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# Beyond Data: Conceptualizing Human-Centric Digital Twins for the Future of Construction

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## Abstract

**Research Question**: How can Human-Centric Digital Twins (HCDTs) be conceptually structured and practically implemented in construction projects to integrate physiological, behavioral, cognitive, and environmental data for improving worker safety, well-being, and operational performance?

**Purpose**: To propose a comprehensive HCDT framework for construction and to present a structured implementation roadmap that translates this conceptual framework into a practical and phased deployment strategy.

**Research Design/Method**: A conceptual research design supported by a structured literature review.

**Findings**: The paper proposes a novel three-layer HCDT framework consisting of (1) data collection and acquisition, (2) data processing and analysis, and (3) decision-making and feedback. In addition, a four-phase implementation roadmap is developed, guiding organizations from readiness and governance to pilot deployment, scaling, and enterprise-level institutionalization.

**Limitations**: The study is conceptual in nature and does not include empirical validation or real-world case studies. The feasibility, cost implications, worker acceptance, data privacy challenges, and technical performance of HCDTs in active construction environments remain untested.

**Academic merits**: For research, the paper provides a foundation for empirical investigations into HCDTs, including physiological and cognitive monitoring methods, predictive analytics, and human-in-the-loop decision systems. For industry, the roadmap offers a structured pathway for adopting HCDTs while addressing governance, privacy, and workforce integration challenges.

**Value for practitioners**: This paper provides construction practitioners with a clear and phased roadmap for implementing HCDTs in real projects. The proposed approach enables practitioners to move beyond technology-focused digital twins by

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incorporating worker health, fatigue, and environmental conditions into safety and operational decisions. By following the roadmap, practitioners can improve risk detection, design more adaptive work environments, enhance worker well-being, and avoid ad hoc or ethically problematic implementations of workforce monitoring technologies.

**Keywords**: Digital twin, human factors, wearable sensors, environmental sensors, framework, implementation roadmap.

**Paper type**: Full paper

# Introduction

Known for its tardiness in joining the digital transformation era, the construction industry is often described as one of the least digital industries (Greif et al. 2020) and has long been plagued with process and labor inefficiencies. The lack of integration between the construction site and potential digital systems for construction projects has led to lowered management efficiency and information fragmentation (Zhang et al. 2022). However, the construction industry could benefit greatly from digital transformation in the upcoming years (Greif et al. 2020). Therefore, several researchers have been proposing new digital transformation approaches to improve construction performance, including suggesting the broader implementation of Digital Twin (DT) technologies in construction (AlBalkhy et al. 2024).

Defined as creating a digital model of a physical system, DTs provide “real-time monitoring, updating, simulating, analyzing, controlling, predicting, optimizing, validating, and coordinating” throughout the project life cycle (Zhang et al. 2022). The basic architecture of a DT usually consists of (1) a physical layer which includes the physical component and the data acquisition and communication tools, (2) a digital layer which includes the data integration, modelling tools, and data management and analytics systems, (3) an application layer in which reports, dashboard, autonomous activities, and warnings are created, and (4) a users layer which includes the clients, owners, managers, operators, or workers that could benefit from the developed DT (AlBalkhy et al. 2024).

Current DT proposals and developments in construction focus primarily on technical aspects of projects like site logistics (Greif et al. 2020), while others incorporate some human factors, mainly ergonomics, into the proposed construction DTs (Ogunseiju et al. 2021). However, some gaps remain in developing standardized frameworks that integrate a comprehensive human experience, including physiological, behavioral, and cognitive data with construction processes to enable human-centered solutions that are tailored for human needs.

To address this gap, this paper proposes a novel Human-Centric Digital Twin (HCDT) framework that incorporates wearable devices, Internet-of-Things (IoT) sensors, and advanced analytics to create personalized digital representations of workers. This framework aims to enhance worker safety, productivity, and well-being by providing adaptive, real-time insights and predictive capabilities tailored to the dynamic nature of construction sites. First, comprehensive literature review of DTs in construction is conducted, followed by a literature review of DTs with a focus on human factors in construction. Afterwards, a three-layer conceptual framework for a HCDT is proposed, with each layer meticulously described. In addition, a structured implementation roadmap is developed to translate the proposed HCDT framework into a practical, phased deployment strategy for construction projects, addressing technical, organizational, ethical, and human factors associated with real-world adoption. Implications and applications of the proposed HCDT are presented, followed by conclusions. This study aims to lay the groundwork for the development and practical implementation of HCDTs in construction.

# Literature Review

## Digital Twins in Construction

Digital Twins (DT) are digital replicas or representations of physical objects, products, assets, processes, or systems (AlBalkhy et al. 2024) and are implemented in several industry sectors, such as aviation, transportation, manufacturing, medical sciences, and healthcare (Akanmu et al. 2021). Generally, they are supported by technologies such as simulations and digitalization (Kor et al. 2023), sensors, GPS, communication networks, audio technologies, medical and health sensors, and distance, location, and travel measurements (Salem and Dragomir 2022).

