# Towards a Holistic, Self-organised Safety Framework for Construction

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***Abstract*—In this short vision paper we outline a framework incorporating multi-modal sensory information into so-called digital twins in construction sites. Starting from a first-order principle model (i.e., the construction plan), we enrich the digital twin during runtime with additional information such as work plans, identified and mitigated hazard zones, and current location of workers, resources, and mobile equipment. Utilising this information in the digital twin allows executing simulations to predict potentially dangerous situations for workers. Feedback mechanisms allow us to inform workers accordingly but also improve the construction site and the corresponding digital twin during the building process in an autonomous and self-organised fashion.**

***Index Terms*—digital twin, safety, construction, self-organisation**

## I. Introduction

Construction sites are highly dynamic and constantly changing environments. Due to the irregular environment, workers are prone to accidents and construction remains at the top of the fatal accidents list among member states in the European Union [10]. Specifically, in 2018 more than 20% of all fatal accidents are attributed to construction activities, surpassing sectors such as transportation and storage, and manufacturing. Similarly, in the U.S. in 2019 construction was the leading industry sector in fatal work injuries with a 25% (1061 fatalities) share of all fatalities, followed by transportation, warehousing, and agriculture [33].

Safety performance in construction is traditionally evaluated by metrics depicting incidents that happened in the past [14]. Those metrics, referred to as *lagging indicators*, are commonly used for benchmarking within the construction sector, and measure, for example, the frequency or severity of accidents. However, analysing incidents that happened in the past often provides no immediate value in detecting or preventing safety hazards in the short term on a given construction site [30]. Teizer [30] argues that the element of time is essential for improving safety performance in construction, emphasising the importance of real-time data collection and hazard monitoring. The availability and accuracy of data about the current status of a construction process can further improve construction performance [24].

Moreover, the advancement of information technologies and their application in the Architecture Engineering and Construction (AEC) industry has enabled the now wide-spread adoption of semantically rich, three-dimensional (3D) digital representations of construction sites and individual building assets, referred to as Building Information Modelling (BIM); a particular digital representation of a construction site is referred to as a *BIM model*. The term *4D BIM* is used to refer to BIM models that also represent time in the form of a construction schedule. BIM model analysis tools support construction project managers through dimensional quality control [4] and construction management decision support [28].

The Digital Twin concept in the context of BIM aims to align the digital representation of the construction project (*as-designed* building artefacts, *as-planned* processes) with the physical reality of the construction site as it evolves in time, referred to as the *Physical Twin* (*as-built* building artefacts, *as-performed* processes), for the purpose of accurately *envisioning* potential future states of the construction project to provide stakeholders with enhanced decision support [3].[1] We distinguish BIM-based *Digital Twins*, that emphasise the capability of digitally simulating and predicting future scenarios, from BIM-based *Digital Shadows*, that instead only focus on digitally representing the physical construction site as accurately as possible, providing only basic analysis (e.g. dashboard metrics, calculation, and statistics).

Such Digital Twins are usually initiated through first-principle models and refined during the construction phase with real-world data. In return, the developed model of the construction site is used to identify current deviations between the planned state and the state of the physical counterpart, and to predict potential future deviations (e.g. via regression, trend line analysis), enabling construction managers to apply timely mitigation and correction strategies to either the digital twin or the physical twin.

The physical and the digital twin are two concurrent but interdependent systems, where the digital twin represents the state of the physical twin. At the same time, the digital twin can generate recommendations for stakeholders (e.g., safety manager, quality surveyor) directly affecting the physical

[1]BIM standards provide a means of information exchange and software analysis tool interoperability amongst stakeholders with diverse concerns (structural engineers, fire safety compliance experts, construction management etc.) that is further facilitated by the use of a unifying digital twin *platform*.

