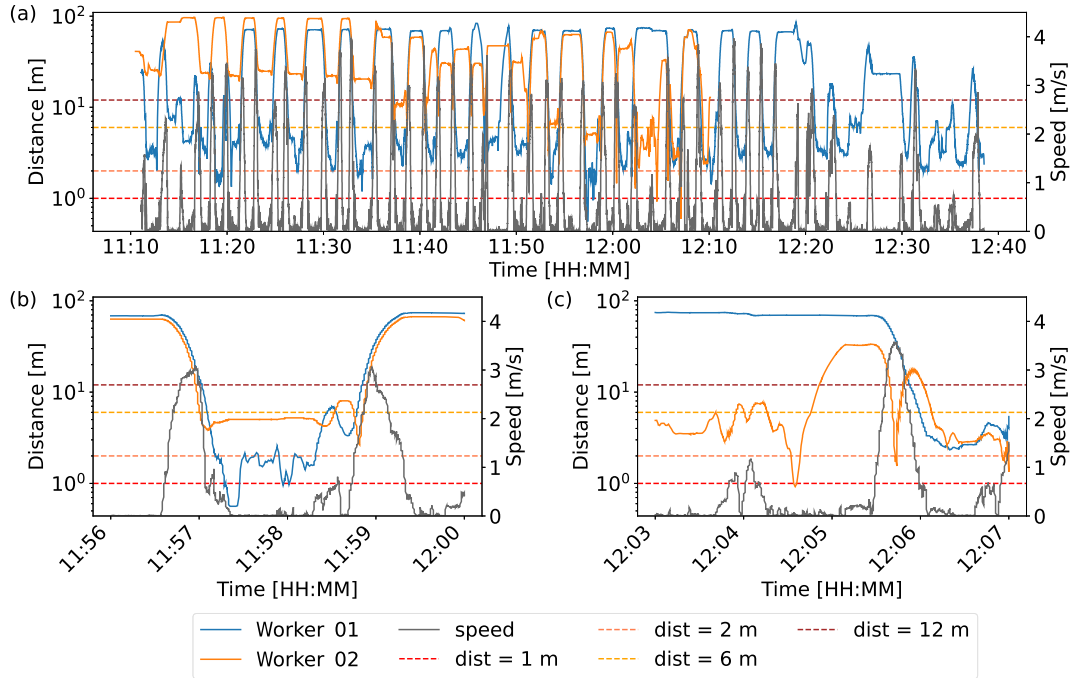


Fig. 11. Preliminary analysis of speed and distance evaluation: (a) diagram showing the distance between the geometric centroids of the pedestrian workers and the telehandler, (b and c) timestamps corresponding to the incidents where the pedestrian workers were within a 1-m proximity to the telehandler.

been outlined in the safety plan, the absence of physical barriers to enforce separation led to deviations in the paths of both the vehicle and the workers. This lack of clear separation resulted in frequent entry into unauthorized zones, placing workers at an unsafe distance from the moving vehicle.

In the first experiment, simplified safety envelopes were adopted for the vehicle and the workers, as depicted in Fig. 8. The vehicle boundary was modeled as a 5×2 m rectangle, while the worker boundary was modeled as a circle with a 0.5 m radius. Safety distances were set at 2 m and 1.5 m. By associating the safety envelopes with real-time location data, two types of incidents were detected: unauthorized entry and too-close proximity. The right part of Fig. 8 also illustrates examples of the two incident types.

A total of 99 unauthorized entries were detected in the dataset. Only 2 instances of too-close proximity were identified, suggesting that the designated zones successfully separated the workers from the equipment movement. The bar plot in Fig. 9 (a) displays the timeline and duration of the unauthorized entry incidents. Table 2 provides a detailed quantitative safety assessment for each worker. Although the number of incidents per worker was relatively similar, the average hazard weight of

incidents involving Worker 03 was substantially higher. The maximum deviation recorded for Worker 03 was 6.13 m, which was three times greater than that of the other workers, indicating that Worker 03 moved significantly deeper into unauthorized zones. This significant deviation may point to a lack of situational awareness or insufficient safety feedback, necessitating further and longer-term investigations and enhanced training interventions.

A density map was generated to visualize where the observed incidents occurred. As shown in Fig. 9 (c), areas with lighter colors represent higher incident frequencies. The coordinates of these high-incident spots were extracted and integrated into the updated safety plan. Polygons where the number of safety incidents exceeded the median value were flagged for further attention and intervention. The identified dense areas of incidents are shown on the left panel of Fig. 10. These zones, marked in brown and red line colors, indicate areas where workers frequently deviated from designated walkways and entered the proximity of the vehicle. It suggests the need for larger and additional protective measures. Additionally, the vehicle was frequently detected entering pedestrian walkways (marked in yellow line color), suggesting the presence of a new traversable zone. The right panel of Fig. 10

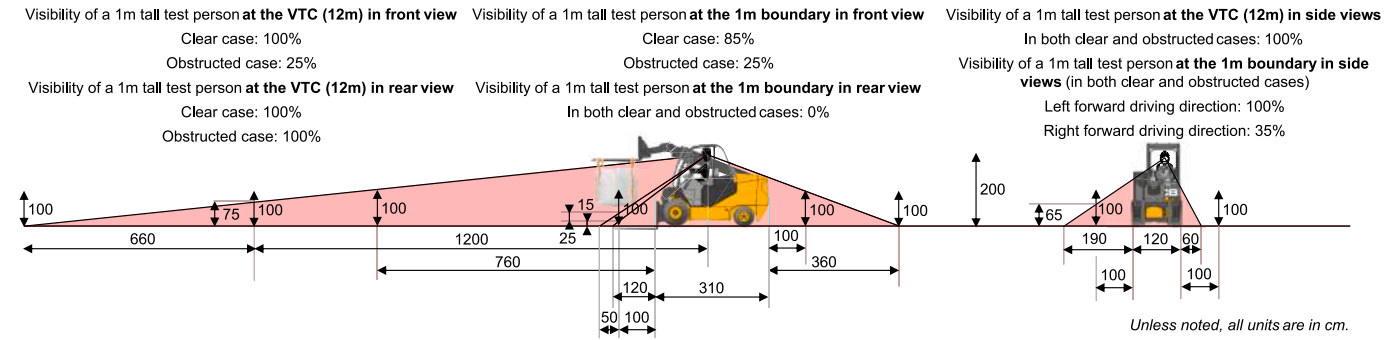
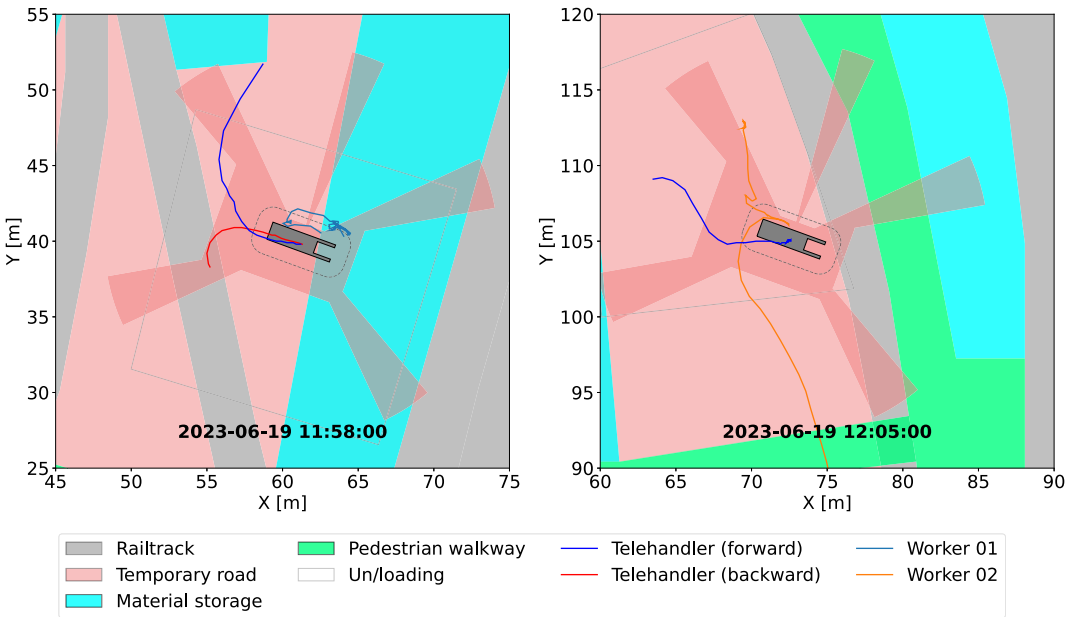
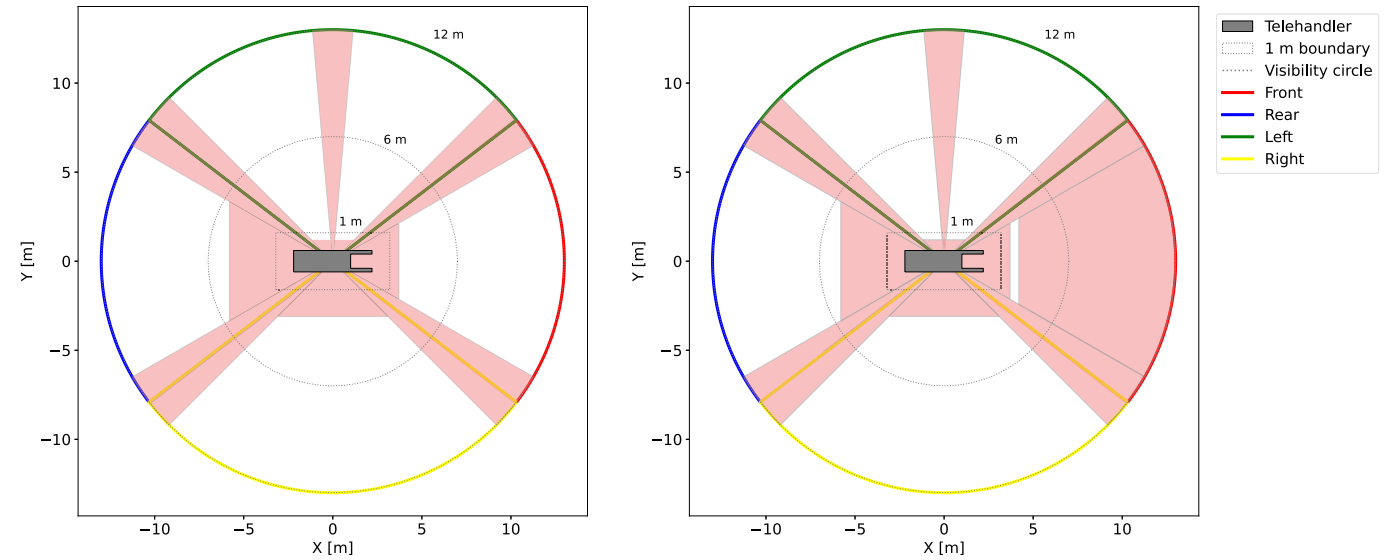


