Real-Time Fatigue Evaluation Using Ecological Momentary Assessment and Smartwatch Data: An Observational Field Study on Construction Workers

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Abstract: Managing the fatigue of construction workers is crucial to productivity, quality of work, and accident risk reduction. However, the current practice for assessing fatigue is limited when applied to construction sites. This study proposed a framework to objectively and subjectively evaluate construction workers' fatigue in real-time using an ecological momentary assessment (EMA) application and smartwatch data. Fatigue data were collected from 100 construction workers over three days. The results revealed that objective fatigue factors (heart rate and physical activity) were easily affected by the characteristics of the construction field (i.e., starting early, changing and demanding schedules, and overworking hours), whereas subjective fatigue steadily increased with working time. Most workers were aware of physical fatigue at the end of work for the day, when the EMA scores were the highest in a day. However, objective and subjective fatigue did not completely concur throughout the work period. Our findings are expected to improve the management of construction site health and safety with priority given to construction workers. The proposed framework, which utilizes EMA and wearable devices as a fatigue assessment method, reflects the comprehensive aspect of work-related fatigue. **DOI: 10.1061/JMENEA.MEENG-4953.**

Author keywords: Construction workers; Fatigue assessment; Ecological momentary assessment (EMA); Health and safety; Safety management.

Introduction

Occupational health and safety have become critically important in construction. Recently, the international construction industry has struggled with an increasing number of work-related accidents and other occupational health problems (Xie et al. 2022; Yu et al. 2019). The construction sector is a challenging place to work (Powell and Copping 2010), as physically demanding tasks and harsh environmental conditions are common (Aryal et al. 2017; Fang et al. 2015; Leung et al. 2016). Fatigue causes human error, and occupational fatigue is one of the principal causes of accidents (Namian et al. 2018; Techera et al. 2019; Wong et al. 2019a). Occupational fatigue is an essential subject, as it may adversely affect an individual's performance, safety, and health (Bhuanantanondh et al. 2021; Caruso 2014). In general, fatigue is multidimensional in terms of physical, mental, and cognitive aspects. Physical fatigue, after excessive workloads, reduces performance efficiency, whereas mental fatigue, resulting from intensive mental effort, reduces behavioral and cognitive performance (Anwer et al. 2021; Nwaogu et al. 2022).

Measurement tools should consider diverse aspects of workers' fatigue for accuracy (Anwer et al. 2021). Objective fatigue is widely understood as physical fatigue, and it can be measured quantitatively (Jebelli et al. 2019b). Subjective fatigue is assessed qualitatively, and it indicates personal perception aspects, such as mental and cognitive fatigue (Jebelli et al. 2019a; Techera et al. 2018). The work environment in the construction field has dynamic and risky characteristics (Fang et al. 2015). Characteristics such as changing and demanding schedules (Chen et al. 2022; Ferrada et al. 2021), project complexity (Xie et al. 2022), climate effect (Cheung and Zhang 2020), and long work hours (Ibrahim et al. 2020; Liu et al. 2020; Powell and Copping 2010) affect individuals' perceptions. As these perceptions cause the time lag between objective and subjective fatigue, quantitative measurements alone may produce inaccurate assessments (Ferrada et al. 2021; Riegler et al. 2021). Therefore, the evaluation of subjective fatigue is critical, particularly in the construction sector (Powell and Copping 2010). Considering multiple aspects of fatigue reduces measurement errors and increases the reliability of the results (Åhsberg et al. 2000b). However, research on multidimensional approaches in the construction field is scarce (Anwer et al. 2021). Thus, to measure fatigue accurately, it is essential to establish a multidimensional evaluation tool.

Extant literature has investigated diverse methods to accurately measure occupational fatigue (Bhuanantanondh et al. 2021; Techera et al. 2018; Xing et al. 2020). However, several limitations exist. First, self-reported methods, such as surveys, do not comprehensively measure workers' physical fatigue. Second, although several measurements of objective fatigue have been attempted using a

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PC-based psychomotor vigilance task (Aryal et al. 2017; Techera et al. 2018), heart rate (HR; Chang et al. 2009; Zhang et al. 2019), and skin temperature (Mehta et al. 2017; Umer et al. 2020), their validity as physiological proxies was limited. Third, most previous experiments were performed in a laboratory and not a real-world setting (Anwer et al. 2020; Aryal et al. 2017; Umer et al. 2020) or in a restricted simulation (Lee et al. 2017; Yin et al. 2019; Zhang et al. 2019). Therefore, work environments should be evaluated both subjectively and objectively in a real-world setting to ensure ecological validity and reliable data collection.

To address these gaps in knowledge, this study aimed to develop a framework using subjective and objective evaluation to measure construction workers' fatigue in actual working environments in real-time. Specifically, this study (1) proposed a multidimensional objective and subjective fatigue measurement approach, (2) assessed construction workers' fatigue levels and influencing factors in real field conditions, and (3) evaluated real-time fatigue measurements during construction workers' working hours. The development of a tool to measure multidimensional fatigue utilizing a real-time approach in field conditions is expected to facilitate the management of worker safety by investigating differences and correlations between subjective and objective fatigue.

Preliminary Research

Literature Review

Methods for Measuring Fatigue

A number of researchers have attempted to measure occupational fatigue. Hsu et al. (2008) measured subjective fatigue symptoms using a self-reporting questionnaire and interviews. These methods have low usability and reliability to immediately measure work-related physical fatigue. As self-report methods only evaluate the final fatigue status or outcomes, the data do not reflect real-time fatigue. Most research focusing on measuring instructed fatigue was performed in laboratory settings (Anwer et al. 2020; McDonald et al. 2016; Umer et al. 2020; Yin et al. 2019). However, the gap between real sites and laboratory settings limits the generalizability of these results to actual work sites. In addition, field studies have been conducted on samples of construction workers to measure physical fatigue using a PC-based psychomotor vigilance task, HR, and skin temperature; however, these studies used a specific work type (Techera et al. 2019) and a controlled measuring condition (Lee et al. 2017; Mehta et al. 2017).

Real-time measurement of work-related fatigues is essential for construction sites that are considering dynamic work (Yu et al. 2019). Therefore, various factors, such as HR and HR variability, skin temperature, and surface electromyography have been employed to objectively measure physical fatigue (Anwer et al. 2020; Ueno et al. 2018; Umer et al. 2017; Zhang et al. 2019). HR (Anwer et al. 2021), chest bands (Chan et al. 2012; Wong et al. 2014), and wearable devices (Anwer et al. 2020) have been frequently employed to obtain an objective measure, as most techniques have emphasized (Anwer et al. 2021). However, the feasibility of sensors and equipment was tested in a controlled environment. In addition, the physical data of construction workers and subjective fatigue were not evaluated concurrently.

Occupational Fatigue Assessment at Construction Sites

As shown in Table 1, a number of studies have investigated suitable tools to measure fatigue among construction workers. Lee et al. (2017) and Guo et al. (2017) examined the reliability and usability of wearable sensors for fatigue monitoring or for measuring physiological and physical data. However, they only tested a small sample size, making it difficult to generalize the results. Yin et al. (2019) proposed a new nonintrusive method for measuring fatigue; however, as they focused only on muscle fatigue, their findings may not accurately reflect work-related fatigue.

Recent studies in the construction field have explored the influencing factors of work-related fatigue. Techera et al. (2019) developed a questionnaire to measure fatigue among construction workers; however, they did not consider physiological data. Umer et al. (2020) and Anwer et al. (2020) collected physiological data using a wearable sensor with HR and skin temperature as proxies for physical fatigue. Although these studies measured subjective and objective fatigue, they were not in real-time and did not target construction workers. In contrast, Zhang et al. (2019) assessed the feasibility of using jerk, which is physical exertion calculated as the time-derivative of the acceleration magnitude (da/dt), as a physical fatigue factor among construction workers.

As such, despite the importance of subjective and qualitative evaluation, most previous studies focused on quantitative measurements of physical fatigue, whereas subjective fatigue has scarcely been evaluated. As shown in Table 2, extant studies have investigated only the possibility of fatigue-related factors (Aryal et al. 2017) or types of tools (Guo et al. 2017) but have not presented the time of occurrence or patterns of fatigue. Despite the importance of evaluating fatigue among construction workers, studies investigating actual construction sites and including large-scale samples are lacking. Therefore, the generalizability of previous findings is limited (Yu et al. 2019). Measurements should be conducted at actual construction sites in real-time to accurately evaluate objective and subjective fatigue.

Research Methods

Questionnaire: The Korean Version of the Swedish Occupational Fatigue Inventory

The Korean version of the Swedish Occupational Fatigue Inventory (SOFI) (Lee et al. 2021) was used to assess self-reported physical, mental, and cognitive fatigue among construction workers at a baseline and after 3 days. The SOFI comprises 20 questions rated on a seven-point Likert scale (0= "not at all"; 6= "highly"). The total score ranges from 0 to 120, and higher scores indicate greater severity of momentary fatigue; however, there are no cutoff criteria (Lee et al. 2021). SOFI has been translated into several languages and is widely used to measure general occupational fatigue (González Gutiérrez et al. 2005; Lee et al. 2021; Leung et al. 2004; Santos et al. 2017). The major advantage of SOFI is the measurement of diverse aspects of fatigue based on multiple items rather than a single item (Åhsberg et al. 2000b). SOFI has demonstrated high reliability for fatigue measurement and differences in various occupational groups (Åhsberg et al. 1997, 2000a, b), including construction workers (Lee et al. 2021). Cronbach's alpha was 0.86 in this study.