twin. This requires a continuous integration of information to accurately represent their counterpart. This leads to a direct feedback control loop between the digital twin and the physical construction site. Considering autonomous machinery, a completely self-organised construction site can be envisioned. Digital Twins in constructions are also used to identify potentially hazardous areas during the planning phase [18], [29]. The concept of Prevention through Design and Planning (PtD/P) is the process of considering construction worker safety early in the design phase to avoid potential hazards and ensure a safe work environment [32]. To proactively enhance safety it is also important to focus on eliminating the incidents that precede serious injuries and even fatalities, because a multitude of unsafe behaviours and close calls precede one minor injury in construction, while numerous minor injuries occur before one serious accident or fatality as highlighted by Teizer et al. [31]. Monitoring and digitally representing the dynamic and constantly changing physical construction environment is an integral part of the Digital Twin concept. A conceptual digital twin framework introduced by Sacks et al. [27], incorporates monitoring of resources, tasks and performance at different frequencies to facilitate the evaluation of design and planning, and the implementation of actions to improve construction. Furthermore, there are several research efforts that identify potentially hazardous situations by tracking and predicting the movement vectors of workers and machines [17], [26], [39]. Nevertheless, the proposed approaches do not consider the semantics of the construction site BIM model that can be used to infer limitations on the potential movement of the workers and machines by testing them in open, unobstructed environments. So far, a holistic framework that is continuously updated with sensory data and combines semantic information, utilised to improve safety during the construction process on multiple levels is missing for the construction industry and self-organised construction.

In this position paper we propose Digital Twin for Construction Safety (DTCS), a self-organising framework that utilises Digital Twins in combination with their physical counterpart, continuously integrating sensory information from the highly dynamic construction environment. We discuss approaches to tackle safety at different times of the construction process and with different impacts on the safety of workers, namely (i) hazard zone identification, (ii) change impact prediction, and (iii) situational accident prediction and worker notification.

## II. Digital Twins for Construction Site Safety

Construction sites undergo rigorous planning and are subject to numerous rules, regulations and laws. Before construction can begin, work and construction plans are developed and required resources are coordinated. This affects the Digital Twins (DTs) as well as the construction site.

DTs are computational models representing physical systems. This representation is constantly kept up to date through simulating the next state and adjusting this state through ongoing sensory information integration. In addition, the digital twin can be used to correct and control the physical counterpart either directly or by notifying human operators to perform correctional measures. On construction sites, digital twin setting have been used to monitor and optimise construction site logistics [13], improve quality control [22], and for operation and maintenance of built assets [21].

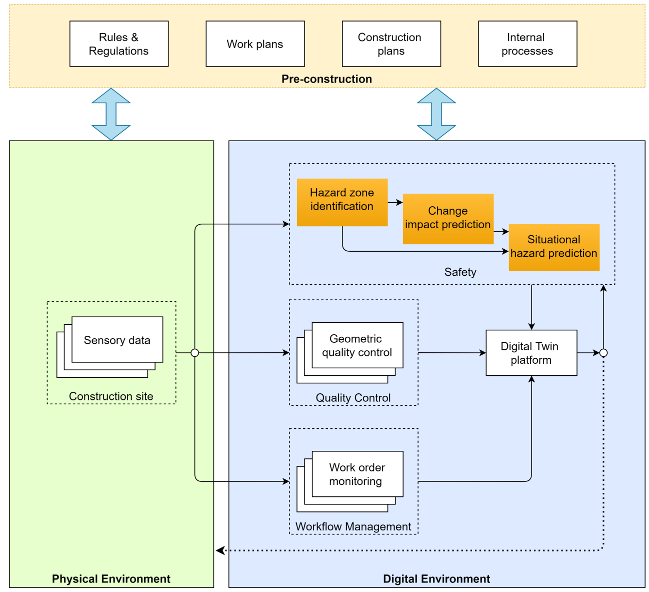


Fig. 1. Interconnected feedback loops between the physical (i.e., construction site) and digital environment (i.e., safety, quality control, workflow management and digital twin platform).

Figure 1 illustrates our vision of Digital Twin for Construction Safety (DTCS), a holistic safety framework incorporating a digital twin for construction sites. The digital twin setting consists of the physical part and the digital component that aims to reflect the current state of the construction process at all times, and is used as a basis for future state prediction through logic-based reasoning and simulation. The physical construction is a highly dynamic process that takes place in the physical environment. During construction, data is acquired through different means such as several *sensors* (e.g., video feeds and other visual sensors, LiDAR, indivdiualised GNSS location sensors) and full Internet of Things (IoT) applications deployed onsite to collect data, as well as feedback from workers, managers, and dedicated observers. In addition to those direct information channels, other information traditionally used in construction can be collected. For example, work-order and scheduling information as well as construction site layout planning can be added manually to the system *a priori* or during runtime.

