Developments in the Built Environment 14 (2023) 100143

Contents lists available at ScienceDirect

Developments in the Built Environment

journal homepage: www.sciencedirect.com/journal/developments-in-the-built-environment

Dynamic human systems risk prognosis and control of lifting operations during prefabricated building construction

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ARTICLE INFO

Keywords:
Dynamic human systems
Risk control
Lifting operation
Modular construction

ABSTRACT

Prefabricated building construction (PBC) involves tedious lifting operations that require multiple cranes to work simultaneously in dynamic workspaces. Such operations involve frequent interactions among human, cyber, and physical environments, creating challenges for risk prognosis and control in dynamic contexts. Unfortunately, human errors pose challenges for achieving resilient lifting operation control. A dynamic human systems risk prognosis and control (DHS RP & C) approach is thus necessary for 1) capturing human errors and 2) controlling risks of human anomalies proactively. This study critically reviews opportunities and challenges for establishing the proposed approach. Challenges exist as 1) how to collect human/team behavior data during lifting operations, 2) how to analyze these data for comprehending the impacts of human factors, and 3) how to respond to operational contingencies with risk control measures. In the end, the authors established a research roadmap for guiding future research activities toward automated lifting operations in PBC.

1. Introduction

Prefabricated building construction (PBC) is now favored by construction practitioners, given its unique advantages for ensuring construction safety and efficiency (Okodi-Iyah, 2012). Typical PBC requires 1) the production of prefabricated building components offsite and 2) the lifting and assembly of prefabricated components using tower cranes onsite (Goh and Goh, 2019). Compared to traditional construction methods (e.g., cast-in-place), PBC requires only lifting and assembly of prefabricated building components on job sites. Typical lifting operations use multiple cranes operated by different teams to work simultaneously in dynamic workspaces with hectic schedules. Each crane operation team includes one crane driver with multiple ground personnel. In the current practice of PBC, rigorous procedures and requirements have been developed to ensure construction safety. Besides, all lifting personnel is to ensure construction safety. All lifting personnel is well-qualified for lifting operations in PBC. Unfortunately, evidence shows that human factors at both individual and team levels could still jeopardize the safety and efficiency of lifting operations. For example, the Bureau of Labor Statistics research found that human errors cause 90% of injuries in crane accidents (Okodi-Iyah, 2012). In addition, lifting operations during prefabricated building construction (PBC) are facing more unique challenges compared to other lifting operation scenarios of traditional construction projects (e.g., cast-in-place construction). For example, PBC involves tedious lifting operations that require multiple cranes to work simultaneously in dynamic workspaces. Such lifting operations require lifting and moving a significant amount of prefabricated building components on site. Besides, the weight and volume of these components are usually larger than those of traditional lifting objects, which brings significant challenges to the lifting operations of PBC. Moreover, lifting operations during PBC also involve the installation of prefabricated building components. Maintaining certain postures and positions of building components during lifting operations is vital for precise and effective installations. Hence, the human behaviors of crane drivers and other lifting operation personnel on the ground are vital for ensuring safe and effective lifting operations during PBC.

Previous studies have conducted extensive efforts to synthesize human factors that cause accidents during lifting operations. Besides, practitioners have implemented various control strategies during safety training for mitigating risks induced by human factors based on historical accident records. However, existing practices and knowledge capture limited dynamic human and workspace factors during frequent H-CPS interactions during lifting operations of PBC. Hence, human

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https://doi.org/10.1016/j.dibe.2023.100143
Received 6 January 2023; Received in revised form 16 February 2023; Accepted 6 March 2023
Available online 13 April 2023

performance deteriorations in dynamic contexts still need further investigation because these dynamic human systems issues cause accidents and near-misses during lifting operations of PBC. For example, fatigue and omission errors could occur with the decaying of human perception and reaction capability in processes with varying workloads in changing workspaces. At the team level, communication errors may jeopardize team situation awareness and performance during lifting operations involving moving objects and human reactions.

Given the dynamic human systems challenges mentioned above, a dynamic human systems risk prognosis and control (DHS RP & C) approach for risk prognosis and control of lifting operations is necessary to 1) capture anomalous human behaviors during lifting operations, 2) examine impacts of human reliability issues on the performance of lifting operations, 3) simulate and predict the impacts of such captured anomalies on lifting operation safety and efficiency, and 4) examine various control strategies for mitigating the impacts of captured human anomalies. Still, challenges exist for systematically implementing appropriate DHS sensing techniques and artificial intelligence (AI) algorithms for achieving DHS RP & C for safe and efficient lifting operations in PBC (Hodges and Sanders, 2014).

Typical lifting operations usually involve multiple tower cranes and lifting personnel simultaneously. Multidimensional interactions among humans, cyber (e.g., technologies, algorithms, data, etc.), and physical environment occur during lifting operations of PBC. Inappropriate executions of scheduled lifting activities or communication errors could lead to severe accidents and near-misses. Establishing a DHS RP & C approach for predictive risk control of lifting operations is thus vital for ensuring the safety of PBC (shown in Fig. 1). However, the system dynamics within the DHS RP & C pose several challenges to capturing the system behaviors and achieving predictive control. Fig. 1 shows that dynamic interactions pose unique challenges for collecting data that captures these interactions. For example, ground lifting personnel must strap and tie the prefabricated components properly to ensure the lifting processes' stability and safety. In addition, lifting personnel needs to exchange information about field discoveries through radio communications or flag signals and make timely decisions based on the discovered anomalies. Besides, crane drivers must continuously monitor numerous digital indicators on the control panel and the changing job site environment during lifting operations. Examining all such digital indicators for discovering operation anomalies is vital for mitigating collision and falling risks during lifting operations. The central command staff needs to monitor the lifting process and identify anomalies based on the data transmitted from tower cranes.

The proposed DHS RP & C investigation has two goals. The first goal is to synthesize DHS data collection, processing, and anomaly detection techniques and algorithms targeting lifting operation personnel (Section 3). This goal is trying to answer three questions, 1) *what data needs to be collected for examining DHS behaviors*, 2) *how to capture numerous DHS behaviors*, and 3) *how to detect anomalies of DHS during lifting operations*? The second goal is to summarize reliability analysis and risk control models that could help examine and mitigate the impacts of human factors on lifting operation safety. This goal is trying to answer two questions, 1) *how to examine the impacts of dynamic human and team reliability issues on lifting operation safety*, and 2) *how to mitigate DHS risks*? Hence, to achieve these two goals, the authors established the following objectives, 1) collecting dynamic human systems data during lifting operations (Section 3.1), 2) capturing and mining of human and team behaviors (Section 3.2), 3) detecting anomalous human and team behaviors through anomaly detection methods (Section 3.3), 4) examining the impacts of dynamic human systems reliability issues on lifting operation safety and efficiency (Section 4.1), and 5) establishing proactive risk control policies for optimizing lifting operation control actions (Section 4.2).

In the proposed DHS RP & C system, human behaviors of tower crane drivers and ground personnel occur during H-CPS interactions and could be captured. On the one hand, the inappropriate wearing of personal protective equipment (PPE) (e.g., hard hat, safety vest) of ground personnel and crane drivers should be identified in time to send out alert messages and request immediate corrections. Besides, capturing the interactions between humans, cyber components, and the physical environment needs effective data collection techniques for collecting DHS data (e.g., visual data, log data, audio data, biometric data, etc.). Besides, the proposed system should also capture the body postures, head poses, and facial expressions of ground personnel and crane drivers to capture human behavior anomalies. On the other hand, audio data (i.e., communications), biometric data (i.e., temperature, blood pressure, and heart rate), and log data (i.e., control actions) are also vital for comprehending the physical and psychological conditions of all lifting operation personnel. Then, using such captured H-CPS interactions shall provide data support for risk assessments and control policy optimization during crane operations.

Following this introduction, Section 2 synthesized the motivation and potentials for conducting this literature review based on recent development of PBC and human factors studies in the civil engineering domain. This section also illustrates the three types of interactions within the H-CPS during lifting operations of prefabricated buildings, including human-human (HH) integrations (i.e., communications), human-physical (HP) integrations (i.e., operations), and human-cyber (HC) interactions. According to the identified three types of human-cyber-physical interactions and related human risks during lifting operations, Section 3 synthesized potentials and challenges from literature with a focus on dynamic human-systems behavior data collection and anomaly detection methods targeting personnel during lifting operations of prefabricated buildings. Section 4 summarizes the dynamic human systems reliability analysis models for examining reliability issues during lifting operations at individual and team levels. This section

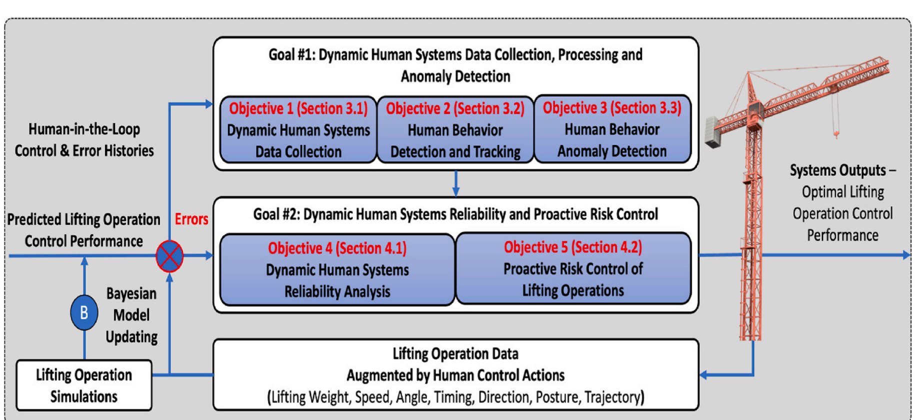

Fig. 1. Dynamic human systems risk prognosis and control (DHS RP & C) of lifting operations.

also synthesizes process modeling, simulation techniques, and control measures for safe lifting operation control. Section 5 presents the findings associated with human factors in lifting operations discovered in previous sections. Focusing on the identified challenges from the previous section, the developed research roadmap aims to guide future research activities for addressing the identified challenges toward DHS RP & C of lifting operations in PBC. Section 6 concludes this paper by emphasizing the fundamental challenges for achieving DHS RP & C in lifting operations of prefabricated buildings. Ultimately, the authors envision the transformation from automation to autonomy during construction.