Fig. 12. Blind spot measurement of the JCB 35D telehandler (in cm) in side view (left image) and front view (right image).



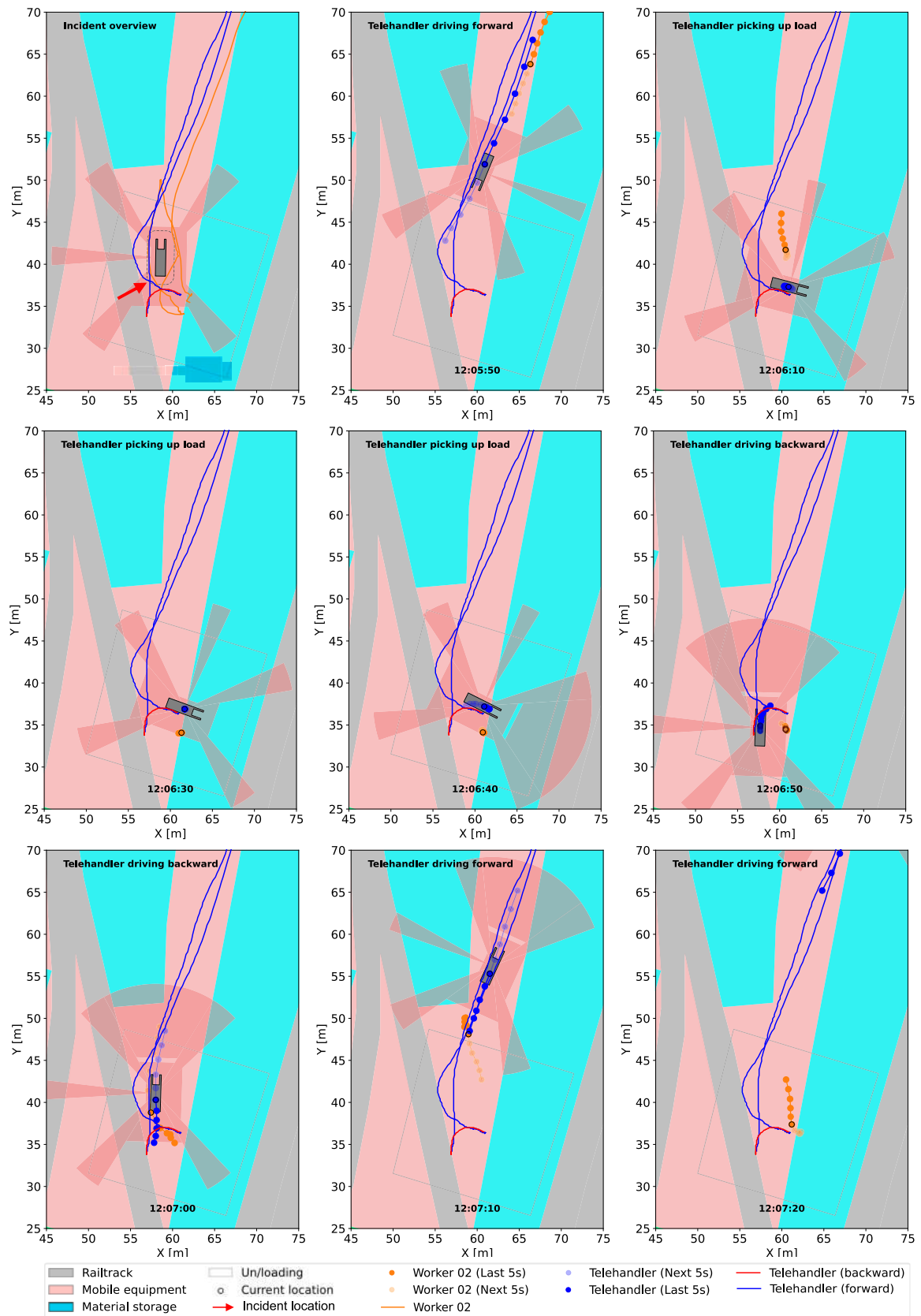


Fig. 15. Selected time-lapse imagery of the trajectories related to the pedestrian worker and telehandler during the ballast material transportation task that involved forward and reverse movements of the equipment (note: the observed incident at the rear left of the vehicle occurred at around 12:07:00).

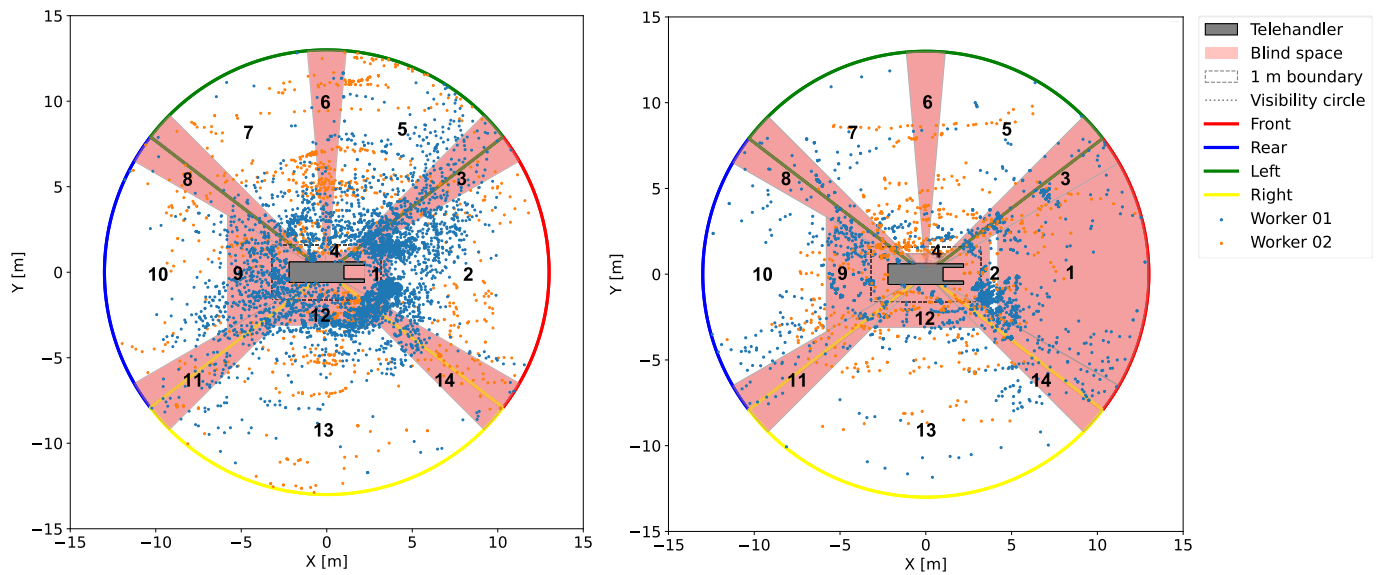


Fig. 16. Workers' presence within the telehandler's blind spots (location data collected at 5 Hz): clear front view (left) and obstructed front view when carrying a load (right).

displays the proposed intervention areas, where the installation of concrete barriers, the extension of pedestrian walkways, and the designation of traversable zones are recommended.

4.4. Experiment 2: Monitoring dynamic hazard zones in active work environments

The second experiment focused on real-world operations involving 1 telehandler and 2 pedestrian workers. The telehandler used was a JCB 35D model. In this setup, Worker 01 was tasked with directing the telehandler operator to load ballast bags onto the telehandler's fork, while Worker 02 conducted random inspection tasks in the staging area. This setup allowed for close observation of dynamic hazards associated with the telehandler's movement and worker-equipment interactions.

A preliminary analysis was conducted to evaluate the speed of the telehandler and its proximity to nearby workers. Fig. 11 (a) illustrates the distance maintained between the telehandler and the two workers during the ballast loading operations. Incidents were recorded when workers breached the telehandler's safety envelopes at distances of 12 m, 6 m, 2 m, and 1 m. The lower two panels also depict two high-risk events in which workers entered the 1-m proximity zone, a critical area associated with elevated struck-by risk.

Compared to the passenger vehicle used in Experiment 1, mobile construction equipment, such as the telehandler, has a significantly more complex geometry. To determine accurate hazard zones, the blind spaces around the telehandler were measured on-site, according to safety standards [45], including its real conditions and the equipment.

