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Review

Fatigue in construction workers: A systematic review of causes, evaluation methods, and interventions

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ABSTRACT

Construction is a highly hazardous industry characterized by numerous occupational fatalities, injuries, and illnesses, with fatigue identified as a major causal factor. To prevent construction accident fatalities and injuries, extensive research efforts have been directed toward fatigue among construction workers. However, no systematic review has been reported regarding the identification, evaluation, control, and management of fatigue among construction workers. To elucidate the state-of-the-art research, uncover related issues, and propose potential improvements, this study presents a systematic review of fatigue-related research on construction workers, focusing on the causes of fatigue, evaluation methods, and related interventions. Based on a mixed-review approach combining systematic review and bibliometric analysis, this study examines the evolution of research themes and methods related to worker fatigue and highlights key findings. The analysis reveals various causes of worker fatigue, including work-related, environmental, and personal factors. Additionally, this study highlights subjective and objective practical methods for measuring, monitoring, and predicting worker fatigue and describes interventions to alleviate fatigue, from individual- to industry-level measures. Moreover, the relevant research challenges are identified, and future research directions are recommended. The findings of this study can promote further research on construction worker fatigue and contribute to the enhancement of occupational health and safety in the construction industry.

1. Introduction

The construction industry is widely recognized as one of the largest, most complex, and dynamic sectors, contributing to 13 % of the world's gross domestic product and providing employment opportunities for millions of people worldwide (Ribeirinho et al., 2020). However, this sector involves various risks, with a high incidence of fatalities, occupational injuries, and illnesses reported annually (Employment and Social Development Canada (ESDC), 2020; Eurostat, 2020; Occupational Safety and Health Administration (OSHA), 2021). For instance, the construction industry in the European Union accounts for over one-fifth of all workplace fatalities (Eurostat, 2020), and approximately 50 % of European construction workers suffer from considerable pain and musculoskeletal disorders (MSDs) (European Agency for Safety and Health at Work (EU-OSHA), 2020). In the United States, less than 5 % of the workforce is employed in the construction industry. However, the industry accounts for one in five work-related deaths (OSHA, 2021). Moreover, 43 % of construction workers suffer from back MSDs, and 16 % have reported shoulder MSDs (United States Bureau of Labor Statistics (USBLS), 2015). In Ontario, Canada, the construction industry is responsible for over 25 % of occupational fatalities, and MSDs account for over 40 % of all lost-time compensation claims (Workplace Safety and Insurance Board (WSIB), 2013).

Construction workers are susceptible to occupational fatigue as they must typically perform physically demanding tasks in awkward working postures over long working hours (Aryal et al., 2017). Such conditions may lead to frequent errors, thus increasing the risk of work-related accidents and other occupational health problems (Wang et al., 2023). Fatigue is widely acknowledged as a principal cause of construction accidents (Wong et al., 2019), has been categorically identified as one of the "fatal four" causes of fatalities in the construction industry (OSHA, 2015), and is the primary contributor to approximately four out of five accidents in oil and gas construction projects (Chan, 2011). Therefore, it is necessary to investigate construction worker fatigue (CWF) to identify

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the causes of fatigue and effective strategies for its evaluation and alleviation. These strategies could yield tremendous interventions to safeguard construction workers against occupational illnesses and harm.

Given the significance of fatigue in the construction industry, many review studies have been conducted on CWF (Abuwarda et al., 2022; Ahn et al., 2019; Anwer et al., 2021). Some reviews have outlined the physiological metrics used for measuring physical fatigue among construction workers (Abuwarda et al., 2022), and some have summarized the wearable sensing technologies for fatigue measurement (Ahn et al., 2019; Anwer et al., 2021), and data processing methods for the physiological signals captured by such devices (Anwer et al., 2024). However, these previous reviews have focused mainly on the fatigue measurements of construction workers and have failed to provide a systematic understanding of the broader research landscape for the identification, evaluation, control, and management of CWF-related issues. Investigating the root causes of fatigue helps comprehend the internal mechanisms of fatigue incidence among construction workers and lays a foundation for subsequent research on CWF measurement, evaluation, and alleviation. It is also essential to explore effective interventions for CWF since it can help protect construction workers from occupational diseases and accidents induced by fatigue and improve work efficiency and productivity. In general, previous reviews have neglected the root causal factors of CWF and potential alleviation strategies, failing to provide a comprehensive overview of CWF from its origins to evaluation methods and potential interventions.

To fill this gap, this study presents a systematic review of CWF-related studies by analyzing published literature on a wide range of research topics, from the root causes of fatigue to potential interventions. The findings can help pave the way for future researchers to capture a comprehensive and clear understanding of the topic and conduct more in-depth research. Specifically, this study contributes to the field in the following ways: (1) This systematic review of CWF provides an enhanced understanding of the related causes, evaluation methods, and interventions. Additionally, by examining the state-of-the-art advancements and identifying the challenges related to fatigue evaluation and intervention, this review facilitates the proposal of various promising directions for further research. (2) This review provides practical insights into effectively measuring, monitoring, predicting, and mitigating CWF. Through these guiding principles and best practices, construction companies and relevant stakeholders can effectively manage CWF, thereby improving the safety management level of the industry. Overall, this systematic review can promote further studies on CWF and contribute to improving the occupational health and safety of construction workers.

2. Definition of fatigue

Fatigue is a prevalent symptom in both acute and chronic illness, as well as in the daily lives of healthy individuals (Aaronson et al., 1999). According to the *Oxford English Dictionary*, fatigue in humans is defined as "lassitude or weariness resulting from either bodily or mental exertion" (Oxford English Dictionary, 2023). Several researchers have presented relevant definitions of this concept (Hancock and Verwey, 1997; Phillips, 2015; Van Der Linden et al., 2003). From these definitions, the following shared characteristics of fatigue can be summarized:

- Caused by exertion, resulting in feelings of discomfort, tiredness, or exhaustion;
- Correlated with physical or mental tiredness and exhaustion;
- Causes a temporary reduction in functional capacity.

Workers' fatigue remains a prominent issue in numerous industries and is primarily attributable to the demanding nature of jobs, prolonged working hours, disruptions to circadian rhythms, and accumulation of sleep debt, for instance, in the case of vehicle drivers (Sikander and Anwar, 2019), clinicians (Gaba and Howard, 2002), nurses (Geiger-Brown et al., 2012), and seafarers (Wadsworth et al., 2006). In the construction industry, due to the heavy workload and dynamic hazards on construction sites, construction workers must exert significant physical energy and exhibit a high degree of mental alertness to ensure on-site safety. Therefore, both physical and mental fatigue have garnered significant research attention. Physical fatigue is commonly defined as a decrease in the ability to engage in physical work due to prolonged physical exertion (Anwer et al., 2021; Gawron et al., 2000). In contrast, mental fatigue arises after prolonged mental workloads and may lead to deteriorated performance in tasks requiring alertness and manipulation and retrieval of information stored in memory (Boksem et al., 2005; Boksem and Tops, 2008). Since both physical and mental fatigue have a significant impact on the work performance of construction workers, they may pose potential risks to their occupational health and safety on construction sites. Consequently, this review focuses on the root causes, evaluation methods, and interventions of both physical and mental fatigue among construction workers.

3. Research methodology

After reviewing the definition of fatigue, the mixed-review approach, which incorporates both quantitative (bibliometric analysis) and qualitative (systematic review) methods, was used to explore the major research findings. Bibliometric analysis is a common method that utilizes descriptive statistics to provide an overview of existing literature (Linnenluecke et al., 2020), while systematic review is often used to understand the substantive findings of a series of studies or epistemological trends in the literature (Hallinger and Kovačević, 2019). Given its emphasis on leveraging the strengths of both strategies, the mixed-review method has been widely used for not only reviewing and synthesizing literature but also in research on construction and engineering management (Pan and Zhang, 2021; Shaban et al., 2023). To retrieve relevant literature on CWF, the Scopus and Web of Science (WoS) databases were selected; these are the largest online academic databases and are extensively utilized by researchers for conducting literature reviews and feature the most influential academic contributions (Li et al., 2018; Liao et al., 2023). To ensure comprehensiveness, the timeframe of the articles was selected from 2014 to 2023. This was because of the simplistic and intuitive nature of articles published before 2014. With the evolution of information technology, scholars began to integrate CWF research with emerging technologies, resulting in a significant increase in the quantity and depth of articles after 2014. Subsequently, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) technique was used to screen and evaluate the included papers from the selected databases (Moher et al., 2009), which helped to improve the reporting quality of the review through a transparent literature selection process (Page et al., 2021). According to the PRISMA protocol, the paper extraction process was divided into four steps: identification, screening, eligibility, and included, as shown in Fig. 1.

Following the PRISMA protocol, in step 1, a comprehensive desktop search was conducted in the Scopus and WoS databases from 2014 to 2023. The selected keywords adhered to the following rule: ("fatigue" OR "exertion" OR "tiredness" OR "physical effort" OR "muscle fatigue" OR "physical fatigue" OR "mental fatigue" OR "physical stress" OR "mental stress" OR "work limit") AND ("construction") AND ("worker"). The initial search yielded 428 papers in Scopus and 325 papers in WoS. In step 2, peer-reviewed English-language academic articles in journals were used as screening criteria to refine the scope. After removing duplicate articles in the two databases, 364 papers were identified. In step 3, a quick view and thorough examination were performed to ensure the relevance of CWF-related publications. Specifically, the titles and abstracts of all retrieved papers were first screened to align with the research objectives, and full-text reading was then performed to ensure the relevance of the paper content to the research topic. After filtering, 229 papers that were irrelevant to the research topic were excluded. In