Ecological Momentary Assessment of Fatigue

This study used EMA as a momentary fatigue indicator. EMA is a measure of an individual's daily life experiences in real-time and has been severally used in social psychology and health-related studies (Strassnig et al. 2021). It is a method of collecting data "here and now" and should be performed in the natural setting to minimize the control of investigators (Targum et al. 2021). It can also assess the severity and variability of symptoms, activity, cognitive functioning, and biology at the moment and within-person (Kratz et al. 2017; Shiffman et al. 2008; Targum et al. 2021). Recently, the EMA has been applied to several contexts, such as

Table 1. Research composition highlighted in previous studies

Industry	Authors	Category: Experiment design	Participants (sample size)	Experiment period	Considered factor: Objective fatigue (physiological)	Subjective fatigue
Construction	Anwer et al. (2020)	Laboratory study (simulated task)	Healthy individuals (N = 25)	—	Heart rate, skin temperature	Borg's RPE 6-20 scale
	Umer et al. (2020)	Laboratory study (simulated task)	Healthy individuals (Male) (N = 10)	—	Heart rate, skin temperature	Borg's RPE 6-20 scale
	Zhang et al. (2019)	Laboratory study	Masonry workers (N = 32)	—	Jerk (physical exertion metric)	None
	Techera et al. (2019)	Field study	Electrical transmission and distribution workers (N = 143)	1 day	None	Questionnaire (researcher-developed) and interview
	Ueno et al. (2018)	Field study	Construction workers (Male) (N = 23)	3 days	Heart rate, weight loss, urine specific gravity	None
	Lee et al. (2017)	Field study	Roofers (N = 6)	5 days	Heart rate, energy expenditure	Questionnaire
	Guo et al. (2017)	Field study	Construction workers (N = 3)	18 days	Heart rate, skin temperature, calorie consumption, steps	Emotion (PANAS scale)
	Aryal et al. (2017)	Laboratory study	Construction workers (Male) (N = 12)	—	Heart rate, skin temperature, EEG waves	Borg's RPE, PC-PVT
Non-construction	Yin et al. (2019)	Laboratory study (simulated task)	Healthy individuals (N = 12)	—	Heart rate	Borg's RPE 6-20 scale
	Mehta et al. (2017)	Field study	Operators (N = 10)	Questionnaire: 1 day Sensor data: 6 days	Heart rate	Swedish Occupational Fatigue Inventory
	McDonald et al. (2016)	Laboratory study (simulated four tasks)	Healthy individuals (N = 12)	—	Heart rate (EMG), kinetic data (motion capture)	None

Note: Borg's RPE = rating of perceived exertion; and PC-PVT = PC psychomotor vigilance task.

Table 2. Comparison of previous studies with the proposed framework

Comparison items	Previous studies		Proposed framework	
	Fatigue measurement	Fatigue assessment	Fatigue measurement	Fatigue assessment
Scope	Physical	Quantitative	Physical, mental, and cognitive fatigue	Quantitative and qualitative
Method	On-body sensor and survey	Computer simulation and machine learning	Smartwatch sensor and SOFI	Smartwatch data and EMA
Sample size	<50	<30	100	100
Degree	Relative	Specific	Specific	In-depth
Assessment result	Applicability of novel measurement devices and methods	Investigation of fatigue-related factors for assessment	Real-time measurement of subjective and objective fatigue	Patterns of subjective and objective fatigue

utilizing applications for mobile devices and smartphones (Armey et al. 2015). Thus, the EMA was chosen to collect data measuring fatigue during construction workers' work hours using a smartwatch. This method does not significantly interrupt work, as it uses short questions. In addition, the simple scale is not affected by education level differences (Kratz et al. 2017). This study assessed temporal patterns of multiple subjective fatigues among construction workers using real-time EMA of fatigue.

Participants were instructed to rate their momentary feelings using a button on the smartwatch for three days. A number was shown in the window of the smartwatch on a six-point Likert scale (0= "no fatigue"; 5= "severe fatigue"). To prevent interference with work, a survey and interviews on the use of smart devices considering the working environment characteristics of construction workers were conducted. Based on the results, individualized smartwatch prompts, using messages and vibrating alarms to remind participants to complete the EMA, were sent to the participants hourly during work hours (approximately 10 times per day).

Smartwatch

Smartwatches were selected due to their detachability and wearability without interfering with the participants' jobs compared to other equipment or sensors (Appendix S1). Smartwatches have the advantage of allowing the connection of the sensor and data collection in real-time by linking it with a smartphone. In addition, smartwatches enable the installation of researcher-developed EMA applications with UX design for improved usability (Appendix S2).

Physical activity (accelerometer and gyroscope) and HR were measured using a wrist-worn smartwatch (Galaxy Watch Active 2, Samsung Electronics Co., Ltd). The device is equipped with a photoplethysmogram (PPG) sensor, capable of estimating individual beat-to-beat intervals using reflective-light-based technology, to sense the rate of blood flow. It is considered a valid and reliable accelerometer that continually detects wrist movements that reflect activities (Troiano et al. 2008). Data were collected continuously in 1-s epochs and in a 1 Hz environment, for three consecutive days. Participants continuously wore the smartwatch on the nondominant wrist and were instructed to take it off only when taking a bath, charging the smartwatch, or for a few minutes as needed. Furthermore, participants were instructed that the gap between the watch and wrist should not prevent skin contact with the smartwatch sensors. We used LASoR software (applications collaborated with Samsung Electronics for data collection) to export the data.

Framework Development

Framework Design

We conducted an observational field study to evaluate fatigue among construction workers. To measure both subjective and objective fatigue using a real-time approach, a smartwatch equipped with a researcher-developed EMA application was selected as the experimental equipment. The focus of the experimental design phase was to: (1) develop a measurement process for the integrated measurement of subjective and objective fatigue, (2) collect data from construction workers in the field and mine data for evaluation, and (3) evaluate the collected multidimensional (objective and subjective) data between fatigue groups. To verify the framework, low-fatigue and high-fatigue groups were compared (Fig. 1).

Fatigue Measurement

Objective fatigue was measured using physiological indicators, such as HR accelerometer and gyroscope data. HR has been commonly used as an indicator of people's level of fatigue in their daily life (Bishop et al. 2018; Lee et al. 2020). HR is the most commonly used physiological measure to assess and monitor ongoing work fatigue (Aryal et al. 2017; Chang et al. 2009; Hsu et al. 2008; Mehta et al. 2017; Umer et al. 2020). Although HR is an adequate factor for fatigue assessment, physical demands (i.e., activity, energy) can increase it (Chan et al. 2012), and it can be influenced by changes in body posture (Anwer et al. 2021). Therefore, some factors related to physical demands should be considered when HR intends to be used for fatigue assessment (Anwer et al. 2021). This study uses activity value estimated from an accelerometer as a physical demand indicator for complementation HR. The relationship between fatigue and activity has been previously verified in various groups (Lamberts et al. 2010), and activity was found as a crucial component of fatigue routine assessment (Van der Werf et al. 2000). As shown in Table 1, physical demands criteria employed in earlier research were energy (Lee et al. 2017), calories (Guo et al. 2017), and kinetic data (McDonald et al. 2016). Objective factors that combined HR with activity could improve the validity of fatigue assessment. The overall subjective fatigue was self-reported twice, before and after the experiment, using the Korean version of SOFI. In addition, real-time subjective fatigue was reported by the participants using the EMA application.

Validation

Field Data Collection

The experiment period included one day for setting up and adapting to wearing the equipment, three days for data collection, and half a day (6 h) for collecting the equipment and ensuring data loss prevention. Data collection was conducted in small groups at different construction sites, with different collection times depending on the environment and circumstances of each site. We recruited a convenience sample of 100 construction workers at five construction sites in Korea between July and November 2020. The inclusion

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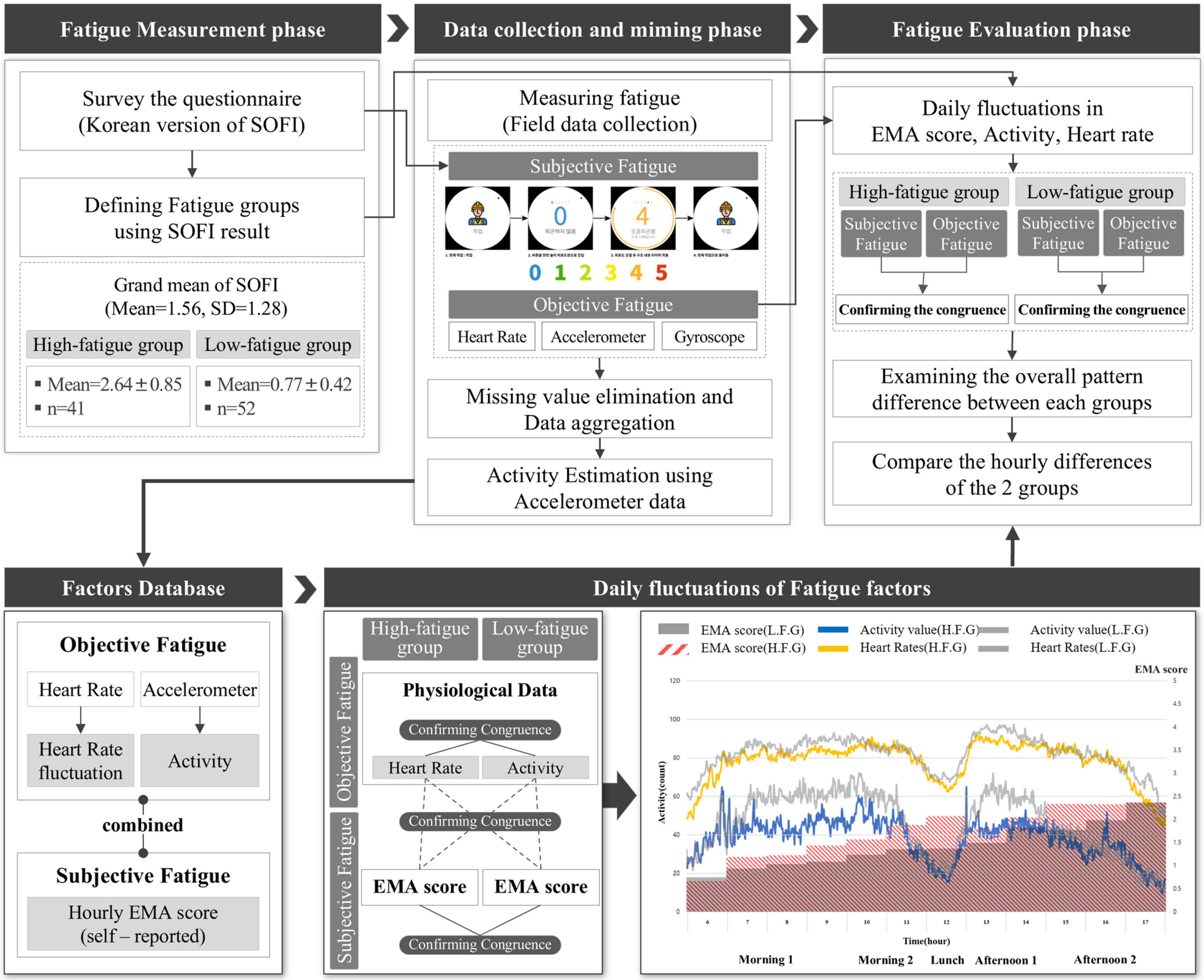

