2025 European Conference on Computing in Construction

CIB W78 Conference on IT in Construction

Porto, Portugal
July 14-17, 2025

INCREASING BEHAVIORAL PREDICTABILITY WITH HAZARDOUS ENERGY IN HUMAN-ROBOT INTERACTION ON SAFE VIRTUAL CONSTRUCTION SITES

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Abstract

Human variability challenges the use of robotics in construction. While research often focuses on robots adapting to humans, reducing human behavior variability is less explored. This paper presents a method using time-expanded graphs to identify safe pedestrian paths during human-robot interaction (HRI). Simulating hazardous energy in a virtual environment provides the safest routes for construction workers in dynamic hazardous environments. Forwarding these paths to pedestrian workers guides them through safe paths. User studies show this approach reduces hazardous exposure and increases behavior predictability, improving safety in HRI. This research underscores that providing safe worker routes enhances safety during HRI.

Introduction

The construction industry faces persistent challenges with high incident rates and low productivity. While industries like manufacturing have significantly enhanced productivity through robotics and automation, construction lags behind (Ma et al., 2022). This discrepancy stems from several inherent reasons, such as the uniqueness of construction projects, the constant change in the construction sites, and the large scale of components compared to industrial manufacturing. On top of that, Human-Robot Interaction (HRI) in construction remains underexplored and represents a knowledge gap (Fu et al., 2024). These factors make the integration of robotics in construction complex.

Construction sites are dynamic environments where workers from diverse trades perform concurrent tasks. Introducing robots adds complexity, as workers require specific knowledge to interact with them. Such HRI can range from direct collaboration on shared tasks to concurrent activities where humans and robots operate independently (Fu et al., 2024). While HRI has focused on robotic arms, autonomous ground vehicles (AGV) as a specification of robots are seldom in focus, despite AGV being developed for construction purposes.

A critical factor in HRI is occupational health and safety (OHS) in such environments. Several components of OHS have been investigated, collisions and interference being the predominant research focus, but other human factors like trust are also relevant (Hopko et al., 2022). A key challenge for robots avoiding collisions lies in the limited predictability and variability of human behavior in construction (Giallanza et al., 2024). Collisions are particularly relevant for AGV, where humans and robots share workspaces. While a designated workspace for each human and robot most effectively avoids collisions, the character of construction may not allow such separation, especially when humans collaborate with the AGV. To avoid collisions, several approaches have been studied, such as trajectory planning, safety zone monitoring, and distance monitoring. These approaches share the robot's perspective when addressing safety enhancements. For instance, Orsag et al. (2023) propose a model for recognizing spatiotemporal human activities to improve robot safety, and Cai et al. (2023) introduce a deep learning model for predicting human movement to prevent collisions. Yet, the key challenge for robots avoiding collisions lies in the limited predictability and variability of human behavior in construction (Giallanza et al., 2024). Limited research approaches the issues relating to HRI from the human perspective. If we had less variance in human behavior, the construction site would be more predictable, and the robots would be more reliable. Reducing the variability in human behavior and increasing its predictability could provide a pathway to addressing this challenge, shifting the focus from solely enhancing robots' abilities.

This paper focuses on the human aspects of HRI and aims to identify the impact of guiding workers along safer routes on behavioral variability and safety performance. This paper proposes a method to identify safe paths using the concept of hazardous energy as presented in previous research (Speiser and Teizer, 2024a) and communicating the safe routes to workers using head-mounted displays (HMD). The method is tested in a virtual environment to provide a first indication of the impact on safety in HRI when using such an approach. It focuses on the aspect of HRI, where AGVs work on concurrent tasks with humans but without direct collaboration. The latest advancements in HMD may also allow such technology to be deployed in real-world scenarios in future studies.

Related work

Quantifying safety performance

OHS performance relates to “the effectiveness of the prevention of injury and ill health of workers” according to the ISO 19650. Measuring the performance is essential to finding objective and measurable safe routes for workers in construction sites. For that reason, the following paragraphs provide an overview of several indicators that express such safety performances.

