Study of Factor Associated with Fatigue in Emergency Medicine Professionals Using Wearable Sensor and Machine Learning

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December 13, 2024

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Abstract. This study investigates the factors associated with work-related fatigue among emergency medical professionals (EMPs) in government and private hospitals in Thailand. Utilizing a cross-sectional descriptive study design, the research employs questionnaires addressing social factors such as age, gender, and economic status, as well as work-related factors including experience, hours worked, and workload. A total of 50 EMPs, comprising nurses, nursing assistants, and paramedics, participated in the study. Health data were gathered through wearable sensors, capturing physiological metrics such as heart rate and electrocardiogram (ECG) data alongside questionnaire responses. To assess work-related fatigue, the Multidimensional Fatigue Inventory (MFI-10) was utilized. The analysis of correlations between various factors and levels of fatigue was conducted using Chi-square tests. Findings indicate that both personal and work-related factors significantly correlate with fatigue in emergency medical personnel, particularly smoking habits, supervisory support, and engagement in emergency work, with P-values < 0.05. Following the identification of related factors, the study further explored the relationship between social factors, sensor data, and post-work fatigue using machine learning models, specifically Gradient Boost, XGBoost, and CatBoost. Results showed that the CatBoost model provided the highest performance, achieving an accuracy of 93.33% compared to the other models. This research contributes valuable insights for health promotion initiatives aimed at improving the quality of life for EMPs, ultimately supporting the sustainability of the healthcare system.

Keywords: Fatigue Assessment, Work-related Fatigue, Workload, Wearable sensor, Machine Learning

1 Introduction

Worldwide, employees are experiencing more stress and pressure than ever before, leading to higher levels of mental health issues and fatigue. The COVID-19 outbreak has particularly highlighted how employees manage these pressures [1]. Work patterns have changed dramatically, with workers not only coping with the stress of the epidemic but also facing increased workloads and uncertainty regarding their working hours and styles. Consequently, fatigue rates have risen above normal levels globally. In Thailand, there are currently 38.66 million people of working age, accounting for 58.41% of the total population [2]. This demographic advantage is significant, as a working-age population is essential for promoting social and economic development.

However, the country is currently grappling with a shortage of public health personnel, which hampers its ability to effectively respond to public service needs [3]. Similar challenges are observed in developed countries like the United States, which anticipates a shortage of 10 million healthcare workers by 2030 [4]. During the COVID-19 pandemic, emergency medical personnel have been crucial in helping individuals navigate this crisis [5]. Data indicates that the number of emergency medical responders at various levels has been insufficient to meet current demands. This shortage leads to several challenges, as various factors—including extensive job responsibilities, long working hours, and high-pressure emergency situations—contribute to fatigue among these professionals.

This fatigue manifests in physical symptoms such as exhaustion, discomfort, poor sleep, lack of concentration, memory issues, and aches and pains. Additionally, it negatively impacts operational efficiency, decision-making abilities, communication skills, and overall work performance. Researchers studied the symptoms that occur when fatigue occurs from work. Based on the theory of Muldary [6] which is commonly used for studying fatigue from work [7], it explains that fatigue from work can be divided into 3 aspects: physical, mental, and behavioral.

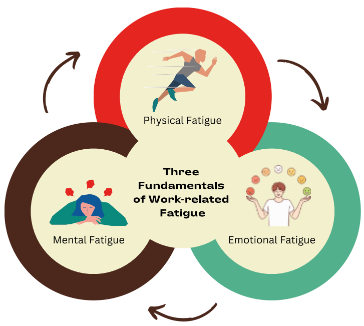

Fig. 1. Basic factors of work-related fatigue

In literature review investigates job burnout, focusing on its prevalence, contributing factors, and assessment within the context of emergency medical services (EMS) personnel, particularly in Thailand. The review begins by defining burnout according to the World Health Organization (WHO) as a syndrome resulting from chronic workplace stress, characterized by: 1) energy depletion or exhaustion; 2) increased mental distance from one's job, or feelings of negativism or cynicism related to one's job; and 3) reduced professional efficacy [8]. This definition, based on the International Classification of Diseases (ICD) criteria, highlights burnout's global recognition as an occupational phenomenon. The review highlights research from the Netherlands, showcasing the Netherlands Organization for Scientific Research (NWO)'s significant contributions to understanding burnout's etiology and consequences, including studies on acute daily fatigue and adjustment difficulties related to work [9].

