Volume 22, No. 2, July 2025; Page: 213-218;

DOI: https://doi.org/10.31964/jkl.v21i2.1035

# MICROSLEEP AND OCCUPATIONAL SAFETY: INTEGRATION OF BIOMETRIC DETECTION, WEARABLE TECHNOLOGY, AND PREVENTIVE POLICIES FOR THE MODERN INDUSTRY

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#### **Article Info**

#### Article history:

Received August 11, 2025 Revised August 11, 2025 Accepted August 18, 2025

### Keywords:

Microsleep Fatigue Detection Wearable Technology Occupational Safety Fatigue Management

#### **ABSTRACT**

Microsleep And Occupational Safety: Integration Of Biometric Detection, Wearable Technology, And Preventive Policies For **The Modern Industry.** Microsleep is one of the factors that causes a decrease in vigilance that can have a serious impact on occupational safety, especially in industrial sectors with high risk levels such as heavy equipment and vehicle operations. This condition occurs suddenly and often escapes the detection of conventional surveillance systems, thus increasing the likelihood of work accidents. These challenges are even greater in a work environment with high operational burdens and rotating work patterns that affect the quality of sleep of workers. This study was conducted to evaluate the application of biometric-based detection technology and wearable devices combined with fatigue prevention policies. The study used a systematic literature review method on 25 primary articles published in the period 2020–2024 in a number of indexed international journals. The results of the analysis showed that the integration of real-time biometric monitoring with flexible work policies can increase the accuracy of microsleep detection by up to 85% and help reduce the potential for work accidents. This integrated approach is expected to be able to encourage the transformation of the occupational safety system to be more proactive, adaptive, and data-based, so as to create a safe and sustainable work environment.

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# **INTRODUCTION**

The development of modern industry, with its high operational demands, often leads to excessive worker fatigue. Microsleep—very brief episodes of sleep (1–15 seconds)—has been identified as a major cause of accidents in high-risk work environments, such as heavy machinery operation and driving<sup>[1,2]</sup>. This phenomenon is a serious concern due to its implications for occupational safety<sup>[3]</sup>. Factors such as shift work patterns and long working hours are known to worsen workers' sleep quality, thereby increasing the likelihood of drowsiness during work<sup>[4]</sup>.

Several recent studies have shown that the application of deep learning to Electroencephalography (EEG) signals can significantly improve the accuracy of microsleep detection compared to conventional methods<sup>[1,2]</sup>. A comprehensive review analysis of EEG-based microsleep prediction highlights the importance of proper feature extraction to identify this drowsiness condition<sup>[5]</sup>. Furthermore, the exploration of artificial intelligence-

based contextual monitoring modules has also been conducted to complement physiological data and enhance drowsiness detection accuracy [6].

In addition to brain signal monitoring, wearable devices equipped with physiological sensors such as heart rate variability (HRV), electrooculography (EOG), and electromyography (EMG) offer practical alternatives for real-time fatigue detection<sup>[7,8]</sup>. Field studies, for instance through the analysis of dashcam recordings of truck accidents, indicate that microsleep behavior is evident not only from eyelid closure but also from changes in posture and lack of responsiveness to the surrounding environment<sup>[9]</sup>. Meanwhile, conventional camera-based observation methods—such as the percentage of eyelid closure (PERCLOS) index—generally achieve only 60-70% detection accuracy [10,11], making the development of real-time biometric sensors critically important. In the aviation sector, wearable-based early warning systems have been proposed to reduce accident risks caused by pilot and crew drowsiness [12-14]. Most previous studies tend to separate the analysis of detection technology from preventive policy interventions. This gap calls for an integrative approach that not only combines multiple biometric data sources through machine learning algorithms (e.g., Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), or reservoir computing) to optimize detection accuracy<sup>[7,15]</sup>, but also links detection outcomes with adaptive policy interventions, such as adjustments to work schedules and rest durations [16-<sup>18]</sup>. Moreover, several studies have emphasized the importance of combining technological interventions with worker education programs as part of a comprehensive fatigue management strategy<sup>[19]</sup>.

This integrative approach is increasingly crucial given the variability of individual physiological responses and differences in operational contexts across industrial sectors [10,21]. Some research also indicates that subjective factors—such as boredom levels or individual predisposition to fall asleep easily—play a significant role in microsleep incidents [17,22]. Therefore, an ideal drowsiness detection strategy should take into account not only physiological signals but also cognitive and behavioral variables[23].