2. Literature review – a perspective of dynamic human systems reliability for resilient control of lifting operations

This section illustrates the background for motivating the proposed study on dynamic human systems risk prognosis and control (DHS RP & C) of lifting operations during PBC. Section 2.1 shows the recent developments of PBC and illustrates the domain requirements, techniques, and challenges encountered in various PBC around the world. This section also demonstrates various human factors that cause accidents and fatalities during PBC. Section 2.2 illustrates the classified three types of DHS reliability in lifting operations.

2.1. Human factors in prefabricated building construction (PBC)

Lifting operations during PBC involve many interactions between humans, cyber processes, and physical environments. All such interactions are vital for ensuring safe and effective lifting operations. Human factors during such interactions should be identified and extensively examined to comprehend the impacts on lifting operation safety and efficiency (Wang et al., 2022). For example, communications among the commander, the tower crane driver, and ground personnel are critical information exchange processes for delivering lifting operation commands and reporting field discoveries. Communication errors could occur that jeopardize the entire lifting process. Besides, fatigue and high workload could also affect human performance during lifting operations. Table 1 below summarizes the human factors behind the most common accidents and near misses during lifting operations.

Human system engineering (HSE) is defined as a new interdisciplinary subject that aims to study the multidimensional interaction of Human-Cyber-Physical-Systems (H-CPS) (Niu, 2020–09). In addition, this emerging discipline aims to study the impact of various human factors in many engineering scenarios and human reliability issues. The subject has been systematically studied in many industries (Li et al., 2021a). Several studies have examined HRA models to examine the impacts of numerous reliability issues (individual and team-level reliability) on the safety and efficiency of civil infrastructure operations and maintenance activities (Zhou, 2013). Some studies in the construction domain aim to investigate human errors in construction accidents to improve the safety training of construction personnel. Still, limited studies have systematically summarized technologies and algorithms for capturing various human behaviors during tedious construction processes (Gai, 2013). Challenges still exist in examining *dynamic human reliability issues* during construction. Examples of these challenges include 1) *how to collect various human and team behaviors during tedious construction processes*, 2) *how to track human behaviors and identify anomalies that could form construction bottlenecks*, and 3) *how to assess the impacts of human-related anomalies on construction safety and efficiency*.

Table 1
Summary of human factors during typical lifting operation failures (Jiang, 2020).

Types of accidents or near-misses	General human factors	Specific human factors
Collision accidents	- Communication errors - Fatigue - Perception errors - Situation awareness	- Wrong information exchanged - Extended working hours - Improper lifting operational (e.g., oblique hanging, procedure errors)
Overturning (collapse) accidents	- Communication errors	- Wrong information exchanged - Improper lifting operation
Falling accidents	- Communication errors - Situation awareness	- Wrong information exchanged - Improper lashing - Improper hook of components
Broken and folding arm accidents	- Maintenance errors - Insufficient supervision	- Improper lifting operation - Inappropriate safety monitoring
Crush accident	- Communication errors	- Wrong information exchanged - Wildcat operation

Currently, most human factors studies in the construction domain focus on 1) establishing sensing methods for capturing human behavior during construction processes, 2) establishing correlations between human factors and construction risks, and 3) optimizing construction workflows by mitigating human-related risks. For example, Ding (Ding et al., 2004) conducted a statistical analysis on the accident types, causes, and injury sites of ten thousand casualties in construction accidents in China from 1994 to 2002. Zhang (2012) established the cognitive model and cognitive failure mode of construction workers' behavior and developed the unsafe behavior recognition tool. Wei et al. (ShaominTian and Chen, 2003) explored the impacts of human factors on coal mine production systems. Huang et al. (Huang, 2013) compared the coal mine production process considering human factors using fault tree analysis and grey correlation analysis. Jiang et al. (Jiang, 2013) investigated the causality of unsafe behaviors by constructing a system dynamics model based on the overall factors and local conditions during construction. Guo (Guo et al., 2020) used the complex network theory to discover the transition mechanisms of hazardous behaviors that eventually cause accidents during subway construction. Wong (Wong et al., 2019) established a logistic regression method for analyzing relationships between accidents and the behaviors of construction workers.

In this paper, "human factors engineering", "human reliability analysis'", "human behavior", "human factors", "team cognition", "team dynamics", "team situation awareness" and "human systems engineering" as keywords for searching literature. The authors have retrieved 752 related articles published in between 2017 and 2022 from the Web of Science database. Through analysis, the research hotspot map of human systems engineering is obtained (see Fig. 2). It can be seen from the figure that most human factors studies aim to develop human behavior models for modeling human behaviors in complex engineering scenarios. In recent years, the research on human system engineering, human-computer interaction, and human-machine teaming in artificial intelligence is increasing. However, limited studies have explored the issues of dynamic human reliability in civil engineering. How DHS reliability issues affect the safety and efficiency of the construction, operation, and maintenance of civil infrastructure systems is unclear.

2.2. Dynamic human systems reliability in lifting operations

Typical lifting operations involve three operating techniques (i.e., central command system, ground operating system, and tower crane operating system) to ensure safe and effective lifting operations. Using such operating techniques requires all lifting personnel to have good team situation awareness about field discoveries and make timely decisions based on the discovered anomalies and a large amount of lifting operation data. Besides, effective coordination and collaboration among all lifting personnel are also vital for ensuring good team performance during lifting operations. Hence, various interactions exist among lifting operation personnel, cyber (e.g., technologies, algorithms, data, etc.), and physical environment in dynamic lifting workspaces. Fig. 3 shows

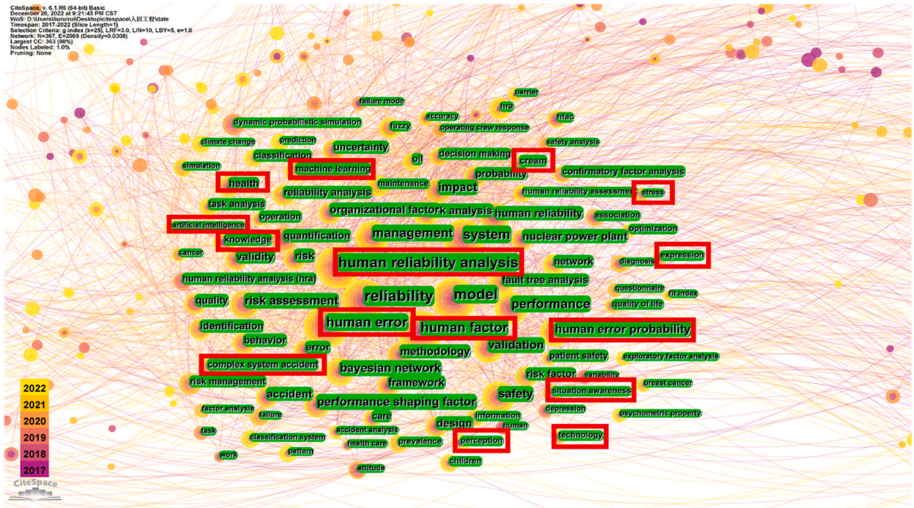

Fig. 2. A research hotspot map of human systems engineering (HSE) studies.

Fig. 3. Multidimensional interactions and data collection of DHS during lifting operations.

three types of interactions within H-CPS of lifting operations (Li et al., 2021b; Zhong et al., 2018), 1) human-human (HH) interactions (i.e., for defining the communication behaviors among multiple lifting personnel), 2) human-physical (HP) interactions (i.e., for defining the interactions when lifting personnel is interacting with the physical environment), and 3) human-cyber (HC) interactions (i.e., for defining the interactions when lifting personnel is interacting with various cyber elements (e.g., the control panel of a crane). Besides, this figure illustrates dynamic human systems data collection for capturing human behaviors and examining dynamic human systems reliability in lifting operations.

During lifting operations, the central command system issues instructions to tower crane operators and ground command personnel. Ground command staff will coordinate the component installers and truck crane drivers. After the preparation, the tower crane operators receive instructions to start the lifting process. The tower crane will continuously transmit data to the central command system throughout the process. The central command staff must always observe the lifting process to identify anomalies. Instructions will be sent out to all relevant lifting operation personnel if any urgent anomalies have been detected. The system will automatically send alerts when the demand time for all these elements is greater than the demand time to prevent a specific event or incident. Hence, comprehending interactions within the H-CPS is vital for effective DHS RP & C of lifting operations. How to integrate emerging sensing techniques, data analysis algorithms, and simulation models for 1) capturing dynamic human systems behaviors, 2) examining dynamic human systems reliability issues, and 3) predicting and controlling the risks of captured human anomalies is thus important.