In construction, despite the slow pace of digitalization, DT research and implementations have been gaining momentum. A study by El-Din et al. (2022) conducted a systematic review on the lack of standardization for DTs in the AEC industry and proposed a conceptual framework for DT development for construction assets using existing BIM information management standards. They identified the most recurrent fields of investigation in DT studies in the AEC industry and found that facility management was the research field with th most studies, followed by structural health monitoring, concept framework, construction management, and finally, circular construction (El-Din et al. 2022). In construction management, they found that the studies were divided into robotics in construction, safety management, and project performance monitoring, with the latter two focusing on workers or humans.

Another study shed light on the importance of increasing DT and cyber-physical systems' deployment in the construction industry and described the integration of emerging technologies with the physical systems as the next generation DT for improving workforce productivity, health, and safety, lifecycle management of building systems, and workforce competency (Akanmu et al. 2021). The study also explored enabling technologies for next generation DTs, which included virtual design and modeling technologies, sensing technologies, data analysis techniques, data storage techniques, data communication technologies, human-computer interaction technologies, and robotics (Akanmu et al. 2021). A key observation by this study is that workers' ability to perform work safely can be enhanced through personalized feedback (Akanmu et al. 2021).

A study by Salem and Dragomir (2022) reviewed the literature on DT in construction project management and proposed a framework for analyzing and supervising the development of DT. They also identified three existing and envisioned stages for DT implementations in construction, the first being BIM, the second being building control techniques and applications, and the third being the development of DTs for construction projects, which is described as the improvement on the first two stages (Salem and Dragomir 2022).

Yang et al. (2024) analyzed the commonly used architectures for digital twins in construction literature and summarized the commonly used technologies to implement them. They focused on seven digital technologies, which are: artificial intelligence, machine learning, cyber-physical systems, Internet of Things, data mining, virtual reality, and augmented reality (Yang et al. 2024). They also explored how DTs can used throughout the different phases of a construction project's lifecycle, including design, construction, operation and management, and demolition and restoration (Yang et al. 2024).

In another study by (Ammar et al. 2022), interviews were conducted to understand construction practitioners' perceptions on the use and challenges of DTs. Through thematic analysis pf the collected data, they found that contractual awareness and knowledge, data understanding, preparation, and usage, financial uncertainties, human capital development, organizational structure and processes, and technology deployment were among the most commonly reported challenged for DT implementation in construction (Ammar et al. 2022).

Omrany et al. (2023) conducted a systematic literature review to understand current DT implementation in construction and explore technologies enabling their operation. They identified eight key areas of DT implementation including virtual design, project planning and management, asset management and maintenance, safety management, energy efficiency and sustainability, quality control and management, supply chain management and logistics, and structural health monitoring (Omrany et al. 2023). They also identified challenges hindering their widespread adoption in construction and recommended some measures to address these challenges.

Some studies dug deeper into how DTs can be used in specific domains in the construction industry, like Greif et al. (2020) who focused on site logistics processes, characterized by limited visibility and inefficient organization. They designed and implemented a decision support system for silo-dispatch and replenishment activities on construction sites. Their DT included order data, silo data, and truck data that are obtained from real-world processes and are analyzed to feed the decision support system with proper silo repositioning and replenishment planning (Greif et al. 2020).

From another perspective, Zhang et al. (2022) proposed a framework for utilizing DTs and extending the existing level of details (LODs) of BIM in construction site management. They analyzed and improved the operation principle and mechanism of DTs, including the BIM-based digital representation, Internet of Things, data storage, integration, and analytics, and interaction with the physical environment (Zhang et al. 2022). They also conducted questionnaires and interviews that showed that their developed framework acknowledges the contribution of LODs' extension to construction site management.

In a study focused on integrating deep learning with DTs, qualitative and quantitative analysis of collected data from interviews and questionnaires were used to develop a conceptual model of a framework that integrates deep learning and DTs (Kor et al. 2023). They also suggested the use of technologies like BIM, sensors and data communication technologies, and Internet of Things and explained the benefits of using machine learning in construction (Kor et al. 2023).

## Human-Centric Digital Twins in Construction

Given that DT implementations in construction are still in their early stages, it is unsurprising that human-centric DTs (HCDTs) in construction are even less prevalent. However, a study by (Soman et al. 2025) developed a framework for human-DT interfaces and evaluated it on a real construction project. The framework integrates a several technologies, like BIM, artificial intelligence, GIS, and real-time data sources like cameras and sensors. They found that control rooms can serve as dynamic interfaces within the DT ecosystem and highlighted the importance of real-time data visualization, user-centric design, and predictive analytics to anticipate project risks and constraints (Soman et al. 2025). Despite challenges like data integration and stakeholder adaptation, the study highlights the potential of human-centered digital twins to transform construction management through enhanced collaboration and efficiency.

Another significant contribution to the HCDT domain is the comprehensive review by Asad et al. (2023), which highlighted technologies, such as sensors, artificial intelligence, and simulation tools that enable HCDTs to monitor and optimize human performance, ergonomics, and safety. The study identified six major application areas for DTs with strong human involvement: ergonomics and safety, robotics training, user education, design validation, cybersecurity, and healthcare. By integrating real-time data from humans and machines, HCDTs can create adaptive, efficient, and safe environments.