Fig. 1. Multidimensional evaluation framework.

criteria were (1) being ≥ 19 years old, (2) being Korean, and (3) having at least six months of work experience in construction. Participants received gifts worth US $100 for completing three days of data collection. The researchers described the experiment procedure in person to each participant individually using the smartwatch and provided illustrative materials, including a guide and video demonstration to fully understand the experimental method (Appendix S3). All participants provided written informed consent, and the institutional review board of the affiliated university approved the study. There was no difference in baseline information depending on recruiting seasons and sites.

Defining Fatigue Groups

As seven participants had missing data in the baseline SOFI, 93 participants were classified into two groups based on the degree of general fatigue. The evaluation framework was validated by classifying the participant into two groups based on the SOFI average score (mean $= 1.56 \pm 1.28$) considering the overall fatigue level (Hernandez Arellano et al. 2015; Lee 2016). The high-fatigue group (mean $= 2.64 \pm 0.85$, $n = 41$) was above the mean, and the low-fatigue group (mean $= 0.77 \pm 0.42$, $n = 52$) was below the mean (Fig. 2).

Data Processing

Data preprocessing began with downloading raw data and its conversion into analyzable data. Triaxial data were calculated as a degree of activity count. Based on the characteristics of the signal data collected in the time series at every 1-s interval, null or abnormal values 60 s or more in a row due to the user or device error were checked and excluded from the analysis. If a participant removed the device, the triaxial accelerometer recorded values of 0 to indicate the duration of time for which it was not worn. Natural human behavior involves micromovements sensed by the accelerometer even during sleep; therefore, periods with a continuous absence of movement indicated device removal.

The raw HR and accelerometer data were aggregated into 1-min epochs optimized for aggregating this data using a script written in Python. Data were excluded from the analysis when (1) there were outlier measures in 60 s despite the indication of wearing status or (2) more than 50% of a participant's data were missing in one day. In the data processing phase, 17 subjects, from the high-fatigue group ($n = 8$) and the low-fatigue group ($n = 9$), were excluded due to missing EMA reports, devices, and networking programs. Finally, data from 76 participants (high-fatigue group: $n = 32$, low-fatigue group: $n = 44$) were used for analysis (Fig. 2).

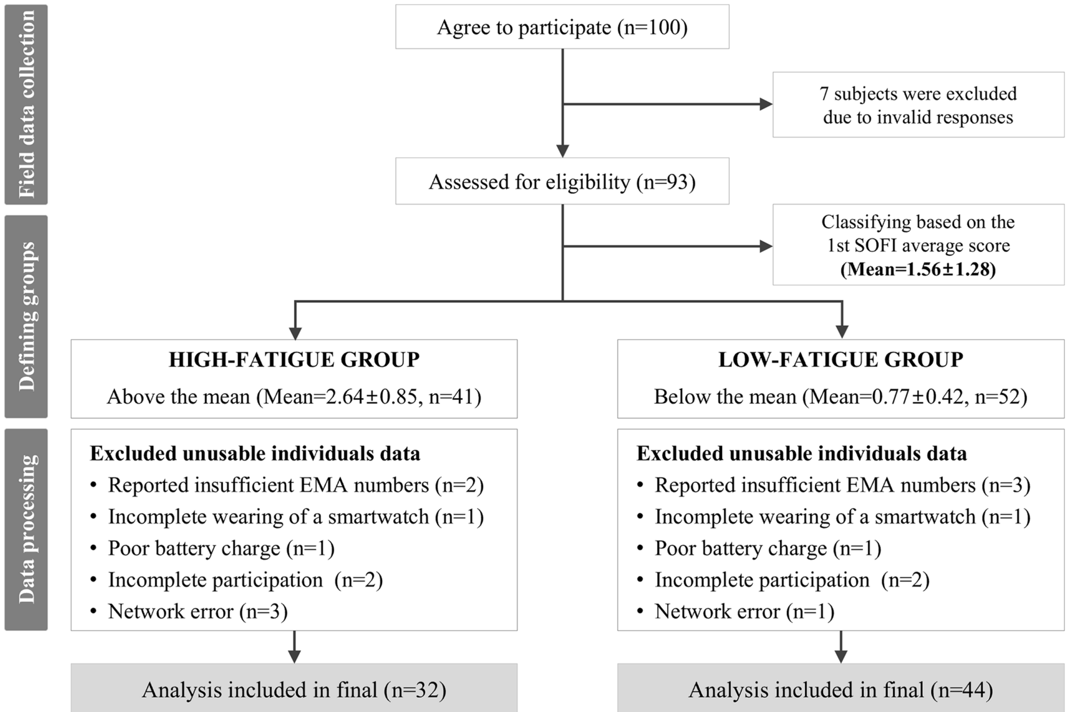

Fig. 2. Data selection process.

The average age of the participants was 46 ± 11.29 years. Most participants ($n = 74$, 97%) were men, and approximately half of the participants had up to high school education ($n = 35$, 46%). On the basis of the occupational fatigue assessment, 42% ($n = 32$) of the participants were classified into the high-fatigue group. Raw sensor data were processed using the aggregation, data selection, and reaggregation steps to standardize the assessment outcome.

Activity Estimation

Activity was calculated using an accelerometer in the smartwatch. Among the data collected by the smartwatch sensors, an accelerometer detects the degree of movement, whereas a gyroscope has been mainly used for motion recognition through movement patterns. We focused on measuring the degree of activity rather than patterns among construction workers, as work types were diverse. The activity calculation process (Fig. 3) comprised three steps: (1) aggregating raw accelerometer data at an interval of 60 s, (2) adjusting the weight of the three-axis of difference value (Kim et al. 2021)), and (3) converting difference value to energy value using signal vector magnitude.

Fatigue Evaluation

The fatigue evaluation process was designed based on the collected physiological and self-reported data. Objective factors were evaluated as physical fatigue, and the subjective factor was evaluated as mental and cognitive fatigue. The evaluation was performed with three factors, the EMA score as the subjective factor and HR and activity (physiological indicators) as objective factors collected from the smartwatch. Physical status evaluation using HR and physical routine awareness using activity value are two interpretations of the assessment of physical fatigue. The process contained three parts of (Fig. 4): (1) interaction between each factor, (2) congruence between subjective and objective fatigue in each group, and (3) overall fatigue patterns between high- and low-fatigue groups.

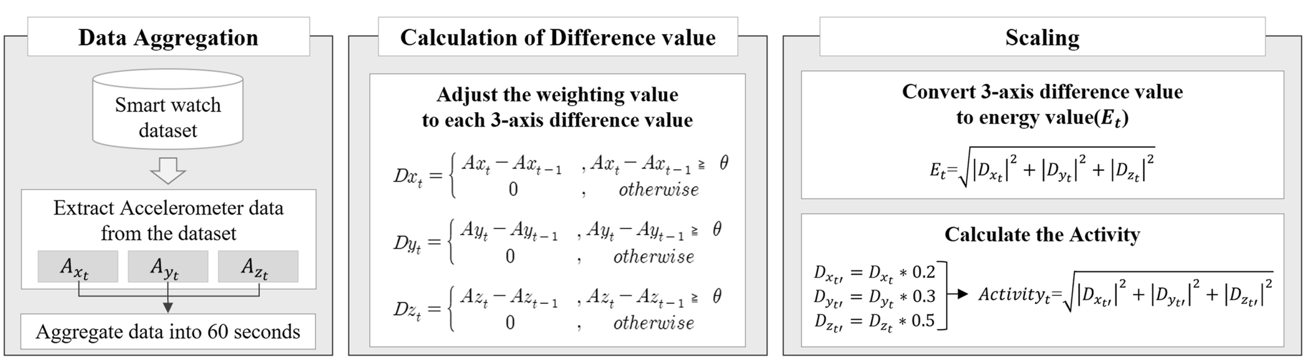

Fig. 3. Procedure for calculating activity value.