This study aims to comprehensively examine integrative approaches that combine wearable-based detection technologies with preventive fatigue policies. Through a literature review covering the years 2020 to 2024, this article seeks to develop a data-driven framework to enhance early microsleep detection effectiveness and provide a foundation for adaptive operational interventions to create safer work environments<sup>[24,25]</sup>. With this approach, it is expected that occupational safety systems can transform into more proactive and data-driven mechanisms<sup>[25]</sup>.

# **MATERIALS AND RESEARCH METHODS**

This study employed a systematic literature review (SLR) method to comprehensively examine various primary studies addressing microsleep detection using technology, wearable devices, and the application of fatigue prevention policies. The SLR process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) stages, consisting of four steps.

First, identification or literature searching was conducted using keywords such as "microsleep," "fatigue detection," "wearable devices," and "occupational safety" across several reputable scientific databases, including IEEE Xplore, ScienceDirect, Frontiers, and Google Scholar. Reference management was carried out using Mendeley, while the Publish or Perish application was used to assess article relevance based on citation index and publication metadata<sup>[25]</sup>, resulting in 112 articles at this stage.

Second, in the screening stage, duplicate articles were removed, leaving 98 unique articles. After screening based on titles and abstracts, selected articles were analyzed using a systematic data extraction method. Data collected included research objectives, type and location of study, microsleep detection methods, technologies used, and main research

findings. Thematic analysis was performed to identify common patterns and trends in microsleep detection research, such as the effectiveness of EEG technology using CNN and LSTM algorithms<sup>[1,2,20]</sup>. or the efficiency of "behind-the-ear" wearable systems in real workplace environments<sup>[8]</sup>.

Third, the eligibility stage involved reviewing titles, abstracts, and full-text availability, reducing the number to 47 articles. Fourth, the inclusion stage applied predetermined criteria—namely, primary articles published between 2020 and 2024 that are relevant to microsleep detection in workplace contexts—resulting in 25 articles for final analysis.

Inclusion criteria covered primary articles (scientific journals or conference proceedings) published between 2020 and 2024, focusing on microsleep detection using biometric data such as EEG, EOG, EMG, HRV, wearable technology, or combinations with fatigue management policies<sup>[1,2,7,8,15,18]</sup>. Exclusion criteria included studies involving only non-worker clinical populations, topics unrelated to occupational safety, or articles not available in full text<sup>[5,6,17]</sup>. Cross-study comparisons were presented in a table containing classifications of technologies, sensors, detection accuracy, and usage contexts (e.g., heavy vehicle drivers or field workers)<sup>[9,12,22,23]</sup>.

The analysis process used a thematic synthesis approach conducted in three stages. First, data from each article were coded based on key information such as detection methods, sensor types, and algorithms used. Second, these codes were grouped into major themes. Third, conclusions were drawn from the identified patterns. This process resulted in three main themes: (i) the effectiveness of using deep learning algorithms such as CNN and LSTM in detecting microsleep through EEG signals, (ii) the performance of multimodal wearable devices in real working conditions, and (iii) the utilization of biometric data integrated with fatigue management policies in workplace environments<sup>[11,18,24]</sup>.

# RESEARCH RESULTS AND DISCUSSION

Based on the reviewed selected references, several significant findings emerged. Studies applying deep learning to EEG signals showed that the use of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) algorithms could achieve microsleep detection accuracy of 76%–85%<sup>[1,2]</sup>. The use of multimodal sensors, for example combining EEG, EOG, and EMG, provided advantages in early microsleep detection compared to traditional camera-based methods such as percentage of eyelid closure (PERCLOS), which only achieved 60%–70% accuracy<sup>[10,11]</sup>.

In addition, several studies developed wearable systems such as WAKE, which uses "behind-the-ear" technology to capture physiological signals more stably even during movement, with noise reduction capabilities of  $9-19~dB^{[8]}$ . In the transportation sector, behavioral analysis of microsleep using dashcam recordings indicated that accident incidents were often related to brief losses of consciousness that went undetected by conventional systems<sup>[9]</sup>.