An interesting study by Ogunseiju et al. (2021) developed a DT-driven framework for improving self-management for ergonomic risks by using wearable sensors to track the kinematics of floor framers' body segments. The proposed DT communicates the ergonomic risks via an augmented virtual replica, revealing the potentials of DTs for personalized posture training and paves the way for future research on DTs for improving construction workers' health and wellbeing.

However, despite the advancements in DT technology and its integration with human-centric approaches, existing research in the construction industry primarily focuses on technological innovations, such as BIM, IoT, and predictive analytics, with limited attention to the comprehensive incorporation of human factors within DT ecosystems. Current studies highlight the potential of HCDTs in optimizing safety, ergonomics, and performance through real-time monitoring and adaptive measures. However, some gaps remain in developing standardized frameworks that integrate human physiological, behavioral, and cognitive data with construction processes to enable human-centered solutions that are tailored for human needs. As a result, current research directions struggle to translate human-centered digital twin concepts into scalable and ethically governed real-world implementations, limiting their practical impact on worker-centered safety and operational decision-making. To address this gap, this research proposes a novel HCDT framework that incorporates wearable devices, IoT sensors, and advanced analytics to create personalized digital representations of workers. This framework aims to enhance worker safety, productivity, and well-being by providing adaptive, real-time insights and predictive capabilities tailored to the dynamic nature of construction sites. This study aims to lay the groundwork for the development and practical implementation of HCDTs in construction.

# Methodology

This study follows a conceptual research approach to develop a Human-Centric Digital Twin (HCDT) framework for construction, integrating insights from digital twin models, human-computer interaction, and construction safety research. A literature review was conducted to identify existing digital twin research in construction and key gaps in their implementations. Afterwards, a three-layer conceptual framework was developed, aligning with existing DT architectures while incorporating novel human-centric enhancements. Building on this framework, a structured implementation roadmap was also developed to translate the conceptual HCDT model into a practical, phased deployment strategy that addresses technical, organizational, ethical, and human factors associated with real-world adoption. While this study presents a conceptual model, the proposed roadmap provides guidance for future pilot implementations and empirical validation, including assessing the effectiveness of real-time physiological monitoring, adaptive safety interventions, and AI-driven workforce optimization in construction environments.

# Conceptual Framework for HCDT in Construction

In the process of developing the conceptual framework for an HCDT, three layers that will form the overall structure of the framework are identified. The three layers are (1) a data collection and acquisition layer, (2) a data processing and analysis layer, and (3) a decision-making and feedback layer (Figure 1).

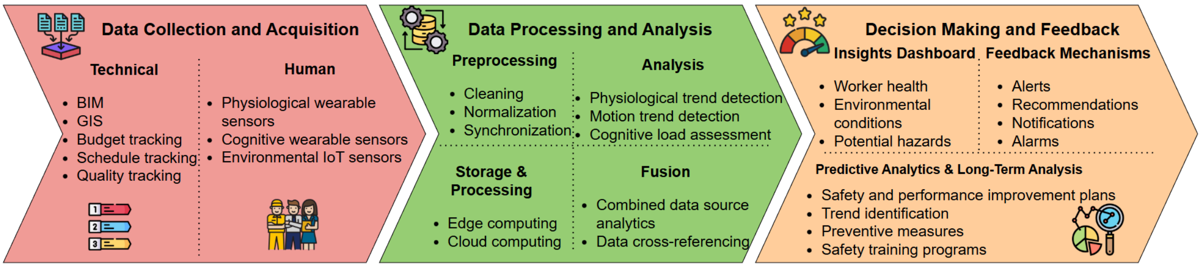


**Figure 1. HCDT Conceptual Framework Layers**

## Data Collection and Acquisition Layer

The data collection and acquisition layer includes some key components that are needed to ensure a comprehensive and reliable system. In this layer, traditional components of a construction DT are included, such as Building Information Modelling (BIM), Geographic Information Systems (GIS), and real-time data sources for schedule, budget, and quality tracking and measurement. These measurements are used provide continuous updates on construction site conditions, equipment status, and structural integrity. The traditional components enable building the foundation of digital representation in construction projects by integrating various data sources from the physical system to reflect real-world conditions dynamically.

However, in an HCDT, this layer extends beyond traditional DT elements to incorporate physiological behavioral, cognitive, and even environmental data collected from workers working on the project in real-time. To achieve this, additional data sources that involve the state, wellbeing, and health of the workers are deployed to bridge the gap between digital modelling and human factors.

First, to ensure real-time monitoring of the physiological, behavioral, and cognitive data of project members, wearable sensors are key (Shehab et al., 2025). Wearable sensors can be used to collect physiological data in real-time, which can later be translated into meaningful information regarding each member's psychological, behavioral, and cognitive states. This information is essential for determining each worker's physical and mental readiness, identifying stress or fatigue levels, and optimizing task assignments based on individual capabilities. For example, Electrocardiogram (ECG), Photoplethysmogram (PPG), and Electrodermal activity (EDA) can be used to assess stress (Lee & Lee, 2024)(Lee & Lee, 2024), fatigue (Lee et al., 2024)(Lee et al., 2024), risk perception (Lee et al., 2021)(Lee et al., 2021), and workload (Shehab & Hamzeh, 2023). Electromyography (EMG) sensors also have good potential in tracking muscle activity and fatigue, which helps in assessing ergonomic risks among workers and project members

(Shehab & Hamzeh, 2024). Skin temperature sensors can also be used to measure temperature variations that may indicate physical exertion, stress (Lee & Lee, 2024)(Lee & Lee, 2024), or potential heat exhaustion, which is a common and possible risk on many construction sites. Moreover, blood oxygen monitors can be utilized to ensure proper oxygen levels, especially in hazardous environments with poor ventilation. Finally, eye-tracking sensors can be used to monitor visual attention, providing insights into situational awareness and risk assessment abilities.

