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AI-driven biomedical perspectives on mental fatigue in the post-COVID-19 Era: trends, research gaps, and future directions

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Abstract

Mental fatigue is a complex condition arising from various neurological processes and influenced by external factors such as stress and cognitive demands. This comprehensive review elucidates the primary neurological mechanisms underlying mental fatigue, particularly emphasizing how it was elevated or otherwise affected during the COVID-19 pandemic. We explore the intricate relationship between prolonged cognitive tasks, chronic stress, and the development of mental fatigue, emphasizing the impacts that mental fatigue has on mental health across diverse populations. Utilizing advanced artificial intelligence techniques, including machine learning and deep learning, this study identifies and quantifies the patterns of mental fatigue. The innovative approach deployed in this study enhances our understanding of the complex interplay between mental fatigue and psychological disorders, uncovering potential predisposing factors and underlying mechanisms. A thorough bibliometric analysis highlights global research trends, key contributors, and emerging interdisciplinary methods in mental fatigue research. This paper identifies gaps in knowledge and methodological challenges. It proposes promising avenues for future investigations that emphasize multidisciplinary approaches and the development of novel diagnostic and treatment tools tailored to address mental fatigue. By integrating insights from neurological studies with the psychological implications of mental fatigue, this study aims to inform better interventions to improve mental health outcomes. Our findings have significant implications for healthcare professionals, researchers, and policymakers working to mitigate the impact of mental fatigue in various contexts.

Keywords: Psychological disorder, Mental fatigue, Artificial intelligence, COVID-19, Signal, Bibliometric analysis, Stress, Neurological disorder, Machine learning, Deep learning

Introduction

Mental fatigue is a state of cognitive exhaustion caused by prolonged mental effort, stress, or workload, leading to reduced focus and impaired decision-making. Mental fatigue has emerged as a critical concern across multiple domains, including healthcare, workplaces, education, and transportation [1–3]. It is characterized by as a decline in cognitive performance and attention due to prolonged mental exertion, mental fatigue remains a pervasive yet often underestimated phenomenon [4]. Mental fatigue not only affects individual well-being but also poses significant risks to productivity, safety, and overall quality of life [5–7]. In recent years, the global rise in stress-related disorders, exacerbated by events such as the COVID-19 pandemic [8, 9], has intensified the need to better understand and address mental fatigue. This condition, if left unmanaged, can lead to severe consequences, ranging from impaired decision-making in high-stakes environments to long-term mental health challenges.

The study of mental fatigue spans multiple disciplines, integrating insights from neuroscience, psychology, engineering, and computer science. The neurological mechanisms underlying state mental fatigue are more complex and not completely comprehended [10]. However, there has been empirical evidence of changes in the brain's cognitive control and default mode networks [11]. Mental fatigue typically has a connection with the frontal and occipital cortical zones of the brain, modifying the glutamate network in the brain to cause major changes [5, 12]. The mechanisms resulting in mental fatigue are unclear. Considering its increasingly recognized adverse impact, the neurological mechanisms associated with this phenomenon seemingly remain understudied.

Analysis of mental fatigue as a concept in biomedical science reveals that it is a well-known phenomenon that is defined as a decrease in cognitive and emotional performance due to continuous cognitive demand in the absence of adequate rest. This is accompanied by signs such as dizziness, a sleepy state, poor concentration, disorder in thinking, and inability to make the right decisions. Still, mental fatigue is one of the least researched and defined phenomena that can be characterized by rather vague and ambiguous conceptualization. Such terms as brain fatigue, mental fatigue and, in the most basic sense, fatigue are often used to describe this state, a fact that draws attention to the existing variability in the literature [13]. The current review uses the term "mental fatigue" to capture all these different meanings. Mental fatigue is not just an academic curiosity, it has drastic consequences for both physical well-being and the overall human experience.