As shown in Fig. 12, blind space measurements considered various operational angles and distances within the 12-m radius from the telehandler operator, whose viewpoint was assumed to be 2 m above the ground level. The results revealed that the telehandler's single lifting arm substantially restricted visibility on the right-hand side (forward direction), where the operator's ground view was obstructed up to 1.9 m from the equipment boundary—compared to only 0.6 m on the left-hand side. Similarly, rear visibility was limited to 3.6 m behind the telehandler. In contrast, forward visibility under normal, unloaded conditions extended to 1.2 m. However, when the telehandler arm was raised in a load-carrying position, visibility was considerably reduced, with the operator able to see the ground only at a distance of 18.6 m ahead. Consequently, operators were frequently observed leaning out of the window to gain a better view of the area in front. Furthermore, the metal

frame of the telehandler's protective cabin created additional visual obstructions, contributing to extended blind space.

Based on the blind space measurements, a 2D operator visibility diagram was created, as shown in Fig. 13. This diagram illustrates the operator's field of view, highlighting the contrast between areas with clear visibility and those obstructed. It is evident that the front view of the telehandler was more than less completely obstructed when it was carrying a load. The area within the 1-m boundary, combined with the telehandler's blind spots, was designated as the dynamic hazard zone associated with the equipment. During the experiment, any entry into these zones was recorded as a recordable incident.

Fig. 14 illustrates the trajectory and locations of the telehandler and workers during the two incidents previously shown in Fig. 11. In both incidents, although the telehandler was stationary, the lifting operation still posed a hazard to the assisting pedestrian workers, particularly when they were in the operator's blind spaces. In contrast, the telehandler posed a higher-level hazard when it was moving to workers moving within its vicinity. Fig. 15 displays the snapshot images of one such incident. One worker was observed walking within the 1-m boundary and rear region of the telehandler while it was reversing. When it accelerated, it eventually overtook the worker. This incident occurred in the loading zone, where the telehandler was observed to follow a repeated pattern: moving forward to the pickup position, lifting the load, reversing into the driveway, and proceeding to the unloading zone.

Unlike Worker 01, who consistently assisted the telehandler from a safe waiting position, Worker 02 entered the telehandler's safety envelope and blind space, unaware of this routine. This incident had an increased risk of escalating from a close call into an accident. The rather complex and abrupt relative movement between the telehandler and the pedestrian worker created limited situational awareness. The worker being outside of the operator's field of view created a condition of mutual lack of control, increasing the risk for both parties involved.

To identify similar incidents, the distances between the pedestrian workers and the telehandler were analyzed. Fig. 16 shows the telehandler in the center, with its heading direction aligned with the positive x-axis, as the layout in the equipment visibility diagram. For each recorded telehandler position, the relative location of nearby workers is mapped accordingly. The figure displays the relative locations of the two pedestrian workers within the 12-m radius of the telehandler throughout the experiment—on the left under clear visibility conditions

Table 3

Distribution of the pedestrian workers' presence relative to the telehandler's position in clear and obstructed visibility.

Front visibility	Worker	Presence count [No.]				Total
		Front (Zones 1,2,3,14)	Rear (Zones 8–11)	Right (Zones half of 11, 12, 13, half of 14)	Left (Zones half of 3, 5, 6, 7, half of 8)	
Clear	01	2896	809	1284	1403	6392
	02	226	122	570	445	1363
Obstructed	01	1362	531	434	337	2664
	02	119	154	279	143	695

Table 4

Count of workers appearing in various blind spot segments of the telehandler [No.]

Segment	Clear front view		Obstructed front view	
	Worker 01	Worker 02	Worker 01	Worker 02
1	1670	5	867	102
3	644	30	335	26
4	60	5	0	4
6	68	77	7	42
8	104	36	120	52
9	576	34	357	71
11	180	45	59	36
12	614	171	185	37
14	576	178	207	18
Sum	4492	581	2137	388

and on the right under obstructed visibility. This visualization enables a spatial analysis of worker distribution around the equipment and helps identify potentially hazardous periods when workers were present within dynamic hazard zones.

The number of location data points is proportional to the duration of a worker's presence in a given area. Table 3 summarizes the spatial distribution of workers' presence relative to the telehandler, confirming that both pedestrian workers were predominantly in front of the equipment. The data show that Worker 01 was most frequently located in the front zones, especially under clear visibility, with a total of 2896 entries, reflecting their role in assisting the telehandler during ballast loading. In contrast, Worker 02 had significantly fewer appearances in the front and was more evenly distributed, consistent with inspection tasks performed at a safer distance. Under obstructed visibility, both

workers' presence in the hazard zones decreased.

Further analysis of the workers' presence within the blind space segments is presented in Table 4, which details the number of times both workers appeared in them. While Worker 01 was more frequently observed in blind spots located at the front of the telehandler, Worker 02 showed a more even distribution across various segments.

A Gaussian KDE density map is generated to visualize the movement patterns of both workers around the telehandler, as shown in Fig. 17. As described in the methods section, the density was computed using a Gaussian kernel on a 100×100 grid, with bandwidth selected via Scott's Rule [57]. Color intensity in the heatmaps reflects the relative density of position data points, which corresponds to the duration of worker presence in specific areas. Brighter regions represent areas where the workers spent more time. The results reveal that Worker 01 had a concentrated presence on the left and right front of the telehandler, while Worker 02 displayed a more dispersed movement pattern.

The concentrated presence in the right front area, which overlaps with the telehandler's larger blind space area to the right than to the left (as identified in the visibility analysis, Fig. 13), raises the question of whether Worker 01 should operate from the left than right front side (more visibility). This observation underscores the importance of focusing on such high detail. The result is encouraging workers to approach the equipment from safer angles, such as from the left front where visibility is clearer (no lifting arm blocks the operator's field of view). This could further reduce the risks associated with the telehandler's blind spots.

The next part of the analysis broadened the analysis to the entire staging area, not limiting it any more to the pedestrian workers working in the loading area of ballast material only. This enables evaluating workers' behavior not adhering to the designated walkways. As they 'optimized' a poorly designed work site layout that should have connected work areas during related activities more effectively, more too-close proximity incidents were recorded. Fig. 18 shows the timescale, location and density of a total of 86 detected incidents. Table 5 provides a detailed quantitative safety assessment for each worker. While Worker 01 was involved in a higher number of incidents, these incidents were generally of lower severity, as reflected by the lower maximum and average hazard weights. In contrast, Worker 02 had fewer incidents, but they were more severe, with a higher average hazard weight and the highest individual hazard score.

The majority of these incidents took place in the loading and unloading zones and in work areas lacking a defined safe walking path to get to and from. Therefore, further suggestions should be made to

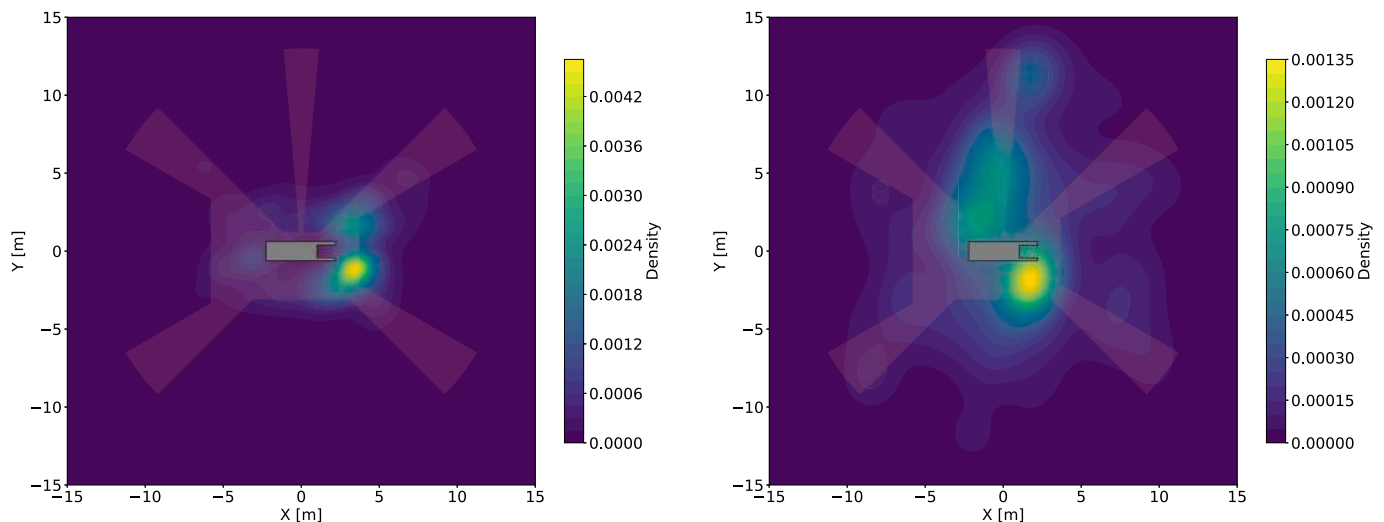


Fig. 17. Density map of pedestrian worker locations around equipment: Worker (a) 01 and (b) 02.