At the same time, the central part of the digital counterpart, namely the DT platform in the digital environment will collect and aggregate all the aforementioned data to construct a digital visualisation of the current state of the physical process. The four-dimensional building information model (4D BIM), consisting of a three-dimensional representation of the physical construction site over time (i.e., the fourth dimension) [15], will be enhanced with critical semantic information about the workflow management, quality control and safety. Enriched with that information, the DT platform allows onsite workers, safety managers, quality surveyors, site managers and other stakeholders and decision-makers in the construction project to improve construction performance in the physical environment (i.e., physical twin) while minimising potential safety risks.

The DT platform in the digital environment consists of several interconnected modules each responsible for performing their respective tasks with regard to (i) workflow management, (ii) quality control, and (iii) safety, as illustrated in Figure 1.

For each module several alternative approaches are available, represented by the additional white rectangles stacked behind each labelled white rectangle. Focusing on safety, we will discuss three aspects, utilising different approaches, and affecting safety at different times of the construction process. These three approaches are highlighted in dark yellow.

All three modules depicted are relevant in DTCS and feed directly back into the physical environment through the digital twin platform. A separate feedback loop going directly from the digital twin to the safety module to allow this crucial component to respond quickly and before physical implementations are executed, potentially leading to new and avoidable hazards. In the following, we describe all three modules in more detail, focusing again on safety and their respective contribution to safety.

### A. Workflow management

Workflow management refers to the process of controlling and monitoring the activities needed in the construction process, from idea conception, through architectural and construction activities, to the successful handover and optionally also construction operations, depending on a given customer's needs and contractual obligations. Subsequently, workflow management in the DT platform will facilitate the verification of construction task completion, asset release, automated financial exchanges and thus, minimise transaction costs and administrative overhead in construction. The workflow management functions, such as *work order monitoring* are depicted in Figure 1 and will feed the DT platform and the 4D BIM model with semantic workflow information. The state of the construction site is taken as an input to make decisions about next steps in the construction process. This can lead to sudden, potentially unplanned changes in the environment due to additional machinery or resources deployed, affecting the working and movement areas of workers. Integrating this in the DT platform allows project managers to utilise this information in the safety planning processes.

### B. Quality control

Ensuring that the construction project meets its quality specifications, such as geometric tolerances and regulatory requirements, is not only a contractual obligation. In addition unplanned remedy works and thus delays and additional costs, are also being avoided. In practice, geometric surveying and visual quality control still requires manual effort despite the development of the surveying technologies (e.g., laser scanning). The *geometric quality control* function of the quality control module in the digital environment will make use of modern surveying and information technologies to automatically detect defects from processing 3D point clouds and 2D images. Information from quality control will enhance the 4D BIM model visualisation in the DT platform with quality-relevant information, allowing for changes to be made to the physical construction site in a continuous manner to optimise performance, increase productivity, and reduce safety hazards. This continuous exchange of semantic information between the quality control module, the DT platform and the construction in the physical environment is depicted in Figure 1 as interconnected feedback loops. Information from the construction site is taken as input into the DT platform and is utilised to refine and correct the DT. Unplanned changes, potentially affecting the safety of workers, can be represented in the DT platform and further utilised to improve worker safety on the construction site.

### C. Safety

DTCS is at the core of the digital platform and utilises Quality Control and Workflow Management through the Digital Twin Platform. In contrast to the Quality Control and Workflow Management components, the Safety component receives feedback directly from the DT platform to respond immediately to rapid changes triggered by the other components. Safety in construction establishes a safe and healthy occupational environment for the construction personnel. To achieve that, safety planning typically includes the risk and hazard identification process and the selection of corresponding safety measures [38]. In Figure 1 the safety module consists of three functions, namely the *Hazard Zone Identification*, *Change Impact Prediction*, and the *Situational Hazard Prediction*. These three functions comprise DTCS and tackle safety hazards and risks, resulting from different causes and having various spatio-temporal impacts, by utilising information at runtime. Hazard Zone Identification and Change Impact Prediction are performed at strategic and decisive points in time during the construction process, while Situational Hazard Prediction is a continuous monitoring process. However, Hazard Zone Identification aims to identify the potential hazard zones while Change Impact Prediction analyses potential alternatives in deploying machinery or resources and materials and their respective impact on hazard zones.

**Hazard zone identification** utilises two approaches to check for potential hazard zones on the construction site: (i) a rule-based approach using Answer Set Programming (ASP) extended to support spatial reasoning and (ii) a multi-agent simulation approach highlighting potential dynamics on the construction site leading to hazards.