The review emphasizes burnout's high prevalence in service-oriented and high-pressure professions. It cites Thai studies on burnout among firefighters and healthcare workers, underscoring the impact of staff shortages, particularly in the public health sector. Table 2-1 reveals the concerningly low ratio of healthcare professionals to population in Thailand in 2021[2]. Further highlighting the personnel shortage of emergency medical personnel in Thailand from 2021 to 2023 [5], emphasizing the critical role and demanding workload of Emergency Medical Technicians (EMTs) in providing pre-hospital emergency care, including assessment, initial treatment, and patient transport.

Burnout assessment is discussed using the Multidimensional Fatigue Inventory (MFI), specifically comparing the 20-item (MFI-20) and the shorter 10-item (MFI-10) versions. The review highlights MFI's established reliability and validity across diverse populations [10], [11], [12], referencing studies involving cancer patients, individuals with chronic fatigue syndrome, psychologists, medical students, residents, and military personnel. A cut-off score of 60 or higher is indicated for classifying high levels of burnout [13], [14]. The review integrates a model to understand burnout's multifaceted nature, categorizing its components into physical, psychological (affect and attitude), and behavioral dimensions [6], [7].

Factors contributing to burnout are categorized as individual (age, gender, marital status, education, parenthood), work-related (workload, experience, job characteristics, job satisfaction), and health-related. Studies are cited demonstrating the association between increased workload, long work hours, experience levels, and burnout, especially among EMS professionals [15], [16], [17], [18].

Finally, the review explores the use of machine learning (ML) in predicting burnout, particularly among EMS personnel, utilizing data from wearable sensors. Different ML approaches—supervised, unsupervised, and reinforcement learning—and specific algorithms such as Random Forest, CatBoost, and XGBoost are discussed [19], [20]. The review concludes by emphasizing the urgent need to address burnout among Thai EMS professionals, considering the existing staff shortages and the demanding nature of their work.

2 Related Work

Research on work-related fatigue among medical professionals has garnered increased attention, particularly considering the rising demands placed on healthcare systems, especially during the COVID-19 pandemic. Several key studies have explored various aspects of this issue.

Jaiswal et al. [21] aimed to develop a tool for assessing fatigue using various wearable sensor technologies combined with machine learning techniques. Their analysis revealed that traditional survey instruments can suffer from bias, as respondents may withhold critical information, leading to inaccuracies. By employing wearable sensors, they could evaluate both physical and psychological fatigue effectively. Their findings indicated high classification accuracy, with a Long Short-Term Memory (LSTM) algorithm achieving 84.1% accuracy and a recall rate of 90%.

Khan et al. [17] investigated the relationship between shift work, sleep, mental health, and movement in emergency medical personnel in Australia. Their research found significant statistical differences in sleep patterns across different shifts, highlighting increased stress and fatigue levels during night shifts and weekends ($p < 0.001$). The study underscored the critical importance of addressing the unique challenges associated with rotating shifts to mitigate fatigue.

A study conducted in 2020 explored factors contributing to fatigue in aviation professionals, linking sleep deprivation and lifestyle disruptions to negative impacts on performance and health. This systematic review emphasized the heightened risk of fatigue-related incidents when working extended hours without adequate rest.

Aryal et al. [22] examined fatigue in the construction workforce, highlighting that prolonged working hours and stressful environmental conditions contribute significantly to fatigue, affecting productivity and increasing the risk of accidents. They utilized wearable sensors to detect physical fatigue, achieving an impressive classification accuracy of 82%.

Panich [23] compared the efficiency of various machine learning models, including Decision Trees and Neural Networks, for predicting student grades in educational technology. Their research demonstrated the superior performance of Neural Networks, which improved prediction accuracy from 88.89% to 92.59% after parameter optimization, suggesting that advanced analytical techniques can significantly enhance performance assessment in various fields.

Liu et al. [19]focused on predicting fatigue in emergency medical personnel using machine learning models based on data collected from smartwatches. The study involved 110 participants and showed that CatBoost emerged as the most effective model for identifying work-related fatigue, particularly among younger nurses under 35 years.