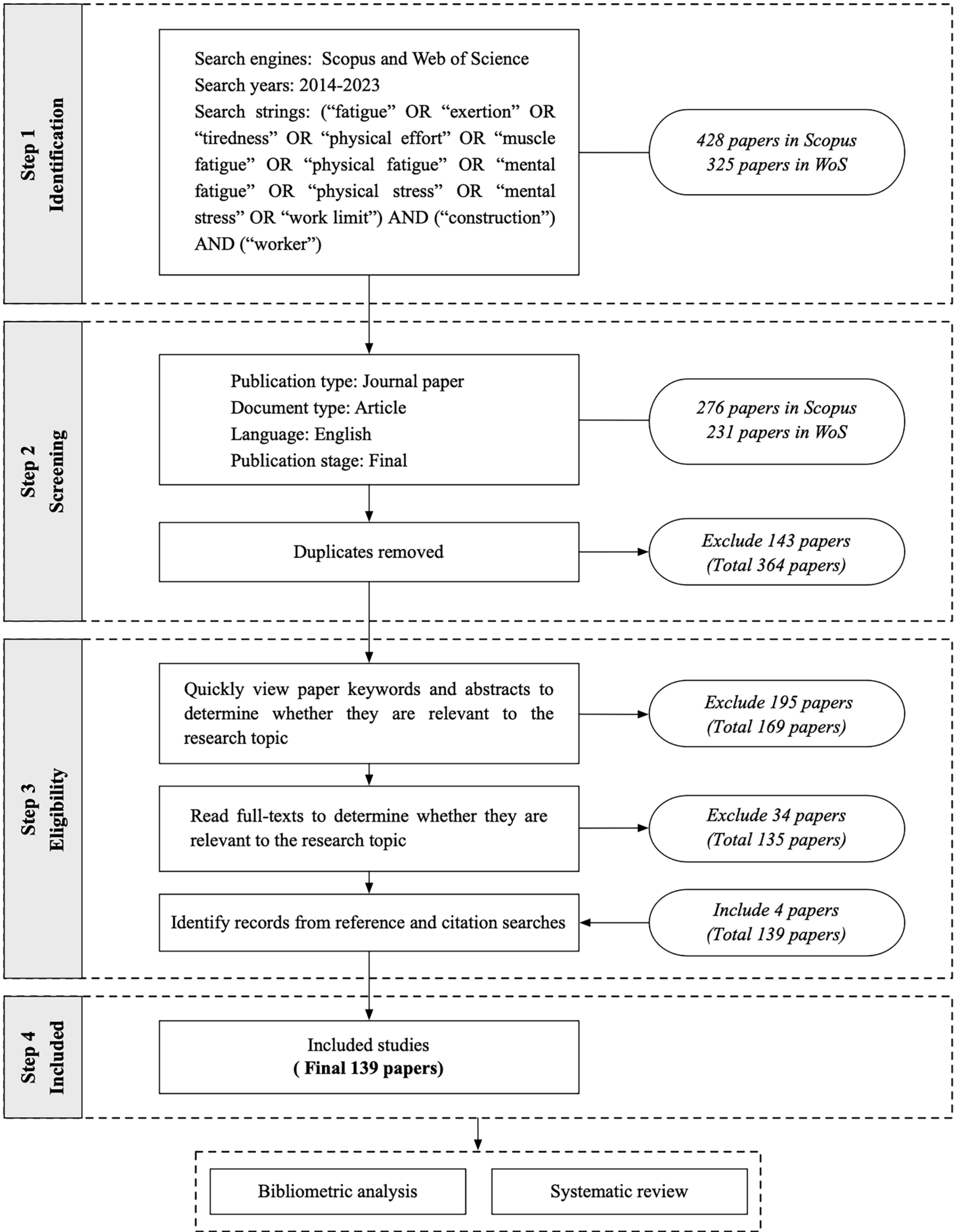


Fig. 1. The mixed-review method following the PRISMA protocol.

addition, a manual search step was performed to identify papers that might have been missed during the search process. By identifying records from reference and citation searches, four papers related to the studied topic but not previously targeted by the above keywords were added. To ensure the quality assessment of the included papers, step 3 was conducted by two independent reviewers (HZ and WY). Any disagreements were resolved by the third reviewer (MA). Eventually, 139 published papers related to CWF were identified in step 4. The bibliometric analysis and systematic review are discussed in sections 4 and 5, respectively.

4. Overview of construction worker fatigue (CWF) publications

The year-by-year trend of published journal papers related to CWF is shown in Fig. 2. The number of papers on CWF exhibited an overall upward trend from 2014 to 2023, with minor peaks observed in 2017 and 2018, followed by a slight decline. However, recent statistical data indicate a revival of research activity, resulting in a new peak with a remarkable growth rate of over 50 % in the number of papers in 2023. This trend underscores the escalating importance of fatigue among construction workers as a research hotspot.

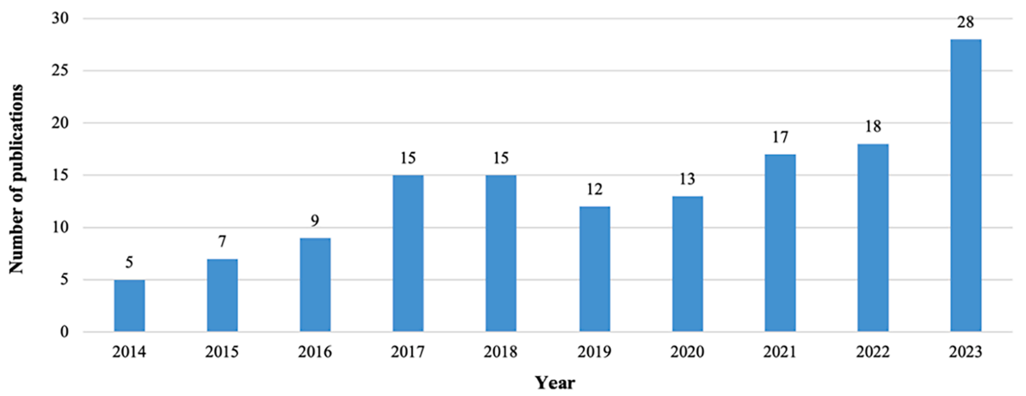


Fig. 2. Annual publication trends on construction worker fatigue (CWF).

In terms of journal sources, statistical data reveal that the 139 selected papers were published across 63 distinct journals, demonstrating the attractiveness of CWF to researchers from diverse academic disciplines, which has led to a comprehensive exploration and discussion of this topic from various perspectives. Table 1 indicates the top 10 journals with the largest number of related papers. Among these journals, *Automation in Construction* (19 papers), *Journal of Construction Engineering and Management* (13 papers), *Safety Science* (10 papers), and *Applied Ergonomics* (10 papers) lead in publication volume. This information can serve as a reference for future CWF studies, indicating suitable journals for researchers to submit their scholarly work.

In terms of geographical distribution, statistical data show that the affiliations of the first authors from the 139 selected papers span 29 different countries/regions. This global distribution indicates the significance and influence of CWF in the international academic community, with scholars from various countries/regions dedicated to advancing knowledge in this domain. Fig. 3 indicates the top 12 countries/regions contributing the most papers on CWF, with the United States leading with 36 papers. This reflects a high level of concern within the academic community and construction industry in the United States toward safeguarding the occupational health and safety of construction workers. Additionally, Hong Kong and China rank second (27 papers) and third (13 papers), respectively, indicating the importance of CWF in these countries/regions. The total number of papers published by the first author in the top 12 countries/regions accounts for 82.7 % of the total number of papers in the target journals (115 out of 139 articles). This substantial percentage underscores that the contribution of these authors to research on CWF is significantly higher than that of authors from other countries/regions, reflecting the top countries/regions' emphasis on construction workers' health and safety, as well as technological innovation and reform.

To gain a comprehensive understanding of the research topics related to CWF, this review utilized CiteSpace, a commonly used scientific visualization tool, to analyze large-scale literature data (Jiang et al., 2023; Pan and Zhang, 2021). Cluster analysis in CiteSpace can identify and group related items within a bibliographic network (Azam et al., 2021). Fig. 4 visualizes 11 identified clusters on CWF. To provide a clearer understanding of the evolution trend, Table 2 displays the average publication year and scale of each cluster. Table 2 indicates that early research on CWF primarily emphasized physical fatigue, as exemplified by the clusters "hazardous posture," "muscle fatigue," "work-related musculoskeletal disorders (WMSDs) symptom," "lifting posture," "physical fatigue," and "physical work demand." This is because physical fatigue is the most tangible and easily discernible form of fatigue. As scholars have delved deeper, the importance of mental fatigue has become increasingly recognized. This shift in focus is evident in the emergence of clusters of "mental stress" and "mental fatigue." Additionally, there has been a growing emphasis on the implementation of protective equipment to safeguard construction workers, as exemplified by the cluster "cooling vests." Recent years have witnessed a shift toward using wearable sensing devices as an effective tool for monitoring fatigue. Thus, research themes have shifted toward clusters such as "fatigue detection" and "wearable sensor," highlighting the industry's commitment to improving the health and safety of construction workers through digitization and intelligence.

The variation of keywords related to research methods over time is shown in Fig. 5. Early research mainly performed controlled studies or cross-sectional studies to explore the causal or correlational relationships between variables. Over time, there has been a gradual shift toward conducting clinical studies or behavioral studies, which are effective in assessing the efficacy of fatigue intervention measures. With the development of wearable sensing technologies, the amount of data available has increased. In response, data processing methods have gradually evolved from descriptive, correlation, and variance analyses to more complex techniques using machine learning and deep learning algorithms. This indicates that researchers in the field of CWF are actively using emerging technologies for deeper data analyses, providing more comprehensive insights regarding CWF.

To provide a more comprehensive understanding of CWF, Fig. 6 demonstrates the evolving landscape of research themes and methods/technologies in this field over time, drawing insights from both bibliometric and content analyses. Early studies on CWF largely delved into the factors influencing CWF and fatigue symptoms (Ekpenyong and Inyang, 2014; Oksa et al., 2014) employing traditional research methods such as questionnaires, interviews, and field studies (Ekpenyong and Inyang, 2014; Visser et al., 2014). Subsequently, researchers shifted their focus toward the measurement and real-time monitoring of CWF (Maciukiewicz et al., 2016; Tsai, 2017), with wearable sensing devices making notable contributions to this area (Hwang et al., 2016; Hwang

Table 1
Top 10 journals by number of papers on construction worker fatigue (CWF).