The rule-based approach extends ASP to support spatial reasoning for safety checking of 3D geometric data (e.g. 3D meshes and 2D polygons) [18], [19], [34], [35]. Based on encoded rules, it identifies areas on the BIM model that can lead to hazards, such as leading edges and holes which can cause fall from height accidents. The inferred safety hazards enrich the semantic information of the 4D

BIM model in the DT platform and the safety information is used to further improve workflow management, quality control and safety in the DT platform as well as in the physical environment through the onsite personnel receiving information from the DT.

The multi-agent simulation-based approach allows us to explore dynamics on construction sites. We will utilise work orders, planned work teams, and deployed machinery, and construction plans in order to simulate the movement of different entities. This allows us to highlight areas where workers are potentially have to move through hazard zones created by machinery (e.g., areas where loads are moved by cranes or areas where trucks drive).

Both approaches allow the project manager to identify and mitigate occupational hazards in a timely manner. While current construction sites still rely on manual operation to establish safety measures, future construction sites may utilise autonomous systems, leading to a fully self-organised construction site incorporating human users alongside autonomous machinery.

**Change Impact Prediction** will analyse alternative plans for changes on the construction site. As certain elements of the constructed buildings, such as walls, ceilings, doors, etc. can not be significantly changed with respect to dimensioning, orientation and placement, DTCS focuses on elements where the respective location in the construction environment has more flexibility during the construction process itself, such as job sites (e.g. where machines such as cutting saws are located for on-site work), temporary material storage areas, etc. Specifically, we analyse the impact of placing such resources on the hazard zones of the construction environment. We take as input the information from the digital twin including the current state of the construction extracted from the quality control data and next steps in the construction process from the workflow management. Furthermore, we incorporate previously identified hazard zones. We utilise the workflow management data to identify resources with high flexibility in their position and create alternative plans for their final location. For each of these plans, we analyse the impact on existing hazard zones but also utilise multi-agent simulation to study the impact of changes on the dynamics of the construction site. An example is the delivery of bricks on the construction site. Their precise location is not as important as long as they do not block work or travel zones for machinery and workers. However, certain locations might result in workers taking alternative, unintended travel paths leading to higher risks of accidents. The exploration of potential alternatives allows project managers to reduce the risk of such situations occurring.

**Situational Hazard Prediction** aims to predict potential accidents in the near future and alert workers through the DT platform before they can occur and cause harm. This approach will not only use Hazard Zone Identification information but also the spatial and temporal semantic information from the enriched 4D BIM model in the DT platform, such as planned work tasks or the construction site layout. Furthermore, we utilise direct tracking information from work teams based on GNSS. This information will be used to extrapolate the movement path of workers to estimate potential collisions with machinery and previously identified hazard zones. We limit the extrapolation function with semantic information in order to achieve more accurate predictions. Combining this information will provide the prediction model with significant contextual knowledge to identify potential accidents in the near future, given the complex and dynamic construction environment. An example for this is the elimination of extrapolated paths that would directly lead into walls. Based on the identified potential collisions of workers with hazard zones or machinery, we can send feedback directly to the workers using smartphones or wearable devices (e.g. smart watch). Additionally, this information is fed into the DT platform for future reference and consideration in updating and identifying hazard zones and the impact of changes.

The aforementioned information flows in the DT platform (see Figure 1) are not synchronous but operate in their own frequencies. For instance, Quality Control functions operate slower than Workflow Management and Safety. This variation of operating frequencies among the Digital Twin modules is necessary due to the different timescales of critical events assessed in each module. Safety critical events, such as workers approaching unprotected leading edges, are likely to occur several times in a day, whereas significant changes in the construction to be checked take more time and thus, occur less frequently. Therefore, synchronous operation of the modules would be redundant and computationally expensive.

Additionally, even within modules, different frequencies are expected. This is because the various functions of a module assess different aspects of the construction process that operate differently. In Safety for example, hazard zone identification performs safety checking of 3D geometric data to identify potentially hazardous zones. Since construction processes are laborious and require time, changes in the 3D structure occur less frequently than workers or mobile equipment moving in the construction site with a potential of being involved in hazardous situations. Therefore, situational hazard prediction is required to assess potential hazards more frequently than the hazard zone identification.

Nevertheless, updated semantic information will be stored at the DT platform and enrich the 4D BIM model as soon as updates occur, in order for each module to be able to collect that information whenever required. In a similar fashion, feedback to the physical twin is not performed at predefined intervals (dotted arrow in Figure 1). Safety approaches will need to inform the physical counterpart more often than workflow management or quality control.