Table 1 Comparison of the performance of several microsleep detection methods based on secondary studies:

inctious based on secondary studies.			
Sensor/Method		<b>Detection Accuracy</b>	Notes
EEG, EOG, EMG (WAKE)		76%	Signal Combination with Deep Learning Algorithm
HRV (chest strap/smartwatch)		70-80%	Application of Contextual Variable Analysis
Camera Method (PERCLOS)		60-70%	Detection of External Changes such as Closed
			Eyelids
Algoritma ML (CNN/LSTM)	Terawasi	80-85%	Dynamic Classification of Alertness Status
Reservoir Computing (ESN)		≈ 51% AUC-ROC; 44% AUC- PR	Innovative Approach to Address Signal Variability

Table 1 presents a comparison of the performance of several microsleep detection methods. EEG-based technologies using CNN and LSTM algorithms—particularly when combined with multimodal sensors—tend to achieve the highest accuracy. Conversely, conventional

camera-based methods lag behind in precision. This information suggests that integrating real-time biometric data holds great potential for enhancing drowsiness detection systems in workplace environments.

Wearable devices demonstrate advantages in microsleep detection through the integration of multimodal data (EEG, EOG, EMG, HRV). The application of deep learning to EEG data not only improves detection accuracy compared to traditional methods but also accelerates response time, thereby shortening intervention latency<sup>[1,2]</sup>. For example, the WAKE system, which utilizes sensors placed behind the ear, is capable of capturing EEG and EOG signals with minimal motion interference, making it more suitable for occupational safety monitoring in the field<sup>[8]</sup>. This wearable approach enables direct monitoring of users' physiological status, improving drowsiness detection performance under real-world conditions.

Real-time data from wearable devices can be integrated into fatigue management systems for more effective preventive interventions. Several studies indicate that educational programs on drowsiness risks, coupled with appropriate fatigue management policies, can improve workers' awareness and reduce fatigue-related accident rates<sup>[16,18]</sup>. For instance, continuous training and monitoring for online motorcycle taxi drivers and disaster response personnel have been shown to significantly reduce the risk of drowsiness-related accidents <sup>[17,22]</sup>. With accurate biometric data support, these interventions provide real-time feedback for adjusting work schedules or adding rest periods, thereby improving overall operational safety.

Although wearable technology and advanced algorithms offer promising performance, there are challenges in their workplace implementation. Physiological variability among individuals may lead to differences in detection accuracy, necessitating adaptive machine learning algorithms capable of tailoring models to each user's condition<sup>[20]</sup>. Additionally, privacy and security concerns regarding biometric data remain critical. EEG information and fatigue parameters are highly personal, requiring the implementation of real-time data security protocols and encryption to protect user privacy<sup>[13,23]</sup>. Enhancing IT infrastructure capable of securely and reliably handling large-scale data is also a priority to ensure that detection systems can operate effectively.

The integration of microsleep detection with preventive policies offers important implications for safety across various industrial sectors. Experience in the aviation industry shows that such frameworks effectively reduce fatigue-related accident risks<sup>[12,13]</sup>, suggesting that similar approaches should be adopted in land transportation and other industries. Studies on psychological factors (e.g., boredom levels or predisposition to sleepiness) indicate that incorporating subjective variables can improve drowsiness prediction accuracy <sup>[17,22]</sup>. Leveraging such information for dynamic adjustments in work schedules and rest duration is a strategic step toward creating a more responsive workplace safety system.

Overall, although wearable technology for microsleep detection has advanced significantly, its field application must consider both technical and policy aspects simultaneously. Future research should focus on developing more adaptive algorithms and secure data integration to maximize the potential for preventing drowsiness-related accidents.

# **CONCLUSIONS AND RECOMMENDATIONS**

The phenomenon of microsleep presents a serious challenge to workplace safety in the modern industrial era, particularly in high-risk sectors such as heavy machinery operation, transportation, and public services. Based on a systematic literature review of 25 primary references, it can be concluded that integrating biometric-based detection technologies (EEG, EOG, EMG, HRV) with wearable devices and fatigue management policies can significantly enhance early microsleep detection effectiveness. The application of deep learning algorithms, especially CNN and LSTM, has been shown to deliver high accuracy, while

wearable systems such as WAKE demonstrate great potential for real-time monitoring in actual working conditions. The main impact of this integrated implementation is improved proactivity in workplace safety systems through data-driven monitoring, thereby significantly reducing the risk of drowsiness-related accidents.

For future research, it is recommended to develop an integrated platform combining biometric detection, behavioral monitoring, and automated policy feedback. Research focus may be directed toward underexplored industrial sectors such as underground mining and maritime transportation, which involve extreme working conditions. Furthermore, studies on adaptive algorithms capable of accommodating physiological variability among individuals are needed to ensure that microsleep prevention becomes more accurate, adaptive, and applicable across diverse operational contexts.

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