Journal name	Number of papers
Automation in Construction	19
Journal of Construction Engineering and Management	13
Safety Science	10
Applied Ergonomics	10
Engineering, Construction and Architectural Management	5
Sensors	5
International Journal of Environmental Research and Public Health	4
International Journal of Industrial Ergonomics	4
Journal of Computing in Civil Engineering	4
Ergonomics	4

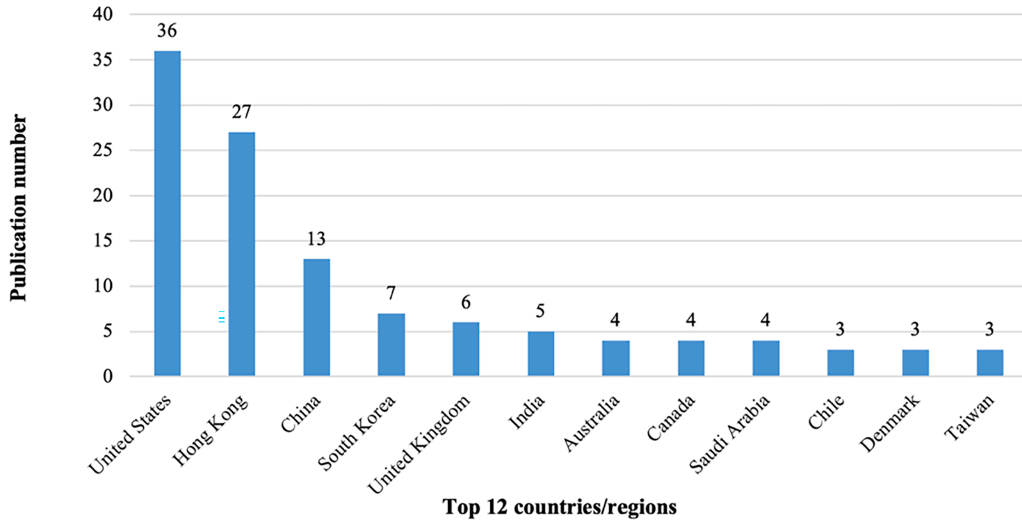


Fig. 3. Top 12 countries/regions by number of papers on construction worker fatigue (CWF).

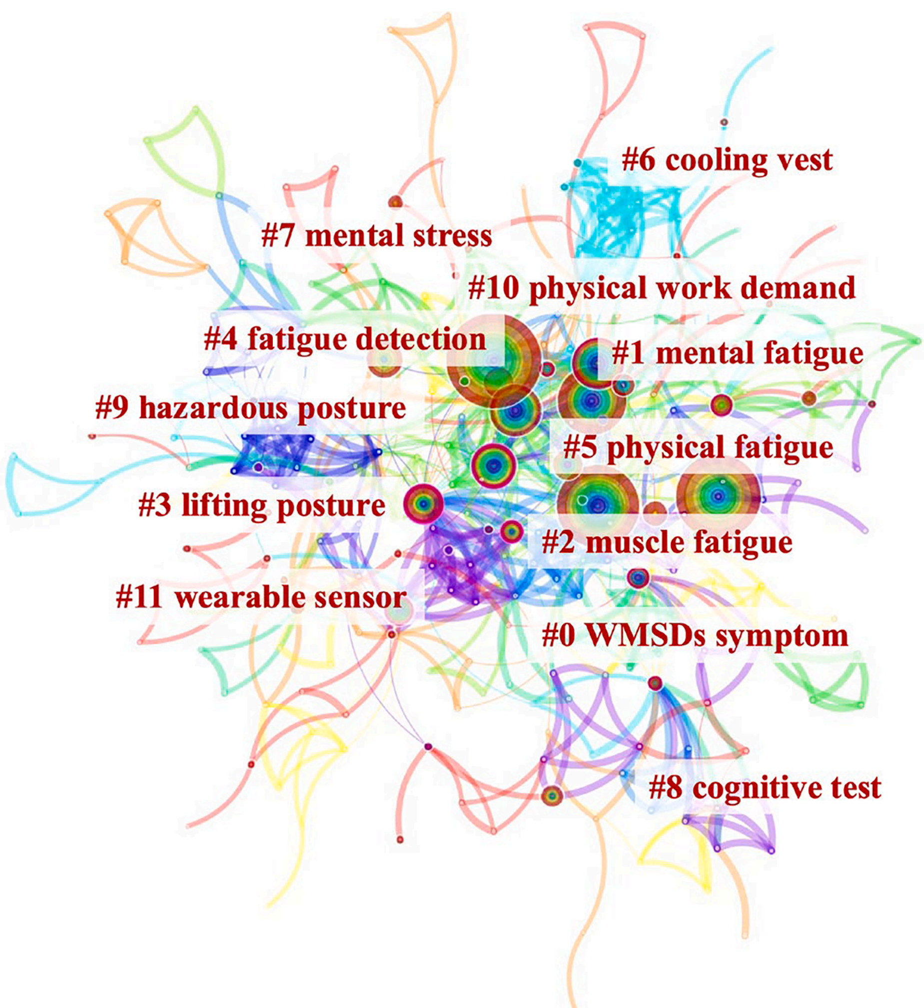


Fig. 4. Main research themes on construction worker fatigue (CWF).

and Lee, 2017). Simultaneously, certain studies emerged on interventions for CWF, with experimental research gaining prominence as the preferred research method. (Chan et al., 2017; Umer et al., 2017). As the demand for CWF management escalated, researchers gradually focused on CWF modeling and prediction (Antwi-Afari et al., 2020; Umer et al., 2020), with data processing methods evolving to incorporate more advanced machine learning and deep learning algorithms (Ghafoori et al.,2023; Ke et al., 2021). Recently, scholars have shown

Table 2
Summary of the identified clusters.

Average publication year	Cluster ID	Cluster topic	Size
2015	9	Hazardous posture	11
2016	2	Muscle fatigue	32
2017	0	WMSDs symptom	37
2017	3	Lifting posture	29
2017	5	Physical fatigue	25
2017	8	Cognitive test	20
2017	10	Physical work demand	11
2018	6	Cooling vest	25
2018	7	Mental stress	24
2019	1	Mental fatigue	36
2020	4	Fatigue detection	29
2021	11	Wearable sensor	9

interest in investigating the downstream effects of CWF and examining the relationships between CWF and work performance, as well as safety behavior (Bendak et al., 2022; Zhang et al., 2023).

5. Critical review of construction worker fatigue (CWF)

Following a bibliometric analysis of selected papers, a systematic review was conducted to further explore the research achievements in the field of CWF, encompassing the root causes, evaluation methods, and potential interventions. In addition, the challenges encountered within the area of study were addressed, and recommendations for future research directions were made. Fig. 7 shows the framework for the systematic review. Specifically, the review focused on three distinct aspects of CWF-related research: causes of CWF, CWF evaluation methods, and interventions for CWF. The research findings are presented below.

5.1. Causes of CWF

5.1.1. State-of-the-art studies on risk factors affecting CWF

Fatigue is widely acknowledged as the major cause of construction accidents (Swaen et al., 2003; Umer et al., 2023). It is caused by the continuous or excessive use of body systems, leading to energy depletion, metabolic acidosis, dehydration, hyperthermia, and ion imbalance (Phillips, 2015). Its occurrence is closely related to body system functions, such as cardiovascular and thermoregulatory functions (Ament and Verkerke, 2009), as shown in Fig. 8. To effectively mitigate CWF, it is crucial to identify risk factors that contribute to its occurrence. Numerous studies have identified risk factors affecting CWF across various construction activities, such as rebar bending (Yi et al., 2016), steel tying (Lim and Yang, 2023), heavy lifting (Antwi-Afari et al., 2017), pipe installation (Yung et al., 2014), concrete pouring (Arias et al., 2023), and equipment operation (Li et al., 2020). Common approaches adopted by researchers to identify risk factors affecting CWF can be classified as (1) experimentation and (2) focus group and interview. Experimentation is a powerful quantitative research method for understanding cause-and-effect relationships, allowing researchers to manipulate variables and observe effects (Mohajan, 2020). Laboratory experiments and quasi-experiments are typical methods used to explore risk factors affecting CWF. Laboratory experiments are often conducted to investigate the impact of work-related risk factors on CWF, such as the effects of long-time operation (Li et al., 2020), repetitive lifting (Antwi-Afari et al., 2017), overhead work configurations (Maciukiewicz et al., 2016), and various load-carrying techniques on worker fatigue (Anwer et al., 2022). In contrast, quasi-experiments are typically conducted on construction sites to identify the impact of specific environmental factors, such as high ambient temperature (Chong et al., 2020) and elevation (Hsu et al., 2016). Focus groups and interviews are prevalent qualitative research methods in the construction industry, aimed at collecting information through open-ended queries (Hancock et al., 2001). They are often used in conjunction, with focus groups aimed at reaching consensus opinions through worker-group interactions followed by individual interviews with industry experts or project managers to validate research findings. Compared with experimentation, the results of a focus group and interview method are more subjective and are often used to obtain a macro understanding of the fatigue situation of certain types of construction workers at the industry level. For instance,

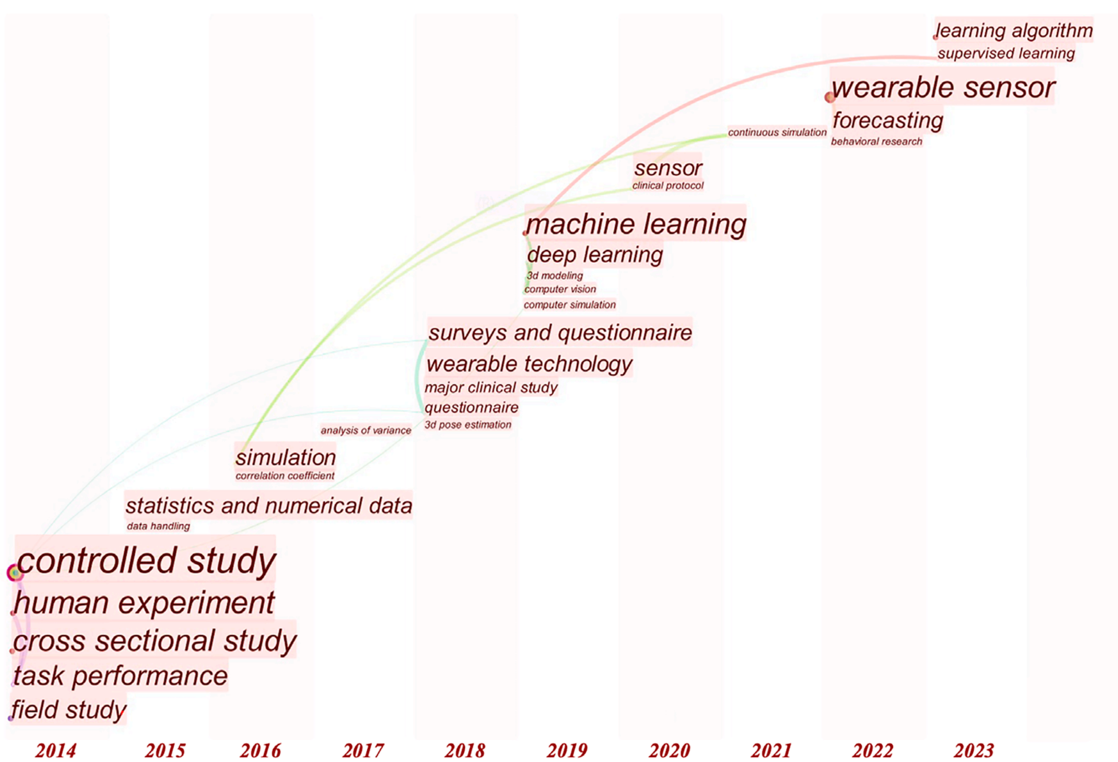


Fig. 5. Timeline map of keywords (related to research method) concurrence network.