The proposed DTCS framework can be integrated in conventional construction as well as in self-organised construction and hybrid cases, where traditional construction methods coexist with modern autonomous technologies. However, it is important to emphasise that in conventional construction deployment of sensors is crucial to perform the continuous information exchange required by the safety framework, whereas in self-organised and hybrid construction, autonomous robots are already equipped with the sensors to achieve such function.

## III. Challenges

To achieve our vision of an holistic safety framework, we have to tackle several challenges.

**Online tracking** Detecting, identifying, and locating objects and people in the environment is an intensively researched topic on its own [37]. Not only do we have to ensure that we re-identify objects correctly within and across sensors, we also have to ensure that this is achieved in a timely fashion to allow for early enough warning signals to the workers. Deep learning for object tracking in visual data has improved the performance in field over the past years [7].

**Sensors** Selection of type of sensors as well as their placement is crucial in order to allow to track changes on the construction site whether these changes are caused by humans, machinery, resources, or construction elements. Line-of-sight sensors are prone to occlusions while wearable devices might be inaccurate and unreliable. In self-organising construction, autonomous robots are equipped with various sensors [12] that allow them to communicate with and directly transmit the required information to the safety framework.

**Human behaviour** In order to make predictions based on human behaviour, we need to model this behaviour beforehand. However, human behaviour is subject to many factors such as their current physical and social environment or their own well-being and confidence. Various simple models have been proposed for the movement and behaviour of humans [11], [16], [20].

**Runtime data integration** When data comes from different sources in the physical environment, synchronisation is required [9]. Utilising and integrating this data to be meaningful will further require an understanding of where this information is coming from and how it relates to other information, whether these are spatial, temporal, or causal relations [1], [2].

**Automatic semantic annotation** In order to allow for classification of hazards and prediction of movements in the environment, we require knowledge about how the environment affects the hazard zones and movement patterns, respectively. (Semi-)Automatic semantic annotation in images can help to generate this semantic information [23], [25]. However, there is still need for automatic multi-modal semantic annotation in the absence of image information.

**Long term prediction** Trajectory prediction of resources in construction is largely performed by exploiting computer vision-based methods and machine learning for object detection and tracking of movement in space, while predicting the short term trajectory, typically for a few seconds in advance, to avoid collision accidents [6], [17], [39]. Long term prediction for enhancing construction safety however, still need to be explored.

**Interoperability** In construction, several stakeholders work collaboratively to perform various tasks, from geometry design and structural analyses, to cost estimation and work planning, several applications generate data often in different formats with varying properties and restrictions [8]. This creates interoperability issues that need to be addressed when a holistic framework for safety in construction is conceptualised. The Industry Foundation Class (IFC) data model is a standardised, platform neutral and open file format for information exchange of the built environment [5] typically used in construction.

**Privacy** Digital Twins are built upon the idea of continuous information exchange between the physical system and its digital counterpart. This introduces privacy concerns with regard to the transmitted data and dictates the need to ensure high privacy and security during transmission, for example by applying encryption methods on personal data [36]. DTCS framework should not overlook the privacy and security of not only identification data of the persons involved in the construction, but also safety-critical and proprietary information about the infrastructure being constructed.

**Accuracy and speed** As mentioned in the previous section, safety critical events in construction occur at different frequencies ranging from several times per minute, hour, or day, to weekly or monthly occurrences. These events have the potential to compromise the safety of workers or cause damage to equipment and infrastructure. To reduce accidents on self-organised, hybrid, and traditional construction sites, accurate predictions and rapid information exchange are key to notify affected parties and avert safety critical situations.

## IV. Conclusion

In this paper, we have introduced Digital Twin for Construction Safety (DTCS), a holistic safety framework in close interaction with a Digital Twin platform for construction sites to reduce potential hazards. The DT continuously integrates sensory information from the highly dynamic construction environment. The safety framework consists of three functions, namely (i) hazard zone identification, (ii) change impact prediction, and (iii) situational accident prediction and worker notification. It tackles safety hazards and risks, resulting from different causes and having various spatio-temporal impacts, by utilising information at runtime.

## V. Acknowledgements

The work leading towards this paper has been partially funded by the EU-projects COGITO (Grant agreement ID: 958310) and BIM2TWIN (Grant agreement ID: 958398)

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