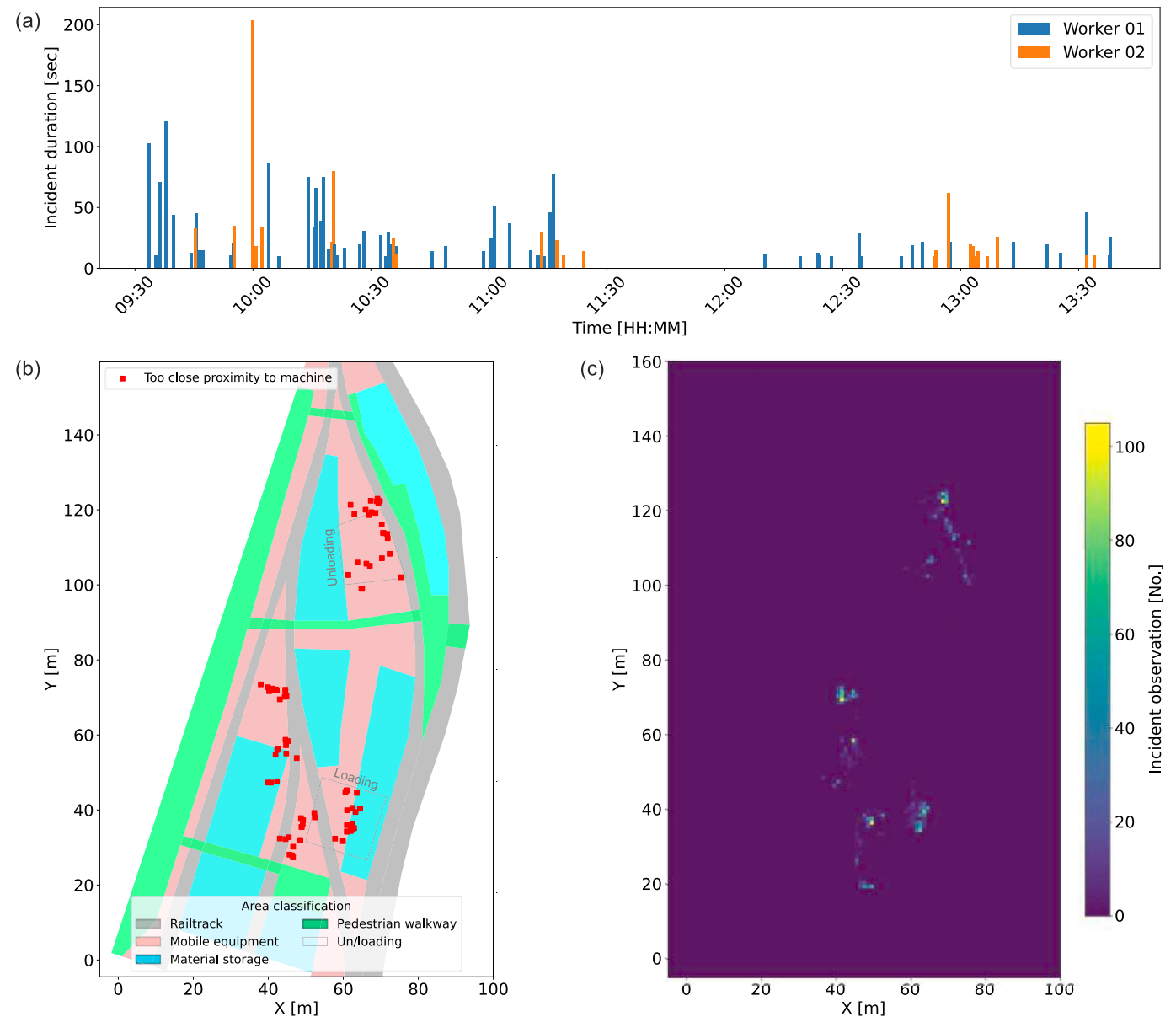


Fig. 18. Safety incidents of workers entering the safety envelope of the telehandler: (a) safety incidents count and duration by workers, (b) incident locations, and (c) density map of incidents.

Table 5
Summary of the incident detection results related to workers.

Worker	Incident count [No.]	Max hazard weight of involved incidents ($w_{i,max}$)	Avg. hazard weight of involved incidents ($\bar{w}_i$)	Integrated hazard weight ($\bar{w}_{h,i}$)
01	64	2.5	2.1	1.02
02	24	4.1	3.0	0.68

enhance safety in these zones. An example of separating the worker-equipment in the loading zone is made. As outlined with red edges in Fig. 19, both workers primarily occupied the four regions, which are derived from the presence histogram. Notably, the vast majority of these regions (70.2 %) overlapped with the dynamic hazard zone (def. The area encompassing both the equipment's blind spaces and its 1-m buffer when equipment is still in motion and carrying load).

To mitigate struck-by equipment risks, a designated safe 'waiting area' should (have) be(en) designed into the site safety plan (safeBIM).

The most frequently occupied space, where workers regularly positioned themselves to guide the telehandler during rigging tasks, was designated as the 'rigging area'. This would then allow pedestrian workers to stay in the waiting area until the telehandler comes to a complete stop. This conclusion can be made from just a few hours' worth of data, but on the first of nearly 30 days that involve handling ballast material. The potential impact of addressing change very early on and creating a safer work environment can be large.

4.5. Experiment 3: Enhancing overall safe baseline plans

Additional trajectory data was analyzed to create alternative safe baseline plans within the DTCS. The data involved interactions between pedestrian workers and heavy equipment—specifically two wheel loaders and one telehandler—engaged in material handling and site cleanup. Their overlapping movement zones created struck-by hazard risks, further intensified by equipment speeds, necessitating alternative safety plans while maintaining worksite efficiency.

To demonstrate how hazardous activities impacted walkway design,

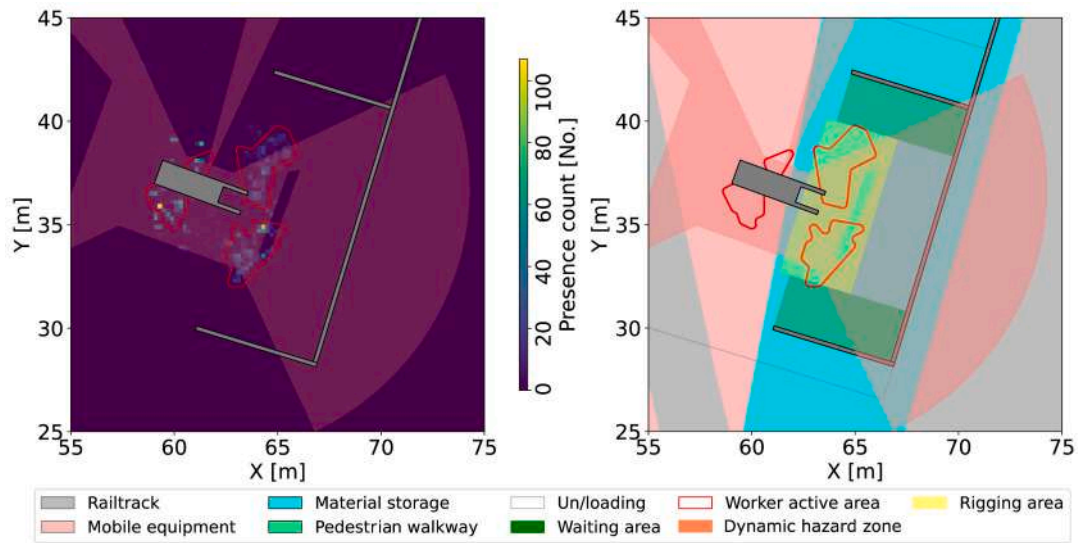


Fig. 19. Density map of worker presence in the loading zone (left image) and suggested layout improvement for safe work (right image).

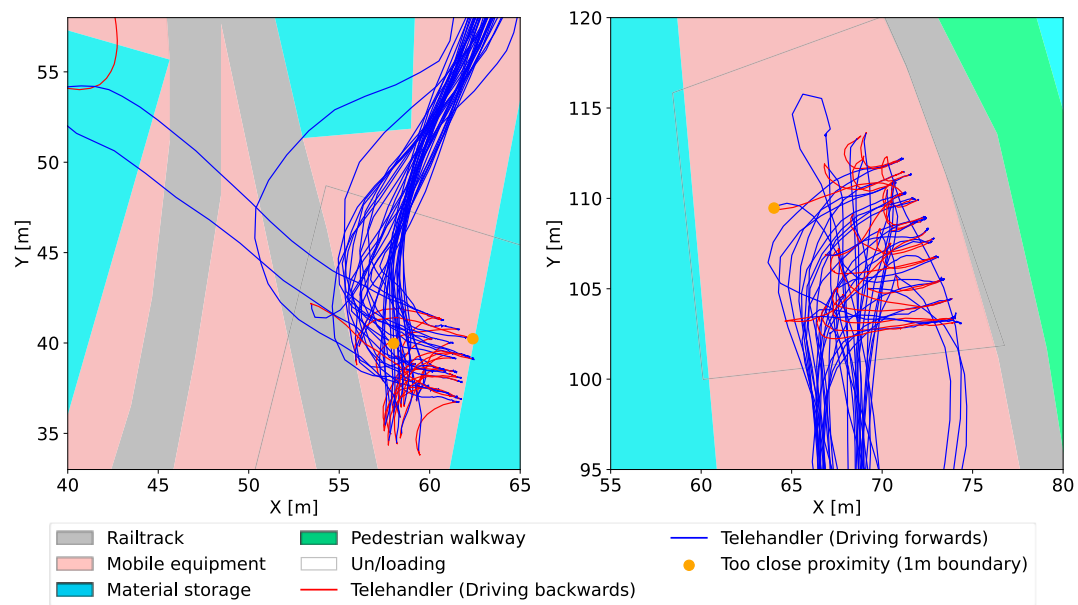


Fig. 20. Forward and reverse trajectories of the telehandler across 21 cycles in the loading area (left image) and unloading area (right image).

the analysis focused on evaluating two high-risk behaviors of the telehandler. It was frequently observed reversing, posing visibility challenges for the operator and exposing nearby workers. Without gyroscopic sensors, an empirical rule-based algorithm was applied to differentiate between forward and backward motions based on trajectory. The algorithm assumed that the telehandler could not change its direction by more than 90 degrees per second without reversing first. Fig. 20 shows 21 trajectories, color-coded as forward (red) and backward (blue). Numbers were confirmed by a manual review of video coverage that was taken during the experiment. Note, such trajectory analysis allows performing additional reasoning, for example, times and lengths to each of the operational modes, which were not explored in

this study.