2.2.1. Human-human (HH) interactions and reliability issues during PBC

Human-Human (HH) interactions during lifting operations include communications among multiple lifting operation personnel. Lifting operation personnel usually 1) communicate with others who work for the same crane or 2) coordinate crane operations with personnel who work for other cranes. Typical lifting operation communications contain interpersonal communications and flag signals for exchanging field information and clearances (e.g., direction, height, and speed). Reliable communications are thus necessary to ensure multiple cranes' safe and efficient lifting operations. Even though communication protocols have been well developed for ensuring effective information flows during lifting operations. Communication errors still occur and result in accidents and near-misses during lifting operations. HH reliability refers to the reliability issues when lifting operation personnel communicate during lifting operations to exchange information. Observing and quantifying tedious communication processes among lifting operation personnel is vital for examining the effectiveness and reliability of communication.

2.2.2. Human-physical (HP) interactions and reliability issues during PBC

Human-Physical (HP) reliability refers to uncertainties arising during interactive processes among lifting operation personnel with all physical elements in dynamic workspaces during lifting operations. Physical environments for lifting operations usually contain a complex site layout with numerous machines and equipment located in high proximity. Such a complex environment demands the lifting operation personnel to 1) travel effectively and precisely within the job site, 2) select necessary tools, and 3) execute the scheduled lifting operational activities promptly. For example, the gravity center of lifting components may be unstable and could cause it to drop too fast or wander in the air, resulting in decoupling accidents due to centrifugal inertia during lifting operations. The improper selection of lifting points has an irreversible impact on the quality of components and the management safety of lifting operations. This requires the tower crane operators to locate the prefabricated building components on the ground, lift the components off the ground and move to the correct location without collision with other personnel or objects. Hence, the cognitive and execution capability of tower crane operators is vital to ensure safe and efficient lifting operations.

2.2.3. Human-cyber (HC) interactions and reliability issues during PBC

Human-Cyber (HC) reliability refers to the uncertainties that arise during the data analysis and decision-making processes that require data analysts to analyze lifting operation data and discover abnormal trends. Capturing such HC reliability is important for 1) diagnosing the impacts of human factors on the data analysis results, and 2) ensuring objective and trustworthy data analysis results that support safe and efficient lifting operations. For instance, lifting operators in the central command room on site are required for 1) monitoring and examining various system indicators located within high proximity, 2) identifying abnormal values of various indicators, 3) investigating root causes of the captured anomalies, and 4) conducted control actions for mitigating safety risks promptly. Unfortunately, such challenging processes demand extremely high cognitive capability and decision-making skills for discovering and resolving cyber anomalies.

3. Dynamic human systems data collection, processing, and anomaly detection targeting lifting operation personnel

Human factors play a major role in lifting operations during PBC. Unfortunately, current practices during PBC could hardly capture all such human-related data for examining risks caused by human errors. Emerging techniques could help capture dynamic human systems behaviors. However, practitioners must still identify the pros and cons of all such techniques and the appropriate use cases. For example, the visual information could have privacy issues, and the biometric sensors attached to lifting personnel may cause discomfort. Besides, not only the anomalies of human behaviors need to be collected, but also some seemingly normal behaviors before anomalies should be paid sufficient attention. Such normal behaviors could be predictors of behavioral anomalies during lifting operations. For example, many types of information can help indicate human fatigue, such as facial expressions, eyeblinks, postures, heart rates, etc. Hence, this section illustrates DHS data collection, processing, and anomaly detection tools and techniques targeting lifting operation personnel.

This section summarizes and analyzes the recent development of data acquisition, processing, and anomaly detection methods and techniques targeting dynamic human systems during lifting operation of PBC. The authors used keywords such as "behavior data collection", "behavior data processing", and "abnormal value analysis" for conducting the literature search within the past five years based on the Web of Science database. 39 articles have been collected for in-depth analysis.

3.1. Dynamic human systems data collection

3.1.1. Visual data collection

Visual data collection using various emerging sensing devices are important for capturing anomalous human behaviors from various interactions of DHS during lifting operations. Of all reviewed literature related to visual data collection during dynamic construction processes, most studies have used of CCTV cameras for collecting human behavior anomalies during tedious construction processes. Some studies developed vision-based detection method based panoramic cameras for visual data collection. A number of studies proposed intelligent on-site sensing systems by integrating CCTV cameras with panoramic cameras. Fig. 4 shows the imagery data collection equipment for capturing various human and team behaviors that could be implemented for establishing the proposed DHS RP&C approach during lifting operation of PBC.

The collected visual data of construction workers include construction postures, facial expressions, head poses moving trajectories and working progress. All such visual data could provide basis for on-site safety management. Vision-based workflow prognosis for capturing

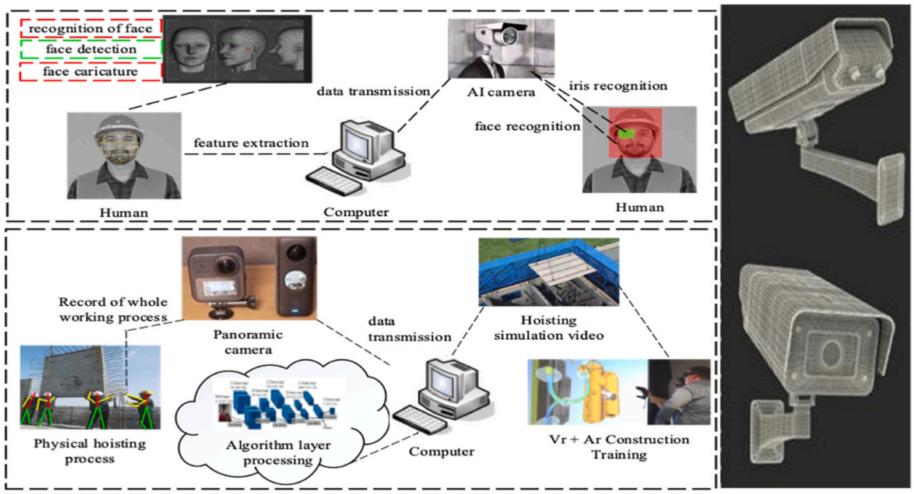

Fig. 4. Imagery data collection equipment for capturing various human and team behaviors (Chi et al., 2011).

behaviors of multiple objects in the collected visual data (e.g., video frames) simultaneously emerges as an alternative for non-contact job site monitoring. The emergence of affordable video cameras motivates the increasing use of job site cameras for job site monitoring of not only machinery but also human behaviors. Most construction job sites involve collaborative activities that require field workers to communicate and interact with other workers or computer systems (Yang et al., 2010). Tracking behaviors and interactions of multiple workers at the job site are necessary to provide situational awareness of how objects interact and form construction management bottlenecks (Chu et al., 2020; Roberts et al., 2020; Schimanski et al., 2021).

3.1.2. Audio data collection

Precise and effective communications among various crane drivers and lifting personnel are important during tedious lifting operations of PBC processes. Such communications include clearances about lifting objects, height, speed, direction, and timing. Besides, lifting operation personnel needs to exchange information about field discoveries and contingencies through interpersonal communications. Hence, it is thus necessary for capturing such communication processes from the collected audio data and identifying communication errors for ensuring safe and efficient lifting operations during PBC. Besides, such audio data could help in achieving effective coordination among various crane drivers and lifting personnel. In the current practice, walkie-talkie has been widely used for information exchanges during lifting operations. Such communication equipment could be used for recording communications among various lifting operation personnel during dynamic construction processes. Fig. 5 shows the audio transmission acquisition equipment and processes for collecting communication behaviors. Interpersonal communications through the radio channel could be recorded to capture the interactions among various crane drivers and lifting personnel.

3.1.3. Biometric sensory data collection

For onsite lifting personnel, biometric data is vital for examining the physical and phycological status. For example, using such biometric data could help to capture if the lifting personnel is fatigued or mentally overloaded. In addition, managers could also use such data to evaluate if certain personnel need to be replaced during lifting operations. Of all selected literature, scholars have developed methods for capturing biometric sensory data using various equipment and sensors, such as smart helmets, wearable wrist sensors, wearable ear clip sensors, and wearable chest strap sensors and wearable finger sensors. Fig. 6 shows the biometric data collection equipment and processes that could be

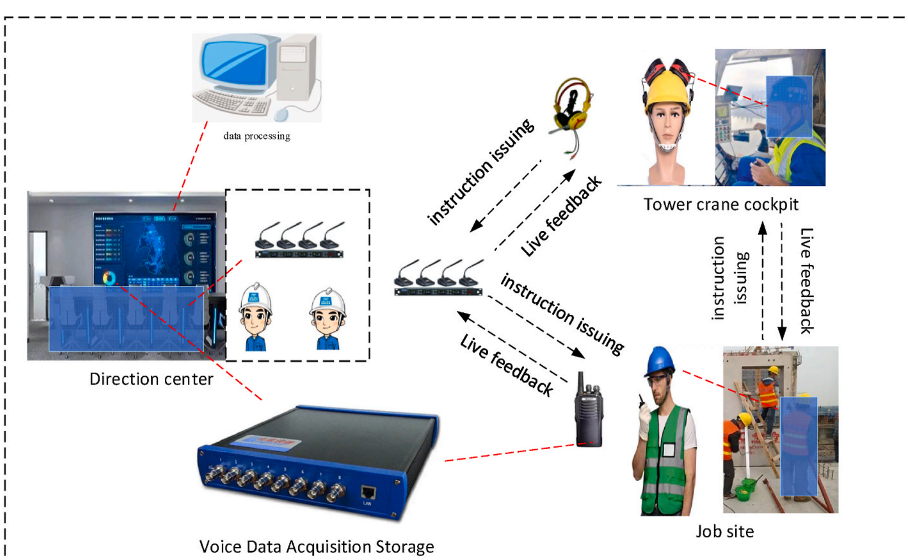

Fig. 5. Audio transmission acquisition equipment for collecting communication behaviors (Tipaldo et al., 2008).

