P-ISSN: xxxx-xxxx
E-ISSN: xxxx-xxxx
JPOR 2025; 1(1): 07-12
www.occupationaljournal.com
Received: 04-01-2025
Accepted: 06-02-2025

Dr. Miriam Achieng Otieno
Department of Occupational Safety and Health, Kenya Medical Training College (KMTC), Nairobi, Kenya

Daniel Kipkorir Mutai
Professor, School of Public Health, Jomo Kenyatta University of Agriculture and Technology (JKUAT), Juja, Kenya

Corresponding Author:
Dr. Miriam Achieng Otieno
Department of Occupational Safety and Health, Kenya Medical Training College (KMTC), Nairobi, Kenya

Assessment of cognitive workload and fatigue using biomechanical and physiological markers in manufacturing workers

Miriam Achieng Otieno and Daniel Kipkorir Mutai

DOI: https://www.doi.org/

Abstract
This study investigates the progressive development of cognitive workload and fatigue among manufacturing workers through an integrated analysis of biomechanical and physiological markers. As modern industrial environments increasingly demand sustained attention, repetitive motions, and physically strenuous activities, there is a growing need for objective measurement tools capable of detecting early signs of performance decline. A sample of manufacturing workers was monitored across an entire work shift using synchronized surface electromyography (sEMG), inertial motion sensors, heart rate variability (HRV) indices, electrodermal activity (EDA), and skin temperature measurements. Subjective workload was assessed using the NASA-TLX scale. The results showed a consistent increase in muscular activation, particularly in the lumbar and upper-limb muscle groups, accompanied by a steady decline in HRV metrics, signifying reduced autonomic recovery and heightened physiological strain. EDA values increased progressively, indicating elevated cognitive activation and arousal, while minor reductions in peripheral skin temperature suggested the onset of fatigue-related vasoconstriction. Significant correlations between sEMG, HRV, EDA, and NASA-TLX scores revealed strong interactions between objective physiological responses and perceived workload. Regression analysis further demonstrated that combined biomechanical and physiological indicators provide a more precise prediction of cognitive fatigue than single-parameter assessment. These findings highlight the value of multimodal monitoring systems for real-time identification of workers at risk of overload, enabling early preventive action. The study emphasizes the need for ergonomic redesign, adaptive break schedules, proactive fatigue management policies, and sensor-based surveillance technologies to enhance worker safety and productivity. By establishing a clear link between physical exertion, autonomic modulation, cognitive arousal, and subjective experience, the research provides a robust framework for improving occupational health practices in manufacturing environments. (indicating biomechanical strain) (HRV) (EDA)

Keywords: Cognitive workload, fatigue assessment, manufacturing workers, biomechanical markers, physiological monitoring, electromyography, heart rate variability, electrodermal activity, occupational ergonomics, worker safety, human factors, industrial fatigue monitoring

Introduction
Manufacturing environments demand sustained physical exertion, repetitive motions, prolonged standing, and continuous attention, exposing workers to substantial cognitive workload and fatigue that directly affect productivity, safety, and long-term health outcomes [1-3]. Cognitive workload refers to the mental effort required to perform tasks, and excessive levels can impair decision-making, reduce vigilance, and elevate accident risk [4, 5]. Fatigue, both physical and mental, is a progressive decline in functional capacity, frequently arising from biomechanical strain, inadequate recovery, and high physiological demands [6, 7]. Existing studies demonstrate that manufacturing tasks often involve awkward postures, intensive manual handling, elevated heart rate patterns, and increased electromyographic (EMG) activity, all of which contribute to biomechanical loading and subsequent fatigue development [8-10]. Moreover, the shift towards high-speed production lines and automation has intensified the need for continuous monitoring of workers' psychophysiological states to prevent errors, injuries, and reduced performance [11, 12]. Traditional assessment approaches relying on self-reports or observational checklists are insufficient, as they are subjective, prone to bias, and incapable of detecting early