Furthermore, the telehandler exceeded the permissible speed limit when traveling between the loading and unloading zones. This relates to 6.9 % of its total operational time in the experiment, reaching a maximum forward driving speed of 3.97 m/s (14.3 km/h). Fig. 21 reveals the times and locations of these occurrences. Of the 20 speeding incidents recorded, 8 took place while the telehandler was transporting ballast material bags in the forward direction (generally not advisable), and 15 occurred as the telehandler crossed designated pedestrian walkways.

To better understand where hazardous activities most frequently occurred, spatial analysis was conducted to identify high-activity zones

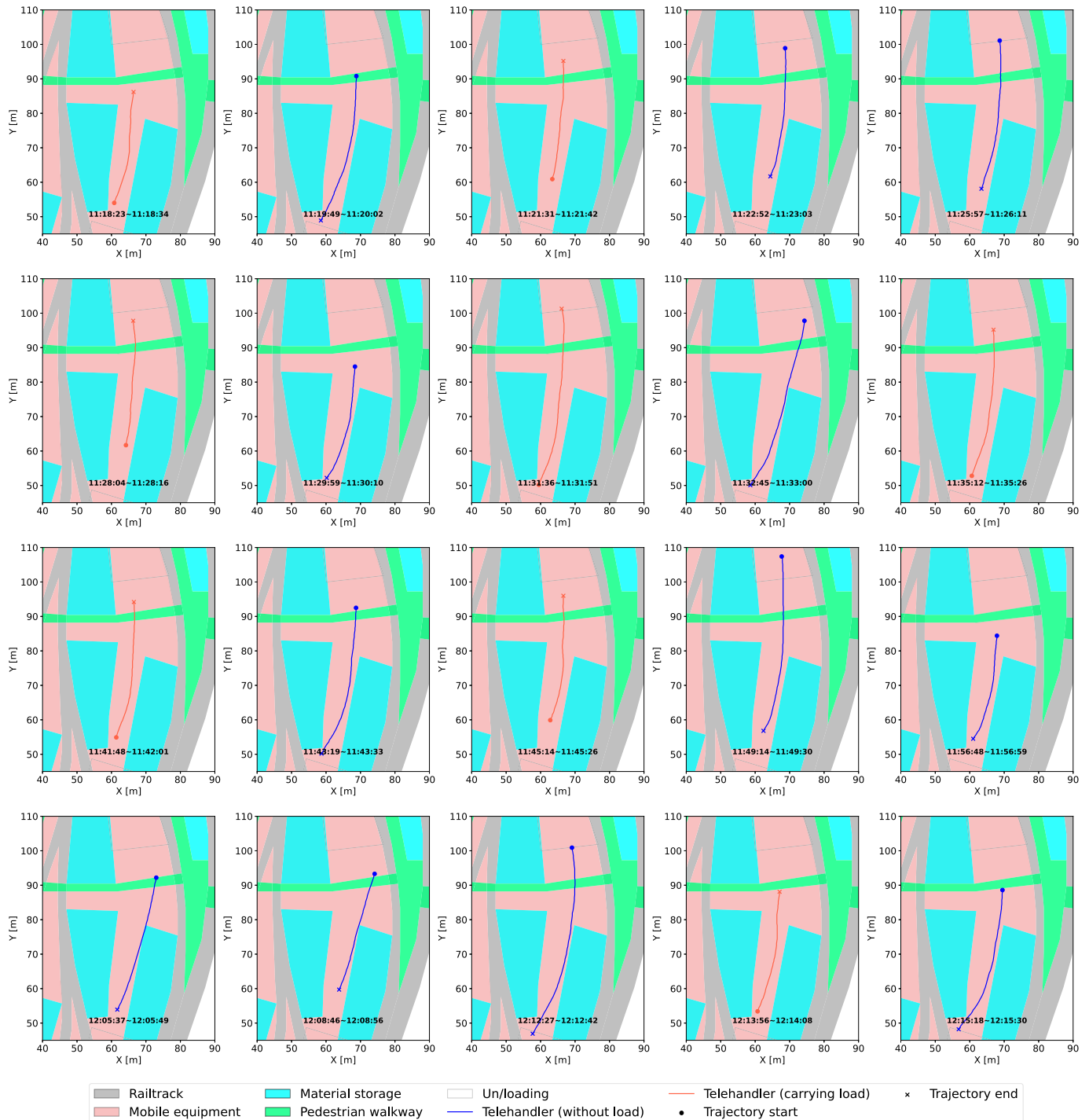


Fig. 21. Times and trajectories of the telehandler exceeding the speeding limit (red, telehandler is in carry position) between loading and unloading zones ('straight path' travels). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

related to equipment operations. This involved evaluating not only the general movement patterns but also instances of unsafe behavior, such as excessive speed and reverse motion. Fig. 22 presents four density maps that visualize the telehandler's overall movement, areas of frequent operation, excessive speed, and backward motion. The legend explains the coloring of the polygons. The computational algorithms identified these marked zones automatically. A higher level of risk of being struck-by exists for pedestrian workers when these overlap with their walkways, as indicated (orange areas).

Spatial conflicts were also observed between the pedestrian workers and the other equipment (wheel loaders). Despite the designated

pedestrian walkways and equipment driveways outlined in the safe baseline plan, pedestrian workers (not knowing their tasks) often took alternative walking routes for accessibility and efficiency reasons. Trajectories plotted in Fig. 23 illustrate such examples, where pedestrian workers' trajectories sometimes point to such movements outside the designated walkways.

Fig. 24 maps the most frequent movement areas of pedestrian workers and equipment, along with their intersections. Notably, the overlap accounted for 56.3 % of the equipment movement area and 71.4 % of the pedestrian worker movement area. These significant overlaps indicate a busy work area that may demand further protective control,

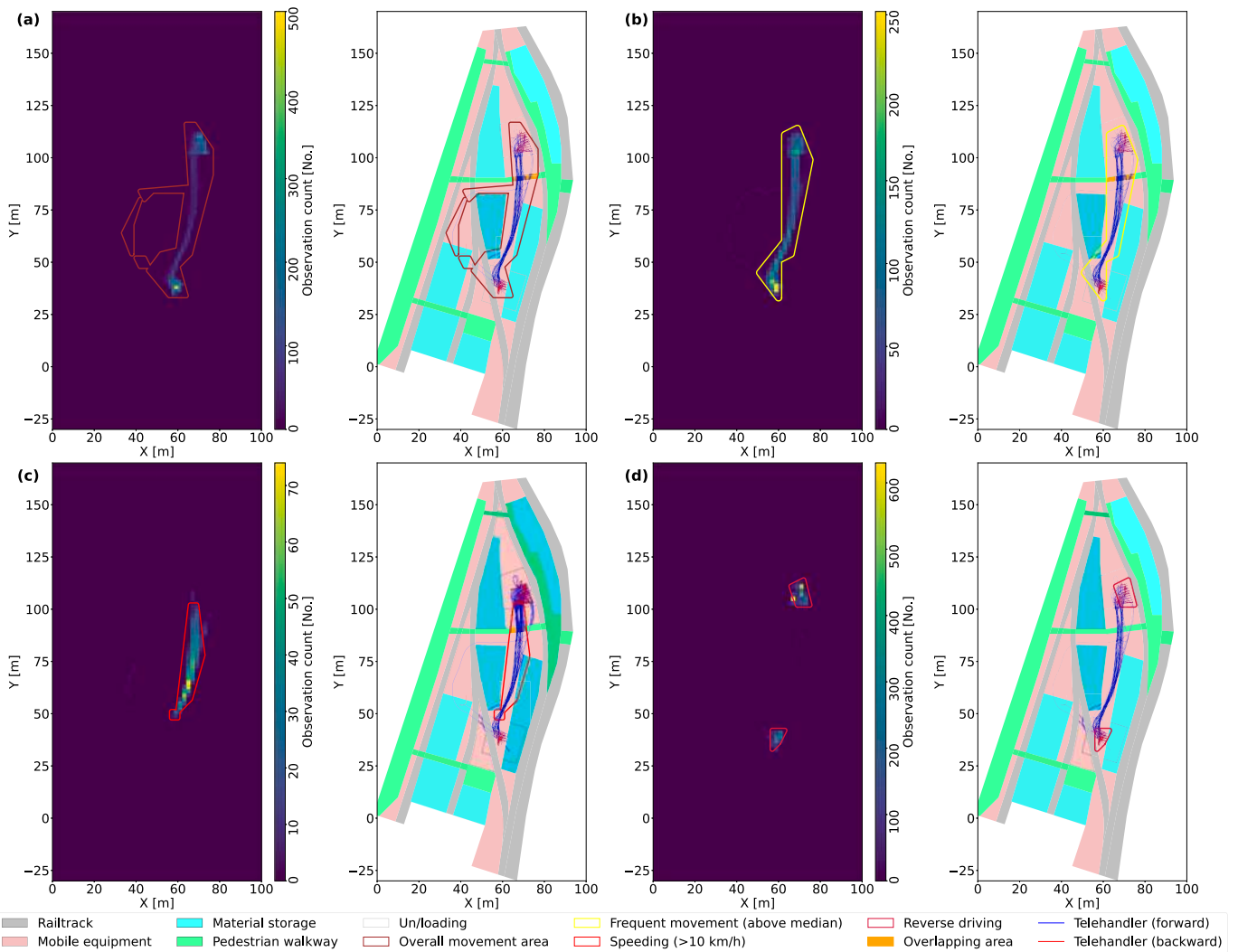


Fig. 22. Density maps (left images) to the telehandler operations (right image): (a) general movement area, (b) most frequented area, and areas (c) when speeding (>10 km/h) and (d) of driving backward.

and a new site safety plan may be needed.