Over the years, several indicators have been proposed to provide measurable results expressing the OHS performance. Some of the most common indicators are the total recordable incident rate (TRIR) or the day away, restricted work, or transfer (DART) injury rate. The indicators aim to provide information for contractors to assess their safety performance compared to the industry average or other firms (Hinze et al., 2013). These indicators, however, have two major shortcomings. First, organizations may be prone to not reporting all incidents to keep the numbers low. Second, they are lagging indicators, meaning that they express historic safety performances and are linked to the outcome of already occurred incidents (Hinze et al., 2013; Toellner, 2001). Lagging indicators cannot predict future performance. Especially in construction safety, this is problematic because non-predictive indicators can only assess change in performance after accidents occur. In comparison to lagging indicators, leading indicators are predictive.

Leading indicators can be used as predictors of future levels of safety performance. As Hinze et al. (2013) outline, leading indicators are predictive, heading, and positive indicators, while lagging indicators are historic, trailing, and negative. Examples of leading indicators are the percentage of certified workers in a team or project, or the number of training sessions. The number of reported close calls is also considered a leading indicator. More recently, Erkal and Hallowell (2023) introduced the high-energy control assessment (HECA) as a leading indicator. The HECA score expresses the percentage of controlled high-energy hazards compared to the total number of high-energy hazards, referring to the findings that the severity of incidents correlates with the energy potential.

The underlying theory of HECA is that the severity of an accident correlates with the hazardous energy released during the accident (Hallowell et al., 2017). The hazardous energy can, therefore, also be considered a leading indicator of safety performance on a much smaller level. Speiser and Teizer (2024a) showed that a construction site could be described through a graph of energy levels where each possible motion in a site has an energy defined. This paper utilizes the graphs described but enhances them by adding dynamic resources. The finding of a safer path is then not only possible within this graph but requires a more sophisticated algorithm.

Graphs, networks, and optimal paths

Path planning has gained increased importance in construction with the rise of autonomous vehicles and robots. Path planning algorithms often leverage graphs to determine a feasible or optimal route from a starting point to a destination. Graph theory, a mathematical framework used to model relationships between entities, plays a key role in this process. A graph is composed of a set of nodes and edges, which represent various entities and their interconnections (Bondy and Murty, 1976). These nodes and edges can symbolize a wide range of elements and relationships across different fields. Graph theory has been widely applied to solve problems such as assignment tasks, transportation challenges, knowledge representation, and path planning (Bondy and Murty, 1976). To find an optimal route, weights - also referred to as costs - are assigned to the graph’s edges. Whether directed or undirected, these edges link nodes with specific costs that reflect the expense of using that edge. These costs can represent various measures like travel time or distance (Bondy and Murty, 1976).

In construction, numerous studies have explored path-planning challenges. Several have focused on designing operation paths for construction vehicles (Akegawa et al., 2022; Cheng et al., 2012; Hammad et al., 2012), while others have identified optimal routes for crane operations (Hu and Fang, 2020; Kang and Miranda, 2006; Lin et al., 2020). Notably, Hu and Fang (2020) incorporated safety considerations into their work, whereas other studies primarily emphasized time and distance. Fewer studies, however, have addressed path planning for workers. For example, Cheng et al. (2012) identified paths using workers’ trajectories, while Wang and Qin determined safe routes by evaluating fall hazards through BIM models (Wang and Qin, 2018). Lastly, a prior publication by the authors introduced hazardous energy simulations to identify the safest paths on construction sites in static environments (Speiser and Teizer, 2024a). However, as HRI involves inherently dynamic activities, time-based considerations remain crucial.

Time-expended networks are a solution to finding optimal paths in such dynamic environments. Introduced by Ford and Fulkerson (2010) to describe time-expended flow in networks, they also function to find optimal paths. More efficient, however, in regard to performance and memory requirements, are time-dependent graphs that help find the shortest routes (Cooke and Halsey, 1966). Their approach also has the advantage of considering varying travel times for each edge, which may be relevant to construction sites as well.