Second, while wearable sensors can be used to monitor human conditions, environmental sensors can be deployed across construction sites to monitor environmental conditions, such as temperature, noise levels, and air quality, which can impact workers' performance and safety. For example, temperature and humidity sensors can be used to prevent possible accidents emerging from extreme cold or heat conditions. Air quality sensors can also be employed to measure dust, $CO_2$, Volatile Organic Compounds (VOCs), and other pollutants that are commonly found in construction sies, in order to mitigate respiratory risks. Next, noise sensors may be used to monitor excessive noise levels arising from heavy machinery and construction equipment, which may cause hearing loss or cognitive fatigue. Light sensors are also an essential tool that can be used to detect inadequate lighting conditions, especially in night shifts, which could lead to eye strain or accidents. Finally, gas sensors can be used to identify hazardous gases such as methane and carbon monoxide, triggering safety protocols in enclosed spaces.

## Data Processing and Analysis Layer

Ater data collection, data processing and analysis is key to transform raw data into meaningful information. This layer integrates advanced computing technologies, including Artificial intelligence (AI), machine learning (ML), and computer simulations to analyze and interpret the collected data.

The first step in this layer is data aggregation and preprocessing. After physiological, behavioral, and environmental data are collected, they must undergo data cleaning and synchronization to ensure accuracy and reliability. Filtering techniques can be used to remove noise, outliers, and irrelevant data caused by sensor malfunctions, signal errors, or external interferences. Normalization is also performed to ensure consistency across the different sensor types and units. Finally, synchronization is performed to align multiple sensor data streams, such as heart rate variability with environmental temperature, to provide a holistic understanding of the workers' physical and cognitive conditions.

Once the data is preprocessed, ML algorithms are used to analyze the complex datasets and to detect patterns and trends among the preprocessed data. These models are used to evaluate and detect trends in vital physiological markers, such as heart rate variability (HRV), EDA, and skin temperature fluctuations. They are also used to detect patterns in motion tracking data to identify inefficient body movements, unsafe postures, or repetitive strain that could potentially lead to musculoskeletal injuries. Additionally, cognitive load assessment techniques analyze brainwave activity and eye movement patterns to determine a worker's level of attention, focus, and situational awareness.

Beyond individual assessments, data fusion techniques combine multiple sensor inputs in order to enhance the reliability and accuracy of the processed data. By integrating physiological, behavioral, and environmental data, a more comprehensive understanding of worker conditions is achieved, ensuring that single data sources are not interpreted in isolation. Multi-sensor data fusion methods enhance the accuracy of fatigue detection by corroborating findings from heart rate variability with electrodermal activity and motion tracking. Similarly, environmental hazard assessment is strengthened by cross-referencing temperature and air quality sensor readings with physiological stress indicators, improving the reliability of risk evaluations.

To support real-time data interpretation, processing occurs at multiple levels: (1) Edge computing, on one hand, enables immediate **local** analysis of sensor data on-site, allowing for continuous monitoring of workers and site conditions with minimal latency (Bajic et al., 2019). This ensures that physiological and environmental data are processed without significant delays, allowing for real-time assessments of stress, fatigue, and exposure to harmful conditions. (2) Cloud computing on the other hand, facilitates **long-term storage** and analysis, enabling pattern recognition over **extended periods** and improving the precision of predictive models (Bajic et al., 2019). The employment of both based analysis techniques refines machine learning algorithms by continuously learning from new data while improving the accuracy of physiological and environmental risk assessments over time.

## Decision Making and Feedback Layer

The decision making and feedback layer is the final component of the proposed HCDT conceptual framework. It is responsible for translating the processed data into suggestions for decisions, interventions, or even corrective and preventive measures.

At the core of this layer is the decision support system (DSS), which provides real-time insights into worker health, environmental conditions, and potential hazards. The DSS consolidates output from AI and ML models to generate situational awareness dashboards for project managers, safety officers, and site supervisors. These dashboards display real-time physiological and cognitive conditions of workers, environmental risk levels, and predictive safety alerts, which allows decision-makers to implement timely interventions. For example, if environmental sensors detect elevated levels of harmful gases, automatic safety alarms can be triggered, including ventilation adjustments or site evacuations.

In addition to decision-making level interventions, this layer incorporates automated feedback mechanisms that deliver real-time alerts and recommendations directly to workers and site supervisors. These feedback mechanisms can take multiple forms, such as wearable device notifications, mobile alerts, or audible site alarms, ensuring that safety recommendations are effectively communicated. For example, if motion tracking sensors detect an unsafe posture, workers may receive instant haptic or vibrational feedback through their wearable devices, prompting them to adjust their movements to prevent injury. Similarly, if AI models predict high levels of cognitive overload, workers may receive an alert advising them to take a short mental break before resuming high-risk activities. These interventions are more personalized to ensure that safety and well-being measures are seamlessly integrated into daily construction activities.