Temporarily controlled walkways were proposed to address spatial conflicts between pedestrian workers and equipment while also providing optimized routing within and between work areas. Workers assisting the telehandler, for example, are requested to travel frequently between the loading and unloading zones. They can follow straighter paths from the loading to the unloading station, avoiding long detours that would first take them to their temporal office containers and then to nearby buildings.

For this reason and as explained earlier, a graph-based algorithm was applied to determine the optimal route between the start and end points. These were selected based on the actual work areas and where workers and equipment were most present. As a baseline, Scenario A assumed no equipment movement intersecting the pedestrian walkways, allowing workers to take the shortest route within the permitted walkable area, as shown in Fig. 25a. However, in reality, this shortest route traversed areas of frequent equipment movement and other high-hazard zones. The travel cost was increased due to the safety weight w , which factored in hazard levels, resulting in a higher overall travel cost despite the same travel distance. Consequently, workers had to bypass the high-risk areas, as shown in Scenario B (Fig. 25b), resulting in a 41 % increase in travel distance to achieve the lowest-cost path.

Trajectory analysis revealed that on the day of the experiment, workers rarely followed the originally designed walkways. Therefore,

the existing walkway was extended by actual trajectory data, resulting in an optimal route that avoided moderate and high-hazard areas (Fig. 25c). Table 6 summarizes the travel costs and distances with respect to three scenarios. The optimal route in the extended scenario (C) significantly reduced both the travel cost and distance compared to the other optimized routes in Scenarios A and B.

As a result, a temporarily controlled walkway based on the optimal route was subsequently incorporated into the revised safety plan, as shown in Fig. 26. The walkway was extended into a 1.5-m-wide polygon, designed to provide a safer, more direct route between work areas while minimizing exposure to equipment traffic. This temporary walkway was validated by comparing it against the equipment trajectories recorded the following day. The identification of active and frequent equipment movement zones followed the dense area detection method outlined in Algorithm 2. The results confirmed a significant reduction in spatial conflicts and demonstrated improved connectivity between the loading zone, unloading area, and office zone.

However, it is worth noting that the implementation created new input data requesting a further iteration of the safety plan. The reason was some occasional rail traffic on a track segment that passed through the entire material staging area and from external trucks delivering new ballast material (see new overlap areas highlighted in red in Figs. 26b & 26c). While a completely isolated and yet safe walkway for the pedestrian workers seems impractical given the highly dynamic state of the

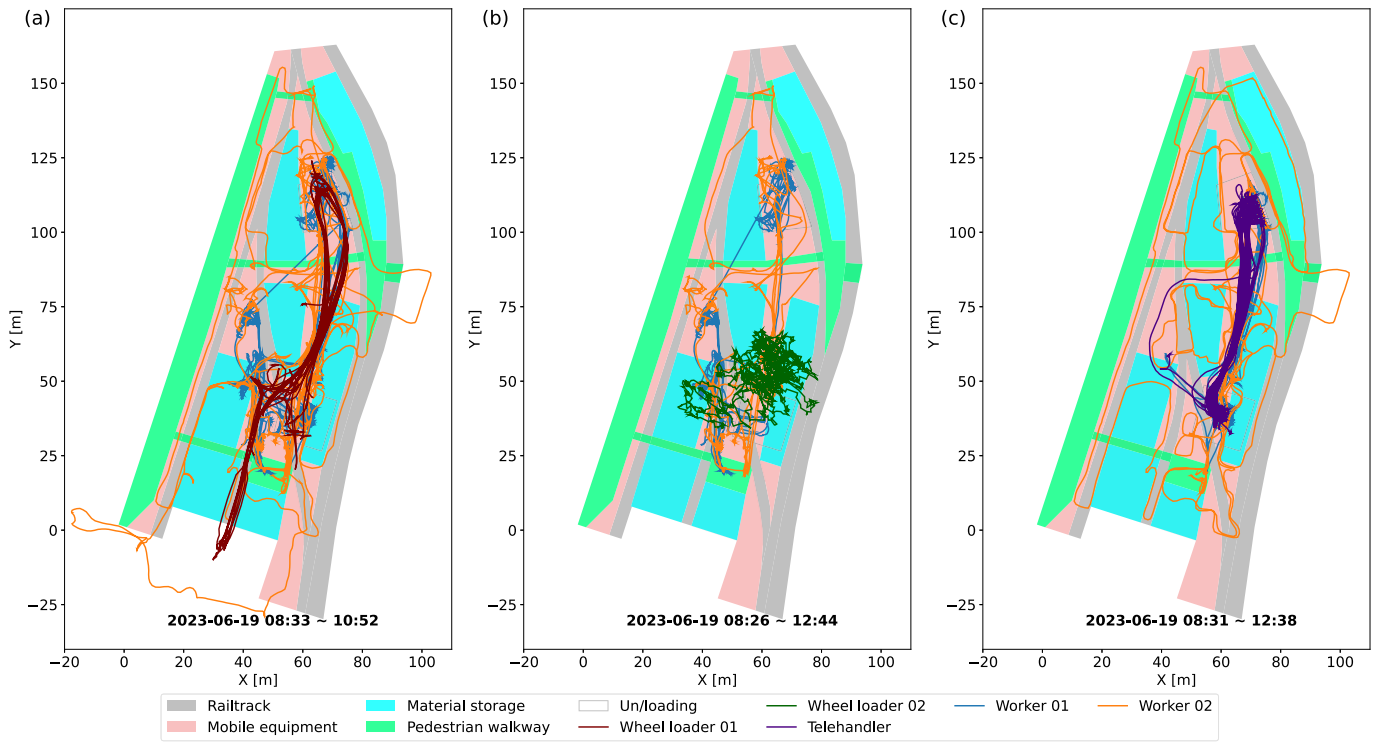


Fig. 23. Trajectories of workers on foot when (a) wheel loader 01, (b) wheel loader 02, and (c) telehandler were in operation (plotted on the extracted safe baseline plan at the given time).

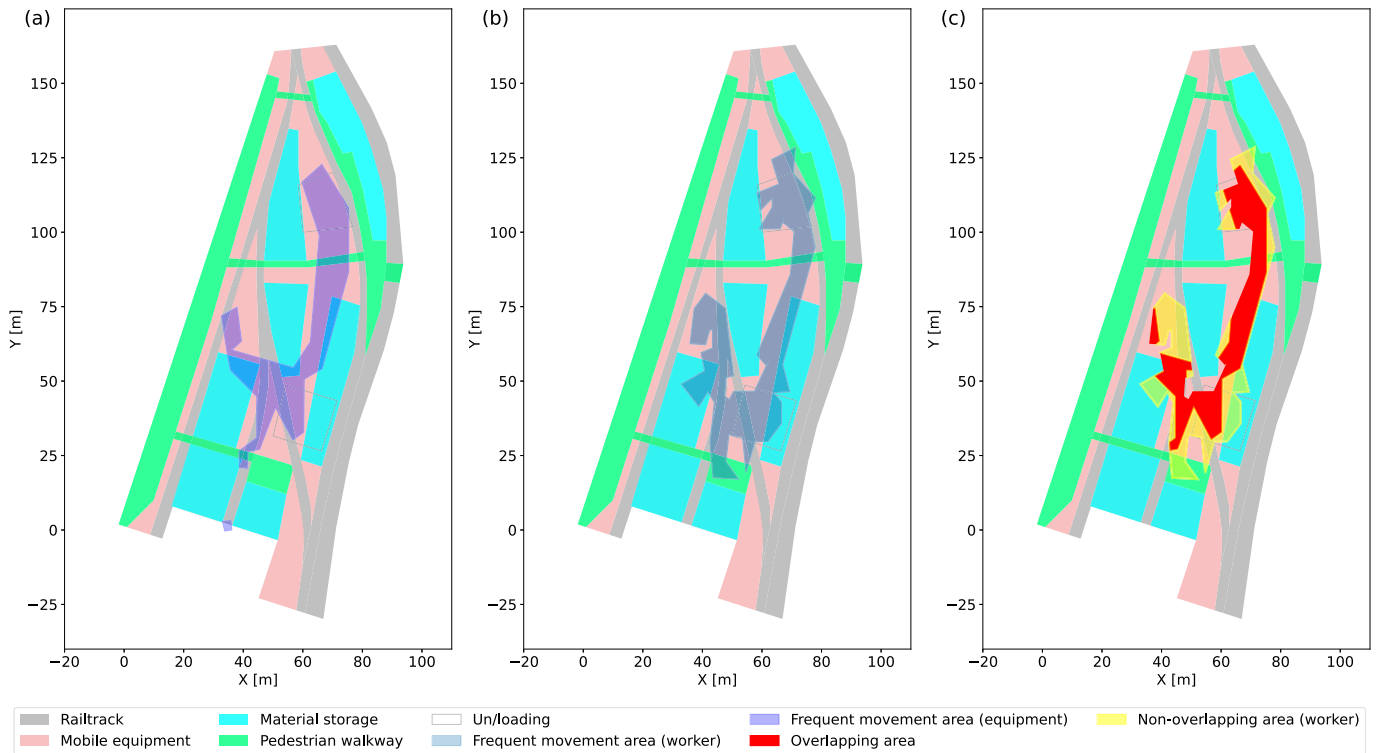


Fig. 24. Identified frequent movement areas of (a) all equipment, (b) pedestrian workers, and (c) overlapping areas.

construction site is, and yet may never be feasible, existing measures should not be forgotten that help establish a safety culture, among which are hazard awareness and control techniques on site. Among such examples are the daily risk assessments among the working team and, if needed, additional temporary installations of protective equipment (e.

g., signs, cones, and barriers) before work can safely start.