Building upon the existing literature, this research utilizes the previously presented algorithm and enhances it into a time-expanded graph to support dynamic hazards like moving equipment.

Virtual environments for simulations and testing

Testing and simulating in virtual or synthetic environments have become particularly popular during the last decades for training artificial intelligence (AI) systems (Cooke and Shope, 2004). In construction, such environments have been particularly researched for safety training. When real-world data like BIM and IoT are included, a digital twin can be modeled (Speiser and Teizer, 2023b; Teizer et al., 2024). When such data is used, the user can experience real-world scenarios in virtual reality (VR) (Speiser and Teizer, 2023a). A similar approach has been used to test a smart glove during crane operations (Speiser et al., 2024), investigating the impact of suggesting safe paths on human variability. Such experiments are challenging to perform in real-world scenarios as they would expose humans to hazards.

Previous research confirmed that virtual environments enable the testing of dynamic real-time optimizers before real-world deployment, allowing for cost-effective studies and increased confidence in technology performance through controlled simulations (Oliveira-Silva et al., 2023). The hazard exposure is also not real and, therefore, allows us to perform experiments that were not even possible in reality (Chryssolouris et al., 2000). Virtual environments allow researchers to isolate design variables and measure human responses safely. They provide a platform for standardized testing, enabling the collection of behavioral and physiological data, which can be transferred to real-world settings for technology evaluation (Kalantari et al., 2021).

In this research, we utilize a simulated environment presented in previous research to quantify the change in safety performance when a user is guided along a safe path while interacting with autonomous vehicles. The VR environment allows a more flexible study design where no hazards need to be available, like real construction equipment. Moreover, it allows us to expose users to hazards, a test that is more challenging to design in a real-world case study.

Research methods

The research method shown in Figure 1 includes an iterative process of a literature review and definition of research objectives. Based on these, the path planning approach was developed and evaluated.

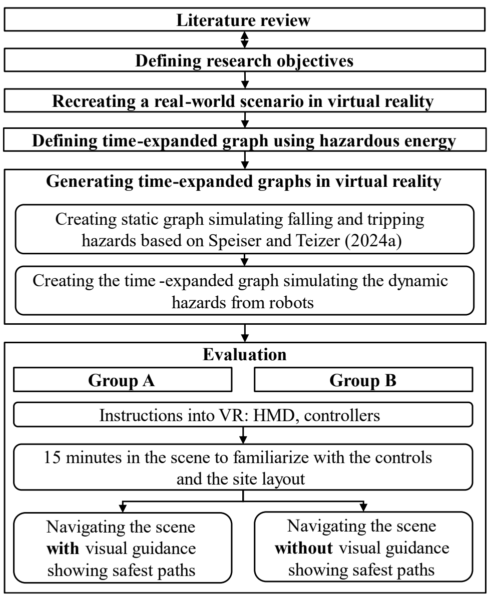

Figure 1: Development and evaluation methods.

Recreation of a real-world scenario

The authors opted to recreate a real-world scenario in VR. By relying on data collected from a real-world construction site, the artificial scenario includes a situation that workers could face in reality. Additionally, the collected data ensures that the machinery active in the construction site moves to a certain extent, as in reality.

The virtual environment created in Unity has been developed using a method presented by the authors in a previous study (Speiser and Teizer, 2024b) that includes the BIM model of the construction site, objects resembling the equipment (three machines), human avatars for the pedestrian workers, and additional elements to further refine the construction site layout.

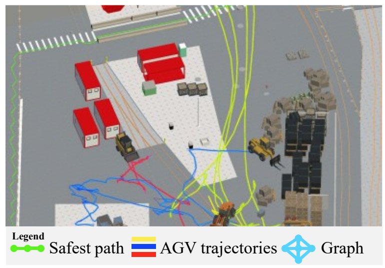

Figure 2: Overview of the virtual test environment, including realistic site geometry and machinery trajectories.

Figure 2 overviews the scene at the beginning of the simulation, where the machines are in their initial position. It augments the trajectory of the vehicles that were collected in the real world using real-time kinematic GNSS technology. These sensors are highly accurate in open spaces and, therefore, suited for this scenario (Hong and Teizer, 2023).