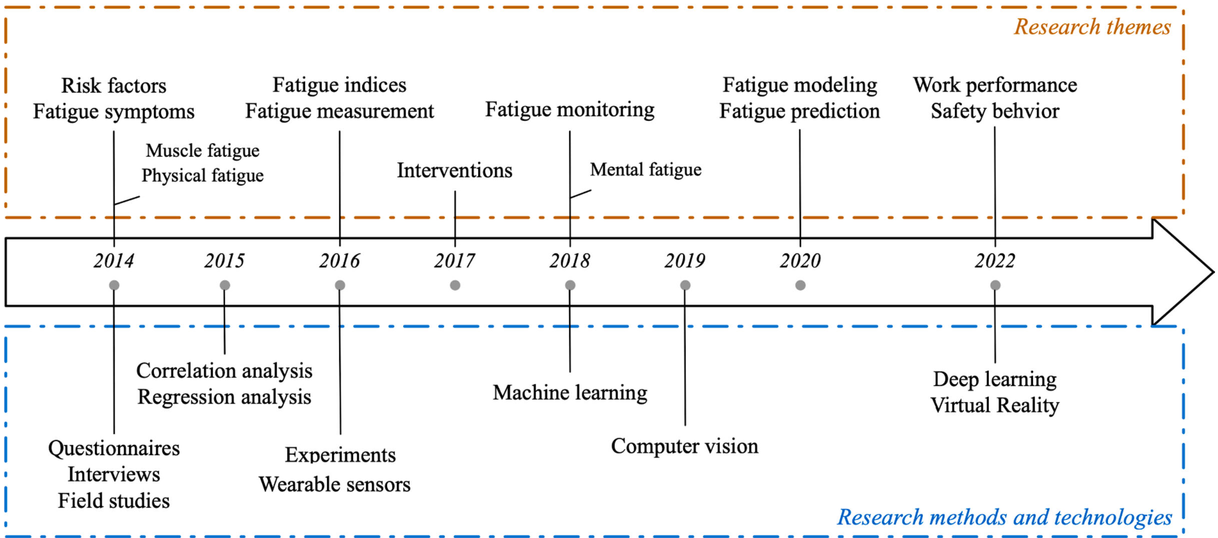


Fig. 6. Evolution landscape in research themes and methods/technologies for construction worker fatigue (CWF).

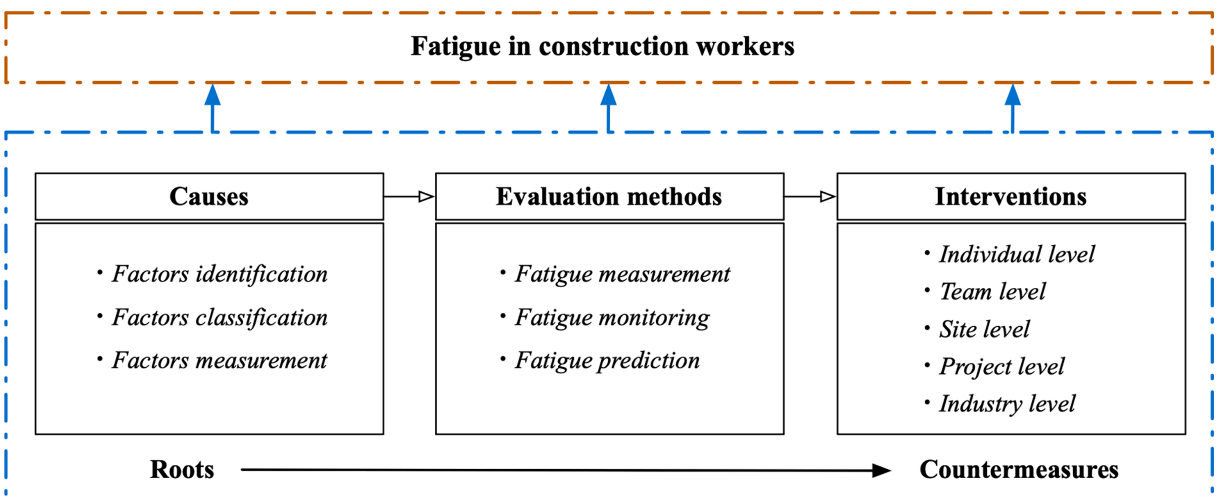


Fig. 7. Framework for analyzing construction worker fatigue (CWF).

Techera et al. (2019) interviewed 143 transmission and distribution workers and found that extreme weather and long shifts were the main factors affecting CWF in the transmission and distribution industry. Maynard et al. (2021) conducted focus group surveys and interviews with frontline workers and managers on a large-scale tunnel construction project and found that the physical environment, repetitive monotonous tasks, variable shift patterns, and manual work were the main causes of CWF in the tunnel industry.

According to these research methods, three major categories of risk factors affecting CWF can be identified: work-related factors, environmental factors, and personal factors, as shown in Fig. 8. Work-related factors are the most direct causes of CWF, as they directly lead to excessive strain on body systems, resulting in energy consumption and metabolic accumulation (Phillips, 2015). These factors include job nature, work duration, and workload (Chan et al., 2012; Yi et al., 2016). Long-term and high-intensity work are common causes of fatigue in all industries, but the job nature that triggers fatigue is particularly unique to construction workers. Unlike other sectors such as driving or piloting, the construction industry encompasses a wide variety of job types, and the fatigue formation mechanisms of different job types are different. For instance, excavator operators performing repetitive operations are more prone to mental fatigue due to overwork of the brain nervous system (Li et al., 2019), while rebar workers, who exert physical energy and maintain awkward postures for a prolonged time, are more susceptible to physical exhaustion due to perspiration, dehydration, and lactic acid accumulation (Anwer et al., 2022).

Environmental and personal factors also considerably influence CWF, as they can potentially influence the mechanism of fatigue occurrence (Davis and Walsh, 2010). Environmental factors including heat/cold stress, air pollution, noise pollution, and elevation, can exacerbate the difficulties faced by construction workers in performing their tasks, thereby strengthening the operation of related fatigue mechanisms (Szer et al., 2017). For instance, working in a hot and humid environment places more emphasis on fatigue mechanisms related to dehydration and hyperthermia than working in a cool environment (Nybo et al., 2014). It is worth noting that the role of the strengthening effects of these environmental factors is closely related to the job nature of construction workers. Specifically, outdoor construction workers are particularly susceptible to heat and cold stress during the onset of fatigue (Karthick et al., 2022; Yi et al., 2016), pavement construction workers or drillers are more prone to air pollution (Chong et al., 2014; Shalaby et al., 2019), equipment operators face a high risk of noise pollution (Ke et al., 2021b), and high-rise building construction workers may encounter the unique challenge of working at great heights

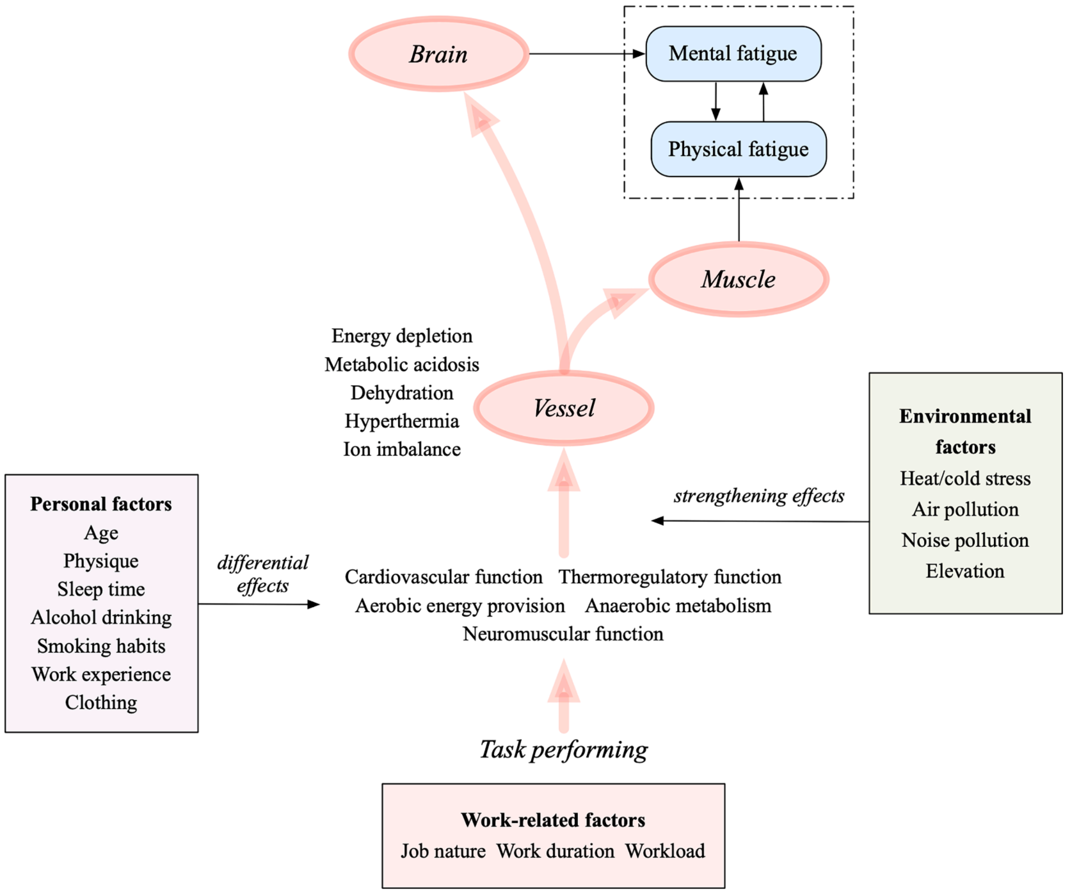


Fig. 8. The mechanisms and risk factors of construction worker fatigue (CWF).