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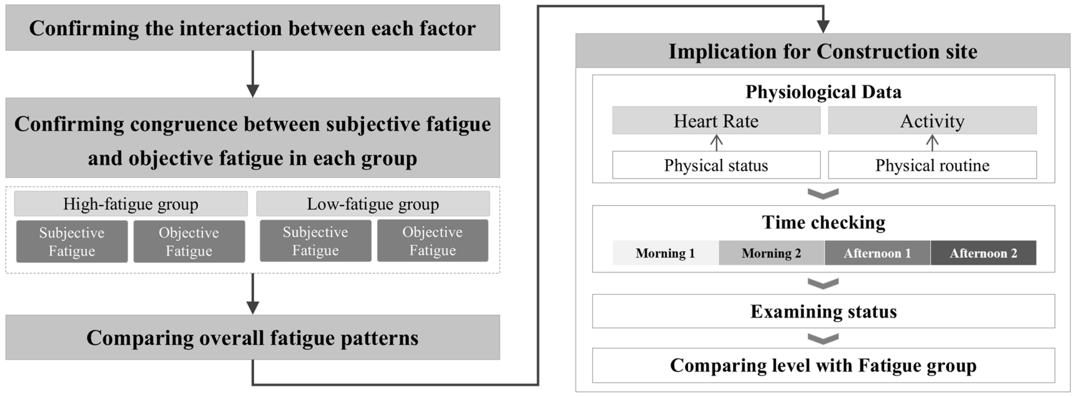

Fig. 4. Fatigue evaluation process.

Table 3. Mean differences by time

Variables	7 a.m.–10 a.m.	10 a.m.–12 p.m.	12 p.m.–3 p.m.	3 p.m.–5 p.m.
Ecological momentary assessment				
High-fatigue group	1.32 (0.89)	1.97 (1.16)	1.99 (1.03)	**2.28 (1.29)**
Low-fatigue group	1.02 (0.86)	1.35 (0.96)	1.61 (0.95)	**2.09 (1.21)**
Difference	0.30	0.62	0.38	0.19
P value	0.140	0.013	0.104	0.519
Activity				
High-fatigue group	42.39 (42.14)	37.57 (31.71)	**44.16 (31.86)**	26.41 (29.95)
Low-fatigue group	52.63 (27.32)	45.37 (25.68)	**57.62 (32.79)**	24.75 (30.99)
Difference	−10.23	−7.80	−13.45	1.65
P value	0.042	0.463	0.073	<0.001
Heart rate				
High-fatigue group	77.45 (27.71)	78.75 (19.11)	**87.39 (21.04)**	68.06 (19.43)
Low-fatigue group	82.77 (20.89)	80.73 (19.31)	**92.11 (16.67)**	72.50 (22.27)
Difference	−5.31	−1.97	−4.72	−4.44
P value	0.181	0.118	0.105	0.645

Note: Bold represents maximum value in the group.

Results

Mean Differences at Different Times

The Mann–Whitney U test was performed to identify daily fluctuations in EMA, activity, and HR and compare the mean differences between the two groups at a specific time (Table 3). Although EMA reports were collected hourly, the initiation of individual report times slightly differed. Therefore, the results are provided as time frames to ensure a sufficient number of samples. Time frames were determined based on the general break and lunch times of construction workers. The high-fatigue group reported higher EMA scores throughout the day. However, the high-fatigue group had lower levels of activity and HR in most frames compared with the low-fatigue group.

Furthermore, both groups showed the highest EMA scores at the end of the workday, between 3 p.m. and 5 p.m. This indicates that workers felt greater fatigue when finishing work. The highest levels of activity and HR in both groups were observed between 12 p.m. and 3 p.m., followed by 7 a.m. to 10 a.m. The high-fatigue group had higher EMA scores and lower HR and activity than the low-fatigue group in all time frames.

Fatigue Assessment

EMA scores were processed as follows: (1) exploring fatigue awareness patterns based on each participant's daily EMA scores, (2) confirming congruence between subjective and objective fatigue, and (3) examining differences in the overall patterns between the groups. Fig. 5 shows changes in EMA scores, activity, and HR during work for all participants over three days. Changes in activity and HR were similar. As activity increased or decreased, HR followed the same pattern, indicating a correlation between the two factors.

As shown in Fig. 5, the fatigue pattern of construction workers differed in the morning and afternoon. In the morning, EMA scores increased slightly as working time passed (0.71 to 1.67) and activity constantly stayed high, whereas in the afternoon, EMA scores increased and activity decreased, indicating concurrence of subjective and objective fatigue. In particular, the time frame between 3 p.m. and 5 p.m. demonstrated a sharp increase in subjective and objective fatigue. Furthermore, unique fatigue patterns and significant changes in activity were reported for 7 a.m., which is the start of the work day, and 1 p.m., which is the usual time of returning to work after lunch. This pattern implies that resting or sleeping helps relieve physical fatigue and indicates the need for rest before 3 p.m. to 5 p.m. when there is a rapid increase in objective fatigue.

The contrast between the two fatigue groups is shown in Fig. 6 to examine (1) the congruence between subjective and objective fatigue, and (2) the difference in overall pattern between the high- and low-fatigue groups.

Congruence between Subjective and Objective Fatigue

In the high-fatigue group, EMA scores increased as working time passed (0.66 to 2.06), and activity and HR remained constant with

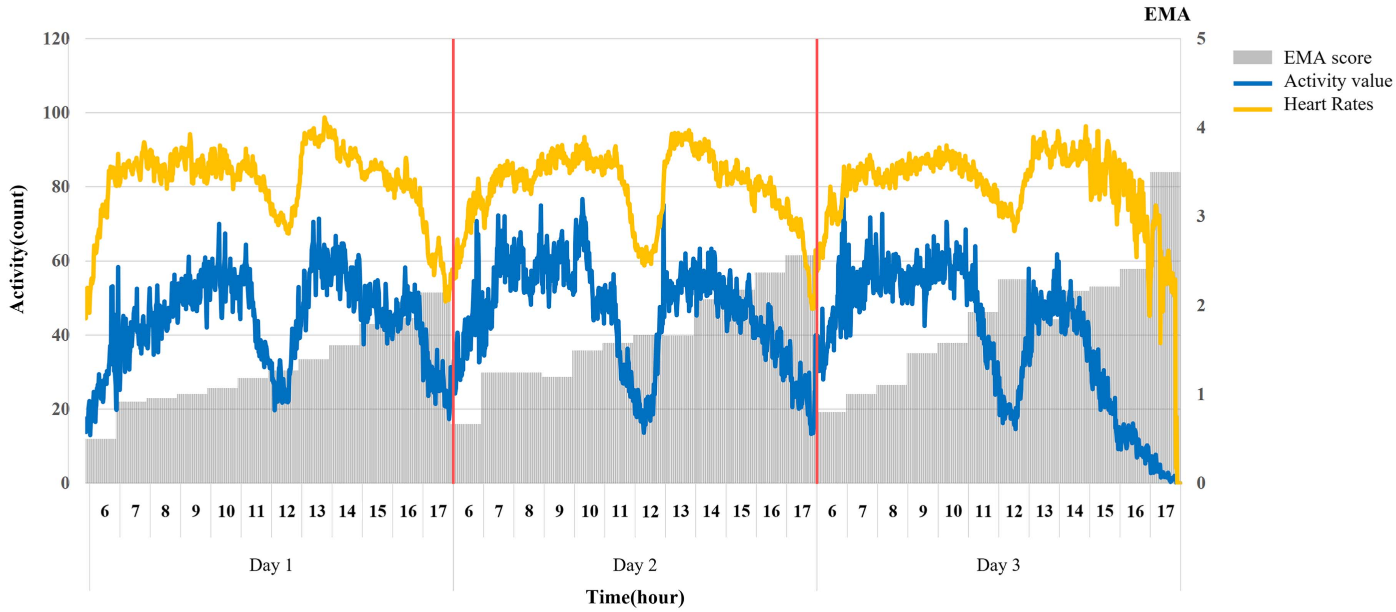

Fig. 5. Fatigue pattern for the whole experiment period.

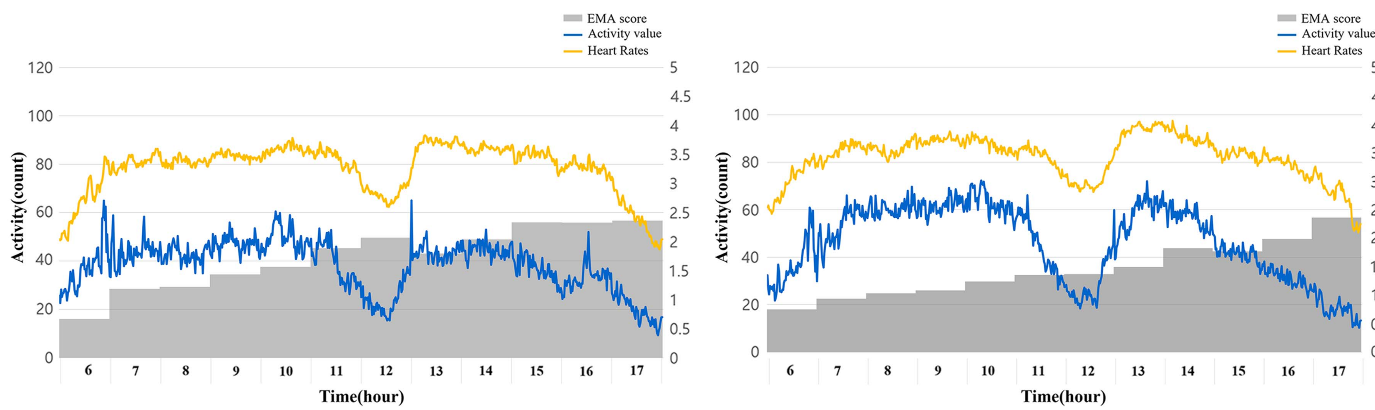

Fig. 6. Daily fatigue pattern: activity, HR, EMA score.

no considerable pattern change in the morning. In the afternoon, EMA scores increased (1.79 to 2.36), and activity (43.73 ± 4.18 to 19.50 ± 5.15) and HR (88.41 ± 2.75 to 57.44 ± 7.53) decreased. The subjective and objective fatigue factors showed an inverse pattern. This means two fatigue types are matched.