Lastly, the mitigation measures developed across the three experiment scenarios were incorporated into the SafeBIM through creating and inserting spatial artefacts in the IFC model, as illustrated in Fig. 27. These artefacts include the newly proposed temporary walkway,

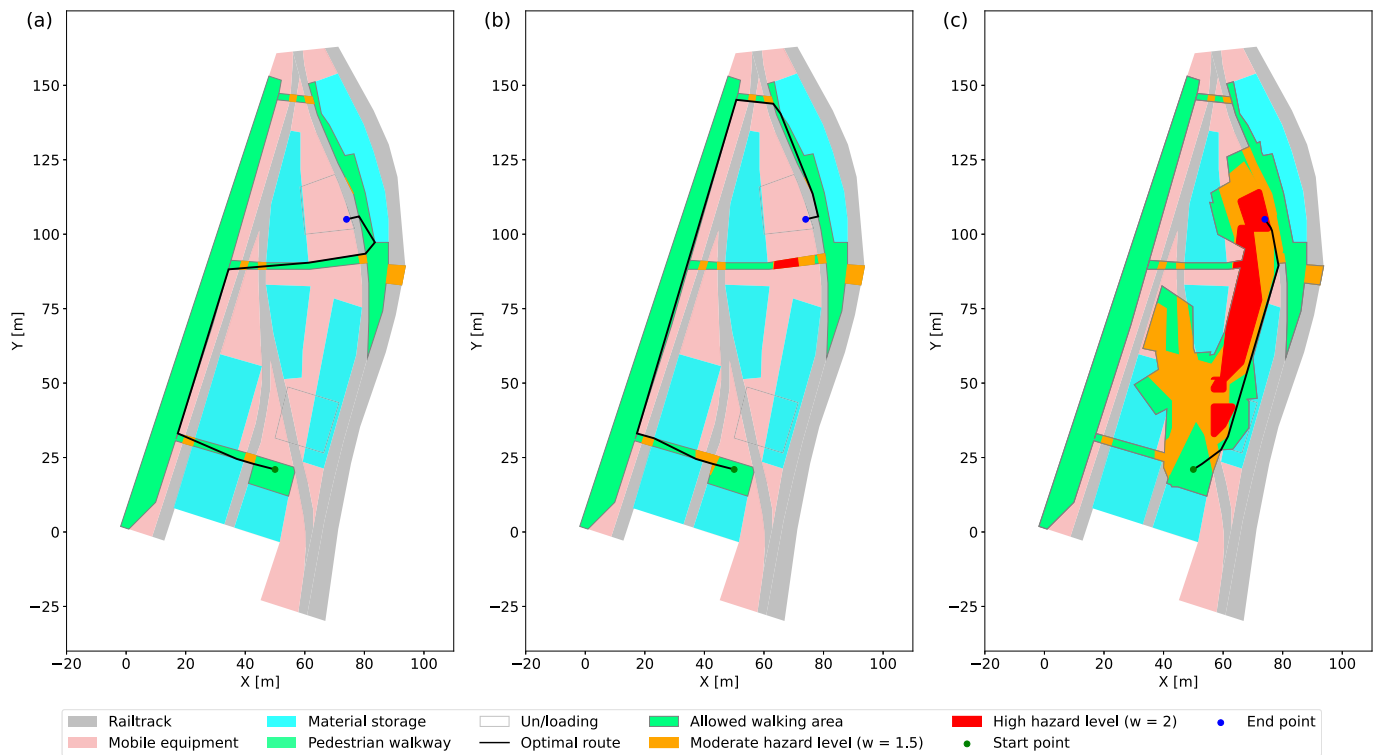


Fig. 25. Route selection: (a) baseline scenario (scenario A), (b) adjusted route avoiding hazard zones (scenario B), and (c) optimal route with a temporary controlled walkway (scenario C).

Table 6

Comparison of safety-weighted travel costs of the optimal route in different scenarios.

Scenario	Route	Travel cost [m]	Travel distance [m]
A – Pedestrian walkway according to safe baseline plan (without any of the observed equipment movement)	1	182.6	161.6
	2	230.1	214.9
	3	–	–
B – Pedestrian walkway according to safe baseline plan (with the observed equipment movement)	1	250.1	161.6
	2	230.1	214.9
	3	–	–
C – Adjusting safe plan by extending the walkway (with equipment movement and moderate hazard level)	1	250.1	161.6
	2	230.1	214.9
	3	161.8	92.8

protective concrete barriers, and, as needed, expanded or rerouted pedestrian walkways.

5. Discussion and limitations

The work performed demonstrates that RTK-GNSS offers enhanced accuracy and precision for outdoor workplace tracking, thereby reducing the need for extensive post-processing and enabling effective real-time alerts and analysis (RQ1). The combination of digital worksite layout baseline planning and construction resource location tracking results in safer work alternatives (RQ2) and leads to a more detailed understanding of the root causes that contribute to fragmented on-site safety behavior (RQ3). As such, three experiments specific to too-close proximity or struck-by equipment incidents were showcased to generate previously unavailable knowledge. To name a few examples: workers' presence inside equipment blind spaces, limited operator visibility, entry of resources into other than designated zones, various

dangers involved in forward and reverse motions, some occasional speeding, and design of internal traffic plans, incl. Providing protected pedestrian walkways and separated driveways. All these play important roles in analyzing the current, predicting the future, and eliminating struck-by hazards in daily operations. Once modifications were suggested, these led to positive changes (RQ4). Applying standard Prevention through Design and Planning (PtD/P) approaches using the proposed digital support provided access to detailed proactive feedback (here: safer logistics in material handling operations involving machinery).

From a research point of view, this work shed light on the underlying semi-static and dynamic hazard zones. These were associated with pedestrian workforce and heavy equipment interacting in complex and highly dynamic construction settings. Several key parameters of engineering out safety risks were identified that otherwise would compromise pedestrian worker safety. Particularly, these are brought into a quantifiable context of limited equipment operator visibility, equipment operating at higher speeds, and, among other recurring hazards related to on-site logistics, when moving material in overlapping work zones between the loading and unloading stations.

A broader finding of this study is how real-time data can help create safer work site layouts. Traditionally, safety planning is linear, design-based on pre-defined conditions, and seldom updated. However, by incorporating real-time data and analysis, this work emphasizes the need for a transformation towards a more circular approach, where safety plans are continuously refined based on actual site conditions. This then ensures that hazard zones, for example, once detected and updated in runtime, are protected as construction progresses.

However, this approach does have some limitations. It demands the use of advanced technologies, such as the proposed safeBIM and RTK-GNSS. These must work reliably together and within the proposed DTCS [44]. To reinforce the complexity of this thought, this study found that many incidents occurred when workers entered *semi-static hazard zones*, for example, where pedestrian and equipment pathways overlapped and when they were insufficiently separated from each other (e.