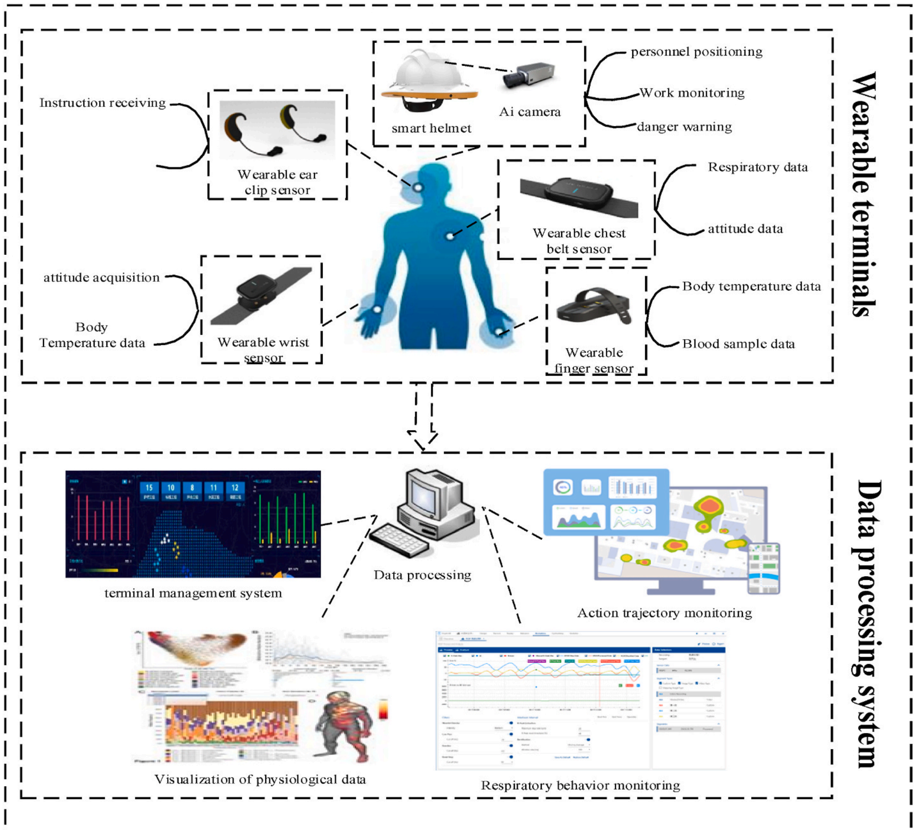

Fig. 6. Biometric data collection equipment (Kurien et al., 2018).

implemented for capturing biometric information of lifting operation personnel.

Physiological information, such as blood pressure, respiratory data, and blood oxygen concentrations of construction personnel, can be collected through wearable devices. The data collected by such equipment could be further processed and visualized, which can assist in the management of personnel, such as worker motion monitoring, physiological information visualization, and fatigue warning (Cheng et al.,

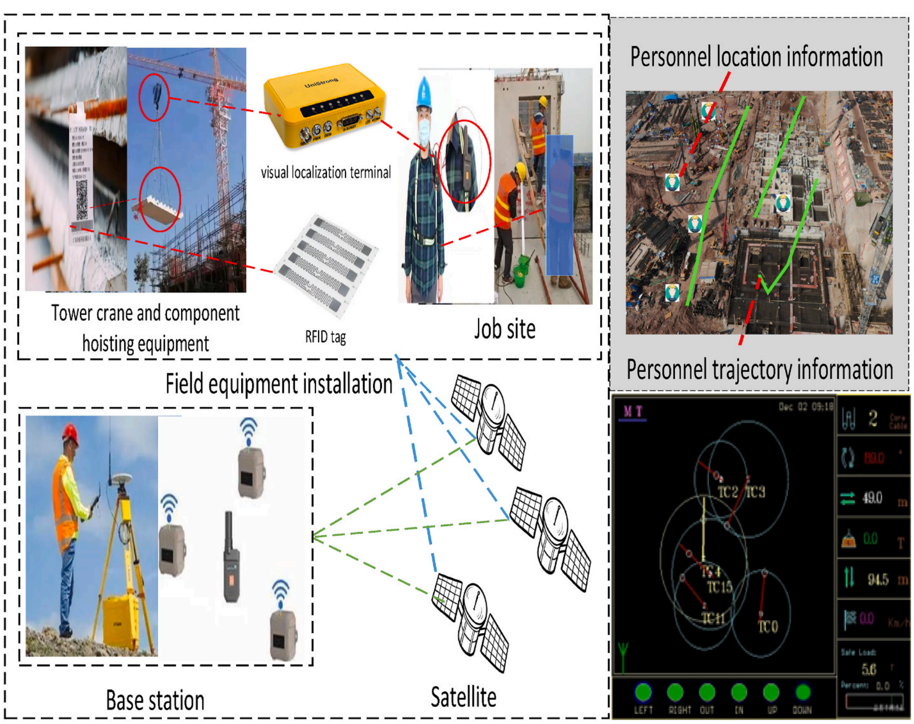

Fig. 7. Localization equipment for acquiring position information of construction workers (Labant et al., 2017; Valero and Adán, 2016; Sleiman et al., 2016).

2013; Yadav et al., 2022). In addition, the management team could also monitor the construction process based on the collected personnel posture data and moving trajectories.

3.1.4. Localization data collection

Relative locations among lifting personnel, cranes, and prefabricated building components are important to mitigate collision risks. Localizing various lifting personnel in dynamic workspaces during lifting operations of PBC is necessary to ensure construction safety (Nichols, 1996; Zhu et al., 2022). Personnel positioning management allows for safe personnel management. Through the investigation of literature related to localization data collection, most studies have developed methods based on Global Navigation Satellite System (GNSS), Beidou Navigation Satellite Systems, and active Radio-frequency identification (RFID) tags. All such techniques can warn personnel in hazardous areas using precise and efficient positioning information (shown in Fig. 7). RFID tags attached to all prefabricated components could help achieve precise localization of all components (Altaf et al., 2018a; Chen et al., 2020). First, a movable positioning terminal needs to be installed on the hook, and personnel with RFID tags attached to all prefabricated components. Then, the management team could locate any prefabricated components onsite based on the signals received from the receiving base station. Using such localization techniques during PBC could help to achieve safety assurance of lifting operation personnel and tower cranes by monitoring the real-time positions and trajectories (Hwang, 2012).

3.2. Human behavior detection and tracking methods

This section summarizes human behavior detection and tracking methods for capturing the human behaviors of crane drivers and lifting personnel during lifting operations.

3.2.1. Computer vision (CV)

Computer vision (CV) methods could achieve human behavior detection and tracking at four levels, 1) human pose detection, 2) facial expression detection, 3) PPE detection, and 4) multi-object tracking (Paneru and Jeelani, 2021) (see Fig. 8). Firstly, CV methods could help to detect human bodies and the behaviors of construction workers on site. During tedious PBC processes, CV could be used to capture outfits and hand-hold construction personnel's equipment (Baduge et al., 2022). For example, CV algorithms could help to examine whether workers are wearing the required safety outfits (e.g., helmets, fluorescent suits, and gloves) properly during lifting operations. For workers who did not wear the required safety outfits, CV algorithms could provide timely detections and warnings (Wu et al., 2022; Cai and Cai, 2020; Fang et al., 2022a, 2022b; Chow et al., 2020; Han and Lee, 2013; Liu et al., 2020; Nian, 2021; Yuan et al., 2017). Previous studies have shown the potential of using CV methods for tracking multiple objects using the video collected by the onsite video cameras. Gong, Park, Tang, Chen and others have used machine vision to build related systems to check or capture the behavior of relevant personnel and improve their work efficiency (Gong and Caldas, 2011; Park and Brilakis, 2012, 2016; Park et al., 2015; Tang and Golparvar-Fard, 2021; Chen et al., 2016). Table 2 illustrates the most commonly used CV methods and algorithms that