(Hsu et al., 2008; Hsu et al., 2016). Personal factors include age, physique, sleep time, alcohol drinking/smoking habits, work experience, and clothing (Karthick et al., 2022; Salas et al., 2016; Yi et al., 2016). Some studies have demonstrated that different construction workers may experience different levels of fatigue while performing the same work tasks (Jebelli et al., 2019; Umer et al., 2022). This variation is attributable to differences in the functioning of body systems among construction workers, which can result in variations in the operation of their fatigue mechanisms. For instance, age differences may lead to variations in muscle groups (Lynch et al., 1999), and disparities in physique may result in variances in cardiovascular function, thermoregulatory function, and nerve control (Wallin and Charkoudian, 2007), influencing fatigue onset speed and duration (Green, 1997). In addition to the aforementioned risk factors, physical and mental fatigue experienced by construction workers have also been proven to interact and mutually influence one another (Umer et al., 2022; Xing et al., 2020). When workers experience physical fatigue, their brains may exert additional effort to maintain bodily functions, potentially inducing mental exhaustion (Meeusen et al., 2021). Conversely, mental fatigue can disrupt their brains' ability to regulate and control the body, thus affecting physical functions (Van Cutsem et al., 2017).

Numerous researchers have attempted to measure the risk factors associated with CWF (Chan et al., 2012; Chong et al., 2018; Yi et al., 2016), using approaches involving (1) questionnaire surveys and (2) instruments. Data related to work characteristics and basic personal information (e.g., age, sleep time, alcohol drinking/smoking habits, and clothing) are typically collected through questionnaire surveys. Typically, participants are required to fill out personal data collection forms before starting interviews or experiments. Data regarding environmental conditions and the personal physiological conditions of construction workers are usually measured using instruments. Researchers have used heat stress monitors to collect on-site dry bulb temperature, wet bulb temperature, globe temperature, relative humidity, and airspeed data (Chong et al., 2020; Yi et al., 2016), and employed environmental quality sensors to monitor on-site air and noise quality (Calixto et al., 2023). Personal physiological data, such as weight, fat rate, and body mass index, can be collected through electronic healthcare scales (Chong et al., 2018).

5.1.2. Challenges faced by risk factors affecting CWF

Although the abovementioned studies have systematically examined the root causes of CWF, most risk factors have been studied individually in laboratory settings or identified through qualitative focus group and interview approaches, and the prioritization of the importance of these risk factors remains to be examined. In addition, some studies have identified implicit risk factors, such as the workplace atmosphere, colleague relationships, and family pressure, that can trigger employees' mental fatigue (Bültmann et al., 2002; Kreitzer et al., 2020). However, the exploration of these implicit risk factors within the realm of CWF remains inadequately investigated. Several crucial research questions require further investigation:

- What is the order of importance of the risk factors affecting CWF?
- How do implicit risk factors, such as social environment and social relationships, potentially affect CWF?

5.2. CWF evaluation methods

Accurate and reliable evaluation methods for CWF are crucial for implementing appropriate countermeasures to mitigate or prevent the adverse effects of CWF. Numerous studies have been devoted to CWF measurement and monitoring and its subsequent prediction. This review focuses on both aspects to perform a systematic analysis.

5.2.1. State-of-the-art studies on measuring and monitoring CWF

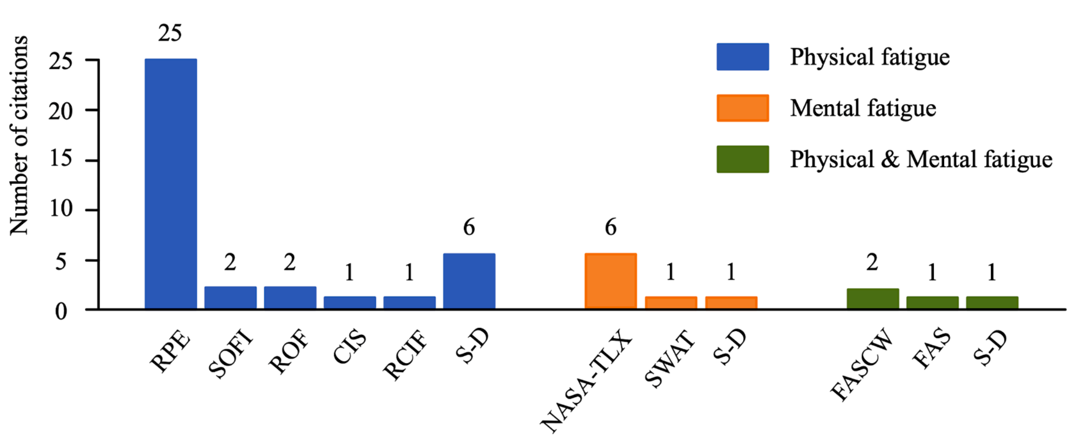
CWF can usually be reflected by the measurement of various indices, which are categorized as subjective and objective. Subjective fatigue indices typically correspond to individuals' self-rating of their current fatigue state based on subjective fatigue assessment scales, while objective fatigue indices generally describe people's fatigue level based on objective measurement methods, such as physiological measurements or biomechanical analyses. CWF measurement has been predominantly based on objective indices (47 papers) or a combination of subjective and objective indices (41 papers). Only a limited number of studies have relied solely on subjective indices for evaluation (4 papers).

In the construction industry, subjective fatigue assessment scales are commonly used to subjectively measure CWF. Owing to the variety of scale types, the subjective fatigue assessment indices used across different studies may differ. Fig. 9 shows the number of citations for subjective fatigue indices in the reviewed literature. The Rating of Perceived Exertion (RPE), which focuses on measuring the intensity of physical activity, is the most commonly used subjective fatigue index in evaluating the physical fatigue level of construction workers. The RPE index has only one score, ranging from 6 to 20 (Borg-20 scale) or 0–10 (Borg CR-10 scale), making it simpler and easier to apply in practice than other indices (Borg, 1998). Fig. 9 also illustrates that the NASA Task Load Index (NASA-TLX) is the most frequently used subjective fatigue index in measuring the mental workload or mental fatigue of construction workers. This index is considered to be more sensitive compared to the Subjective Workload Assessment Technique (SWAT), particularly for low mental workloads, because its measured dimensions are more detailed (Nygren, 1991). In addition, the Assessment Scale for Construction Workers (FASCW) is the index usually adopted to measure both the physical and mental symptoms of CWF, as it includes measurement dimensions of physical inactivity and mental fatigue (Fang et al., 2015). However, the fatigue index score of construction workers obtained using the traditional subjective fatigue assessment scale may not fully represent their actual fatigue level. Therefore, some studies have proposed relevant indices to objectively measure CWF.

Objective fatigue indices include a range of physiological and kinematic indices that provide valuable insights into the measurement of CWF. The number of citations for these objective fatigue indices is shown in Fig. 10, and their corresponding sensing measurement technologies and application wearable devices are summarized in Table 3. Cardiovascular indices are the most widely utilized physiological indices reflecting CWF, among which heart rate (HR) is the most commonly used. Numerous studies have proven the positive correlation between HR and physical or mental workload (Anwer et al., 2022; Shu et al., 2018), and some have directly linked HR to fatigue, revealing a strong relationship between HR and RPE (Anwer et al., 2020; Chang et al., 2009) or classifying HR values to distinguish different fatigue levels (Adi and Ratnawinanda, 2017). Heart rate variability (HRV) is another index gaining popularity for CWF measurement (Anwer et al., 2023; Umer et al., 2020). However, studies in other industries have found inconsistent results regarding the correlation between HRV and fatigue (Lu et al., 2022), while suggesting that HRV monitoring at rest is more suitable (Aubert et al., 2003; Djaoui et al., 2017). Electrocardiography (ECG) and photoplethysmography (PPG) are the two most prevalent sensing technologies for the measurement of cardiovascular indices in construction workers. ECG captures cardiac activity by directly measuring the electrical signals produced by heart contraction and relaxation through electrodes placed on chest straps (Prineas et al., 2009). In contrast, PPG measures cardiac activity indirectly by monitoring blood flow changes caused by heart contractions, which may result in a time lag in the results (Lu et al., 2009). However, PPG uses only a single optical sensor that is typically placed on the wrist, giving it an advantage over ECG (Allen, 2007).

Thermoregulatory indices rank as the second most popular physiological indices for CWF measurement. Numerous studies have revealed a significant relationship between skin temperature (ST) and CWF, as well as an association between ST and fatigue-induced unsafe behavior (Anwer et al., 2020; Zhang et al., 2023). Some studies have further explored the efficacy of using ST to assess CWF and highlighted that the ST outperforms HR in accuracy. Moreover, combining the information from both indices results in the most accurate measurement of CWF (Umer et al., 2020). Additionally, some studies have directly used the CT index to reflect CWF (Chong et al., 2018; Yi et al., 2017), as the measurement of ST is more easily affected by the surrounding environment than the measurement of CT. ST is typically measured by infrared temperature sensors that can be embedded in a chest strap or wristband or attached to a helmet to measure facial skin temperature (Aryal et al., 2017; Umer et al., 2022), with monitoring sites that are less susceptible to external airflow being more accurate (Psikuta et al., 2014). In contrast, the measurement of CT is more complicated. Some studies have used ingestible sensors for tracking CT (Yi et al., 2017), which may be invasive for construction workers.