The equipment follows the path that has been recorded using an algorithm presented before to visualize the motion of the equipment (Speiser et al., 2023). The real-world trajectory ensures that the scenario could occur in reality. A limitation that needs to be mentioned, however, is that the equipment was human-operated. It has not been possible to collect a dataset of an autonomous forklift. Nevertheless, within the objectives of this study, the data from the human-operated vehicle functions as an imitation of an AGV in a construction site where the future states are known through the collected trajectory.

With the machine's trajectory, the exact state of the construction site is known in advance. In reality, an autonomous vehicle may also predict its position and state at any given time in the future based on the task ahead. Uncertainty arises from non-controllable impacts such as human intervention. As we aim to decrease the occurrence of such in this work, we do not consider uncontrollable impacts in this study. The machine will follow the path without any exception and even hit the workers. Future work, however, should investigate how changes in the predicted states caused by human intervention could impact the safest paths.

The last aspect of the virtual environment is the avatar and the mission for the user. The environment includes an avatar for the pedestrian worker, which has to collect several objects in the virtual environment while the machinery is active. The avatar can be controlled using a Head-mounted display (HMD) and two controllers. The implementation uses openXR, which should support different HMDs but is tested with an HTC Elite XR. While the users complete the task, they should avoid hazards by choosing safe paths. The created environment allows users to either ask the user to find the safe paths on their own or augment the safest path in the scene directly so that they can follow it.

Time-expanded graph definition

The concept of hazardous energy is introduced to find the safest paths as described in previous studies (Speiser and Teizer, 2024a). The safest paths correspond to the path where a worker is exposed to a minimum of hazardous energy. While the previous study has presented how trips and falls can be determined in a simulation (Speiser and Teizer, 2024a), this work extends the scope to include dynamic equipment. The proposed approach uses time-expanded graphs to model the proximity of workers to such dynamic hazards over time.

$G = (V, E)$ represents the construction site where V is a set of nodes, and E is a set of edges. Each node on the construction site denotes a 1m square and connects to the adjacent six nodes with edges. Each edge $e = (u, v)$ has a constant transit time $t(u, v) = 1$, as nodes are spaced 1m apart and workers are assumed to walk at a constant speed of 1m/s. Each edge also has a time-dependent cost $c(u, v, t)$, representing the safety implications of traversing edge $e(u, v)$. In this study, $c(u, v, t)$ either retains the initial static value $c(u, v, t = 0)$, indicating no dynamic hazard near the edge, but static hazards caused by falls or trips may be relevant or become infinite when the robot is close to the node, effectively making the edge unavailable at that time. This simplification of an infinite value accounts for high-energy hazards caused by forklifts, where exact energy levels are less relevant. Furthermore, the time horizon T denotes discrete time steps throughout the analyzed task.

To construct the time-expanded graph $G_T = (V_T, E_T)$, we explicitly model the time-dependent cost. For each node $u \in V$ in the original Graph G, a copy of the node for each discrete time step $t \in [0, T]$.

$$V_T = \{(u, t) | u \in V, t \in [0, T]\} \tag{1}$$

In equation 1, (u, t) represents the node *u* at time *t*. The time-expanded graph defines edges based on transit times and time-dependent costs. Travel edges connect nodes based on the transit time. Yet, in some cases, it may be safer to idle at a spot and let the robot pass. For this reason, the graph also includes waiting edges that allow for staying at a node u. The idling is enabled through edges that connect node u with itself and have a cost assigned of zero, as shown in equations 2 and 3.

$$\big((u, t), (u, t + 1)\big) \in E_T \; for \; t \in [0, T - 1] \tag{2}$$

$$c_T\big((u, t), (u, t + 1)\big) = 0 \tag{3}$$

The objective of a worker in the HRI construction site is to travel as safely as possible. Hence, the goal is to minimize the cost of traveling from the source $(s, 0)$ to the target node (t, T). The objective function is defined as equation 4 where P is the path in the time-expanded graph. G_T and $c_T(e)$ is the time-dependent cost of edge e. Traditional algorithms such as Dijkstra or A* can be used to find the safest path. This study employs a simple A* algorithm to minimize the total cost of traversal and determine the safest path for workers.

$$Minimize \sum_{e \in P} c_T(e) \tag{4}$$

This approach provides a practical method for finding safe paths in construction sites with dynamic hazards and can be extended to include additional factors such as multi-robot interactions or falling loads in future research.