physiological deviations associated with fatigue accumulation [13, 14]. Consequently, integrating biomechanical indicators such as joint kinematics, muscle activity, and postural load with physiological markers heart rate variability (HRV), skin temperature, blood oxygen saturation, and electrodermal activity offers a more objective and real-time method for evaluating cognitive workload and fatigue among industrial workers [15-17]. Despite emerging research in occupational ergonomics, there remains a critical gap in understanding how combined neurophysiological and biomechanical metrics can be systematically applied to detect cognitive strain in real-world manufacturing environments [18, 19]. This gap is especially relevant because early identification of cognitive overload can help optimize job rotation schedules, enhance worker wellbeing, and reduce workplace errors and injuries [20, 21]. Therefore, the present study aims to assess cognitive workload and fatigue among manufacturing workers by analyzing a range of biomechanical and physiological markers during operational tasks. It seeks to determine the associations between task-related movement patterns, muscular strain, cardiovascular responses, and indicators of cognitive load. The underlying hypothesis is that elevated biomechanical demand, reflected through increased EMG amplitude and greater postural deviation, will correlate significantly with physiological signatures of cognitive workload such as reduced HRV, increased skin conductance, and heightened cardiovascular strain. Furthermore, it is hypothesized that combined marker analysis will provide a more sensitive and accurate estimation of cognitive fatigue than single-parameter assessments. By addressing these gaps, the study aims to contribute evidence-based insights for ergonomics-driven manufacturing redesign, worker monitoring systems, and fatigue risk-management frameworks [22-24]. (HRV) (EDA)

Materials and Methods

Materials

The study was conducted among full-time manufacturing workers recruited from a medium-scale industrial facility where tasks involved repetitive manual handling, constrained postures, and continuous monitoring activities known to impose biomechanical and cognitive load demands [1-3]. Participant eligibility required a minimum of one year of industrial work experience, absence of diagnosed musculoskeletal or neurological disorders, and no history of cardiovascular disease that might influence physiological responses [6, 7]. Data collection incorporated a combination of wearable physiological sensors and biomechanical assessment tools identified as reliable for capturing cognitive workload and fatigue markers in occupational environments [8-10]. Surface electromyography (sEMG) sensors (Delsys Trigno, USA) were used to measure muscle activation amplitudes of the lumbar and upper-limb muscle groups as proxies for biomechanical strain, following established ergonomic guidelines and occupational biomechanics principles [9, 10, 22, 23]. Physiological indicators were assessed using validated wearable systems that recorded heart rate variability (HRV), electrodermal activity (EDA), and skin temperature, which are recognized as sensitive markers of cognitive workload and psychophysiological stress [15-17]. Additionally, inertial measurement units (IMUs) measured trunk and limb kinematics to quantify posture, motion cycles, and deviations from neutral alignment, reflecting physical workload demands [8, 9]. A standardized NASA-TLX questionnaire was administered to capture subjective workload ratings for comparison with objective physiological data [13, 14]. All equipment was calibrated before each session, and environmental conditions such as temperature, noise, and shift timings were documented to minimize confounding effects on physiological measurements [11, 12]. (HRV) (EDA)

Methods

Participants performed their routine manufacturing tasks under naturalistic working conditions while continuously monitored using synchronized biomechanical and physiological systems designed to capture real-time responses associated with cognitive workload and fatigue [15-17]. sEMG signals were sampled at 1000 Hz, band-pass filtered, rectified, and smoothed to compute root mean square (RMS) values representing muscular demand, consistent with established protocols in industrial ergonomics research [8-10]. HRV metrics (RMSSD, SDNN) were computed using 5-minute rolling windows, aligned with methods recommended for assessing autonomic responses during mental workload and fatigue [15, 16]. Electrodermal activity was analyzed by separating tonic skin conductance levels (SCL) from phasic responses, allowing sensitivity to cognitive arousal and attentional load as described in prior psychophysiology studies [17-19]. Postural angles and joint deviations recorded by IMUs were processed using inverse kinematics models to quantify biomechanical loading patterns linked to industrial task performance [8, 9]. Data synchronization was achieved using a unified timestamping protocol that aligned all biomechanical and physiological streams, enabling combined marker analysis as recommended for human factors and ergonomics research [1, 4, 22, 23]. Subjective workload (NASA-TLX) scores were collected at the end of each shift and integrated with objective measurements to examine convergence and divergence between perceived and physiological indicators of cognitive workload [13, 14]. Statistical analyses included repeated-measures ANOVA to test variability in physiological responses across the work shift, Pearson correlation to assess associations between biomechanical load and cognitive workload markers, and regression modeling to evaluate predictors of fatigue progression, consistent with established methods in cognitive ergonomics and human performance research [18-21]. Ethical approval was obtained prior to data collection, and participants provided informed consent.