The low-fatigue group had a similar morning pattern to that of the high-fatigue group. However, an inverse proportion between subjective and objective fatigue factors appeared in the afternoon. Particularly, the lowest activity level and highest EMA score were observed at the end of the workday at 5 p.m. Decreased activity (indicating physical fatigue) corresponded with an increase in EMA scores (indicating subjective fatigue) due to accumulated work.

Increasing EMA scores matched objective fatigue after lunchtime. However, the subjective fatigue pattern did not match the objective fatigue pattern in the early morning (7 a.m. to 10 a.m.). These results indicated that most construction workers are not conscious of fatigue during work, as they have experienced prolonged adaptation work (Dong 2005; Kamardeen and Hasan 2022) and a high focus on work (Gürcanli and Müngen 2009). Nevertheless, both groups felt strong fatigue at the end of the work day (3 p.m. to 5 p.m.). From 3 p.m., physical fatigue increased sharply when work was continued without rest. However, from 1 p.m. to 3 p.m., right after lunchtime, two fatigue types increase gently as compared with the next time section. This suggests that taking some breaks or napping could help to reduce fatigue. It is necessary to relieve workers' physical fatigue by creating a break time with a particular term. Although the two fatigue patterns are not matched, the values of both fatigues had low values compared to other time sections.

Difference in Overall Pattern between the Two Groups

Changes in activity and HR in both groups were similar, with more frequent changes in the high-fatigue group. The low-fatigue group had higher activity throughout the working period than the high-fatigue group. A difference in level appeared from 7 a.m., when work started (low-fatigue group: 52.58 ± 7.73, high-fatigue group: 43.27 ± 5.19). There was a significant disparity between the two groups after lunchtime. The activity patterns of the two groups throughout the afternoon showed different shapes. In particular, the average activity value between 1 p.m. and 3 p.m., which is just after lunchtime, showed a mean difference of 14.48 (fatigue $= 43.73$, nonfatigue $= 58.21$). This result revealed a difference in physical fatigue between the two groups. In both groups, the activity level decreased as they approached 5 p.m. However, the decrease was sharper in the low-fatigue group, and the activity level of the two groups was similar at 5 p.m. Continuous report of low HR and activity was interpreted as the high-fatigue group being more likely to be affected by fatigue than the low-fatigue group.

Activity patterns of the two groups were different in the morning and afternoon, the same as general objective fatigue. The high-fatigue group reported significant changes and low activity in the morning compared with the low-fatigue group. The activity of the high-fatigue group increased from 36.42 (±9.41) to 49.28 (±5.09) in the morning. As described, frequent activity changes indicate frequent rest and work interruptions (Wong et al. 2019b; Yu et al. 2019). Despite taking a break, the high-fatigue group experienced physical fatigue again late in the afternoon. The overall subjective and objective fatigue of construction workers during work and physical fatigue with time differed. Furthermore, the results confirmed that defining fatigue groups in this study similar was valid, which was in line with previous studies (Chen et al. 2003; Pelders and Nelson 2019; Zhang et al. 2015).

EMA scores were analyzed by time frame and changes in daily fatigue between the two groups were compared. Both groups showed a steady upward curve working from 6 a.m. to 5 p.m., with the highest score at the end. However, the highest scores in the morning and afternoon were observed in the high-fatigue group. In the morning, the EMA score of the high-fatigue group showed a steeper upward curve compared to the low-fatigue group. A difference of 0.85 points (high-fatigue group = 2.14 and low-fatigue group = 1.29) was recorded at 12 p.m., which is estimated for the start of lunch. In the afternoon, the high-fatigue group had high scores from 1 p.m. to 5 p.m., without significant changes in the EMA score. On the other hand, the scores of the low-fatigue group continued to rise after lunchtime, with the highest EMA score appearing at 5 p.m. The EMA score increased as working time passed in both groups and workers were in a state of fatigue due to accumulated work. There is probably an interaction between subjective fatigue and prolonged work time (Leung et al. 2016; Umer et al. 2020). Construction site work starts earlier compared to other fields (Powell and Copping 2010). When the morning work time is long, workers are prone to fatigue. Work-related fatigue originated from several problems at construction sites, such as starting early (Ibrahim et al. 2020; Powell and Copping 2010), heavy workload (Fagan et al. 2012; Hartmann and Fleischer 2005), changing and demanding schedules (Chen et al. 2022; Ferrada et al. 2021), overtime work (Ibrahim et al. 2020; Powell and Copping 2010), poor work conditions, and hot stress (Aryal et al. 2017; Cheung and Zhang 2020). Work-related fatigue affects continued work. Therefore, fatigue caused by work should be monitored. In particular, according to the results, it is necessary to manage overtime work, and it is necessary to prepare an intervention for the high-fatigue group in the overtime work situation.

A mixed linear model was used to identify differences in changes in EMA scores between the two groups for each time period, and the significance level was set at $p = 0.05$ (Table 4). The model consisted of fixed effect = Time, Group, Time × Group, and dependent variable=EMA score. The high-fatigue group scored 0.36 ± 0.16 points higher than the low-fatigue group ($P = 0.027$). A within-group effect and changes in fatigue through time were observed. There was a difference in EMA scores by time and EMA scores within the groups; however, there was no difference in the curve shape of EMA scores between the two groups. EMA scores increased as working time passed, and the score of the high-fatigue group was higher than that of the low-fatigue group (Fig. 7).

Table 4. Differences in outcomes according to fixed effects (N = 76)

Outcome measure	B	S.E	t	*p* value
G1 (ref = 0.00)	0.336	0.085	3.960	<0.001
G2 (ref = 1.00)	—	—	—	—
Time (ref = control)	0.121	0.022	5.315	<0.001
G1 × time	0.004	0.035	0.141	0.888
G2 × time	—	—	—	—

Note: G1 = high-fatigue group; G2 = low-fatigue group; Outcomes = effects on EMA score; S.E = standard error; and all *p*-values were generated from linear mixed models.

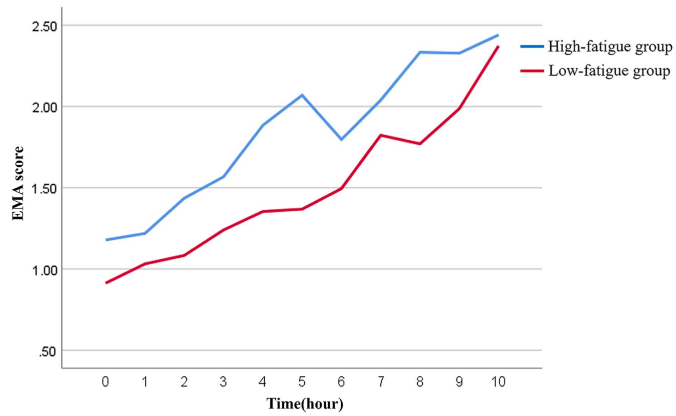

Fig. 7. Group mean plot for the EMA score measure.

The EMA score pattern of the two groups was similar; however, a value gap was detected. The high-fatigue group reported higher levels than the low-fatigue group, though many participants were not conscious of their fatigue due to various reasons, such as work experience, adapting to work, and ability to concentrate on work. The results indicated that the high-fatigue group was more conscious of subjective fatigue than the low-fatigue group, which was in line with Zhang et al. (2019, 2015). Therefore, subjective fatigue should be measured accurately and considered on construction sites. Managers should be aware of the possibility of potential severe fatigue for the high-fatigue group owing to their tendency to record mainly high subjective fatigue levels at all working times.

Discussion

Strengths and Weaknesses of the Evaluation Framework

This study successfully constructed a framework for measuring fatigue among construction workers in real-time using subjective and objective observations. Our evaluation framework was constructed to (1) perform in actual construction fields and not in laboratory settings (Anwer et al. 2020; Umer et al. 2020; Zhang et al. 2019); and (2) propose a multidimensional system for measuring and evaluating subjective and objective fatigue, which has only been performed separately in previous studies (Lee et al. 2017; Mehta et al. 2017; Techera et al. 2019). Particularly, this study provided a method to evaluate subjective fatigue in real-time, which was previously assessed using survey methods. Further, the result indicates that defining fatigue groups is valid in this study similar to previous studies (Chen et al. 2003; Pelders and Nelson 2019; Zhang et al. 2015).

Table 5. Difference in baseline fatigue between seasons

Season	N	Mean	Standard deviation
Summer round	43	1.50	1.15
Autumn round	50	1.60	1.04

Note: Summer round = 1st and 2nd rounds (July to August); and Autumn round = 3rd to 5th rounds (September to November).

The framework has weaknesses when compared to existing studies. First, the framework could not reflect diverse physical data as existing studies (Aryal et al. 2017; Guo et al. 2017; Ueno et al. 2018) have done, as we used only smartwatches to collect data. Especially, we used raw heart rates measured on the PPG sensor rather than HR variability. Second, the framework could not consider a predicting phase to assess fatigue automatically (Techera et al. 2018; Umer et al. 2020; Yu et al. 2019). Defining a formula for increased subjective fatigue (EMA score) based on increased physical fatigue (HR, activity) is a challenge, as the construction sector has too many variables, such as various work types, career deviation, and weather, to generalize. Despite these limitations, this study has made significant progress in that measurement and evaluation were attempted in actual work conditions with 100 on-site construction workers, and multiple aspects of fatigue were reflected using EMA and smartwatches. This study performed field data collection. Therefore, field conditions may have caused some data collection issues. First, field data collection may be affected by seasonal effects. Data collection was planned for the summer season when fatigue is the highest over a short period (Ueno et al. 2018). However, there is significant variability of human resources at construction sites, and data collection was delayed. To improve the generalizability of the results of the proposed framework, seasonal effects were examined. Experiments were divided into two groups: the summer and the autumn groups. We checked the seasonal effects by comparing the baseline SOFI result between the two groups (Table 5). The seasonal effect on the baseline SOFI result was not significant; to be specific, baseline fatigue was not affected by seasonal differences.