Time-expanded graph generation

The graph is generated using a two-fold approach. First, a static graph G is generated by refining a simulation presented in previous research (Speiser and Teizer, 2024a). The simulation illustrated in Figure 3 detects trip and fall hazards moving an agent in the Unity scene between every node while detecting the hazardous energy exposure. As the scene in this study comprises a grid of 80x90 nodes, the simulation has been changed to use 800 agents simultaneously, where each agent only explores nine nodes. Additionally, diagonal edges between adjacent nodes are added. Lastly, the environment includes traffic zones, where workers should also not enter. Figure 3 shows the graph generated in the simulation that creates the initial graph G for $t = 0$, which is stored in a JSON file for further processing. It includes the nodes and all edges, as well as the relevant costs for tripping and falling hazards in the environment. These hazards are considered static. In the second step, the time-expended graph is constructed.

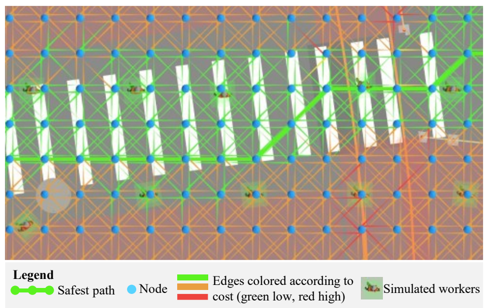

Figure 3: The simulation generates the static graph measuring hazardous energy while moving the agents to adjacent nodes.

Algorithm 1 describes the creation of the graph. First the static graph is copied for each timestep in T, comprising 300 seconds in our study. For each of the 300 time steps, the graph is first copied with all edges and associated, now time-dependent cost. With the assumption of a 6m-sphere around each equipment center, we can define the cost to all edges around the forklift. The cost of the edges around the forklift is replaced by infinite for each timestamp.

Algorithm 1: Pseudo code to create the time-expanded graph.

Input: Static graph $G(V, E)$, equipment trajectory TR_{Eq}, Time horizon T, Hazardous extent H

Output: Time-expanded Graph $G_T = (V_T, E_T)$

Load H
Load TR_{Eq}
For each node $u \in V$:
  For each timestep $t \in [0,T]$:
    Add (u,t) to G_T
For each edge $(u,v) \in E$:

```
    For each timestep t∈[0,T−1]:
        Add travel edge ((u,t),(v,t+1)) with cost c(u,v)
        Add waiting edge ((u,t),(u,t+1)) with cost 0
For each timestep t∈[0,T]:
For each piece of equipment:
        Find equipment position (xc,zc)= TR_Eq[t]
        For each node (x, z, t) within the H:
            Set costs of outgoing edges to ∞
Save G_T as JSON.
```

Figure 4 and Figure 5 illustrate exemplary time expansion and pathfinding in a simplified example. With the set of graphs, we can now find the safest path in the construction site. While the previous research could run Dijkstra algorithms on the static graph, the inclusion of dynamic equipment entails more complexity, as we have a different graph for each timestamp. We assume a constant motion speed of the pedestrian worker when computing the graph and only calculate it once, and do not update it continuously.

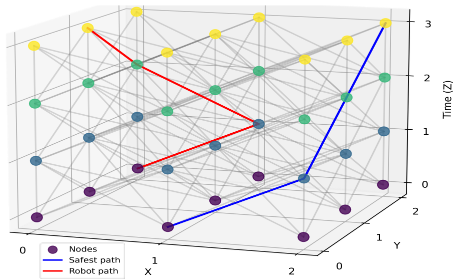

Figure 4: The time-expanded graph copies the nodes for t and updates the edges according to the dynamic hazards.