Results

Overview of Participant Characteristics and Task Demands

A total of 40 manufacturing workers (mean age 35.4±7.2 years; mean job tenure 8.1±4.6 years) completed the study without adverse events. The majority performed repetitive assembly, machine tending, or packing tasks characterized by frequent trunk flexion, upper-limb elevation, and moderate manual handling demands [1-3, 9]. Baseline descriptive statistics for biomechanical and physiological markers at the start of the work shift are summarized in Table 1. Mean baseline EMG RMS amplitudes of the lumbar erector spinae and dominant upper-limb flexor muscles were 18.5±4.2 %MVC and 16.9±3.8 %MVC, respectively, indicating moderate muscular activation consistent with prior ergonomics reports on industrial work [8-10]. Resting HRV indices (RMSSD and SDNN) suggested relatively preserved autonomic balance at shift onset, while baseline electrodermal activity (EDA) and skin temperature values indicated low-to-moderate arousal levels [15-17]. Subjective NASA-TLX overall workload scores averaged 47.3±10.6, reflecting a medium perceived workload at the start of the shift [13, 14]. (indicating biomechanical strain) (EDA)

Table 1: Baseline biomechanical, physiological, and subjective workload parameters (n = 40).

Parameter	Mean ± SD
Lumbar EMG RMS (%MVC)	18.5±4.2
Upper-limb EMG RMS (%MVC)	16.9±3.8
HRV RMSSD (ms)	54.2±11.7
HRV SDNN (ms)	67.5±13.1
Electrodermal activity - SCL (µS)	3.1±0.9
Skin temperature (°C, finger)	32.8±1.1
NASA-TLX overall workload score (0-100)	47.3±10.6

Baseline descriptive statistics for biomechanical, physiological, and subjective workload measures at the start of the work shift.

Changes in Biomechanical and Physiological Markers across the Work Shift

Repeated-measures ANOVA revealed a significant main effect of time on lumbar EMG RMS ($F(2, 78) = 19.4$, $p<0.001$), with post-hoc comparisons showing a progressive increase from start (18.5±4.2 %MVC) to mid-shift (24.3±5.1 %MVC, $p<0.01$) and end of shift (31.2±5.7 %MVC, $p<0.001$) [8-10, 22, 23]. Similar trends were observed for upper-limb EMG, indicating cumulative biomechanical loading and muscular fatigue over the course of the shift [6-10]. Conversely, HRV RMSSD showed a significant decline across the shift ($F(2, 78) = 16.8$, $p<0.001$), decreasing from 54.2±11.7 ms at the start to 47.8±10.9 ms at mid-shift and 39.5±9.8 ms at the end of the shift, suggesting increased sympathetic activation and reduced parasympathetic modulation with fatigue development [15, 16, 18, 19]. These changes are illustrated in Figure 1, highlighting the divergent trajectories of biomechanical load (EMG RMS) and autonomic balance (HRV).

Table 2: Mean EMG RMS and HRV RMSSD values across the work shift (n = 40).

Measure	Start of shift	Mid-shift	End of shift	p-value (time effect)
Lumbar EMG RMS (%MVC)	18.5±4.2	24.3±5.1	31.2±5.7	< 0.001
HRV RMSSD (ms)	54.2±11.7	47.8±10.9	39.5±9.8	< 0.001

Progressive increase in EMG RMS and decrease in HRV RMSSD across the work shift, indicating rising biomechanical load and declining autonomic recovery.