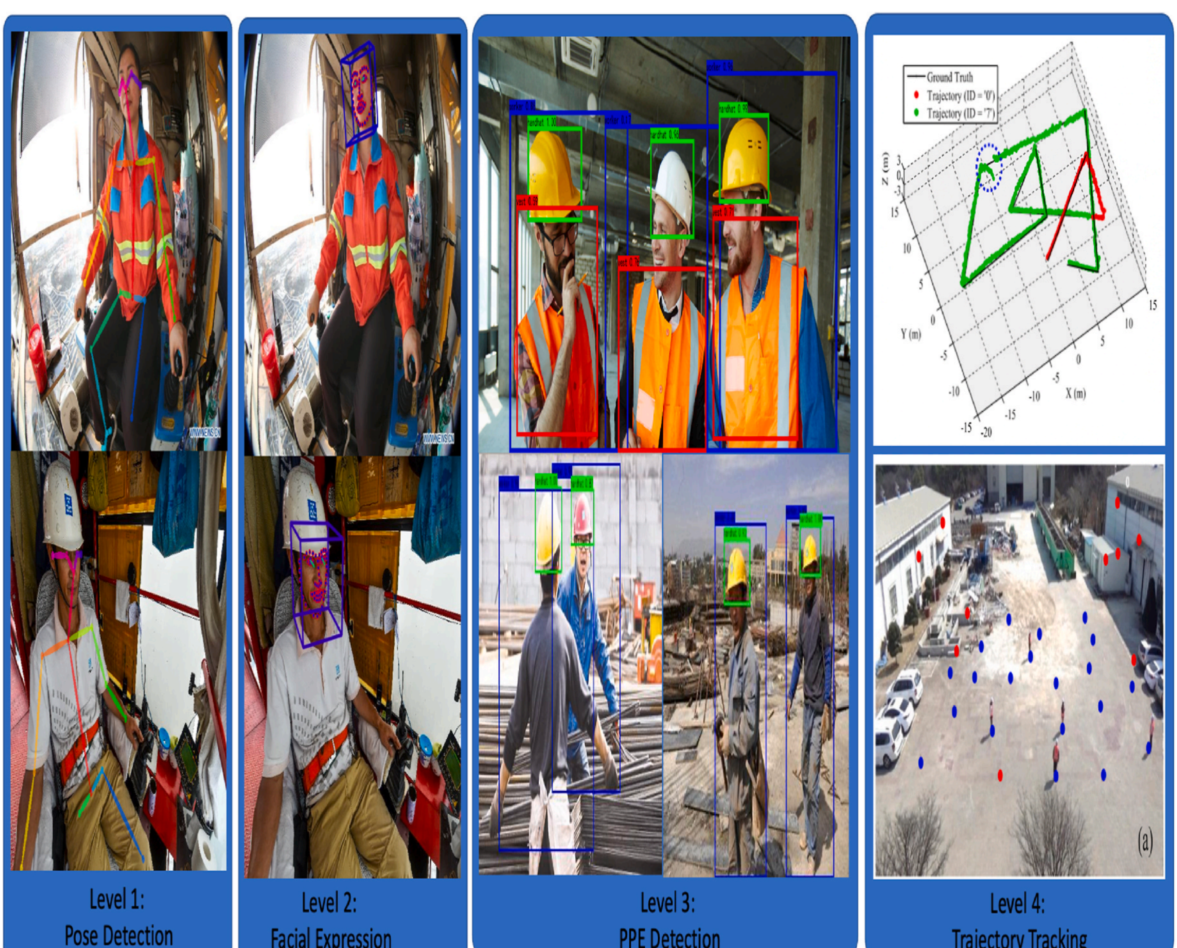

Fig. 8. Four-level detection and tracking methods examined in previous computer vision studies (Xu, 2022).

Table 2
Summary of commonly used CV methods for construction safety assurance and progress monitoring.

Methods	Algorithms	Purposes
Object Classification	Support Vector Machine (SVM), LetNet, AlexNet, VGGNet, ResNet, DenseNet, etc.	- Progress monitoring, safety hazards classification, etc.
Object Recognition	R–CNN, SPP-Net, Fast R–CNN, Faster R–CNN, You Only Look Once (YOLO), Single Shot MultiBox Detector (SSD), etc.	- Detect workers and equipment; Evaluate construction workers' productivity
Object Tracking	Histogram of Oriented Gradient (HOG), K-NearestNeighbor (KNN), MOG2, GMG, etc.	- Multi-object tracking, trajectory monitoring, etc.
Activity Recognition	Bayesian, Regional Multi-Person Pose Estimation (RMPE), Alpha Pose, openpose, etc.	- Recognize workers' behaviors (actions and activities)
Image Segmentation	K-means, GrabCut, DeepLab, Mask R–CNN, U-Net, etc.	- Segment objects based on color thresholds; background subtraction

could be used for capturing human anomalies during lifting operations.

Multi-object tracking (MOT) using video frames for 1) tracking multiple objects in congested workspaces without losing identity information of tracked objects and 2) plotting trajectories for different moving objects for capturing and understanding critical behaviors of objects that form workflow bottlenecks (Luo et al., 2021). Unfortunately, false detection and frequent identity (ID) switches due to occlusions are still the main issues that cause MOT failures when using a single camera (Luo et al., 2018a). The ID switch problem usually generates errors in object detections and discontinued trajectories (Luo et al., 2018b). Previous studies have not yet systematically characterized ID switch scenarios according to the results of the MOT approach. As a result, challenges remain for 1) examining various factors that could influence the ID switch issues in the MOT results and 2) examining the impacts of the captured ID switches on workflow bottlenecks (Shan et al., 2009).

Facial and motion behaviors could also be indicators of the underlying physical and phycological conditions of crane drivers and lifting personnel during lifting operations of PBC. Lifting operations involve many cognitive activities that rely heavily on physical and phycological processes. For example, fatigue and distractions of crane drivers and lifting personnel could cause omission errors when executing crane operation activities and jeopardize the safety of PBC processes. Such anomalous behaviors could occur due to high workload, increase the probability of human errors, and cause lifting operational failures. Previous studies have investigated how video surveillance cameras could help to detect abnormal human behaviors through facial expression analysis. Rhodes (Rhodes et al., 2005) has developed an algorithm to assess the anxiety of humans through facial expression analysis. These studies show the potential to detect anomalous human behaviors of crane drivers and lifting personnel.

3.2.2. Automatic speech recognition (ASR) and natural language processing (NLP)

Communications among crane drivers and lifting operation personnel are vital to mitigate risks of collisions between cranes and ensure safe lifting operations. Such communications include lift timing, direction, speed, and discoveries of dynamic lifting workspace. Identifying essential contents and detecting communication anomalies during lifting operations is thus necessary to prevent accidents and near-misses. Communication parameters are essential and can be used as indicators for capturing communication anomalies. Example parameters are articulation clarity, wording simplicity, meaning clarity, and signal accuracy. How to timely capture such communications and detect communication errors is still challenging.

Automatic speech recognition (ASR) has the potential to detect communication anomalies using the captured audio data. However, ASR still requires language analysis techniques to interpret the captured audio sound, for example, NLP (Natural Language Processing) or NLU (Natural Language Understanding). NPL and NLU algorithms are usually used to translate and interpret the captured communications during human-cyber and human-human interactions. NLP and NLU could be used to extract information (e.g., root causes, consequences, etc.) from textual reports (e.g., accident reports) and conduct linguistic analysis in the current practice of construction (e.g., key words identification, word frequency statistics, information retrieval, etc.). Integrated use of ASR, NLP, and NLU is vital for analyzing the collected voice and understanding the operation of the construction personnel. Table 3 illustrates the most commonly used ASR and NLP methods and algorithms that could be used for capturing anomalies during lifting operations.

Fig. 9 illustrates the interactive processes between lifting operation personnel and the synchronous processing system. When lifting personnel issues clearances through interpersonal communications, the system could automatically capture audio signals and transcribe them into textual commands through ASR. The system could also generate vocal responses as feedback to the lifting operation personnel through text-to-speech (TTS). Lifting operation personnel will check to see if all commands have been executed properly (Tsai et al., 2007).

A large number of studies have examined AI algorithms that use sound signals to detect anomalies. The project schedule is used to provide construction personnel with a pre-notification method for safety hazards, a machine learning method for checking the status of construction equipment in audio signals, and a residual neural network method for classifying human activities using sound data. Methods have been developed for activity recognition and anomaly detection using audio signals during PBC.

3.2.3. Operation log analysis

Lifting operations always generate many operation logs that record frequent interactions of the H-CPS, which also affects the subsequent

Table 3
Summary of commonly used ASR and NLP algorithms (Merz and Scrivner, 2022; Wang and Hodges, 2005; Zhang et al., 2020; Zhou et al., 2020).

Methods	Algorithms	Purposes
Word Segmentation	forward-max matching, backward-max matching, semantic incorporation	- Preprocessing of textural files (e.g., accident reports)
Sentence Parsing	RNN, LSTM, Support Vector Machine (SVM), Max-Markov Networks (MMKN), Conditional Random Fields (CRF), Shift - Reduce Algorithm,	- Analysis of words in a sentence and providing a structure based on the sequence of words
Text Classification	K-means, SVM, Logistic Regression (LR), Random Forest (RF), KNN, Decision Tree, Recursive Neural Network (ReNN), Multilayer Perceptron (MLP), RNN, CNN, Attention, Trans, Graph Neural Networks	- Construction accident classification, document management, accident analysis, etc.
Text Pair Matching	MaxMatch, CNN, Bidirectional Encoder Representation from Transformers (BERT), Term Frequency - Inverse Document Frequency (TF-IDF)	- Provision identification in construction specification, similarity case identification, automatic compliance checking, etc.