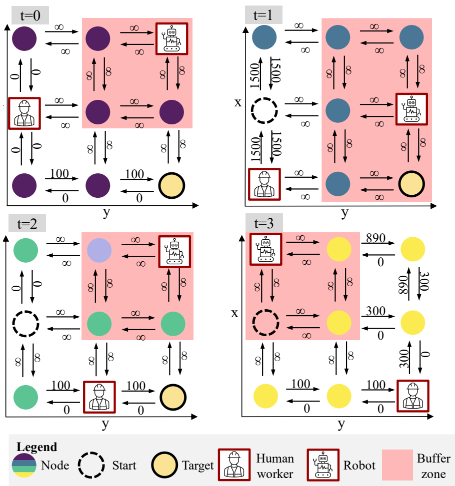

Figure 5: Plan view of pathfinding in the time-expanded graph (Note: the diagonal edges are not shown for simplification).

Based on these assumptions, we find the optimal path using the above-mentioned time-expended graphs. Such graphs essentially duplicate each node for each timestamp. A default path search would now also require specifying a starting time and an end time, as the nodes are defined as (x, y, t). We start at the node $t = 0$ but do not restrict the arrival time at the target node. For this reason, the optimal path search needs to identify the optimal path for each of the arrivals in the timeframe and then find the optimal (safest) one. The safest path can then be read in the virtual environment to visualize the path (see Figure 6).

Evaluation in a user study

The system was evaluated through a user study involving 6 participants, including students and researchers, split into two groups (see Figure 1). Both groups were asked to navigate from a starting point in the virtual environment to a target point. Group A performed the task with the safest path guidance provided by the system, and Group B without the safest path guidance.

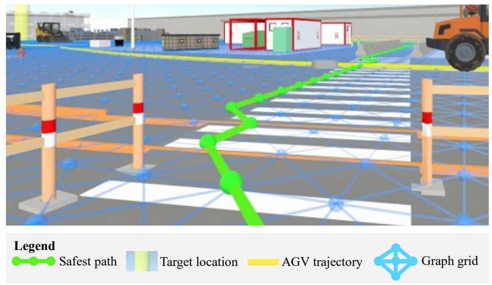

Figure 6: Example of a user's viewpoint (Note: the blue grid is not visible in the scene but is shown to indicate the graph).

In both scenarios, the Unity environment was used to detect interactions with the modeled hazards. This was achieved using collision detection methods as described in previous research (Golovina et al., 2019; Speiser and Teizer, 2024c). This approach allowed us to measure the actual exposure of participants to hazardous energy levels while performing their tasks. These energy levels were recorded and compared across the two conditions.

By analyzing the results, we aim to determine whether providing optimal path guidance improves the safety performance of users during task execution. The collected data is analyzed with regard to the variability between paths and the hazard exposure. To quantify the variability, we first determine a mean path representing the centroid of all paths at each timestamp, determined with formula 5. For a given timestamp, the centroid (t) node is calculated where N is the number of paths. As some users may arrive at the target faster, we assume that they remain in this position. The deviation from this mean path can then be expressed for each individual path using formula 6. The deviation is then expressed as the standard deviation to obtain an indicator to express predictability. The second indicator is the total hazard exposure, compared for each of the subject groups.

$$centroid(t) = \frac{1}{N}\sum_{i=1}^{N} x_i(t), \frac{1}{N}\sum_{i=1}^{N} y_i(t) \qquad (5)$$

$$dt(P) = \sum_{t=1}^{T} \sqrt{(x(t) - x_{ctr}(t))^2 + (y(t) - y_{ctr}(t))^2} \qquad (6)$$

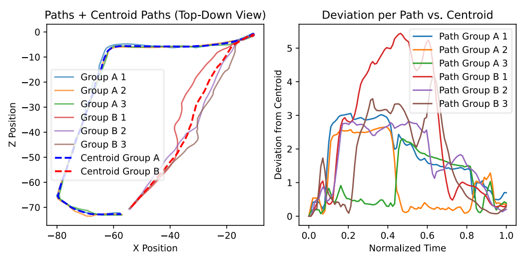

Figure 7: The trajectories of the users and the centroid path for both groups (left) and the deviation (right).