A key aspect of this layer is also the incorporation of predictive analytics and long-term trend analysis. This enables construction firms to develop strategic safety and performance improvement plans. By analyzing historical data on worker stress levels, fatigue patterns, and environmental exposures, the models can identify trends that contribute to accidents and inefficiencies over time. This allows decision-makers to implement preventative measures, refine safety training programs, and optimize shift schedules based on data-driven suggestions.

To further enhance decision-making effectiveness, Human-In-The-Loop (HITL) integration is incorporated into the feedback loop, allowing for human oversight and judgment in critical situations. HITL, which is a sub-discipline of Human-Computer Interaction (HCI), refers to systems that enable direct human intervention during AI model operations (Wilchek et al., 2023). It combines AI and automation with human decision-making, ensuring that complex processes benefit from both computational efficiency and human expertise. In the context of the proposed HCDT, HITL allows construction site decision makers, like supervisors and safety managers, to interact with AI-driven insights, validate automated recommendations, and make informed adjustments based on real-world conditions. While AI and automation can provide risk detection recommendations, supervisors retain the ability to override automated recommendations based on contextual knowledge and on-site conditions. This balance between automation and human expertise ensures that decision-making remains both data-driven and adaptable to complex and real-world scenarios.

# HCDT Implementation Roadmap

An implementation roadmap (Figure 2) is designed to translate the proposed HCDT framework into a structured and practical deployment strategy for construction projects. It outlines a phased approach that enables gradual adoption while addressing technical, organizational, ethical, and human factors. The roadmap emphasizes starting with limited, high-impact use cases, building worker trust through transparency and governance, and maintaining HITL decision-making to ensure that AI-driven insights remain context-aware and ethically grounded. The proposed phases move from organizational readiness to pilot implementation, evaluation, scaling, and enterprise-wide institutionalization.

## Phase 0: Readiness, Governance, and Use-Case Selection

### 0.1 Define “why now” and choose primary use cases

The first step in implementing an HCDT is to establish a clear organizational rationale for adoption and to select a limited number of high-impact use cases. These use cases should address pressing safety or operational challenges, rely on measurable indicators, and enable actionable interventions. Suitable initial applications include heat stress and dehydration risk management, fatigue and cognitive overload monitoring for high-risk tasks, and exposure management for dust or air quality hazards. By focusing on a small set of well-defined use cases, organizations can demonstrate early value, minimize complexity, and refine the system before broader deployment.

### 0.2 Stakeholder mapping and operational ownership

Successful HCDT deployment requires clearly defined roles and responsibilities across project stakeholders. Senior leadership provides strategic sponsorship and resource allocation, while site superintendents and construction managers oversee daily integration. Safety managers define intervention thresholds and response protocols, worker representatives ensure co-design and trust, and data stewards manage privacy and governance. Digital and BIM leads integrate project context, analytics teams manage model performance, and Information Technology (IT)/Operational Technology (OT) engineers maintain the technical infrastructure. Establishing this ownership structure prevents the system from being perceived as a purely technological experiment and embeds it within operational workflows.

### 0.3 Governance, privacy, and consent design

Because HCDTs rely on physiological, behavioral, and environmental data from workers, governance must be established before any data collection begins. Privacy-by-design principles should define the purpose of data use, limit collection to what is strictly necessary, and ensure transparency about how data are processed and accessed. Participation should initially be voluntary to foster trust, and retention periods for raw data should be minimized. Supervisors should view only risk indicators rather than raw biosignals, and workers should be able to review system inferences about them. Clear procedures for data access, appeals, and overrides help protect worker rights while enabling responsible system use.

### 0.4 Baseline definition and success metrics

Prior to implementation, baseline measurements should be established to evaluate the impact of the HCDT. Safety indicators may include heat-related symptoms, near-miss rates, or exposure levels, while operational metrics can track unplanned stoppages or task interruptions. Human-centered measures, such as worker acceptance, perceived intrusiveness, and trust, are equally important. Model performance metrics, including false alarm rates and detection accuracy, support technical validation. Defining these benchmarks enables objective assessment of benefits and informs future system refinements.

## Phase 1: Minimum Viable HCDT Pilot

The next step would be selecting a “minimum viable” HCDT pilot scope. It should be conducted in a controlled but realistic environment, such as a single construction site or work zone, involving a limited group of voluntary participants across different roles. Including multiple shift types and environmental conditions ensures meaningful variability in the data. High-risk tasks and dynamic site conditions are prioritized to maximize learning. This targeted scope allows organizations to test feasibility without disrupting broader project operations.

Next, the initial sensing configuration should remain simple and minimally intrusive. Wearable devices capable of measuring heart rate and heart rate variability can provide reliable indicators of fatigue and stress, while environmental sensors can monitor temperature, humidity, and dust levels in key zones. A ruggedized edge gateway collects and buffers sensor data, ensuring continuity during connectivity disruptions. This setup enables real-time monitoring while limiting technical complexity and worker burden.