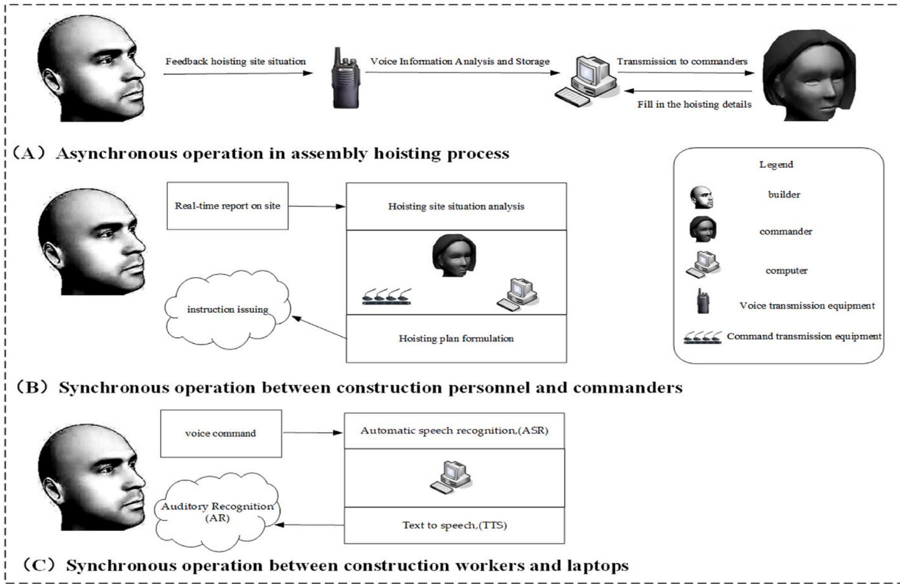

Fig. 9. Synchronous field data acquisition using wireless and voice technology (Tsai et al., 2007).

construction processes. The process of HP interaction usually includes traveling between workspaces during task executions. Most traveling logs during HP interactions are captured by video-based tracking (illustrated in previous sections) and radio-based tracking techniques. For example, Global Positioning System (GPS), Radio Frequency Identification (RFID), Bluetooth Low Energy (BLE), and Ultra-Wide Band (UWB) (Altaf et al., 2018b). HC interaction mainly includes work logs generated during HITL processes when lifting personnel interact with computers, software, data, and algorithms. For example, such log data include 1) operation records when crane drivers operate control panels inside the crane, 2) a series of selections when setting up parameters and constraints in algorithms for analyzing lifting operation data, and 3) logs when lifting operation personnel receive, store, and transmit lifting operation data. Collecting and analyzing such log data could help identify critical lifting personnel behaviors when dealing with cyber issues that form lifting operation bottlenecks. Table 4 illustrates the most commonly used log analysis methods and algorithms that could be used for capturing anomalies during lifting operations.

Kim (Kim et al., 2016) developed a method for identifying safety hazards in laborers' movement paths using location logs. Yarmohammadi (Yarmohammadi et al., 2017) characterized the performance of different modelers based on the duration of similar modeling tasks using modeling log files. Zhang (Zhang and Ashuri, 2018) developed a log mining method for discovering social networks using design logs collected from the design process through Building Information Model (BIM). He established a log mining approach using BIM log data for comprehending knowledge discovery about design productivity. Zhang (Zhang et al., 2018a) also established a framework for command prediction during design processes using Autodesk Revit. Chen (Chen et al., 2018) developed a log mining approach for temporal image analytics to identify abnormal construction activities. Gao (Gao et al., 2021) established a method for investigating 3D modeling behavior using event logs. Gao (Gao et al., 2022) proposed a data augmentation method based on deep learning to improve the prediction accuracy of modeling event logs.

3.3. Anomaly detection methods

Anomaly detection (also known as "outlier detection") aims to resolve challenges when identifying data instances that do not conform to the expected value. Anomalous human behaviors are unfavored during lifting operations of PBC that could be indicators of changes in the physical and phycological conditions of crane drivers and lifting personnel. However, detecting such human-related anomalies during lifting operations of PBC is considered the most labor-intensive and time-consuming. Previous studies proved that timely anomaly detection could ensure safe and efficient construction processes. Detecting anomalies during tedious construction processes is a preventive and proactive action for ensuring all lifting personnel maintain their original anticipated function during the lifting operations of PBC. State-of-the-art techniques for anomaly detection include classification-based, proximity-based, clustering-based, statistical anomaly detection, and PCA analysis. How to implement these methods for capturing anomalous human behaviors is important to ensure safe and efficient lifting operations of PBC.

3.3.1. Classification-based anomaly detection

Classification-based anomaly detection aims to establish classification models for training and classifying objects. The classification-based method requires that records be classified as normal or abnormal. Such a method is widely used in anomaly detection based on time series analysis, behavior series analysis, semi-supervised models, and supervised models.

An anomaly monitoring method based on time series analysis

Table 4
Summary of commonly used log analysis algorithms (Fang et al., 2021; Li et al., 2009).

Methods	Algorithms	Purposes
Log Parsing	SLCT, AEL, Log Key Extraction (LKE), Loop Free Alternates (LFA), LogSig, IPLoM, LogCluster, POP, Drain, Spell, LogMine	- Extract event templates and key parameters, pattern recognition, clustering
Log Mining	K-means, Fuzzy C-means, Hierarchical clustering, Mixture of Gaussians, Instance-based learning, Decision Tree, Bayesian Networks	- Operational anomaly detection - Operation failure prediction - Operation failure diagnosis

includes comparison and loop ratio, which is suitable for scenes with periodic data. Based on the statistical model prediction, such as weighted moving average and exponential moving average. Anomaly detection using behavior sequence analysis, such as the Markov chain, could sort human behaviors into a logical chain and capture abnormal human behaviors by observing the probability of each behavior to any other behavior. Semi-supervised models, such as Bayesian networks, Gaussian mixture models, support vector machines, and generative adversarial networks, are also suitable for capturing anomalies (Gao et al., 2022). The supervised model method has a strong generalization ability and is suitable for data with diverse features. It is divided into the machine learning model and the deep learning model.

The classification-based anomaly detection methods are now widely used for capturing anomalies in head rotation, eye movement, trajectory tracking, trunk recognition, and other scenarios. Jansson (Jansson et al., 2015) proposed a method to detect abnormal eye movement by random anomaly detection. Kamoona (Kamoona et al., 2019) developed a target tracking method that uses a random finite set (RFS) for identifying workers who violate the requirements of wearing construction safety vests. To prevent collapse accidents at construction sites.

3.3.2. Proximity-based anomaly detection

Proximity-based anomaly detection methods include distance-based methods (e.g., Euclidean distance and Manhattan distance judgment) and density-based methods (by calculating the density of the data area, the area with lower density is regarded as the outlier area). For example, using distance measures, K-Nearest Neighbor (KNN) determines the appropriate distance between instances. KNN-based methods assume that the normal data points fall in a dense neighborhood, while the abnormal data points fall far away from the neighborhoods. The advantage is that the data does not need to be pre-marked as normal or abnormal, and the data-driven assumptions about the distribution need not be considered (Chica, 2012). The disadvantage is that it cannot be well extended to high-dimensional data. The KNN algorithm is often used to detect abnormal behavior of valves in the petrochemical industry. For example, abnormal events for video streams in video surveillance. Akusok (Akusok et al., 2014) provided a way to quickly obtain sample classification decisions, classifying as many samples as possible (high coverage) while maintaining the lowest false alarm rate, effectively detecting outliers in the data.

3.3.3. Clustering-based anomaly detection

Clustering-based anomaly detection (known as "density-based anomaly detection") divides the data into various clusters. Data points that do not fall into any of these clusters are defined as outliers. This includes distance-based clustering, partition clustering, hierarchical clustering, density-based clustering, and grid-based clustering anomaly detection.

K-means clustering originates from signal processing and vector quantization methods. The data is divided into K clusters, where each cluster record belongs to the cluster closest to the average. K-means clustering has been widely used for fault detection when monitoring railway conditions. For example, a clustering method is used to find the appropriate parameters to detect and diagnose misalignment faults. This method can diagnose faults with high precision. Park (Park et al., 2018) proposed a clustering-based detection method for identifying outliers.

4. Dynamic human systems reliability analysis and proactive risk control of lifting operations

Examining the impacts of human reliability on lifting operation safety during PBC is vital. Besides, establishing a proactive risk control mechanism for mitigating risks caused by human errors could help achieve resilient lifting operation control.

This section summarizes and analyzes the influence of human reliability on the safety of lifting operation during PBC. 49 articles were selected, which were published on the Web of science in the past five years. The authors used keywords such as "human reliability", "human factors engineering", "team reliability", "human error", "human reliability analysis" for conducting the literature search. By summarizing and criticizing the literature, human reliability analysis (HRA) technology, process modeling and simulation technology, and control theory are summarized and analyzed, and how human reliability supports active risk control of lifting operations is expounded.

4.1. Human reliability analysis (HRA) methods

Effective and proactive assessment of human errors during lifting operations is vital to examine human impacts. Human reliability analysis (HRA) or HRA model is a tool for measuring the impacts of human errors on system performance using human behavior data through qualitative and quantitative measures. This section summarizes HRA methods for examining human reliability issues of crane drivers and lifting personnel during lifting operations.