Figure 7 illustrates the calculation method for the standard deviation from the centroid path for one example. It shows the three paths for the subjects that were provided a safe path and the three that were not of group B. It furthermore shows the centroids for each group. Figure 7 on the right then shows deviation from the centroid paths using a normalized time scale. Without the normalized time, the paths would end at different timestamps, and a comparison would no longer be possible.

Results

The following paragraphs present the results of the user study. It investigates how the use of the time-expanded graph enables an assessment of how the provision of the safest graphs impacts the variability in human behavior and safety performance in a virtual environment. Variability is relevant as one of the main issues in HRI is the unpredictability of human behavior. Once human behavior is less variable, future movements are more predictable and have higher reliability. The safety performance is also relevant as it will show how the hazard exposure changes. In this work, hazardous exposure functions as an indicator. However, other indicators, such as risk, may be more relevant, and future research should include the likelihood instead of purely focusing the assessment on severity.

Error! Reference source not found. Figure 8 shows that the provision of the paths decreases the variability for all paths. However, the difference is much higher for path 2 compared to paths 0, 1, and 3. The low difference in path 0 refers to the short distance of this path. The results of the user study revealed a significant reduction in path variability for Group A (guided by the safest path visualization) compared to Group B (unguided), where the standard deviation is 43 and 227, respectively. Hence, the deviation is reduced by 81%. The reduced deviation in Group A highlights the effectiveness of the safest path guidance system in increasing consistency among participants.

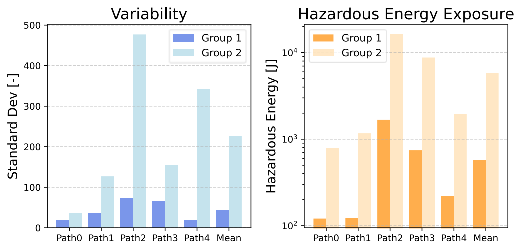

Figure 8: Comparison of the variability (left) and hazardous energy exposure (right) for the two groups (Note: the hazardous energy potential is shown on a logarithmic axis).

Hazard exposure was quantified based on participants' proximity to dynamic and static hazards, detected through collision detection methods in the VR environment. Group A experienced significantly lower hazardous energy exposure compared to Group B. On average, participants in Group A were exposed to 578 joules of hazardous energy, and Group B to 5,280 Joules. The guidance system reduced the hazard exposure by 90%. Looking at the individual paths, the difference is high for all five paths. Figure 8 shows the hazard exposure on a logarithmic scale, and it shows that the hazardous energy exposure reduced similarly for all five examples, between 85% and 92%. These results, however, need to be evaluated carefully. The users who did not follow the guidance paths exposed themselves to the dynamic hazard with greater proximity but were never hit.

Looking at the distance and times that each group presented (see Figure 9), the results show that, on average, group B was faster and took shorter routes compared to the subjects from group B on paths 0, 1, and 3. Only on path 4, group A was faster and took shorter routes. These results show that safety may often result in lower productivity when measured in the short term. However, indirectly, the higher hazard exposure could lead to more incidents and, therefore, limit productivity.

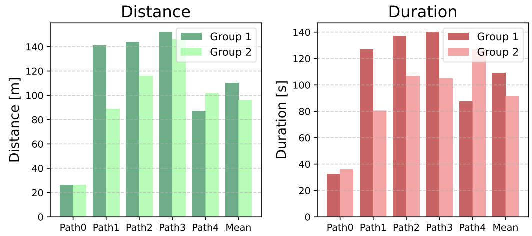

Figure 9: Comparison of the distance (left) and duration (right) for the two user groups for each path and the mean for all paths.

To sum up, the results suggest that providing optimal path guidance in virtual environments not only improves predictability but also reduces the likelihood of hazardous interactions. The following section will discuss these results and outline the limitations of the study.