Mannhart et al. [24] investigated the accuracy of deep learning algorithms for detecting arrhythmias using ECG data from smartwatches. Their results demonstrated that deep neural networks significantly outperformed standard algorithms from multiple smartwatch manufacturers, highlighting the potential for advanced algorithms in healthcare diagnostics.

Research shows a growing need to address fatigue among healthcare workers, especially in high-stress jobs. Wearable technology and machine learning offer promising tools for accurately assessing and managing fatigue, potentially improving well-being and healthcare delivery.

3 Material and Method

This research, the researcher conducted research on work fatigue in emergency medical personnel. This is an important study to find appropriate factors and solutions so that personnel can work more efficiently and have better health. The research process was divided into 5 mains.

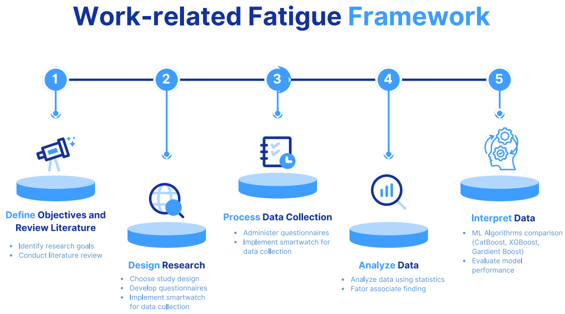

Fig. 2. Work-related fatigue Framework

3.1 Ethical Considerations

The study was approved by the Human Research Ethics Committee of Chulabhorn Royal Academy. Informed consent was obtained from all participants, and confidentiality was maintained throughout the data collection and analysis process.

3.2 The Multidimensional Fatigue Inventory

MFI or Multidimensional Fatigue Inventory (MFI-20) is a multidimensional tool used to measure fatigue in various fields, including general fatigue. There are 20 problems: physical fatigue, mental fatigue, decreased motivation, and decreased activity. 1-5 points, with a total score between 20-100 points. If the total score is high, it indicates extreme fatigue. Research has shown that MFI is good reliability and accuracy. Make it a reliable tool for assessing fatigue among different populations. For researcher reviewed previous study, The original MFI has developed and checked the MFI-20 evaluation form. Due to the inconsistency between some evaluations and their use in research, it is necessary to design a small number of evaluations for the convenience of patients and doctors. Only 10 items were consistent with the study [12] and tested the effectiveness of 20 MFI-20 fatigue assessments. 700 colon cancer patients found that the accuracy of the assessment decreased based on the number of questions in the assessment. This angered evaluators, as some questions were unnecessary.

Therefore, MFI-10 fatigue assessments were used instead of multidimensional fatigue assessments. Inventory is measured by scale, so previous researchers scored between low fatigue levels and high fatigue levels. High levels of fatigue were found to be associated with scores above 60, and are high levels of fatigue [14], [25].

This study explored work-related fatigue among emergency medical personnel, employing a cross-sectional descriptive design to investigate contributing factors and potential mitigation strategies. Purposive sampling was utilized to select 50 participants. Participants were required to be over 18 years old and possess a valid emergency medical license. Individuals with pre-existing circulatory system diseases or diagnosed mental health conditions were excluded to minimize confounding variables and ensure data integrity.

Data collection involved a comprehensive, multi-faceted approach combining self-reported questionnaires and objective physiological measurements. A three-part questionnaire gathered detailed information: Part 1 captured demographic data (e.g., gender, age, marital status, education level, socioeconomic status, smoking and alcohol consumption, exercise habits, family responsibilities); Part 2 focused on work-related aspects (e.g., job title, years of experience, weekly work hours, overtime, perceived workload, organizational and external support systems, consultation frequency, sleep duration); and Part 3 utilized the Thai-translated version of the Multidimensional Fatigue Inventory (MFI-10), a validated instrument measuring various dimensions of fatigue (physical, mental, and motivational). This questionnaire employed a five-point Likert scale, with responses weighted and subsequently categorized into “low” and “high” fatigue groups.

To complement self-reported fatigue levels, objective physiological data were collected using Apple Watch Series 7 devices worn by participants throughout their five-day work week. The smartwatches continuously monitored heart rate and provided additional activity metrics such as steps taken, and distance covered. Electrocardiograms (ECGs) were also recorded twice daily (pre- and post-shift) via the device's integrated sensors. This dual data collection strategy aimed to enhance the study's robustness by integrating subjective experiences with objective physiological indicators of fatigue.