Surface electromyography (sEMG) is a widely used and reliable method for detecting muscle fatigue, and its indices represent the level



Notes: RPE (Rating of Perceived Exertion); SOFI (Swedish Occupational Fatigue Inventory); ROF (Rating of Fatigue); CIS (Checklist Individual Strength); RCIF (Research Committee on Industrial Fatigue) ; NASA-TLX (NASA Task Load Index); SWAT (Subjective Workload Assessment Technique); FASCW (Fatigue Assessment Scale for Construction Workers); FAS (Fatigue Assessment Scale); S-D (self-developed).

Fig. 9. Number of citations for subjective fatigue indices.

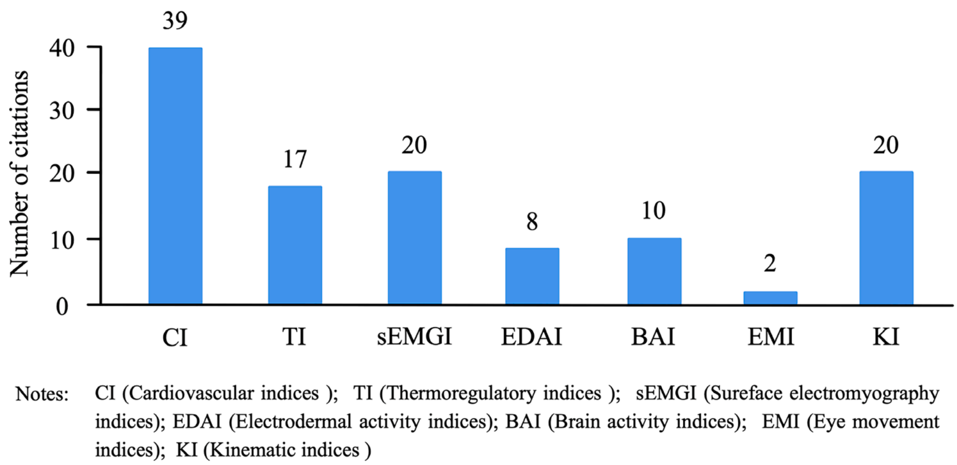


Fig. 10. Number of citations for objective fatigue indices.

of muscle engagement (Li et al., 2017). It is typically measured using two classes of parameters: those in the time domain (e.g., mean absolute value (MAV) and root mean square (RMS)) and those in the frequency domain (e.g., median frequency (MDF) and mean frequency (MEF)). Relevant studies have suggested that muscle fatigue in construction workers can be continuously monitored by measuring the sEMG activity of the target muscle during various tasks (Li et al., 2017; Lu et al., 2015). Sensors for sEMG are typically affixed to the forearms, shoulders, necks, waists, and backs of construction workers, as these areas are more prone than others to MSDs. Although sEMG measurements are noninvasive, the attachment of the sensors can interfere with workers' tasks, and sEMG signals can be easily affected by the skin preparation quality, sweating, ambient temperature, and movement artifacts (Anwer et al., 2021).

Electrodermal activity (EDA), brain activity, and eye movement are three indices used for mental fatigue measurement in construction workers. EDA reflects changes in the electronic properties of the skin due to sweat secretion (Benedek and Kaernbach, 2010) and has been proven to be a reliable method for worker mental fatigue measurement (Kazar and Comu, 2022; Lee and Lee, 2022), and some studies have further used EDA indices to reflect workers' physical fatigue (Jebelli et al., 2019; Umer et al., 2023). EDA sensing technology measures changes in electrical current caused by sweat secretion by applying a constant low voltage between skin contact points (Braithwaite et al., 2013), typically through two wired electrodes attached to the palmar or plantar surfaces. However, recent advancements in wearable sensors have enabled EDA signals to be measured through wristbands without interrupting participants' activities (Jebelli et al., 2019). Brain activity indices are mainly reflected by brainwave amplitude and frequency (Teplan, 2002), and brainwaves in different frequency bands are related to different brain activities. Numerous studies have demonstrated correlations between these brainwave bands (individual brainwave bands and combined forms) and mental fatigue in construction workers (Kazar and Comu, 2022; Tehrani et al., 2022). Electroencephalography (EEG) sensing technology is used to measure brain electrical activity by placing electrodes on corresponding areas of the scalp (Szafir and Signorile, 2011). Wireless helmets or headsets with multiple electrodes are used to collect EEG signals and record signal data for CWF (Li et al., 2019; Wang et al., 2023). Compared with other fatigue indices, the exploration of eye movement indices in the construction industry is limited. This approach mainly measures the mental fatigue of construction workers through blinking (e.g., frequency and time) and pupil behaviors (e.g., diameter and visual attention range) (Li et al., 2019, 2020). Eye-tracking sensing technology is often utilized to measure eye movement indices. This sensing technology can be implemented through lightweight wearable eye trackers, which typically consist of a world camera to detect the scene ahead and eye cameras to record the user's gaze point, blinking, and pupil behavior (Li et al., 2019, 2020).

Kinematic indices, typically calculated from the kinematic data of a set of movements having different directions in the workplace (Hajihosseinali et al., 2022), are widely used to assess CWF (Seo et al., 2015; Yu et al., 2019). Jerk is a novel kinematics index that can assess physical exertion and fatigue by measuring the jerk across various body segments (Zhang et al., 2019). Several studies have used indices of body posture or joint angles between body parts to construct human biomechanical models for assessing CWF (Yu et al., 2019; Dias Barkokebas and Li, 2023). Furthermore, Umer et al. (2018) proposed the use of the postural instability (sway) index to directly assess the fatigue status of the entire body of workers. To measure the above kinematic indices, wearable inertial measurement units (IMUs) are commonly used (Ahn et al., 2019). In capturing whole-body motion information, researchers typically position a single wearable IMU on the back or waist (Umer et al., 2018). When gathering gait motion data, sensors are commonly placed on the ankle (Bamberg et al., 2008). To assess ergonomic risk during activities, multiple IMUs are applied to different body parts to examine body posture and joint angles (Dias Barkokebas and Li, 2023). In addition, wearable IMUs can be combined with other technologies, such as computer vision-based 3D models, to improve the accuracy of their predictions in the construction industry (Yu et al., 2019). These measurement methods, whether used alone or in combination (Wang et al., 2023; Umer et al., 2020), provide a solid foundation for objectively assessing CWF.

Moreover, some studies have also investigated other novel methods to objectively assess CWF, such as plantar pressure detection (Antwi-Afari et al., 2018), worker sweat monitoring (Ma et al., 2023), facial expression recognition (Liu et al., 2021), or blood sugar level assessment (Kazar and Comu, 2022). Furthermore, some studies have utilized fitness-for-duty technologies to measure CWF, particularly mental fatigue (Aryal et al., 2017; Techera et al., 2018). These fitness-for-duty technologies typically measure operators' task performance abilities, such as hand–eye coordination, reaction time, and sustained attention, through computer-based tests to assess their vigilance or alertness and thus determine whether the workers are in a safe state for work (Balkin et al., 2011; Dawson et al., 2014). Since these technologies can only measure workers' current state of fatigue, they are often used for pre-job testing, and there is no evidence to show whether they can predict the fatigue that workers accumulate on subsequent jobs (Dawson et al., 2014). Among many of these fitness-for-duty technologies, the psychomotor vigilant test (PVT), which is used to measure sustained attention and reaction time, is considered to be the gold standard for fatigue detection (Dinges and Powell, 1985; Loh et al., 2004).

Table 3
Fatigue indices, sensing technologies, and wearable devices in the construction industry.

Fatigue indices		Indices characteristics			Sensing technologies		Wearable devices
		Practicality	Measurability*	Effectiveness*			
Cardiovascular indices	HR	Widely used (31 papers)	Easy to measure	Adequately validated	Cardiovascular Sensing	PPG sensing	Equivital EQ02 LifeMonitor Polar HR monitorZephyr BioHarness 3
	HRV	Moderately used (8 papers)	Easy to measure	Moderately widely validated		ECG sensing	Empatica E4 wristband Basis Peak™ Fitbit Charge HR™ Galaxy Watch Active 2 Cosmed K4bˆ2
Thermoregulatory indices	ST	Widely used (16 papers)	Easy to measure, but unstable	Adequately validated	Infrared temperature sensing		Equivital EQ02 LifeMonitor Empatica E4 wristband Infrared temperature sensors MLX90614Infrared pyrometer Omron MC-872
	CT	Moderately used (5 papers)	Difficult to measure, but stable	Moderately widely validated			Cor-Temp™ pill
sEMG indices	MAV; RMS; MDF; MEF	Widely used (31 papers)	Moderately difficult to measure	Adequately validated	sEMG sensing		Noraxon TeleMyo sEMG System Nexus 10 portable EMG system Porti 7 TeleMyo systemParomed Telemetric EMG recorder
EDA indices	EDL; EDR	Moderately used (8 papers)	Moderately difficult to measure	Moderately widely validated	EDA sensing		Equivital EQ02 LifeMonitorEmpatica E4 wristband Shimmer Research
Brain activity indices	Individual and combined brainwave bands	Moderately used (10 papers)	Moderately difficult to measure	Moderately widely validated	EEG sensing		Neurosky Mindwave Emotiv Epoc + mBrainTrain
Eye movement indices	Saccade behaviors; pupil behaviors; blinking behaviors	Narrowly used (2 papers)	Difficult to measure, but stable	Inadequately validated	Eye-tracking sensing		EyeLink 1000 Tobii Pro Glasses 2
Other physiological indices	Sweat	Narrowly used (2 papers)	Difficult to measure, but stable	Inadequately validated	Colorimetric technologies Electrochemical technologies		Gx Sweat Patch
	Blood sugar level	Narrowly used (2 papers)	Moderately difficult to measure	Inadequately validated	Enzyme electrode technology		Dexcom G4 Platinum
	Facial expression	Narrowly used (1 papers)	Difficult to measure, but stable	Inadequately validated	Video/image shooting		Video/ image sensor
Kinematic indices	Jerk	Narrowly used (1 papers)	Easy to measure	Inadequately validated	IMUs sensing		Noitom Perception Neuron MyoMotion system MOCAP system
	Body posture or joint angles	Widely used (16 papers)	Difficult to measure	Adequately validated			MetaMotionRXsens Mti
	Entire body instability	Narrowly used (3 papers)	Moderately difficult to measure	Inadequately validated			Moticon SCIENCE Sensor Insole GmbH
Plantar pressure	Foot plantar pressure	Narrowly used (2 papers)	Easy to measure	Inadequately validated	Wearable insole pressure sensors		Moticon SCIENCE Sensor Insole GmbH

Notes: HR = Heart rate; HRV = Heart rate variability; ST = Skin temperature; CT = Core temperature; MAV = Mean absolute value; RMS = Root mean square; MDF = Median frequency; MEF = Mean frequency; EDL = Electrodermal level; EDR = Electrodermal response; PPG = photoplethysmography; ECG = Electrocardiography; sEMG = Surface electromyography; EDA = Electrodermal activity; EEG = Electroencephalography; IMUs = Inertial measurement units. Measurability: judged by the type and number of wearable devices; Effectiveness: judged by the widespread use of the indices.