Moreover, the framework could not be performed using time-stamp matching of all EMA responses. The time when the mismatch occurred was mainly in the morning, which was caused by a time-stamp matching error. This occurred due to time lag caused by several conditions at each construction site (i.e., work start time difference, construction progress difference). Therefore, EMA response time was not controlled inside the experiments, and a time discordance occurred in work start times. Thus, further studies may consider time-stamp matching because unintended external variables could be controlled.

Currently, the construction site's fatigue management entirely depends on the subjective fatigue reports of the workers. Many researchers have attempted to improve the current fatigue management by investigating objective fatigue assessment factors (Table 1). This study also attempted to consider physical, mental, and cognitive aspects of fatigue and suggested a multidimensional approach using EMA and smartwatch. However, there is still a limitation in that all fatigue elements have not been covered. Therefore, the discrepancy between subjective and objective fatigue may still occur. This is because of the inevitable constraints, such as high variability of sensor data, external variables (i.e., harsh environment, work type), and restrictive information. The causes of discrepancy should be improved for a more accurate assessment. The multidimensional approach for fatigue assessment is still in the preliminary stage, and further studies should be conducted based on the findings of this study.

Managerial Implications

As mentioned earlier, evaluating objective and subjective fatigue is complicated, and fatigue patterns during work have not been considered in-depth. To address these limitations, this study developed a framework to evaluate the fatigue of construction workers using EMA and smartwatches. Fig. 8 exemplifies the utilization of the proposed framework by presenting the overall fatigue pattern and fatigue level at each time section. This facilitates a relative comparison of the overall fatigue pattern and fatigue level in each time frame when compared to the average. This can be used to investigate how severe the current fatigue is when compared generally. It can also be used to investigate fatigue patterns in a specific work environment. The result enables the establishment of a fatigue management plan according to the multidimensional fatigue assessment for construction workers. Thus, the proposed framework provides a more systematic and realistic process and can facilitate fatigue management in the construction field.

From an academic point of view, the proposed method verified that subjective fatigue can be assessed using EMA. Further research can be actively conducted, as it can be used as a real-time self-reporting method for construction workers' physical, mental, and physiological conditions. Especially, it can be extended to research on developing integrated fatigue indicators combined with various objective fatigue factors. As work schedule generally does not consider fatigue among construction workers in the field, fatigue management planning can be established by referring to fatigue

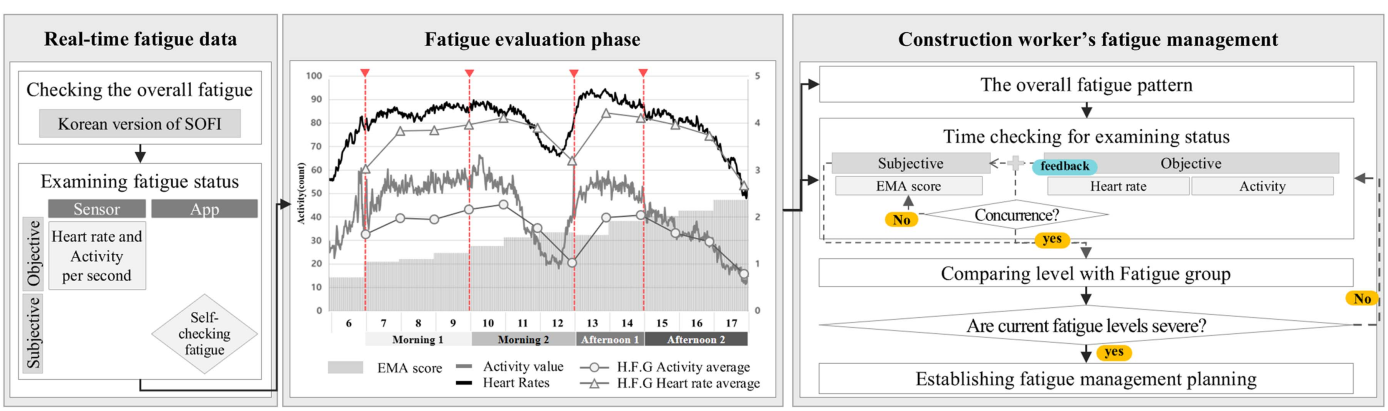

Fig. 8. Utilization of the proposed framework.

patterns, time-checking implications derived in this study, and objective factors, such as HR, skin temperature, activity, energy, and calories, which have been verified in previous studies (Anwer et al. 2020; Guo et al. 2017; Umer et al. 2020; Zhang et al. 2019). Moreover, it can contribute to lowering the possibility of accidents caused by human factors (He et al. 2020; Techera et al. 2018). This study contributes to the literature and knowledge on work-related fatigue management by proposing a framework for evaluating workers' fatigue due to ongoing work.

Findings derived from this study also make some practical implications for managing construction workers' health and safety. The significance lies in the following three aspects. First, to manage workers' fatigue systematically, time sections need to be considered in the assessment interpretation (Fig. 8). The fatigue pattern is different for each time section, and fatigue management according to the characteristics of each section is required as follows. (1) Early morning: owing to personal health status affecting fatigue, it is necessary to check whether they had sufficient sleep and drinking the previous day. (2) 3 p.m.: is the time when physical fatigue increases rapidly. Managers should observe workers' subjective fatigue and objective pattern and then continuously check their fatigue severity. Second, restrictions on work time should be adopted and implemented in the law aspect, like the n-hour workweek rule. Overwork (i.e., early work, night work) cause prolonged work hours and increases workers' fatigue ultimately. Therefore, the manager should carefully monitor how many hours their workers are working per week. The construction industry has long work hours and physically demanding tasks, and overwork is a crucial issue for worker safety. Based on the findings, this study discovered that prolonged work without rest severely affects the two fatigue types and that timely checking of workers' fatigue is needed. Finally, a health manager who can perform appropriate medical aid at construction sites should be employed regardless of the project size. To apply the multidimensional approach in real construction sites, the health manager can help make medical decisions or daily health checking, and manage workers' fatigue factors.

Because of these results, one can conclude that existing assessment methods (e.g., only sensing, survey, and self-report) for construction workers' ongoing work fatigue were insufficient for screening workers at risk for unsafe practices and accidents at sites. The current system determines the unsafe status of workers on the basis of age, blood pressure, and experience of site supervisors (Kamardeen and Hasan 2022; Pereira et al. 2020). Establishing advanced management is required because the current practices have limitations to prevent accidents caused by human errors and work-related fatigue is increasing (Techera et al. 2019; Wong et al. 2019a). Our multidimensional approach using EMA apps and wearable devices provides a possible solution by providing real-time data integrated with the objective and subjective information of construction workers in the field. By combining subjective and objective data, the integrated information also enhances the construction site's current fatigue management strategy. The multidimensional approach can also be utilized for innumerable purposes, ensuring safe working conditions by reflecting fatigue patterns like monitoring high-risk workers, making decisions about work schedules, and innovating new methods for construction duration calculation.

Conclusions

This study aimed to construct a real-time evaluation framework to measure and evaluate construction workers' subjective and objective fatigue using EMA and smartwatches at construction sites. To validate the utility of the proposed framework, subjective and objective fatigue factors of 100 construction workers, who were divided into two groups, were observed over the course of three days.

The fatigue evaluation was examined using three factors. Objective fatigue was measured using HR and activity, and subjective fatigue was measured using EMA scores. Objective fatigue factors (HR and activity) were affected by characteristics of the construction field, such as the early start of work, heavy workload, and poor work conditions. Between 10 a.m. to 12 p.m. and 3 p.m. to 5 p.m., construction workers should be checked for work-related fatigue, and actions should be taken. The participants' subjective fatigue increased as time progressed through the day, and most workers became conscious of physical fatigue at the end of the workday. However, objective and subjective fatigue did not concur completely during the work period, as the participants were not conscious of fatigue due to factors such as work experience, long work hours, and high focus on work. These results explain why objective and subjective fatigue should be considered together. The high-fatigue group appeared to have a high level of fatigue at all working times in both subjective and objective aspects. Especially, subjective fatigue was constantly reported at a high level in the afternoon. It indicates that occupational fatigue should be managed not to cause some adverse effects on their work.

This study makes major contributions to the construction field. First, it explored changes in ongoing subjective and objective work fatigue among construction workers by considering fatigue multidimensionally with a single measure. Second, it confirmed the utility of EMA as a subjective fatigue assessment method by utilizing a real-time framework using EMA in an actual field. As the construction field has several issues, such as work devoted to human resources, industrial accidents, and efficient safety management, the proposed framework can be used as a foundation for constructing safety management with priority given to construction workers. Therefore, this study is expected to provide a foundation for the construction field to further analyze workers' fatigue and improve the working environment.

While this study offers considerable advantages over previous studies, the findings of this study should be interpreted while considering the following limitations. The first relates to the limitation of diversity in data collection. We only collected physical data (HR, accelerometer, gyroscope), which could be collected using a smartwatch sensor. Fatigue-related physical data should be collected diversely by considering various sensors and measurement techniques. In particular, employing a PPG sensor to assess HR variability, presents its respective challenges. Therefore, using the raw HR based on bpm was explored for fatigue evaluation. Environmental factors, such as temperature, humidity, weather, and discomfort index, should also be collected, as they can affect fatigue. These factors are essential for the construction field with a lot of outdoor work, as the consideration of environmental factors can have important implications on productivity. The limitation of data type creates difficulty in evaluating work-related fatigue. The second limitation is the use of sensor data. We only the accelerometer data for estimating activity value. GYRO was excluded because GYRO is better at inferring work type rather than physical fatigue. Therefore, fatigue should be discussed in-depth while considering work type, work characteristics, and action patterns. Third, this study was conducted using data from three days. As such, we did not attempt to identify the accumulation of fatigue or quality of sleep. Although we used physical data (HR and activity) for evaluating fatigue, these data may be limited for understanding personal health.