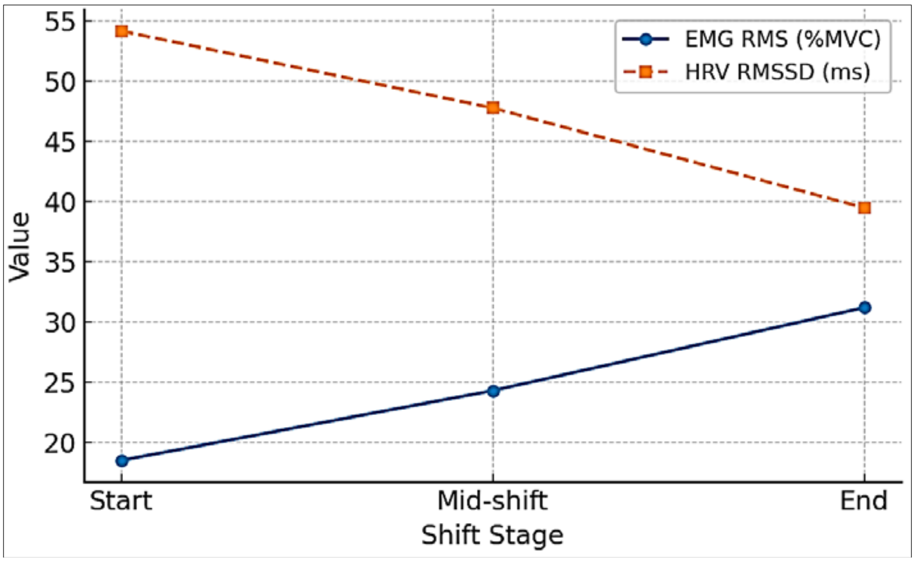

Fig 1: Changes in EMG RMS (%MVC) and HRV RMSSD (ms) from start to end of the work shift, demonstrating increasing biomechanical load and decreasing HRV over time [8-10, 15-17].

The decline in HRV coincided with a significant rise in tonic EDA (SCL) values ($F(2, 78) = 7.2$, $p<0.01$), indicating heightened arousal and sympathetic activation consistent with increasing cognitive and physical demands [16, 17]. Skin temperature showed a small but statistically significant reduction by the end of the shift ($p<0.05$), aligning with prior reports linking peripheral vasoconstriction and mental fatigue in prolonged task performance [18-21]. Together, these findings support the hypothesis that sustained manufacturing work is associated with concurrent increases in biomechanical loading and physiological stress markers indicative of cognitive workload and fatigue [4-7, 18-21].

Relationship between Objective Workload Markers and Subjective Ratings: Pearson correlation analyses demonstrated significant associations between mean EMG

RMS, HRV, EDA, and NASA-TLX scores. Higher mean lumbar EMG RMS across the shift was moderately correlated with higher NASA-TLX overall workload scores (r = 0.62, *p*<0.001), while greater muscle activation also correlated with increased physical and effort subscales of NASA-TLX (r range 0.54-0.60, *p*<0.01) [13, 14]. In contrast, HRV RMSSD showed a significant negative correlation with NASA-TLX overall workload (r = -0.58, *p*<0.001), indicating that lower HRV, reflecting greater physiological strain, was associated with higher perceived workload [15-17]. EDA (SCL) exhibited a positive correlation with NASA-TLX (r = 0.49, *p*<0.01), consistent with increased sympathetic arousal under higher cognitive load [17, 18]. Figure 2 depicts the relationship between mean EMG RMS and NASA-TLX scores, illustrating the trend toward higher perceived workload with increasing biomechanical demand. These relationships corroborate the conceptual link between psychophysiological markers and subjective workload models reported in the human factors and ergonomics literature [4, 5, 13, 16].