5.2.2. *State-of-the-art studies on predicting CWF*

The prediction of CWF is crucial for anticipating the occurrence of occupation fatigue and potential injuries among construction workers and adopting early intervention measures to reduce their risks. Earlier studies primarily have used correlation analysis or established multiple linear regression (MLR) models to predict CWF (Techera et al., 2018; Umer et al., 2020). However, it has been challenged that worker fatigue and fatigue indices (i.e., physiological and kinematic indices) may not exhibit a linear correlation (Malchaire, 1991). Additionally, the wide range of risk factors affecting fatigue (work-related, environmental, and personal factors) and their interactive effects may be far beyond the predictive power of an MLR model (Rowlinson et al., 2014). Therefore, some studies have turned to more advanced machine learning algorithms to address these complex issues. Table 4 summarizes the relevant literature on CWF prediction using machine learning algorithms. Several supervised machine learning classification algorithms, such as K-nearest neighbor (KNN), decision tree (DT), random forest (RF), support vector machine (SVM), boosted tree (BT), and linear discriminant analysis, have proven to be fast, accurate, and effective in predicting CWF and have been widely used in clinical assessments (Anwer et al., 2023; Li et al., 2020; Ma et al., 2023). The input variables for fatigue prediction models that rely on these machine learning algorithms typically consist of multiple fatigue indices, along with work-related, environmental, and personal risk factors that influence CWF (Aryal et al., 2017). Some research has also demonstrated that the CWF can be accurately predicted by using merely a single fatigue index (such as EEG or HRV) (Anwer et al., 2023). The output variable of the prediction model is generally a predicted fatigue score or multi-level classification of

Table 4
Summary of related studies on CWF prediction using machine learning algorithm.

Study	Participants	Environment	Algorithm	Input	Output	Data Size	Accuracy (%)
Anwer et al. (2023)	Construction workers	Construction site	KNN; DT; RF; SVM; ANN	HRV	RPE (no fatigue; mild fatigue; moderate fatigue; severe fatigue)	15 participants (1425 sets)	93.5 (RF)
Ma et al. (2023)	Non-construction workers	Simulated indoor	DT; RF; SVM; KNN; MLP	Sweat rate; Sodium concentration; Glucose concentration; Lactate concentration; FAS	RPE (low fatigue; medium fatigue; high fatigue; very high fatigue)	28 participants (140 sets)	96.4 (KNN)
Antwi-Afari et al. (2023)	Non-construction workers	Simulated indoor	SVM; ANN; RF; DT; KNN	Plantar pressure patterns; acceleration signals (38 dependent variables)	RPE (no-level fatigue; low-level fatigue; medium-level fatigue; high-level fatigue)	10 participants	86.0 (RF)
Wang et al. (2023)	Construction workers	Simulated indoor	CNN	EEG	Fatigue levels (no fatigue; mild fatigue; severe fatigue)	16 participants (151 × 375 × 8)	88.0
Umer et al. (2022)	Non-construction workers	Simulated indoor	ANN	HRV	RPE (no exertion; light exertion; heavy exertion; maximal exertion)	10 participants (1286 sets)	81.2
Ke et al. (2021)	Non-construction workers	Simulated indoor	SVM	EEG	Task performance (focused; distracted)	27 participants (671 sets)	99.67
Liu et al. (2021)	Use public dataset		CNN + LSTM	Facial video	Fatigue levels (alert, low vigilant, and fatigue)	(300 × 300 × 3)	80.3
Umer et al. (2020)	Non-construction workers	Simulated indoor	KNN; SVM; DT; Discriminant analyses; Ensemble classifiers	Age; BMI; HR; HRV; ST; breathing frequency; activity duration	RPE	10 participants (1286)	96.9
Li et al. (2020)	Construction workers	Simulated indoor	SVM; DT; KNN; BT; LDA	Eye movement Features (70 features)	Fatigue levels (fatigue level 1; fatigue level 2; fatigue level 3)	6 participants (216000 data points)	79.5–85.0 (SVM)
Jebelli et al. (2019)	Construction workers	Construction site	KNN; DT; linear SVM; nonlinear SVM; multilayer perceptron,	PPG; EDA; ST	Fatigue levels (low fatigue; moderate fatigue; high fatigue)	10 participants (9216000 data points)	87.0–90 (SVM)
Aryal et al. (2017)	Construction workers	Simulated indoor	DT; BT; SVM	Personal features; temperature signals; HR; work duration	RPE (low fatigue; medium fatigue; high fatigue; very high fatigue)	12 participants (253 sets)	82.6 (BT)
Yi et al. (2016)	Construction workers	Construction site	ANN	WBGT; age; BMI; alcohol drinking habit; smoking habit; work duration; job nature	RPE	39 participants (550 sets)	90.0

Notes: KNN = K-nearest neighbor; DT = Decision tree; RF = Random forest; SVM = Support vector machine; ANN = Artificial neural network; MLP = Multilayer perceptron; CNN = Convolutional neural network; LSTM = Long short-term memory; BT = Boosted tree; LDA = Linear discriminant analysis; HR = Heart rate; HRV = Heart rate variability; ST = Skin temperature; BMI = Body mass index; EEG = Electroencephalography; PPG = Photoplethysmography; EDA = Electrodermal activity; FAS = Fatigue assessment scale; RPE = Rating of perceived exertion; WBGT = Wet bulb globe temperature.

fatigue. Typically, multiple machine learning algorithms are compared in such studies to select the one that best predicts CWF, and the accuracy of these algorithms can usually reach 83–97 %, according to Table 4. Although machine learning algorithms have achieved acceptable accuracy, their inputs are limited to manually developed features, which may affect the model performance on real complex construction sites (Mehmood et al., 2023). Moreover, their processing capabilities for high-dimensional data such as images, videos, and audio are limited (Baduge et al., 2022; Xu et al., 2021). Therefore, certain studies have explored the application of deep learning algorithms for CWF prediction, mainly in processing EEG signals (Mehmood et al., 2023; Wang et al., 2023), analyzing images or videos (Liu et al., 2021), and recognizing actions (Roberts et al., 2020). These algorithms have demonstrated high accuracy levels (i.e., 81 % and 88 %, as indicated in Table 4).

5.2.3. Challenges faced by CWF measurement, monitoring and prediction

Despite the advantages of CWF measurement, monitoring, and prediction techniques based on sensing technologies, only a few studies have applied them at real-time construction sites. The noise and dynamic changes at actual construction sites can lead to more signal artifacts (i.e., unnecessary signals or signals that interfere with the target signal), which may affect the accuracy of data collected. Some studies have explored methods to minimize signal artifacts (Anwer et al., 2024; Kang et al., 2017; Jebelli et al., 2018). However, these techniques may not be effective due to high levels of signal artifacts at construction sites. Integrating multiple sensing technologies or combining emerging technologies may help improve the accuracy of construction site measurement. In addition, measuring CWF at actual construction sites can impede the progress of normal construction. The integration of sensing technology and construction processes has not been adequately explored. Furthermore, current research has primarily focused on short-term observations of CWF, with few studies exploring how CWF develops under the long-term impact of risk factors and how the consequential effects of CWF evolve over an extended period. Although Boschman et al. (2012) investigated the development of MSDs in construction workers over one year, and Boschman et al. (2015) examined the effects of MSD interventions on construction workers over two years, additional long-term studies on the formation, development, and impact of CWF are required to better understand CWF and propose effective interventions. Several crucial research questions require further investigation:

- How can signal artifacts be minimized when using sensing technology to measure CWF at actual construction sites?
- How can various sensing technologies be integrated into applications or utilized in conjunction with cutting-edge technologies to improve the accuracy of CWF measurement?
- How can CWF measurement based on sensing technology be incorporated into current construction workflows?
- How does CWF develop under the long-term influence of risk factors, and how do the consequential effects of CWF evolve over an extended period?

5.3. Interventions for CWF

5.3.1. State-of-the-art studies on interventions for CWF

To safeguard the occupational health and safety of construction workers and minimize the incidence of accidents during construction, interventions to alleviate CWF have been proposed from the perspectives of technology and management. Fig. 11 provides an overview of interventions for CWF at five levels: individual, team, site, project, and industry. The application of wearable sensing devices and personal protective equipment (PPE) are two typical technical interventions for individual construction workers. The development of various sensor-based wearable devices has provided significant opportunities for the real-time monitoring and prediction of the physical and mental fatigue of construction workers. For instance, wearable sensing devices can assess physical fatigue and monitor mental status to prevent fatigue-induced accidents (Li et al., 2019; Yu et al., 2019), detect awkward postures to prevent MSDs (Antwi-Afari et al., 2017; Li et al., 2017), and conduct fall risk assessments to prevent falls at construction sites (Tehrani et al., 2022; Umer et al., 2018). Advancing PPEs for individual construction workers is another technical intervention. Many studies have been devoted to exploring the development of PPE, particularly smart PPE, in which advanced technologies are incorporated to revolutionize safety practices in the industry (Rasouli et al., 2024). For instance, smart vests can be used to monitor workers' biological state (Yan et al., 2017), sense potential fall hazards (Abainza et al., 2020), provide alerts for extreme thermal conditions (Edirisinghe and Blismas, 2015), or assist in alleviating body heat strain (Yi et al., 2017), thereby reducing the risk of CWF.