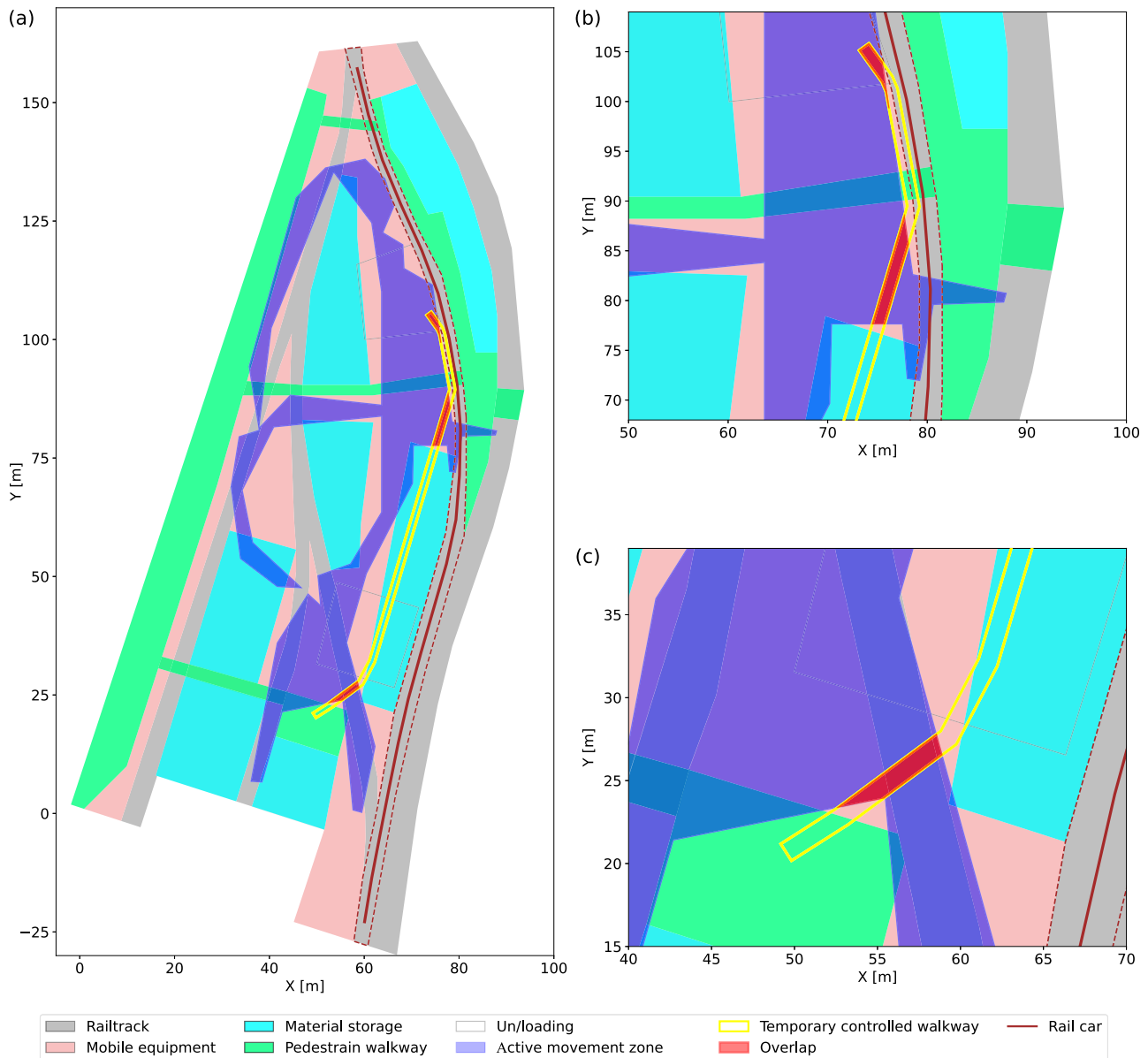


Fig. 26. Validation of the temporary walkway by comparing it with equipment movement on the following day, showing (a) reduced spatial conflict and (b & c) newly identified unavoidable overlaps.

g., by using physical concrete barriers). The standalone use of RTK-GNSS wearable and mobile rovers provided precise tracking, eventually providing critical insights into *dynamic hazard zones*. However, much of the knowledge seems to come from linking it with data that is readily available in DTCS. Another prominent example is data where workers unintentionally enter hazardous zones, particularly equipment operator blind spaces. Yet, even more data is needed to derive knowledge that ultimately triggers confident control measures. The desired data this study was not able to record were confirmations of whether the operator was able to detect the presence of pedestrian workers outside. Yet research exists to solve this need using the head-pose or eye-tracking of equipment operators [65].

While this work made some positive findings, there are a few limitations to note. The presented technical contributions show that advanced real-time location sensing and topographic survey technologies make it possible to quickly and accurately capture live spatial-temporal data of static and dynamic construction resources in multiple simulated and as-built construction environments. However, not all the observed proximity cases can be counted as close calls simply because

the term *safe distance* has yet to be defined. Perhaps a standard is needed.

Future site recordings may want to consider human behavioral patterns as well. Examples are safety literacy levels (e.g., how frequently workers receive safety hazard education and risk awareness training) and perhaps also consider workers' emotional states (e.g., daily feelings).

Despite the contributions of this study, several limitations must be acknowledged. First, the experiments were conducted over a limited time period in a realistic and yet controlled setting. This may restrict the generalizability of the findings to other construction work environments. Future research should expand the data collection period and investigate a larger variety of construction scenarios to account for more diverse operational conditions. Extending the testing scenarios to include other equipment, such as excavators or cranes, could provide a more comprehensive understanding.

Second, although the RTK-GNSS system provided high-precision location data, factors such as signal loss due to obstructions and interferences in certain areas may affect data reliability and the DTCS's runtime approach. In the case observed (the commercial RTK-GNSS

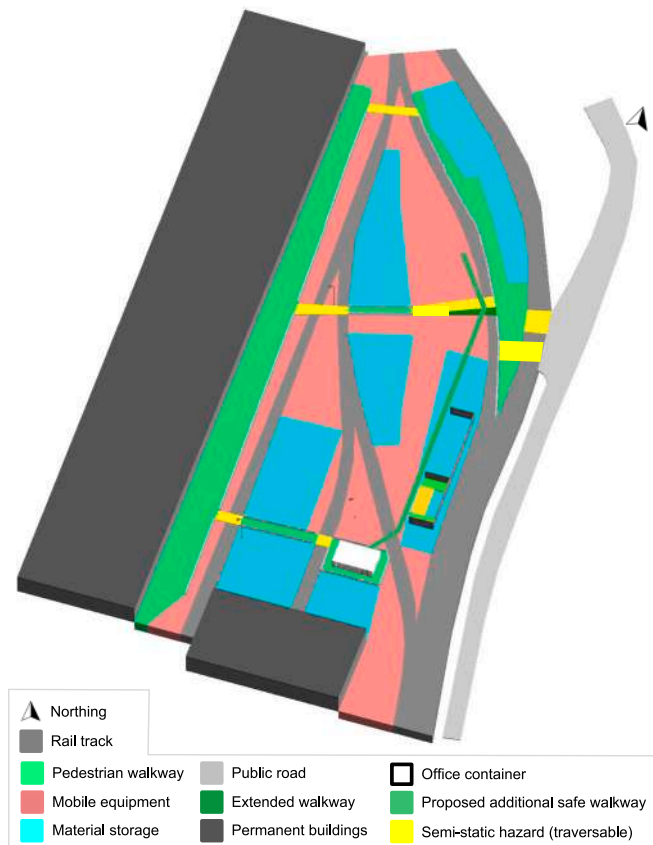


Fig. 27. Updated SafeBIM model with incorporated safety measures, including the proposed temporary walkway, protective barriers, and modified pedestrian routes.

system offers such a mode), less precise data needed further attention (e.g., smoothening or filtering).

Third, RAM may depend on data other than from RTK-GNSS. As shown earlier, in Fig. 7(b), ballast material bags obstructed the operator's field of view. Additional drone flights (that were prohibited) are recommended to capture the actual field conditions. This would allow the detection of other hazardous obstructions. Various types of sensors mounted on an Unmanned Aerial Vehicle (UAV) [66] or Autonomous Ground Vehicle (AGV) [67] could produce valuable additional data input for the DTCS and its RAM module (e.g., volumetric point clouds that monitor progress and inspect conformance). And yet, as of today, human observations capture and process real-life work site conditions.

Fourth, as earlier research already pointed out [68], further studies need to solve the problem of how to implement technology in the field and receive worker acceptance and buy-in. Unstructured interviews with the participants revealed their opinions: The RTK-GNSS data collection technology was simple to use, installed, and removed within a few minutes. Recharging the accompanying smartphone and operating software application to start and end the location tracking required no special expertise either. However, further advancements are necessary in the analysis of large data sets (ref. big data). The help of Artificial Intelligence (AI), which follows strict guidance [69], will eventually push forward even smarter data applications. Additionally, more work is needed in the fields of standards and benchmarking of historical data, such as defining terms and how erroneous data and uncertainty of the developed technology in the harsh, very rapidly changing construction work environment can be reduced.

Fifth and yet another very important aspect is related to research and work practice ethics and privacy rights. These need to follow guidelines according to work councils, Institutional Review Boards (IRBs), research

ethics committees, and government mandated General Data Protection Regulations (GDPR), respectively, to protect human research participants. Participants in this study volunteered. No personal data was recorded and shared or otherwise anonymized. This is a limitation, as the experience and background of individuals contribute further insights into data analysis and reasoning.

6. Conclusions

Construction throughout the world and over the past decades ranks among the workplaces having the highest accident numbers. Of which, *workers being struck by equipment* often lead to Serious Injuries and Fatalities (SIF). The dynamic nature and high energy of equipment operations make it difficult to design out such hazards which makes continuous monitoring in the complex and dynamic, and especially shared, workplaces very much necessary. Empirical data show that control theory applied in construction safety management establishes a positive impact over time. However, the zero-accident goal has by far not been reached yet, partially due to the inefficient and insufficient responses that could be possible once hazards and incidents are identified and detected, respectfully.

From a high-level point of view, this paper showed how important data recordings of live operations on construction sites are, especially when combined with automated analysis and mitigative recommendations. This work provides effortless integration, much needed input values that – once analyzed – generate objective information with no or little human bias attached to the output values. The incorporation of the automated process and the gained information in the proposed Digital Twin for Construction Safety (DTCS) concept, and part thereof Right-time Mitigation and Alerting (RAM) module, creates knowledge based on performance checks once the change is implemented in the field. Applying the sequence of *data-information-knowledge* ultimately creates quicker and better alternatives for establishing safer work conditions.

On the practical implementation side, this paper highlighted the need for data sensing and communication technology (aka. IoT) in the construction environment. As shown in this work, simple-to-use IoT can assist in real-time safety monitoring of live construction site operations and provide rapidly adequate implementation of control measures, as needed. In particular, RTK-GNSS, as a high-accuracy RTLS, enables accurate hazard identification and incident detection, together with the layout model contextualizing location data. On the basis, the developed automated computational algorithms analyzed relevant construction project site geometry and spatial, temporal, and kinematic characteristics of various static or dynamic construction resources. These related to the available site safety and layout plans, volunteering pedestrian workers, and selected pieces of heavy construction equipment. The experimental work has also been qualitatively validated by comparing the results to manual observations and video recordings. The results demonstrate that the developed automation of previous manual efforts can accurately, consistently, and reliably detect and measure pedestrian workers' safety performance under the proximity hazards in the research scope. Furthermore, the algorithms automatically analyzed the overall site safety condition, making aware of hazard and incident hotspots, and accordingly recommends mitigative modifications to the site layout plan.

This work demonstrated that construction safety can be significantly enhanced by addressing two complementary levels: influencing individual worker behavior and adapting construction site layout through automated analysis. Mitigation strategies should target both levels to effectively reduce risks and foster a more worker-oriented construction work environment.

CRedit authorship contribution statement

Kepong Hong: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation,

Conceptualization. **Jochen Teizer**: Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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