In terms of data pipeline and architecture, data collected from wearables and environmental sensors are transmitted to an edge gateway, where preliminary filtering, feature extraction, and threshold-based risk detection occur. Time-critical alerts are processed locally to minimize latency, while cloud-based systems support long-term storage, advanced analytics, and model training. Data are organized into separate repositories for raw signals, processed features, and intervention logs. Integration with BIM and scheduling systems is initially limited to zone-level mapping to reduce privacy concerns and implementation effort.

For HCDTs to produce practical value, alerts must be linked to clear and feasible actions. Interventions are organized into tiers, ranging from personal prompts to supervisor notifications and safety escalations. For example, heat stress alerts may trigger hydration reminders, shaded rest breaks, or task rotation suggestions, while air quality exceedances may prompt ventilation adjustments or PPE reinforcement. Any interventions affecting task assignments or work restrictions require HITL confirmation to ensure contextual judgment and accountability.

Finally, effective onboarding is essential for worker acceptance. Training sessions explain what data are collected, how risks are inferred, and how privacy is protected. Workers are provided with access to simplified dashboards summarizing recent alerts and trends. Anonymous feedback channels allow participants to report discomfort or false alarms. Device comfort and compatibility with PPE are regularly assessed to ensure that monitoring does not interfere with safety or productivity.

## Phase 2: Pilot Evaluation and Iteration

In this phase, the HCDT undergoes technical and human factors evaluations, in addition to a redesign cycle.

The technical performance of the HCDT is assessed by examining data completeness, system latency, gateway uptime, and sensor calibration stability. Identifying connectivity gaps, device failures, or data synchronization issues helps refine the infrastructure and ensures reliable real-time monitoring.

Even simple threshold-based models require evaluation to identify false positives and false negatives. Alerts are reviewed against observed site conditions, incident reports, and contextual factors such as weather or task type. This analysis supports threshold adjustment and helps prevent unnecessary or misleading interventions.

In terms of human-factor evaluation, worker acceptance, supervisor workload, and trust in the system are evaluated through surveys and interviews. If alerts are perceived as intrusive or overwhelming, their frequency, format, or delivery method may be adjusted. Ensuring that the system supports rather than disrupts daily operations is critical for long-term adoption.

Based on evaluation results, the redesign cycle focuses on refining alert thresholds, simplifying dashboards, and updating intervention playbooks to better match site realities. Interpretability is improved by explaining why specific alerts were triggered. This iterative cycle ensures that the HCDT evolves in response to both technical performance and human feedback.

## Phase 3: Scale to Multi-Crew and Multi-Zone HCDT

Once feasibility is demonstrated, the HCDT can be expanded to additional crews, zones, and use cases. Redundancy is introduced through backup gateways and automated device health monitoring. Standardized procedures for device charging, cleaning, and replacement support operational reliability.

Integration with BIM and scheduling systems becomes more systematic, enabling zone-specific hazard mapping and activity-based risk sensitivity. Safety management systems incorporate HCDT insights into toolbox talks and near-miss reporting. This alignment embeds HCDT outputs within established project control processes.

Additionally, governance structures are formalized through data access committees, periodic audits, and transparency reports. These mechanisms ensure that data use remains consistent with stated purposes and that workers are informed about how their data contribute to safety and performance improvements.

As data maturity increases, predictive machine learning models can complement rule-based thresholds. Drift monitoring and retraining schedules maintain model reliability, while HITL oversight ensures that automated recommendations remain context-sensitive and ethically appropriate.

## Phase 4: Enterprise-Level Deployment and Cross-Project Learning

Finally, at the enterprise level, HCDT data enable cross-project comparisons of exposure patterns, intervention effectiveness, and systemic risk drivers. Insights from multiple sites inform improvements in shift design, work packaging, and safety planning at an organizational scale.

With sufficient trust and maturity, advanced applications such as digital worker avatars, simulation-based planning, or integration with assistive technologies may be introduced. These capabilities are deployed selectively and supported by strong safety and ethical justifications.

Eventually, HCDT adoption is institutionalized and becomes part of standard project initiation procedures, with formal safety cases required for high-risk projects. Continuous improvement loops, including regular review boards and threshold tuning, ensure that the system remains adaptive, transparent, and aligned with evolving project needs.