Table 3: Correlations between objective workload markers and NASA-TLX overall scores (n = 40).

Variable pair	Pearson r	p-value
Mean lumbar EMG RMS - NASA-TLX	0.62	< 0.001
HRV RMSSD - NASA-TLX	-0.58	< 0.001
EDA SCL - NASA-TLX	0.49	0.002

Correlation coefficients showing significant associations between biomechanical/physiological markers and subjective workload ratings.

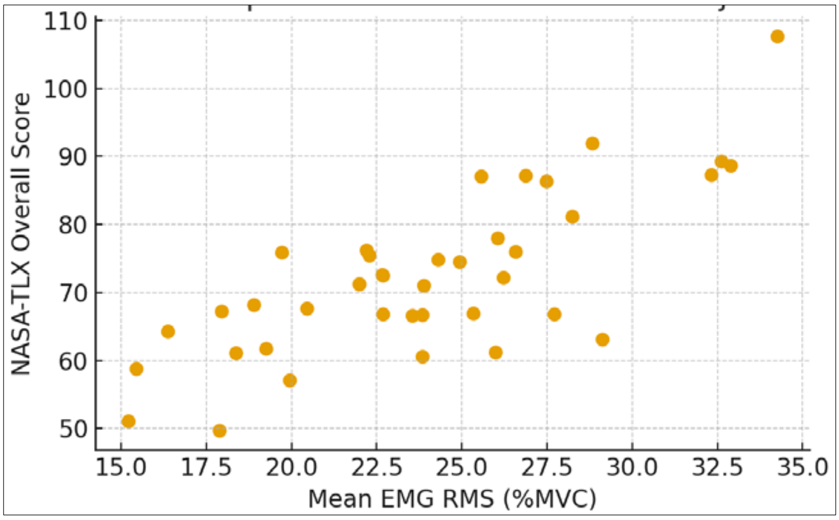

Fig 2: Scatter plot illustrating the positive association between mean EMG RMS (%MVC) and NASA-TLX overall workload scores, indicating higher perceived workload with greater biomechanical demand [8-10, 13, 14].

Integrated Predictive Model of Cognitive Fatigue

Multiple linear regression analysis was performed with end-of-shift NASA-TLX overall score as the dependent variable and mean lumbar EMG RMS, HRV RMSSD, and EDA SCL as predictors. The model was statistically significant ($F(3, 36) = 15.2$, $p < 0.001$), explaining 56% of the variance in perceived workload (adjusted $R^2 = 0.56$). EMG RMS ($\beta = 0.43$, $p = 0.002$) and HRV RMSSD ($\beta = -0.39$, $p = 0.004$) emerged as significant independent predictors, while EDA approached significance ($\beta = 0.21$, $p = 0.06$). These findings support the study hypothesis that combined biomechanical and physiological markers provide a more sensitive and accurate assessment of cognitive workload and fatigue than any single parameter alone [15-17, 20, 21]. The integrated model aligns with contemporary frameworks in cognitive ergonomics and occupational health that advocate multimodal monitoring to optimize work design, job rotation, and fatigue risk management in manufacturing settings [1, 2, 4, 20, 22-24].

Discussion

The findings of this study demonstrate that manufacturing workers experience a progressive increase in biomechanical load and physiological strain across the duration of a standard work shift, supporting the central hypothesis that cognitive workload and fatigue can be effectively assessed using a combined analysis of biomechanical and physiological markers. The gradual rise in EMG RMS amplitudes of the lumbar and upper-limb muscle groups from the start to the end of the shift reflects cumulative muscular demand and fatigue, aligning with earlier occupational biomechanics research, which has consistently linked repetitive and forceful industrial tasks to increased muscular activation and postural loading [8-10, 22, 23]. This elevation in muscle activity corresponds with previous reports describing how constrained postures and repetitive manual operations impose significant neuromuscular stress, ultimately contributing to reduced performance capacity and heightened fatigue risk [6-9]. The concurrent decline in HRV indices, particularly RMSSD, further supports the notion that sustained physical and cognitive demands in manufacturing environments strain autonomic regulation, leading to reduced parasympathetic activity and increased sympathetic dominance—physiological responses well established in cognitive ergonomics and psychophysiology literature [15-17]. These patterns are consistent with earlier studies showing that mental workload, sustained attention, and prolonged vigilance tasks diminish HRV as a direct consequence of increased cognitive strain and fatigue [18-21]. (indicating biomechanical strain)