Data analysis proceeded in three phases. Descriptive statistics (frequencies and percentages) were applied to demographic and work-related questionnaire data to characterize the study sample and highlight key trends. Similarly, descriptive statistics (means and standard deviations) were used to summarize MFI-10 scores and physiological data obtained from the smartwatches. Finally, advanced analytical techniques were employed to investigate the relationships between identified factors and levels of fatigue. Specifically, machine learning algorithms [19] were applied to the combined dataset, assessing model performance using established metrics such as accuracy, precision, recall, and the F1-score. This multi-faceted analytical approach aimed to identify significant predictors of work-related fatigue and inform the development of effective interventions to improve the well-being and productivity of emergency medical professionals.

4 Results

This study examined work-related fatigue among 50 emergency medical professionals, leveraging both self-reported data and objective physiological measurements. Participants completed questionnaires assessing demographics, work characteristics, and fatigue levels using the validated MFI-10 scale. Concurrently, they wore Apple Watch Series 7 devices for five workdays, providing continuous heart rate and activity data. Data analysis involved descriptive statistics, bivariate analyses (Chi-square tests), and machine learning model development and comparison.

The sample was predominantly female (88%), with a mean age of 29.8 years. Bivariate analyses revealed significant associations between fatigue and several factors: smoking status, the frequency of off-site work assignments, the perceived adequacy of supervisory support, and the availability of consultation services for work-related issues. These findings highlight the multifaceted nature of work-related fatigue in this population. As Table 1, The sample consisted of 50 emergency medical professionals, with 44 (88%) being female and 6 (12%) males. The mean age was 29.8 years (standard deviation = 6.1 years for females and 4.4 years for males). The majority (82%) were single, and the largest proportion (62%) held a bachelor's degree. Most participants (84%) reported no pre-existing medical conditions, and a similar majority (86%) did not smoke. The most common pattern of alcohol consumption was occasional drinking (72%). A majority (64%) reported exercising occasionally. The most frequent income bracket was 15,000–30,000 THB (48%). Most participants (54%) reported having sufficient income but no savings. The most prevalent level of family burden was moderate, with occasional concerns about responsibilities (58%).

Table 1 Bivariate Analysis of Factors Associated with Fatigue (Personal Factors)

Factor	Non-Fatigued (%)	Fatigued (%)	Pearson Chi-Square Value	P-value
Gender				
Male	13.64	86.36	1.524	0.217
Female	33.33	66.67		
Marital Status				
Single	19.51	80.49	2.091	0.148
Married	0.00	100.00		
Education Level				
High School/Vocational	20.00	80.00	3.983	0.263
Associate degree	37.50	62.50		
Bachelor's Degree	9.68	90.32		
Post-graduate	0.00	100.00		
Pre-existing Medical Condition				
None	19.50	80.95	1.814	0.178
Yes	0.00	100.00		
Smoking Status			11.543	0.003*
Smoker	75.00	25.00		
Former Smoker	0.00	100.00		
Non-smoker	11.63	88.37		
Alcohol Consumption				
Occasional Drinker	16.67	83.33	0.397	0.820

Factor	Non-Fatigued (%)	Fatigued (%)	Pearson Chi-Square Value	P-value
Former Drinker	0.00	100.00		
Never Drunk	16.67	83.33		
Exercise				
Regular Exercise	0.00	100.00	1.136	0.567
Occasional Exercise	18.75	81.25		
No Exercise	15.38	84.62		
Monthly Income (THB)			0.955	0.620
15,000-30,000	20.83	79.17		
30,001-45,000		10.00		10.00
45,001-60,000		16.67		16.67
Economic Status	13.64		3.401	
Sufficient Income, Savings	33.33	27.78		27.78
Sufficient Income, No Savings		7.41		7.41
Insufficient Income	19.51	20.00		20.00
Family Burden	0.00		1.954	
Low		30.00		30.00
Moderate	20.00	13.79		13.79
High	37.50	9.09		

This table summarizes work-related factors of emergency medical professionals was predominantly nurses (54%), with a mean experience of 6.87 years (SD=5.56). Most worked on-site (74%), reporting a workload they found acceptable (60%), though a considerable proportion reported excessive workloads (38%). Significant deficiencies were reported concerning supervisory (48%) and peer support (78%), alongside sleep (22%). Moderate overall job satisfaction co-existed with a notable percentage (28%) having considered resignation see Table 2 .