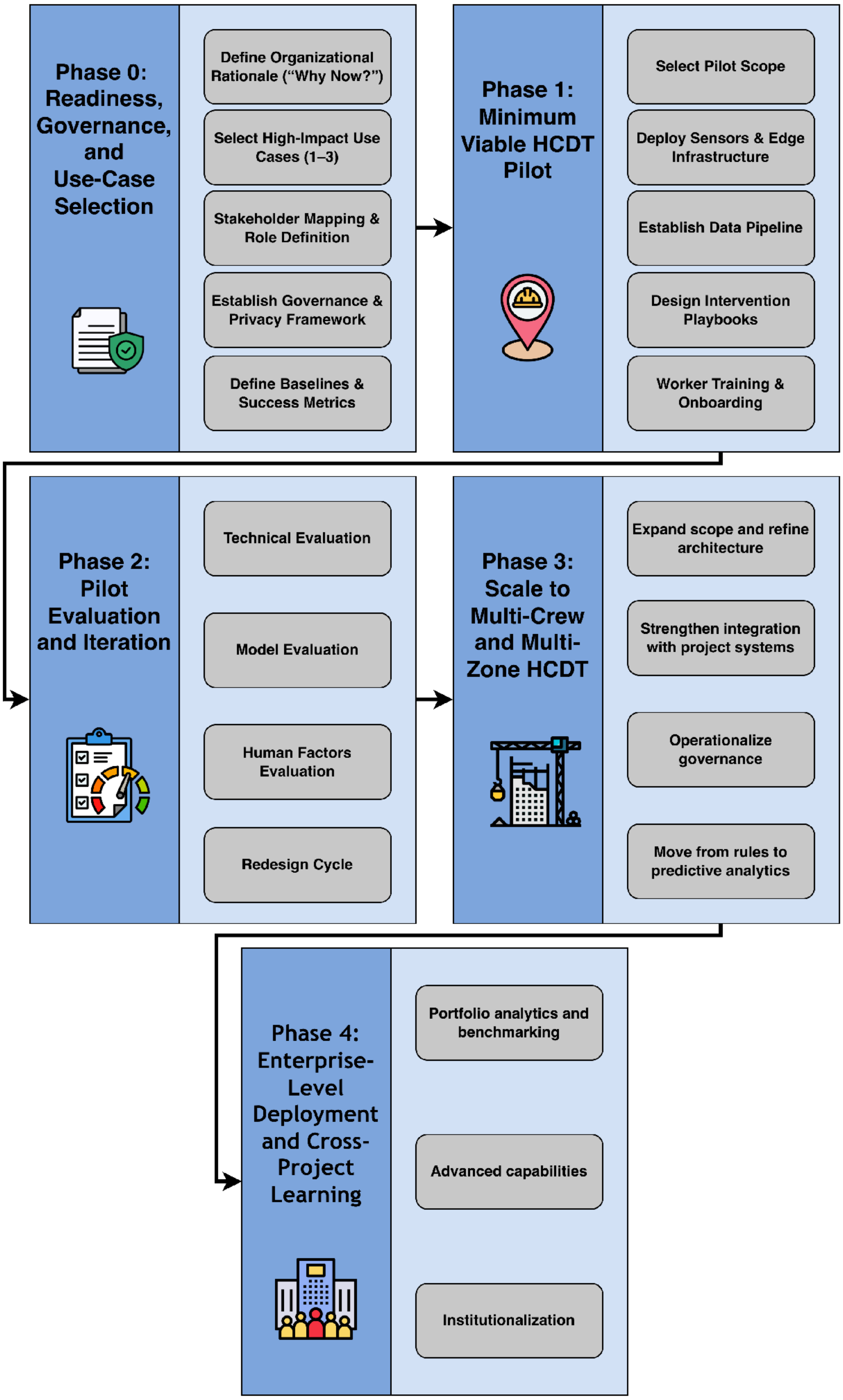


Figure 2. Implementation Roadmap

# Implications of HCDTs in Construction

In general, digital twins in construction and the built environment can aid in improving workforce productivity, health, and safety, which leads to enhanced facility management and workforce proficiency and reduced construction and operation costs (Ammar et al., 2022). Their applications range from structural performance (Majumdar et al., 2013) to structural health management (Hochhalter et al., 2014), work environment safety (Fotland et al., 2020), and more (Opoku et al., 2021).

In the context of HCDT, implications gain a broader scale thanks to the human-centered aspect that they possess. With the proposed three-layer conceptual framework, more transformative possibilities beyond traditional workforce monitoring and safety management can be provided. HCDTs introduce a paradigm shift that extends the role of digital intelligence into human well-being, cognition, and adaptive workforce dynamics by providing instant interventions reinforced by human supervision through HITL systems.

## Personalized AI-driven Work Environments

Traditional construction environments treat workspaces as static, with no adaptation to human needs. HCDTs could revolutionize this concept by proposing construction sites that are self-regulating, which means that they dynamically adjust environmental conditions based on real-time collected human physiological data. This could be translated into smart construction sites where sensors detect workers' fatigue levels and automatically adjust lighting, ventilation, or temperature to optimize performance and well-being. Noise-canceling zones could be activated when stress levels rise, and AI-driven ergonomic interventions could adapt workstations to minimize strain and prevent long-term injuries.

## Cognitive Load Balancing for High-risk Tasks

Cognitive fatigue is one of the most underestimated risks in construction, which often leads to errors, miscalculations, and accidents (Eltahan et al., 2025). By integrating real-time cognitive and eye-tracking data, HCDTs could predict cognitive fatigue and optimize work schedules accordingly. Workers involved in high-risk tasks, such as crane operation, welding, or working at extreme heights, could be assigned to tasks based on their real-time mental alertness and cognitive endurance, rather than a rigid or fixed pre-planned schedule.

## Digital Twin Avatars for Workforce Simulation and Optimization

HCDTs allow for the development of AI-generated digital worker agents or avatars that can simulate and predict workforce behavior under different site conditions. These avatars, built based on real-time physiological and behavioral data, could be used to model how workers respond to different stressors, shifts, and workloads over time. Decision makers could run predictive computer simulations, such as agent-based simulations, to determine the best team compositions for high-stress environments, ensuring that the most cognitively and physically capable individuals are assigned to critical tasks and at the right time.