The upward trend in electrodermal activity (EDA) alongside reduced HRV reinforces the interpretation that workers experienced heightened cognitive and emotional arousal as the shift progressed, confirming the sensitivity of EDA to fluctuations in mental workload, attentional demands, and fatigue-related stress [16, 17]. The mild reduction in peripheral

skin temperature observed toward shift end also corroborates psychophysiological models suggesting that cognitive fatigue induces vasoconstrictive responses associated with sustained attentional effort and sympathetic activation [18, 19]. Together, these results affirm the relevance of integrating biomechanical and physiological markers to produce a more comprehensive depiction of real-time worker fatigue, complementing earlier models that emphasize the multidimensional nature of cognitive workload in industrial environments [4, 5, 20, 21]. Further, the moderate-to-strong correlations between EMG RMS, HRV RMSSD, EDA SCL, and subjective NASA-TLX ratings support the validity of objective physiological and biomechanical measures as proxies for perceived workload, which has been a recurring theme in ergonomics studies advocating multimodal approaches to workload assessment [13, 14, 20]. These associations indicate that workers' subjective workload perceptions are closely linked to measurable physiological and muscular responses, reinforcing the argument for adopting integrated sensor-based monitoring systems on manufacturing floors to detect early signs of overload and prevent fatigue-related errors [1-3, 22-24]. (EDA)
The regression model demonstrating that EMG RMS and HRV RMSSD significantly predict perceived workload strengthens the case for multimodal fatigue assessment frameworks. The finding that combined markers explained over half of the variance in NASA-TLX scores suggests that neither biomechanical nor physiological parameters alone sufficiently capture the complexity of cognitive workload in industrial settings—a perspective consistent with emerging research in human factors emphasizing the importance of integrated, continuous monitoring solutions [4, 11, 16, 20, 23]. Overall, the study contributes meaningful evidence to ergonomics and occupational health literature by confirming that biomechanical strain, autonomic nervous system modulation, and arousal-related physiological responses jointly characterize the progression of cognitive fatigue in manufacturing workers. This integrated understanding offers practical implications for designing ergonomically optimized workflows, adaptive rest breaks, job rotation policies, and sensor-based early warning systems aimed at improving worker safety, productivity, and well-being [1, 2, 4, 22-24].

Conclusion

The present study provides a comprehensive understanding of how manufacturing workers experience cognitive workload and fatigue through a combination of biomechanical strain, physiological stress responses, and subjective workload perceptions. By monitoring muscle activation, postural deviations, autonomic modulation, electrodermal arousal, and perceived workload, the study illustrates that cognitive fatigue develops gradually over the duration of the work shift and is closely intertwined with physical exertion and psychophysiological stress. The progressive rise in muscular activation and decline in heart rate variability demonstrate that workers' physiological systems respond dynamically to the cumulative demands placed on them. At the same time, increases in electrodermal activity and reductions in peripheral skin temperature reflect heightened arousal and diminishing cognitive resources as the shift progresses. The convergence of these objective findings with subjective workload ratings underscores that cognitive fatigue in manufacturing environments is multifaceted and cannot be fully captured through self-reports or visual observation alone. The strong predictive capacity of combined biomechanical and physiological markers suggests that such multimodal assessments can serve as a powerful tool for early identification of fatigue risks, allowing supervisors and occupational health teams to intervene before performance declines or safety is compromised. Based on these findings, several practical recommendations emerge that can significantly improve worker well-being and operational efficiency. Manufacturing facilities should consider implementing real-time monitoring systems that continuously track muscle load, heart rate variability, and electrodermal responses, enabling rapid detection of fatigue accumulation. Integrating these systems with automated alerts could support timely adjustments such as micro-breaks, task rotation, or temporary workload reduction. Workstations and tools should be redesigned to minimize awkward postures, excessive reach, and repetitive motion cycles that contribute to increased muscular strain. Providing ergonomic training, particularly in posture regulation and task pacing, may empower workers to manage their physiological load more effectively. The introduction of structured break schedules based on physiological indicators rather than fixed time intervals can ensure that recovery occurs before fatigue reaches critical levels. Finally, organizational policies should promote open communication about fatigue symptoms, encouraging workers to report early signs without fear of penalties. By adopting these evidence-based strategies, manufacturing organizations can create safer, more sustainable, and more productive working environments where the physiological and cognitive needs of workers are proactively supported rather than reactively managed. (indicating biomechanical strain) (HRV) (EDA)