Future research is necessary to enhance and address a broader variety of factors. The results of this study revealed several areas for useful further investigation. First, the effects of workers' personal characteristics, such as work type, work experience, age, and health, on fatigue should be considered. As work patterns can be inferred using GYRO data, which was not used in this study, it should be considered in future studies. Second, long-term observations of fatigue should be conducted. This study conducted a field experiment over only three days to measure and evaluate fatigue at actual construction sites. In future studies, an enhanced measure and evaluation should be performed on long-term or accumulated fatigue. Accordingly, future studies with diverse datasets and various measurement sensors should evaluate subjective and objective fatigue to provide more accurate and reliable conclusions.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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Supplemental Materials

Appendixes S1–S3 are available online in the ASCE Library (www.ascelibrary.org).

References

Åhsberg, E., F. Gamberale, and K. Gustafsson. 2000a. "Perceived fatigue after mental work: An experimental evaluation of a fatigue inventory." *Ergonomics* 43 (2): 252–268. https://doi.org/10.1080/001401300184594.

Åhsberg, E., F. Garnberale, and A. Kjellberg. 1997. "Perceived quality of fatigue during different occupational tasks development of a questionnaire." *Int. J. Ind. Ergon.* 20 (2): 121–135. https://doi.org/10.1016/S0169-8141(96)00044-3.

Åhsberg, E., G. Kecklund, T. Åkerstedt, and G. Francesco. 2000b. "Shiftwork and different dimensions of fatigue." *Int. J. Ind. Ergon.* 26 (4): 457–465. https://doi.org/10.1016/S0169-8141(00)00007-X.

Anwer, S., H. Li, M. F. Antwi-Afari, W. Umer, and A. Y. L. Wong. 2020. "Cardiorespiratory and thermoregulatory parameters are good surrogates for measuring physical fatigue during a simulated construction task." *Int. J. Environ. Res. Public Health* 17 (15): 5418. https://doi.org/10.3390/ijerph17155418.

Anwer, S., H. Li, M. F. Antwi-Afari, W. Umer, and A. Y. L. Wong. 2021. "Evaluation of physiological metrics as real-time measurement of physical fatigue in construction workers: State-of-the-art review." *J. Constr. Eng. Manage.* 147 (5): 03121001. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002038.

Armey, M. F., H. T. Schatten, N. Haradhvala, and I. W. Miller. 2015. "Ecological momentary assessment (EMA) of depression-related phenomena." *Curr. Opin. Psychol.* 4 (Aug): 21–25. https://doi.org/10.1016/j.copsyc.2015.01.002.

Aryal, A., A. Ghahramani, and B. Becerik-Gerber. 2017. "Monitoring fatigue in construction workers using physiological measurements." *Autom. Constr.* 82 (Oct): 154–165. https://doi.org/10.1016/j.autcon.2017.03.003.

Bhuanantanondh, P., P. Bandidcharoenlert, W. Jalayondeja, C. Jalayondeja, and K. Mekhora. 2021. "Fatigue assessment among onshore oil rig shift workers in Thailand." *Int. J. Ind. Ergon.* 83 (May): 103137. https://doi.org/10.1016/j.ergon.2021.103137.

Bishop, S. A., R. T. Dech, P. Guzik, and J. P. Neary. 2018. "Heart rate variability and implication for sport concussion." *Clin. Physiol. Funct. Imaging* 38 (5): 733–742. https://doi.org/10.1111/cpf.12487.

Caruso, C. C. 2014. "Negative impacts of shiftwork and long work hours." *Rehabil. Nurs.* 39 (1): 16–25. https://doi.org/10.1002/rnj.107.

Chan, A. P. C., F. K. W. Wong, D. P. Wong, E. W. M. Lam, and W. Yi. 2012. "Determining an optimal recovery time after exercising to exhaustion in a controlled climatic environment: Application to construction works." *Build. Environ.* 56 (Oct): 28–37. https://doi.org/10.1016/j.buildenv.2012.02.013.

Chang, F.-L., Y.-M. Sun, K.-H. Chuang, and D.-J. Hsu. 2009. "Work fatigue and physiological symptoms in different occupations of high-elevation construction workers." *Appl. Ergon.* 40 (4): 591–596. https://doi.org/10.1016/j.apergo.2008.04.017.

Chen, J., H.-L. Chi, Q. Du, and P. Wu. 2022. "Investigation of operational concerns of construction crane operators: An approach integrating factor clustering and prioritization." *J. Manage. Eng.* 38 (4): 04022020. https://doi.org/10.1061/(ASCE)ME.1943-5479.0001044.

Chen, M. L., C. J. Chen, W. Y. Yeh, J. W. Huang, and I. F. Mao. 2003. "Heat stress evaluation and worker fatigue in a steel plant." *Am. Ind. Hyg. Assoc. J.* 64 (3): 352–359. https://doi.org/10.1080/15428110308984827.

Cheung, C. M., and R. P. Zhang. 2020. "How organizational support can cultivate a multilevel safety climate in the construction industry." *J. Manage. Eng.* 36 (3): 04020014. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000758.

Dong, X. 2005. "Long workhours, work scheduling and work-related injuries among construction workers in the United States." *Scand. J. Work Environ. Health* 31 (5): 329–335. https://doi.org/10.5271/sjweh.915.

Fagan, C., C. Lyonette, M. Smith, and A. Saldaña-Tejeda. 2012. *The influence of working time arrangements on work-life integration or 'balance': A review of the international evidence*. Geneva: International Labour Organization.

Fang, D., Z. Jiang, M. Zhang, and H. Wang. 2015. "An experimental method to study the effect of fatigue on construction workers' safety performance." *Saf. Sci.* 73 (Mar): 80–91. https://doi.org/10.1016/j.ssci.2014.11.019.

Ferrada, X., S. Barrios, P. Masalan, S. Campos-Romero, J. Carrillo, and Y. Molina. 2021. "Sleep duration and fatigue in construction workers: A preliminary study." *Organ. Technol. Manage. Constr.* 13 (2): 2496–2504. https://doi.org/10.2478/otmcj-2021-0029.

González Gutiérrez, J. L., B. M. Jiménez, E. G. Hernández, and A. L. López. 2005. "Spanish version of the Swedish occupational fatigue inventory (SOFI): Factorial replication, reliability and validity." *Int. J. Ind. Ergon.* 35 (8): 737–746. https://doi.org/10.1016/j.ergon.2005.02.007.

Guo, H., Y. Yu, T. Xiang, H. Li, and D. Zhang. 2017. "The availability of wearable-device-based physical data for the measurement of construction workers' psychological status on site: From the perspective of safety management." *Autom. Constr.* 82 (Oct): 207–217. https://doi.org/10.1016/j.autcon.2017.06.001.

Gürcanli, G. E., and U. Müngen. 2009. "An occupational safety risk analysis method at construction sites using fuzzy sets." *Int. J. Ind. Ergon.* 39 (2): 371–387. https://doi.org/10.1016/j.ergon.2008.10.006.

Hartmann, B., and A. G. Fleischer. 2005. "Physical load exposure at construction sites." Supplement, *Scand. J. Work. Environ. Heal.* 31 (S2): 88–95.

He, C., B. McCabe, G. Jia, and J. Sun. 2020. "Effects of safety climate and safety behavior on safety outcomes between supervisors and construction workers." *J. Constr. Eng. Manage.* 146 (1): 04019092. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001735.

Hernandez Arellano, J. L., J. A. Castillo Martínez, and J. N. Serratos Pérez. 2015. "Relationship between workload and fatigue among Mexican assembly operators." *Int. J. Phys. Med. Rehabil.* 3 (6): 1–6. https://doi.org/10.4172/2329-9096.1000315.

Hsu, D. J., Y. M. Sun, K. H. Chuang, Y. J. Juang, and F. L. Chang. 2008. "Effect of elevation change on work fatigue and physiological symptoms for high-rise building construction workers." *Saf. Sci.* 46 (5): 833–843. https://doi.org/10.1016/j.ssci.2007.01.011.

Ibrahim, M. W., A. S. Hanna, J. S. Russell, I. S. Abotaleb, and I. H. El-adaway. 2020. "Comprehensive analysis of factors associated with out-of-sequence construction." *J. Manage. Eng.* 36 (4): 04020031. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000777.

Jebelli, H., B. Choi, and S. Lee. 2019a. "Application of wearable biosensors to construction sites. I: Assessing workers' stress." *J. Constr. Eng. Manage.* 145 (12): 04019079. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001729.

Jebelli, H., B. Choi, and S. Lee. 2019b. "Application of wearable biosensors to construction sites. II: Assessing workers' physical demand." *J. Constr. Eng. Manage.* 145 (12): 04019080. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001710.

Kamardeen, I., and A. Hasan. 2022. "Occupational health and safety challenges for sustaining construction apprentice programs." *J. Manage. Eng.* 38 (5): 04022042. https://doi.org/10.1061/(ASCE)ME.1943-5479.0001059.

Kim, H., Y. Cho, K. Lim, S. Lee, Y. Kim, and M. Kim. 2021. "Developing multimodal IoMT monitoring system of geriatric depression: A feasibility study." Supplement, *Innovation Aging* 5 (S1): 540. https://doi.org/10.1093/geroni/igab046.2076.

Kratz, A. L., S. L. Murphy, and T. J. Braley. 2017. "Ecological momentary assessment of pain, fatigue, depressive, and cognitive symptoms reveals significant daily variability in multiple sclerosis." *Arch. Phys. Med. Rehabil.* 98 (11): 2142–2150. https://doi.org/10.1016/j.apmr.2017.07.002.

Lamberts, R. P., J. Swart, B. Capostagno, T. D. Noakes, and M. I. Lambert. 2010. "Heart rate recovery as a guide to monitor fatigue and predict changes in performance parameters." *Scand. J. Med. Sci. Sports* 20 (3): 449–457. https://doi.org/10.1111/j.1600-0838.2009.00977.x.