Discussion

The results indicate that guiding workers with augmented safest paths can reduce their exposure to hazards. By focusing on a worker-centered solution, the presented approach could offer a novel and complementary method compared to existing robot-centered approaches like trajectory planning and robot-centered collision avoidance. However, the study was performed in a virtual environment, and real-world studies should investigate if similar behavior shifts are noticeable in real tests.

The results show that users with the augmented path guidance exposed themselves to 90% less hazardous energy. The augmented paths additionally resulted in less variability in chosen paths. This reduction in behavioral variability could contribute to safer human-robot coexistence. This aligns with prior findings that human unpredictability hinders safe HRI (Giallanza et al., 2024) and complements robot-centric safety methods like trajectory prediction (Cai et al., 2023). Unlike those approaches, this paper highlights a human-centered strategy using path guidance and builds on hazardous energy as a leading safety indicator (Speiser & Teizer, 2024a). When workers follow more predictable paths, AGVs, and potentially other robots can more reliably plan their routes, potentially reducing collisions and near misses. This supports the research objective of minimizing human behavioral variability, a topic largely overlooked in prior studies. Although robotic systems still require improvements in reliability, consistent human movement patterns could facilitate their safer integration on construction sites.

Several limitations must be acknowledged. First, the sample size of six participants limits generalizability. The small sample size is sufficient for identifying a trend. The system was tested in a virtual study, and a real-world experiment could now make the claims more robust. Future research should, therefore, implement such a system in a real-world study. With the latest advancements in augmented reality displays, such features should be testable in a case study with construction workers. The practical deployment of such path-guidance systems in real construction settings faces challenges. Construction projects are inherently dynamic, and different trades operate under separate contract structures, communication protocols, and safety regulations. Implementing HMDs or smart glasses for all on-site personnel raises questions about equipment provision, worker training, and interoperability across companies. Achieving acceptance and efficacy will likely require collaborative frameworks, clear data-sharing agreements, and standardized communication protocols that bridge various trades and subcontractors.

Second, the assumed constant walking speeds and a simplified virtual environment cannot capture all the complexities of real-world construction sites. The static walking speed could be solved by continuously updating the path guidance system. No longer, like in the example here, would determine the safest path once at the beginning, but it would continuously update the safest path based on updates on the site. Such a system could then also update based on unknown changes in the robot's trajectory that were caused, for instance, through collision avoidance with other workers or delays in a schedule.

Third, the study is limited to AGVs, and other tasks with other robots need to be investigated. While the study is limited to AGVs, a similar approach could be applicable to other robots like robotic arms. Future research could also investigate how a similar concept can be deployed for robotic arms or autonomous UAVs.

Fourth, metrics other than hazardous energy exposure, such as risk metrics, may be more suitable for quantifying the safety performance of individual routes. Another limitation is that our system proposes one safest route. But if there are several, it will not find the quickest one. This results in additional edges that could be avoided when comparing all safest paths and finding the quickest one.

Although the virtual environment replicated many realistic details, further validation in real-world settings is necessary. Different site layouts, varying robot capabilities, and workforce diversity will demand new approaches to path guidance and user interface design.

Conclusions

This paper proposed an expanded graph to find safety routes in dynamic construction sites. Forwarding these paths to construction workers could decrease variability in human behavior and, hence, increase predictability, which again could help in adopting robotics in construction. Forwarding these paths to construction workers through HMD can enhance safety outcomes in HRI construction environments. Augmented path guidance reduces hazardous interactions and behavioral variability. However, practical and technological concerns must be addressed before such systems can be deployed in reality. Admittedly, these findings are limited to a virtual environment and only six subjects in the evaluation. However, a trend has been identified, and future tests at a larger scale could validate this trend.

The previous section outlines several avenues that future work should consider. By doing so, the construction sector can take a step toward bridging the persistent gap in automation and robotics adoption, ultimately improving both productivity and OHS.

Acknowledgments

This research has been funded by the European Union Horizon 2020 research and innovation program under grant agreement number 101058548 (BEEYONDERS).

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