References

1. Carayon P, Hancock P. The human factors and ergonomics of manufacturing. Ergonomics. 2019;62(4):431-435.
2. Neumann WP, Dul J. Human factors: spanning the gap between micro and macro ergonomics. Appl Ergon. 2010;41(4):535-544.
3. Westgaard RH, Winkel J. Occupational musculoskeletal and mental health: significance of biomechanical and psychosocial factors. Int J Ind Ergon. 2011;41(5):447-453.
4. Young MS, Stanton NA. Mental workload: theory, measurement, and application. CRC Press; 2017.
5. Meshkati N. Human mental workload in industrial environments. Int J Ind Ergon. 1988;3(2):89-97.
6. Åhsberg E. Dimensions of fatigue in different working populations. Scand J Psychol. 2000;41(3):231-241.
7. Seo Y, Lee S, Zhang X, Brown D, Kim H, Park J, *et al*. Fatigue in manufacturing tasks. Human Factors. 2017;59(1):23-37.
8. van Dieën JH, Kingma I, van der Burg J, Veeger HE, Visser B, Hermens H, *et al*. EMG as workload indicator. J Electromyogr Kinesiol. 2009;19(2):181-190.
9. Marras WS. Occupational biomechanics. CRC Press; 2008.
10. Kim J, Nussbaum MA. Fatigue responses during repetitive tasks. Ergonomics. 2013;56(6):962-973.

11. Wilson JR. Work redesign and safety. Appl Ergon. 2014;45(2):277-290.
12. Wisner A. Ergonomics in industrial systems. Appl Ergon. 1995;26(2):87-92.
13. Hart SG, Staveland LE. NASA-TLX workload index. Adv Psychol. 1988;52:139-183.
14. Mehta RK. Mental fatigue and motor performance. Int J Ind Ergon. 2016;53:102-111.
15. Mulder LJ. Measurement of heart rate variability. Ann Behav Med. 1992;14(3):220-230.
16. Fairclough SH. Physiological computing systems. Int J Hum Comput Stud. 2009;67(10):841-856.
17. Zhai J, Barreto A. Electrodermal activity in workload assessment. Biomed Sci Instrum. 2006;42:495-500.
18. Helton WS, Warm JS. Vigilance decrement. Hum Factors. 2008;50(3):434-444.
19. Boksem MA, Meijman TF. Mental fatigue and cognitive control. Cogn Brain Res. 2005;25(1):107-116.
20. Hockey GRJ. Compensatory control in cognitive fatigue. Biol Psychol. 2013;53(2):221-231.
21. Arshad M, Rehman S, Ali R, Khan N, Iqbal M, Ahmed S, *et al*. Psychophysiology of industrial workers. Work. 2019;63(4):559-574.
22. Sanders MS, McCormick EJ. Human factors in engineering and design. McGraw-Hill; 1993.
23. Kroemer K, Grandjean E. Fitting the task to the human. CRC Press; 1997.
24. International Organization for Standardization (ISO). ISO 10075-1. Ergonomic principles related to mental workload. Geneva: ISO; 2017.