## Emotionally Responsive Construction Management

Current construction safety models focus on physical and cognitive well-being, often neglecting the emotional and psychological states of workers. HCDTs could analyze emotional biomarkers such as voice tone and facial expressions to assess worker morale and well-being. This would allow decision makers to detect burnout, dissatisfaction, or anxiety in real-time, which enables emotional interventions such as automated mental health support or dynamic workload adjustments to prevent emotional exhaustion.

## Autonomous Risk Prevention and Worker Assistance Drones

HCDTs could also integrate with AI-powered drones that can assist workers based on real-time physiological and environmental data. For example, drones could deliver water bottles or oxygen masks to workers experiencing dehydration or heat exhaustion. In hazardous environments, drones could deploy smart safety nets or provide real-time visual guidance using augmented reality overlays, assisting fatigued or cognitively overloaded workers in executing complex tasks safely. These autonomous systems would act as an additional safety net, ensuring that early warning signs of worker distress trigger immediate physical assistance rather than mere alerts.

## Physiological Interventions through Exoskeletons

HCDTs could further enhance worker safety and performance by integrating exoskeletons that respond to real-time physiological data. Traditional construction work often leads to musculoskeletal strain, fatigue, and repetitive stress injuries, especially in physically demanding tasks such as lifting heavy materials, operating power tools, and prolonged standing or bending. By using wearable exoskeletons, HCDTs could provide adaptive physical support by reducing fatigue and injury risks.

With real-time monitoring of muscle activity, heart rate variability, and stress levels, exoskeletons could dynamically adjust their level of mechanical assistance based on worker fatigue and task intensity. For example, if an HCDT detects that a worker's muscle fatigue is increasing, the exoskeleton could automatically engage additional support to reduce strain on the worker’s body. Additionally, AI-powered exoskeletons could provide postural correction feedback, ensuring that workers maintain proper lifting techniques and ergonomic postures.

## Applications of HCDTs Across Construction Phases

While the primary focus of HCDTs is real-time site monitoring, their impact extends beyond active construction. Pre-construction planning, real-time execution, and post-construction phases can benefit from an integrated human-centric approach. Before a project begins, HCDTs can simulate various workforce conditions and team compositions to optimize task assignments. By analyzing historical physiological and cognitive data, AI could determine which workers are best suited for high-pressure roles, ensuring that physically-demanding tasks are assigned appropriately. During the construction phase, HCDTs can monitor human factors and site conditions simultaneously. AI-powered adaptive scheduling algorithms could dynamically reassign tasks based on real-time stress, fatigue, and attention levels. In hazardous environments, workers could receive haptic feedback on their smart wearable devices, proactively alerting them of risks before they become too critical or dangerous. The use of HCDTs does not end once construction is completed. After execution, HCDTs can contribute to sector-wide research and policy developments, helping organizations understand how construction work affects long-term worker health, cognitive function, and career satisfaction.

## Conclusions

This paper proposed a HCDT conceptual framework for construction, addressing the gap in traditional digital twins that focus primarily on structural and operational aspects of projects while neglecting the human workforce. A three-layer conceptual framework was developed, integrating various sensors for human and environmental conditions monitoring. AI-driven data processing was suggested for risk assessment and accident prevention, and a decision-making layer incorporating predictive analytics and HITL insights was designed. In addition, a structured implementation roadmap was introduced to guide the practical deployment of the proposed HCDT framework across different organizational maturity levels. These contributions aim to enhance worker safety, productivity, and risk management in construction projects by systematically integrating human factors into digital twin systems.

The implications of the proposed framework extend beyond conventional project monitoring and control by enabling AI-driven adaptive work environments, cognitive-based task allocation, and predictive safety interventions. It supports real-time optimization of working conditions by reducing fatigue-related accidents, enhancing decision-making, and fostering emotionally responsive construction management approaches. The implementation roadmap further strengthens these implications by providing construction organizations with a clear, phased pathway for adopting HCDTs while addressing governance, privacy, and workforce integration challenges. Additionally, the framework's potential integration with autonomous safety drones, exoskeletons, and digital worker avatars paves the way for next-generation, human-optimized construction sites.

Despite its contributions, this study remains conceptual and has not been empirically tested. The lack of real-world implementation and validation presents a limitation, as the feasibility of integrating wearable sensors and AI-driven decision-making into construction workflows remains unverified. While the proposed roadmap offers practical guidance, its effectiveness in real project environments has yet to be assessed. Furthermore, challenges such as data privacy, worker acceptance, cost constraints, and industry resistance to digital transformation must be addressed before widespread adoption can occur.

Future research should focus on pilot studies and experimental validation of both the HCDT framework and the proposed implementation roadmap in real construction environments. This includes testing the accuracy and reliability of physiological and cognitive monitoring, refining AI algorithms for predictive risk assessment, and evaluating the impact of adaptive task allocation on worker efficiency and safety. Further exploration of cybersecurity measures, ethical considerations, and regulatory frameworks will also be essential to ensure the responsible and appropriate deployment of HCDTs. By bridging conceptual development with a structured path to implementation, this study provides a foundation for advancing human-centered digital transformation in construction. HCDTs have the potential to reshape construction safety and workforce management, paving the way for smarter, more adaptive, and human-centric construction ecosystems.

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