4.1.1. Methods for examining human reliability issues during lifting operations

The technique for human error-rate prediction (THERP) was first introduced by Alan Swain in 1962. In the 1960s, Swain (1963) collected much human error data and compiled a detailed performance formation factors (PSFs) scale. Boring (2012) pioneered the field of HRA and is still in use today. The first-generation HRA model was developed to investigate the root causes of human behaviors and derive the probability of human errors. The second-generation HRA model focuses on the internal mechanism of human behaviors and behavioral patterns. Such an HRA model aims to observe and evaluate the mechanism and probability of errors in the process, from cognitive activity to execution in certain situations.

Previous studies on HRA at the individual level have made great progress. Zhang et al. (2001) put forward an in-depth defense system for human factors accidents by analyzing human factors accidents in complex social and technical systems. Due to the differences in HRA methods in research scope, research methods, and underlying models. Boring (Boring et al., 2010) synthesizes HRA studies, including research in psychology and risk and safety assessment. The review presents the lessons learned from these studies to guide the future development of HRA models. Li et al. (2014) summarized the methods of human reliability analysis.

Bruemmer (Bruemmer et al., 2005) examined human reliability issues in human-cyber interaction scenarios through three experiments. The authors let the driver cooperate with the robot control system to complete various search tasks. The reliability of the driver is evaluated by examining the virtual driving tasks, communication behaviors, and errors when interacting with the robot control system. This study has proved that the workload is reasonably distributed among multiple drivers even when the complexity of the environment increases. Besides, the cooperative control of the human-robot system could improve human performance and reduce human errors (Lin et al., 2019). Sun et al. (2020) systematically reviewed human-reliability issues during H-CPS interactions. A case illustrated how the human-cyber interaction between the driver and the control system affects the operational efficiency and safety of nuclear power plant operations. Dai et al. (Dai, 2012) examined human reliability issues during nuclear power plant operations of a pressurized water reactor using an HRA model. Boring (Boring et al., 2015a) considers the influence of human factors in the study of long-term nuclear power plant control systems. In addition, Boring (Boring et al., 2013) established a digital model for a control room inside a nuclear power plant using an HRA model.

The second-generation HRA method includes the Cognitive Reliability and Error Analysis Method (CREAM). CREAM assumes that the environment and scenario could impact human behaviors (Liu et al., 2009). Shen et al. (2005) established a consequence-cause traceability table that could trace the root causes of human errors using CREAM. Stewart (1992) developed a new HRA model to examine the impacts of different human errors on the construction safety of reinforced concrete structures. The established model could explore how human behaviors affect the safety factors (e.g., the number and size of steel rebars, the width of beams, quality of concrete mixing, etc.) of engineering structures through the error rates and error distributions. Results show that reliable performances of the project supervisor could greatly reduce the occurrence of human errors. Though various HRA methods have been well established, the established model is relatively simple and could hardly effectively reflect the process and mechanism of human errors.

4.1.2. Methods for examining team reliability issues during lifting operations

Team performance is critical during lifting operations as most lifting activities require effective collaborations from crane drivers and lifting personnel of multiple cranes. Hence, examining team reliability issues is vital for ensuring safe lifting operations. Previous studies have established methods for examining the influences of team reliability on the safety and efficiency of civil infrastructure operation and maintenance processes. These methods aim to capture tedious interactive processes among multiple team members during cognition, communication, and execution processes of various activities.

Team decision-making is a participatory process in which individuals in the team acting collectively (Cooke, 2015). Such a process usually requires a team to identify problems, evaluate situations, gather information, develop plans and contingencies, and decide the optimal solution among all alternatives (Xiao et al., 2016). A good team comprised of professionals from different disciplines with complementary skills is always effective in decision-making as all team members are working towards the same goal (Smart and Shadbolt, 2012; Cooke et al., 2013; Beersma et al., 2016). Dynamic environment with changing work conditions during lifting operations requires good team decision-making strategies to ensure safe and effective operation in emergent situations. The high physical and mental workload of crane drivers and ground workers always occurs due to the complex workspace with the dynamic environment. For example, drivers of multiple overlapping cranes are required to communicate frequently during tedious lifting operations with hectic construction schedules (Bell et al., 2015a; Salas et al., 2015; Samsam and Chhabra, 2021; Landon et al., 2018).

In human systems engineering, existing studies examine team performance from a static perspective (based on task outcomes or results at a point in time). Recent studies on team interaction dynamics have provided an alternative approach to understanding team process evolution (Joe et al., 2015; Ijtsma et al., 2017; Gonzalez et al., 2013; Bell et al., 2015b). Team decision-making for problem-solving is a dynamic process that involves the changing roles of team members, coordination and communication behaviors, and environmental condition changes. Understanding how the dynamic properties of team processes influence the efficiency and safety of lifting operations is critical.

In addition, transitions between scheduled construction activities usually involve travel within the job site and communication among various project participants (Boring et al., 2015b). Effective control of such activities during transitions could help to reduce non-value-added time and risks of human errors. For example, approval of change orders is time-consuming that requires lots of communication across multiple project participants (St Germain et al., 2015). On the other hand, all such communications are necessary to reduce the risks of exchanging incorrect information. Besides, such communication activities are necessary to help the construction manager for examining field anomalies and mitigating risks through proactive measures (Zhang et al., 2018b).

Cooke (2015) conducted extensive studies in the field of team cognition. Cooke pointed out the team is a complex system that could receive information, collect additional data, prepare plans, and make decisions as a unit. Compared to individuals, the cognitive processes of a team are much more interactive and dynamic. Effective team communication is essential for coordinating activities across multiple team members. Such communications enable good team situational awareness (TSA) and team performance (Cooke et al., 2013). Demir (Demir et al., 2017) studied the role of team verbal interaction in team performance and TSA. This allows a better understanding of human-robot collaboration (HAC). The study found a strong correlation between individual responses to the behavior and information of other team members and effective TSA and team performance. Therefore, rules and mechanisms need to be established to ensure the integrity and accuracy of information transmission to make HAC effective in teamwork in the HAC process. Such rules and mechanisms include central and distributed communication network structures, as compared by Gorman (AbouRizk, 2013).

4.2. Proactive risk control of lifting operations

Unreliable human behaviors could be captured through various sensing techniques and examined through HRA methods. Effectively controlling the captured human anomalies and achieving resilient control is also vital to ensure system-level autonomy of lifting operations. This section summarizes process modeling, simulation techniques, and control models for proactive risk control lifting operations.

4.2.1. Process modeling and simulation

Construction simulation is a science and technique for establishing computational models that could be used for conducting numerical analysis in a simulation environment (Alzraiee et al., 2015). Schedule simulation could help to establish numerical models based on the given construction schedule (Li et al., 2019). Unfortunately, traditional scheduling techniques (e.g., Ghatt chart, PERT model) could hardly represent all schedule details and reflect its behaviors. Using computer simulation tools, the logical behaviors of all connected construction activities, required resources, and environmental conditions could be established and well represented. Besides, existing construction simulation tools could hardly precisely model the complicated spatiotemporal interactions between human factors, tasks, and resources for DHS RP & C. For example, control managers at nuclear power plants use a Gantt chart or PERT model to represent workflows and examine delays (Jafari and Valentin, 2015). All such representations could hardly represent workflows in detail, which creates challenges in examining human behavior's impacts on workflow performance (e.g., delays). Besides, the sequence of scheduled activities during nuclear power plant operations changes frequently due to human factors, which poses significant challenges for traditional scheduling tools. Hence, computer simulation tools enable investigations of relationships among task sequence updates, uncertain human behaviors, and field anomalies. Therefore, new simulation models are needed to integrate dynamic human behavior models and unexpected events into scheduling analysis methods (Sun et al., 2021).

4.2.2. Control theories

Control theory in sociology includes internal and external control systems. Such control systems could be either centralized systems or decentralized systems. Effective and safe control is necessary during the lifting operation processes of PBC. Previous studies have examined various control theories to ensure operational safety and efficiency. Centralized control refers to a system controlled by the central controller with well-known policies (Carvalho et al., 2006). For example, Tsikalakis and Hatziargyriou have examined centralized control for microgrid operations (Tsikalakis and Hatziargyriou, 2011). In this study, the proposed "central controller" aims to optimize the production of distributed generators and power exchange of the Microgrid during interconnected operations (Wang and Davison, 1973). On the other hand, decentralized control is maintained through competition or market share factors. Wang and Davison aimed to stabilize a linear time-invariant multivariable system (decentralized control system) using several local feedback control laws (Wang et al., 1973). Preventative controls are control systems and strategies that are usually implemented before threats to avoid the likelihood and potential impact of such threats on operational safety and efficiency. Preventive control aims at establishing policies and processes for controlling risks (Yale et al., 2012). Helping in post-accident investigations and audits is the primary purpose of reconnaissance controls, including security event log monitoring, detection of host and network intrusion threat events, and antivirus identification (Galloway, 2020; Meerow et al., 2016). Corrective controls aim to mitigate the potential impacts of risky events and to return to normal states. Adaptive control strategies are designed that require a controller to adapt to the system with changing and uncertain (Stachowski et al., 2009; Orgut et al., 2020).

Various techniques have been developed in the construction domain as planned schedules when scheduling the required activities (Awada et al., 2021a). The critical path method (CPM) has been widely used to control the project and minimize delays. The CPM ascertains the project duration based on the early and late start dates of activities derived from logical constraints and task durations (Abdul-Rahman et al., 2015). Unfortunately, the CPM uses the assumption of fixed task durations based on engineering judgments and previous experience (Chang et al., 2021). These assumptions ignore the contingencies and newly discovered field anomalies that always occur during construction processes. Some project planning tools consider the variability of construction-related work by using a distribution of task completion times rather than point estimates. Unfortunately, using the PERT model always results in optimistic duration estimations when ignoring all non-critical path activities (Awada et al., 2021b; Gorman et al., 2006).