Ergonomic interventions are commonly used as management strategies to alleviate fatigue among individual construction workers, worker teams, and construction sites, with the aim of preventing and alleviating work-related MSDs. Studies have proposed a large number of ergonomic interventions. For individual construction workers and worker teams, interventions include optimizing work task configurations (Anwer et al., 2022; Maciukiewicz et al., 2016), building models and frameworks to optimize workflow or operations (Dias Barkokebas and Li, 2023; Li et al., 2017), using exoskeletons to assist with work (Alabdulkarim et al., 2019; Antwi-Afari et al., 2021; De Vries et al., 2021,2022), and providing safety training on ergonomic risks (Nykänen et al., 2020; Hess et al., 2020). At the construction site level, ergonomic risks during construction work can be alleviated by introducing ergonomic tools and equipment (Antwi-Afari et al., 2017; Umer et al., 2017) and improving the workplace layout (Eaves et al., 2016; Golabchi et al., 2015).

Human–robot collaboration (HRC) is another technical intervention that can be applied at the level of individual construction workers and worker teams to reduce the stress of manual labor in dangerous or repetitive tasks by matching robot intelligence with human skills. Numerous studies have explored the application of construction robots in different construction tasks, such as transportation (Yang et al., 2021), excavation (Lee et al., 2019), installation (Lee et al., 2007), and assembly (Gil et al., 2013), in which workers collaborate with robots by assuming different roles. Specifically, workers can act as supervisors to monitor robots' behavior (Kunic et al., 2021), operators to change robots' behavior (Zhou et al., 2020), or teammates to complete tasks with robots (Xiang et al., 2021), thereby improving labor productivity while protecting worker safety. In addition to interactions with individual construction workers, certain studies have proposed collective robotic construction, which is considered to be more time-efficient and less prone to long-term failures. For instance, Leder et al. (2019) designed a decentralized multi-robot system to reduce the fatigue of an entire worker team by having a large number of robots collaborate as a team to perform different construction tasks. Usually, collective robotic construction is more extensively explored mainly in the construction of large-scale buildings or complex structures (Leder and Menges, 2023; Petersen et al., 2019).

Optimal work–rest schedules and appropriate shiftwork patterns are effective management interventions to help construction workers recover from fatigue and are mainly applicable at the project and industry levels. Considering construction workers' physical and physiological conditions, working environment, job nature, and the minimum rest time stipulated by the government (Yi and Wang, 2017), the appropriate work–rest frequency and duration, and timing of rest breaks can be set to reduce CWF while ensuring labor productivity (Hsie et al., 2009). Work–rest schedule and shiftwork pattern designs for construction projects usually need to be constrained by project-specific conditions: for instance, to meet project deadlines, Cheng et al. (2018)

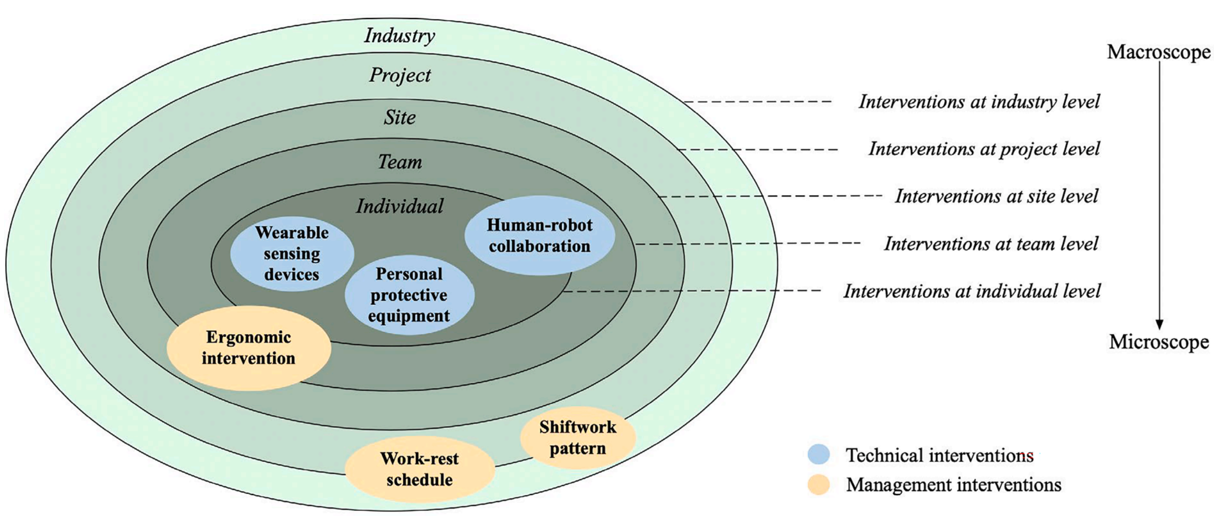


Fig. 11. Overview of typical interventions.

designed a work–rest schedule model based on a shift system to rationalize workers' work and rest. In contrast, work–rest schedules and shiftwork patterns at the industry level are typically more universal. For instance, Yi and Chan (2013, 2015) developed work–rest schedules for the construction industry in hot and humid environments, considering the traditional working hours of construction workers and combining meteorological data and workers' physiological data from different construction sites.

In addition to the construction industry, key fatigue intervention practices in other safety–critical industries can help provide insights into alleviating CWF. Biomathematical models of fatigue (BMMF) are considered key countermeasures to aid in fatigue management in other industries. This approach utilizes sleep data or work schedule data to predict worker fatigue and performance (Mallis et al., 2004). At present, BMMF has been widely adopted in the aviation industry to assist in planning the work hours of flight crew members (CASA (Civil Aviation Safety Authority), 2014), and in the military to optimize duty planning arrangements (Hursh et al., 2004). However, research on BMMF in the construction industry is limited (Pilkington-Cheney et al., 2020), mainly due to CWF being primarily caused by physical exertion in addition to the impact of sleep. Nevertheless, BMMF technology can be integrated into existing CWF prediction methods to optimize workers' work–rest schedules or shiftwork patterns.

Automation is also an important intervention for addressing fatigue in other safety–critical industries. In the transportation sector, autonomous driving technology has been widely studied and applied in practice (Milakis et al., 2017; Yin et al., 2017), and autopilot in aviation has also long been mature and applied (Chialastri, 2012). However, owing to the high complexity, inadequate management, technological lag, and low-cost labor in the construction industry, there remains a gap between the concept and practice of automated construction (Cai et al., 2020). Similarly, Fatigue Risk Management Systems (FRSM), which are data-driven management systems that can consistently monitor fatigue risks to ensure personnel remain vigilant in fulfilling their duties, have been widely used in some industries such as the transportation and healthcare sectors (Gander et al., 2011; Querstret et al., 2020). However, such a refined management method for CWF is lacking. Overall, the intelligence and refinement of CWF management in the construction industry still need to be improved, and this task should be advocated at the industry level. While tackling key technical issues, it is also necessary to establish and improve standard systems, reshape and redefine construction business processes, and reform the project construction organizational model in the construction industry.

5.3.2. Challenges faced by interventions for CWF

Despite extensive research on counteracting CWF, the use of wearable sensor devices and PPE is lacking in industry practice. Studies have found that factors such as comfort, privacy risks, and social impact have influenced the adoption of these advanced technologies by construction workers (Choi et al., 2017; Nnaji et al., 2020). Further research can explore strategies for overcoming the obstacles to implementing new technologies in the field of CWF prevention and optimizing the use of various exoskeletons to reduce workers' physical burden. HRC interventions have promoted the development of collective robot construction, but the optimal deployment of different types of robots, according to task and workspace type, to reduce technical redundancy and resource waste has not been fully explored. In addition, the information exchange among various devices, machines, and robots needs further research to ensure the smooth construction of collective robots and explore the application of digital twin technologies. Moreover, the best practices of fatigue interventions in other safety–critical industries can be studied to promote the management of CWF. Several crucial research questions require further investigation:

- How can barriers to the use of wearable sensing devices and PPE to mitigate CWF be overcome to promote the adoption of these new technologies?
- How can the deployment of different types of robots or exoskeletons according to the task and workspace type be optimized to reduce technical redundancy and resource waste?
- How can interactions between various devices, machines, and robot information systems based on digital twin technology be promoted?
- How can the best practices of fatigue intervention from other industries be leveraged to enhance the management of CWF?

6. Conclusion

CWF has received considerable attention and discussion within the past decades. Based on a mixed-review approach involving systematic review and bibliometric analysis, this study has provided a state-of-the-art review of CWF-related studies, from the root causes of fatigue to potential interventions. The findings of this review provide a foundation upon which scholars can gain more useful insights into CWF and may also help the construction industry to improve workers' occupational health and safety. Specifically, this review evaluates the evolution of research themes and methods related to CWF; identifies the work-related, environmental, and personal risk factors that affect CWF; investigates the measurement, monitoring, and prediction methods of CWF; and summarizes the application of interventions to alleviate CWF across five levels. However, future research faces challenges, which include fully exploring the importance sequence and interaction of risk factors affecting CWF, improving the accuracy of CWF measurement and its adaptation to construction workflow, obtaining long-term CWF observations, and overcoming barriers to the application of new technologies in alleviating CWF.

Although significant effort has been dedicated to reviewing the major developments in research related to CWF, this review is not exhaustive and is limited to the construction industry. Future research could explore occupational fatigue among workers in other industries. Due to differences in job characteristics, fatigue among personnel in other domains will be different from that among construction workers. Additionally, the correlations between different types of fatigue, the association between fatigue and unsafe behaviors, and the impact of fatigue on worker performance, are not fully discussed in this review. Further review efforts can be directed toward exploring these aspects. Overall, the study of occupational fatigue can play a significant role in fostering a safer, healthier, and more productive workforce.

CRediT authorship contribution statement

Haiyi Zong: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Wen Yi:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Maxwell Fordjour Antwi-Afari:** Writing – review & editing. **Yantao Yu:** Writing – review & editing.

Declaration of competing interest

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

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