Table 2 Bivariate Analysis of Factors Associated with Fatigue (Work Factors)

Factor	Non-Fatigued (%)	Fatigued (%)	Pearson Chi-Square Value	P-value
Job Position				
Nurse		3.359	0.339	7.41
Nursing Assistant				25.00
Patient Care Assistant				25.00

Factor	Non-Fatigued (%)	Fatigued (%)	Pearson Chi-Square Value	P-value
Paramedic				33.33
Average Daily Working Hours				
8-10 hours/day		4.503	0.212	12.50
10-12 hours/day				17.65
12-14 hours/day				30.77
More than 14 hours/day				0.00
Off-site Emergency Patient Care Assignments		27.106	0.000*	
No				0.00
Yes				61.54
Perception of Workload				
Too Low		0.201	0.904	0.00
Appropriate				16.67
Too High				15.79
Supervisory Support		5.953	0.015*	
Sufficient				3.85
Insufficient				29.17
Peer Support		2.686	0.101	
Sufficient				0.00
Insufficient				20.51
Availability of Mentorship/Consultation		4.482	0.034*	
Sufficient				0.00
Insufficient				23.53
Sufficient Sleep		1.333	0.248	
Yes				12.82
No				27.27
Satisfaction with Emergency Department Work Environment		1.130	0.288	
Sufficient				9.52
Insufficient				20.69

Factor	Non-Fatigued (%)	Fatigued (%)	Pearson Chi-Square Value	P-value
Job Satisfaction		4.082	0.043*	
Sufficient				0.00
Insufficient				22.86
Consideration of Resignation		2.286	0.131	
Never				28.57
Yes				11.11

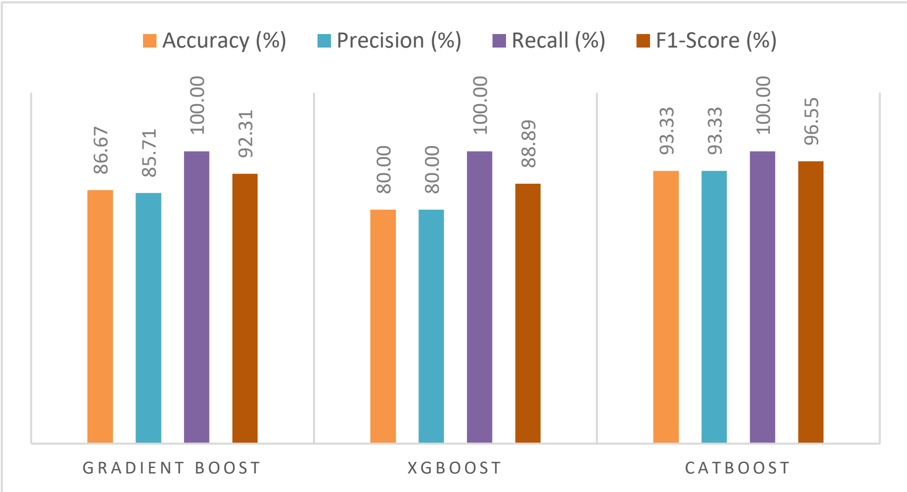

Fig. 3. Performance comparisons used Accuracy, Precision, Recall and F1-score.

To predict fatigue, three machine learning algorithms—Gradient Boosting, XGBoost, and CatBoost—were employed. Two datasets were used: dataset 1 comprised questionnaire data only, while dataset 2 integrated questionnaire and smartwatch data. The CatBoost model consistently outperformed the others. Critically, when trained on dataset 2, the CatBoost model achieved the highest accuracy (93.33%) after parameter optimization (100 iterations, learning rate of 0.1, depth of 7). This accuracy significantly surpassed the performance of models trained solely on questionnaire data (dataset 1) as Table 3.

Table 3 Comparison of the accuracy values of data set 1 and data set 2.