Lee, G., B. Choi, C. R. Ahn, and S. Lee. 2020. "Wearable biosensor and hotspot analysis–based framework to detect stress hotspots for advancing elderly's mobility." *J. Manage. Eng.* 36 (3): 04020010. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000753.

Lee, H. J. 2016. *The effects of psychosocial factors occupational stress, and sleep quality on fatigue among commercial airline pilots*. Seoul: Catholic Univ. of Korea.

Lee, S., S. Seong, S. Park, J. Lim, S. Hong, Y. Cho, and H. Kim. 2021. "Korean version of the Swedish Occupational Fatigue Inventory among construction workers: Cultural adaptation and psychometric evaluation." *Int. J. Environ. Res. Public Health* 18 (8): 4302. https://doi.org/10.3390/ijerph18084302.

Lee, W., K.-Y. Lin, E. Seto, and G. C. Migliaccio. 2017. "Wearable sensors for monitoring on-duty and off-duty worker physiological status and activities in construction." *Autom. Constr.* 83 (Nov): 341–353. https://doi.org/10.1016/j.autcon.2017.06.012.

Leung, A. W. S., C. C. H. Chan, and J. He. 2004. "Structural stability and reliability of the swedish occupational fatigue inventory among Chinese VDT workers." *Appl. Ergon.* 35 (3): 233–241. https://doi.org/10.1016/j.apergo.2004.02.004.

Leung, M.-Y., Q. Liang, and P. Olomolaiye. 2016. "Impact of job stressors and stress on the safety behavior and accidents of construction workers." *J. Manage. Eng.* 32 (1): 04015019. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000373.

Liu, P., H. Chi, X. Li, and D. Li. 2020. "Development of a fatigue detection and early warning system for crane operators: A preliminary study." In *Proc., Construction Research Congress 2020*, 106–115. Reston, VA: ASCE.

McDonald, A. C., C. T. F. Tse, and P. J. Keir. 2016. "Adaptations to isolated shoulder fatigue during simulated repetitive work. Part II: Recovery." *J. Electromyogr. Kinesiol.* 29 (Aug): 42–49. https://doi.org/10.1016/j.jelekin.2015.05.005.

Mehta, R. K., S. C. Peres, P. Kannan, J. Rhee, A. E. Shortz, and M. Sam Mannan. 2017. "Comparison of objective and subjective operator fatigue assessment methods in offshore shiftwork." *J. Loss Prev. Process Ind.* 48 (Jul): 376–381. https://doi.org/10.1016/j.jlp.2017.02.009.

Namian, M., A. Albert, and J. Feng. 2018. "Effect of distraction on hazard recognition and safety risk perception." *J. Constr. Eng. Manage.* 144 (4): 04018008. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001459.

Nwaogu, J. M., A. P. C. Chan, and J. A. Naslund. 2022. "Measures to improve the mental health of construction personnel based on expert opinions." *J. Manage. Eng.* 38 (4): 04022019. https://doi.org/10.1061/(ASCE)ME.1943-5479.0001045.

Pelders, J., and G. Nelson. 2019. "Contributors to fatigue of mine workers in the South African gold and platinum sector." *Saf. Health Work* 10 (2): 188–195. https://doi.org/10.1016/j.shaw.2018.12.002.

Pereira, E., S. Ahn, S. Han, and S. Abourizk. 2020. "Finding causal paths between safety management system factors and accident precursors." *J. Manage. Eng.* 36 (2): 04019049. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000738.

Powell, R., and A. Copping. 2010. "Sleep deprivation and its consequences in construction workers." *J. Constr. Eng. Manage.* 136 (10): 1086–1092. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000211.

Riegler, K. E., E. T. Guty, G. A. Thomas, and P. A. Arnett. 2021. "Sleep deprived or concussed? The acute impact of self-reported insufficient sleep in college athletes." *J. Int. Neuropsychol. Soc.* 27 (1): 35–46. https://doi.org/10.1017/S135561772000065X.

Santos, J., C. Carvalhais, C. Ramos, T. Coelho, P. R. R. Monteiro, and M. A. P. Vaz. 2017. "Portuguese version of the Swedish Occupational Fatigue Inventory (SOFI) among assembly workers: Cultural adaptation, reliability and validity." *Int. J. Occup. Med. Environ. Health* 30 (3): 407–417. https://doi.org/10.13075/ijomeh.1896.00760.

Shiffman, S., A. A. Stone, and M. R. Hufford. 2008. "Ecological momentary assessment." *Annu. Rev. Clin. Psychol.* 4 (1): 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415.

Strassnig, M. T., P. D. Harvey, M. L. Miller, C. A. Depp, and E. Granholm. 2021. "Real world sedentary behavior and activity levels in patients with schizophrenia and controls: An ecological momentary assessment study." *Ment. Health Phys. Act.* 20 (Mar): 100364. https://doi.org/10.1016/j.mhpa.2020.100364.

Targum, S. D., C. Sauder, M. Evans, J. N. Saber, and P. D. Harvey. 2021. "Ecological momentary assessment as a measurement tool in depression trials." *J. Psychiatry Res.* 136 (Apr): 256–264. https://doi.org/10.1016/j.jpsychires.2021.02.012.

Techera, U., M. Hallowell, and R. Littlejohn. 2019. "Worker fatigue in electrical-transmission and distribution-line construction." *J. Constr. Eng. Manage.* 145 (1): 04018119. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001580.

Techera, U., M. Hallowell, R. Littlejohn, and S. Rajendran. 2018. "Measuring and predicting fatigue in construction: Empirical field study." *J. Constr. Eng. Manage.* 144 (8): 04018062. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001513.

Troiano, R., D. Berrigan, K. Dodd, L. Mâsse, T. Tilert, and M. McDowell. 2008. "Physical activity in the United States measured by accelerometer." *Med. Sci. Sport. Exercise* 40 (1): 181–188. https://doi.org/10.1249/mss.0b013e31815a51b3.

Ueno, S., Y. Sakakibara, N. Hisanaga, T. Oka, and S. Yamaguchi-Sekino. 2018. "Heat strain and hydration of Japanese construction workers during work in summer." *Ann. Work Expo Health* 62 (5): 571–582. https://doi.org/10.1093/annweh/wxy012.

Umer, W., H. Li, G. P. Y. Szeto, and A. Y. L. Wong. 2017. "Low-cost ergonomic intervention for mitigating physical and subjective discomfort during manual rebar tying." *J. Constr. Eng. Manage.* 143 (10): 04017075. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001383.

Umer, W., H. Li, Y. Yantao, M. F. Antwi-Afari, S. Anwer, and X. Luo. 2020. "Physical exertion modeling for construction tasks using combined cardiorespiratory and thermoregulatory measures." *Autom. Constr.* 112 (Apr): 103079. https://doi.org/10.1016/j.autcon.2020.103079.

Van der Werf, S. P., J. B. Prins, J. H. M. M. Vercoulen, J. W. M. Van der Meer, and G. Bleijenberg. 2000. "Identifying physical activity patterns in chronic fatigue syndrome using actigraphic assessment." *J. Psychosom. Res.* 49 (5): 373–379. https://doi.org/10.1016/S0022-3999(00)00197-5.

Wong, D. P., J. W. Chung, A. P. Chan, F. K. Wong, and W. Yi. 2014. "Comparing the physiological and perceptual responses of construction workers (bar benders and bar fixers) in a hot environment." *Appl. Ergon.* 45 (6): 1705–1711. https://doi.org/10.1016/j.apergo.2014.06.002.

Wong, F. K.-W., Y.-H. Chiang, F. A. Abidoye, and S. Liang. 2019a. "Interrelation between human factor–related accidents and work patterns in construction industry." *J. Constr. Eng. Manage.* 145 (5): 04019021. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001642.

Wong, I. S., S. Popkin, and S. Folkard. 2019b. "Working time society consensus statements: A multi-level approach to managing occupational sleep-related fatigue." *Ind. Health* 57 (2): 228–244. https://doi.org/10.2486/indhealth.SW-6.

Xie, Q., N. Xia, and G. Yang. 2022. "Do family affairs matter? Work–family conflict and safety behavior of construction workers." *J. Manage. Eng.* 38 (1): 04021074. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000977.

Xing, X., B. Zhong, H. Luo, T. Rose, J. Li, and M. F. Antwi-Afari. 2020. "Effects of physical fatigue on the induction of mental fatigue of construction workers: A pilot study based on a neurophysiological approach." *Autom. Constr.* 120 (Dec): 103381. https://doi.org/10.1016/j.autcon.2020.103381.

Yin, P., L. Yang, C. Wang, and S. Qu. 2019. "Effects of wearable power assist device on low back fatigue during repetitive lifting tasks." *Clin. Biomech.* 70 (Dec): 59–65. https://doi.org/10.1016/j.clinbiomech.2019.07.023.

Yu, Y., H. Li, X. Yang, L. Kong, X. Luo, and A. Y. L. Wong. 2019. "An automatic and non-invasive physical fatigue assessment method for construction workers." *Autom. Constr.* 103 (Jul): 1–12. https://doi.org/10.1016/j.autcon.2019.02.020.

Zhang, L., M. M. Diraneyya, J. Ryu, C. T. Haas, and E. M. Abdel-Rahman. 2019. "Jerk as an indicator of physical exertion and fatigue." *Autom. Constr.* 104 (Aug): 120–128. https://doi.org/10.1016/j.autcon.2019.04.016.

Zhang, M., E. H. Sparer, L. A. Murphy, J. T. Dennerlein, D. Fang, J. N. Katz, and A. J. Caban-Martinez. 2015. "Development and validation of a fatigue assessment scale for U.S. construction workers." *Am. J. Ind. Med.* 58 (2): 220–228. https://doi.org/10.1002/ajim.22411.