5. Research roadmap: DHS RP & C for resilient lifting operation control – from automation to autonomy

Though PBC is widely adopted in the AEC industry, challenges still exist for achieving resilient control of lifting operations due to uncertainties of human behaviors during various H-CPS interactions. Specifically, practitioners and researchers in PBC management do not pay enough attention to the influences of human factors on the safety and efficiency of lifting operations. Lack of systematic research on the impact of human factors on various PBC lifting operation processes. Limited studies have synthesized data collection techniques and processing algorithms for capturing, analyzing, and interpreting massive human behavioral data. Given the above knowledge gaps, the authors proposed a research roadmap toward DHS RP & C of lifting operations during PBC. Such a roadmap is developed based on 1) limitations and knowledge gaps extracted and synthesized from previous literature, 2) needs for achieving intelligent and resilient lifting operations during PBC, 3) the needs towards DHS RP&C for resilient and autonomous lifting operations. Besides, the authors have determined the specific needs of the future PBC lifting operations through discussions with practitioners and engineers of many construction units and proposed this research roadmap.

A typical H-CPS usually includes a control loop containing humans, cyber components, and the physical environment. Such a system is used for 1) collecting time series behavior data of lifting operation personnel, 2) capturing human behaviors and patterns, 3) analyzing cognitive conditions of humans, and 4) predicting human-related risks using various sensors, algorithms, and computer systems installed at the job site. Such a H-CPS combined with Digital Twin (DT) and Building Information Modeling (BIM) techniques could help to realize automated job site planning for ensuring the lifting operation safety of PBC (Jiang et al., 2022).

Future PBC lifting operation control systems should achieve system-level autonomy, which requires optimization of human-automation interactive decision-making processes. To be more specific, performances of lifting activities needed to be automatically monitored and tracked in detail with multivariate human factors information. Besides, the schedule of PBC lifting operations needed to be automatically updated and adjusted with full consideration of human interventions for mitigating the impacts of field discoveries and anomalies. Then, artificial intelligence algorithms (e.g., deep neural networks, convolutional neural networks, etc.) should be integrated as cyber components into the H-CPS for strategy optimization and continuous improvements of PBC lifting operations based on the learned knowledge from historical operation logs. With the help of emerging techniques and computers, the authors envision that more decision-making and control mechanisms could be enabled automatically during PBC lifting operations to reduce the need for experienced lifting operation personnel. All such lifting operation personnel with years of experience and PBC knowledge can be assigned high-level supervision duties for diagnosing and predicting safety risks during PBC lifting operations. Automation techniques will enable automatic self-learning by mining from tedious HC interaction histories and providing recommendations with better HC interactions during PBC lifting operations for achieving not only automation but also autonomy. Fig. 10 synthesizes and visualizes the research roadmap toward DHS RP&C for resilient and autonomous lifting operations.

Although emerging information technologies have been developed and extensively examined in the computer science and engineering domain, establishing a reliable, self-learning H-CPS for PBC lifting operation control system is still challenging for the following reasons, 1) existing sensing and modeling techniques could hardly satisfy the domain needs and capture H-CPS interactions, 2) traditional tools for data analysis could hardly analyze massive data collected during H-CPS interactions, and 3) due to the system complexity and stochastic nature of human behaviors and physical environments, it is challenging to integrate the knowledge rules from various disciplines.

Hence, addressing the above challenges is thus necessary for developing H-CPS in construction. Future lifting operations during PBC will transform from automation toward autonomy. The H-CPS concept is thus vital for supporting such transformation and achieving resilient control of lifting operations. Integrated dynamic human systems sensing techniques, modeling methods, and decision-making algorithms enable effective control of lifting operations through real-time human behavior capturing and safety hazard identification.

The above review efforts from domains of construction engineering, human systems engineering, computer sciences have shown that the proposed method could contribute to the real-world practices of lifting operations during PBC. Implementing the proposed method could help to achieve safe and effective human-machine interactions and autonomous monitoring and control of lifting operations during PBC. In the current practice of construction industry, various sensors have already installed in the background of intelligent construction and smart construction site. All such sensors are installed for sensing various on-site activities and interactions among human, cyber, and physical environment.

Installations of various sensors provide basis for establishing the proposed "Dynamic human systems risk prognosis and control (DHS RP & C) of lifting operations", which aims to establish a control loop that consists of human behavior data collection, human reliability analysis, and human risk control. For example, CCTV cameras for safety monitoring have been installed on the construction jobsite for monitoring construction progress and identify unsafe events. Such cameras also be used for collecting human behavioral data in the designated area for lifting operations. Besides, communications between all lifting operation personnel could be monitored and translated into textual data. Combining with emerging computer vision and natural language processing algorithms, such visual and audio data could help the project manager to capture unsafe human behaviors and communications during lifting operations. Human reliability analysis methods could also be used for examining the impacts of unsafe human behaviors or inappropriate executions of lifting operation activities on the safety and efficiency of lifting operations. Control theories and models could then be

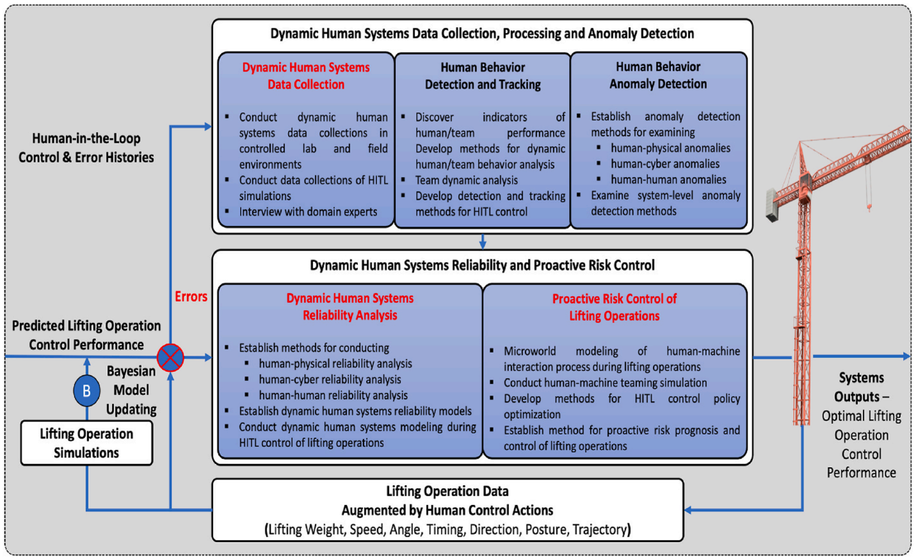

Fig. 10. Research roadmap towards DHS RP&C for resilient and autonomous lifting operations.
(Research directions with immediate needs are highlighted).

implemented for providing guidance of effective control actions to mitigate the identified risks according to the established risk control loop.

6. Conclusion

This paper synthesizes domain requirements, practical challenges, behavioral data collection techniques, and HRA methods for comprehending the potentials and needs of a DHS RP & C of lifting operations during PBC. The authors identified three practical problems for achieving safe and effective lifting operations, 1) effective and precise communication during lifting operations, 2) team situation awareness within and between lifting operation teams, and 3) responding to lifting operational contingencies with proactive measures. To fully address the identified practical issues during lifting operations of PBC, this study proposes the DHS RP & C of lifting operations during PBC for ensuring safety and efficiency.

Through this critical review, multidimensional interactions of the H-CPS, including humans, the physical environment, and information technology in tedious PBC processes, have been captured and analyzed. Identifying such interactions provides the basis for theoretical research and model verification of the PBC lifting operations. The major findings of this paper include: 1) DHS RP & C systems should be able to collect all kinds of human-related information during various H-CPS interactions and make timely decisions that could mitigate the risks during lifting operation control, 2) targeting human factors at both individual and team levels (e.g., mental workload, physical workload, communications, team situation awareness) is the main goal for developing a DHS RP & C system for resilient lifting operations during PBC, and 3) H-CPS is a fundamental research question of DHS RP & C for safe and effective lifting operation control in prefabricated building construction. Extensive studies on cognitive science, computer science, and system science and conduct in-depth logical analysis of complex and dynamic construction scenarios of prefabricated building projects should be conducted to ensure safe and effective lifting operations.

Extensive studies have shown the potential of automatic detection and tracking of various human behaviors during lifting operations. Unfortunately, human interventions and feedback are still needed in the "loop" for setting up numerous parameters and constraints when using all such techniques, methods, and algorithms for risk prognosis and control. The recent development of AI algorithms enables automatic learning of human behaviors during cognition, communication, decision-making, and execution processes. How to fully relieve human interventions from the "loop" and achieve system-level autonomy of risk prognosis and control is still challenging. Hence, this study shed light on achieving system-level autonomy through effective DHS RP & C in various construction scenarios.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgment

This material is based upon work supported by the National Natural Science Foundation of China (NSFC) under Award No. 52178095. NSFC's support is acknowledged. Any opinions and findings presented are those of the authors and do not necessarily reflect the views of NSFC.

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