Model	Accuracy Dataset 1	Accuracy Dataset 2
Gradient Boost	80.00%	86.67%
XGBoost	86.67%	80.00%
CatBoost	80.00%	93.33%

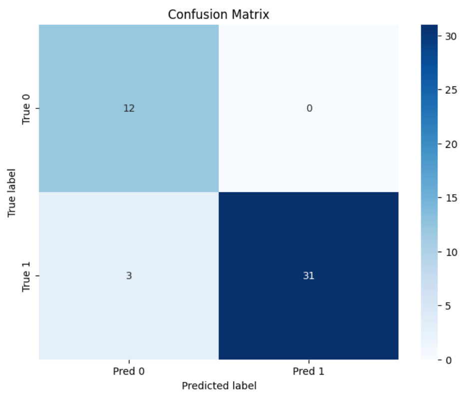

Fig. 4. CatBoots model prediction performance results

The researcher's CatBoost model demonstrated high performance in predicting job burnout, as evaluated using a confusion matrix. The model correctly identified 31 positive cases (individuals experiencing burnout) and 12 negative cases (individuals without burnout). The model achieved an accuracy of 93.48%, indicating strong classification ability. Importantly, the precision was 100%, meaning no false positives were generated. However, three false negatives were observed, resulting in a recall of approximately 91.18%. The balanced F1 score of 95.42% demonstrates a good trade-off between precision and recall.

In conclusion, this study identified key factors associated with work-related fatigue in emergency medical professionals: smoking, off-site work, supervisory support, and access to consultation services. The superior performance of the CatBoost model, utilizing both self-reported and sensor data, suggests a promising approach for predicting and potentially mitigating fatigue in this high-stress profession. The findings underscore the need for comprehensive interventions addressing both individual risk factors and organizational support systems.

5 Discussion

This study's findings underscore the complex interplay of factors contributing to work-related fatigue among emergency medical professionals. The significant associations identified—between fatigue and smoking, off-site work, supervisory support, and access to consultation—highlight the need for multi-pronged interventions addressing both individual behaviors and organizational support systems. The superior performance of the CatBoost model, particularly when incorporating sensor data, demonstrates the potential of machine learning to not only identify individuals at high risk of experiencing significant fatigue but also to inform the development of more precise and effective targeted interventions.

This predictive capability offers a significant advance in proactive fatigue management, allowing for personalized strategies tailored to individual needs and risk profiles. However, the cross-sectional nature of the study limits the ability to definitively establish causal relationships; longitudinal research is needed to confirm these associations and explore the underlying mechanisms driving fatigue in this high-stress profession.

Implications for Future Research

While the CatBoost model demonstrated excellent predictive accuracy in this study, several avenues for future research remain. Firstly, validation of these findings is crucial. Replication studies utilizing significantly larger and more diverse samples of emergency medical professionals from various geographical locations and healthcare settings are needed to confirm the generalizability of the model's performance and the identified predictive factors. Secondly, the cross-sectional design of this study limits the ability to establish causal relationships. Longitudinal studies are necessary to definitively determine the causal pathways between the identified risk factors (smoking, off-site work, supervisory support, access to consultation) and work-related fatigue.

Finally, incorporating additional variables into the model could enhance its predictive power. Future research should explore the inclusion of factors such as workload intensity, sleep quality, social support networks outside of work, and specific aspects of the work environment (e.g., noise levels, staffing ratios, exposure to traumatic events) to create a more comprehensive and predictive model.

Practical Implications

This study's findings offer several crucial practical implications for enhancing the well-being of emergency medical professionals and improving healthcare system efficiency. Organizations can implement targeted interventions to mitigate fatigue by focusing on the identified key predictors. These interventions could include:

Smoking Cessation Support: Implementing comprehensive smoking cessation programs tailored to the specific needs of emergency medical staff.

Work-Life Balance Initiatives: Promoting work-life balance through flexible scheduling options, adequate vacation time, and stress management resources.

Enhanced Leadership Training: Investing in training programs for supervisors to improve communication, empathy, and conflict resolution skills, fostering a more supportive work environment.

Improved Access to Consultation: Providing readily available and easily accessible mental health and employee assistance programs to address work-related stress and burnout.

Proactive Fatigue Management: Utilizing the developed machine learning model to identify high-risk individuals and proactively implement individualized interventions, including adjusted work schedules, additional support, or early access to preventative care.

By addressing these factors, healthcare organizations can create a healthier, more sustainable work environment, reducing fatigue, burnout, and improving the overall well-being and performance of their emergency medical teams. The proactive use of predictive modeling offers a powerful tool to optimize resource allocation and personalized interventions, improving both individual and organizational outcomes.

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