Chronic stress hinders problem-solving skills, self-regulation, and social interactions, hence complicating aspects of one's daily life, not to mention work-related issues.[1] It may manifest as an acute condition or may become a chronic one depending on the strenuous conditions such as chronic stress, sleeplessness, and long tedious mental jobs. From the findings of Tanaka et al. [14], chronic stress has proven to disrupt the central nervous system by deconstructing the facilitation systems as well as the central sensitization of inhibition systems. Increased cortisol levels due to stress effects go on to disrupt normal mechanisms of function, resulting in mental fatigue. From a biomedical point of view, mental fatigue is defined as having several neurological processes that are still not fully explained although there exists scientific evidence of the changes in cognitive control and the default mode networks, especially with the frontal and occipital cortical areas. These changes affect the glutamate connection in the mind and, therefore, cause significant alterations in the cognitive processes. Based on the presented negative effects

[1] https://www.healthline.com/health/mental-exhaustion

of mental fatigue, it is essential to investigate the potential factors and appropriate interventions required to counteract it.

However, significant gaps remain in our understanding of mental fatigue. Current methodologies often rely on subjective self-reports or simplistic metrics, which may lack the precision required for accurate diagnosis and intervention. Furthermore, the diversity of datasets and the variability of fatigue manifestations across individuals present ongoing challenges. To address these limitations, cutting-edge technologies such as deep learning (DL) [15–17] and functional near-infrared spectroscopy (fNIRS) are being explored to enhance detection accuracy and foster real-time monitoring solutions.

This review aims to synthesize existing knowledge on mental fatigue research, emphasizing its implications for healthcare, workplace productivity, and educational settings. By analyzing recent advancements in AI-driven approaches [18–20] and bibliometric trends [21–23], we seek to identify key areas for future exploration and innovation. Our findings underscore the urgent need for improved strategies to combat mental fatigue, offering actionable insights for policymakers, practitioners, and researchers. Ultimately, this work strives to contribute to a deeper understanding of mental fatigue and its multifaceted impact, paving the way for more effective interventions and sustainable outcomes.

Research questions of this study

- How is mental fatigue linked to psychological disorders?
- What impact did COVID-19 have on mental fatigue?
- How is AI helping in mental fatigue research?
- What bio-signals are used to indicate mental fatigue?
- What are the current trends in AI and mental fatigue studies?
- Which institutions are leading mental fatigue research?
- Who is funding and supporting mental fatigue research?
- What gaps remain, and where should future research focus?

Main contributions of the study

- To explores how mental fatigue contributes to the onset or worsening of psychological conditions such as anxiety, depression, and cognitive decline.
- To highlight how pandemic related stressors have intensified symptoms of mental fatigue across various populations.
- To provide a comprehensive overview of how AI models and techniques are being utilized to assess, predict, and monitor mental fatigue.
- To summarizes the most widely used physiological signals in mental fatigue assessment.
- To analyze the annual trends, showing how AI applications in this area have evolved over time.
- To identify key academic institutions contributing to the advancement of mental fatigue research.
- To identify critical knowledge gaps and proposes future research directions.

Related works

The review has sought to aggregate the existing research and proposed methodologies, coupled with the technologies that can be used to understand mental fatigue. The paper identifies and discusses methodologies like support vector machines, neural networks, and advanced approaches like deep learning to analyze mental fatigue patterns. It also revisits the statistical methods, such as hierarchical extreme learning machines, wavelet transforms, and principal component analysis, meant for explaining big data. In addition, methods of intelligent signal processing, like Electroencephalogram (EEG) [24, 25] and Electrocardiogram (ECG) [26], give a basis for knowledge about the physiological roots of mental fatigue.

In an attempt to stimulate an evaluation of potential practical applications of findings in mental fatigue and to stress the interdisciplinary nature of mental fatigue studies, this review aims to outline the gaps in the field and possible directions for its development. The biomedical perspective of mental fatigue is critical for formulating effective solutions for use in healthcare and occupational environments, education and other areas that may be affected by this condition. The following sections will provide a detailed examination of the diverse techniques utilized in mental fatigue investigations, providing a nuanced understanding of this complex phenomenon in Table 1 [27–41].

Methods

The purpose of this review is to establish mental fatigue [42, 43], psychological disorders, and their relation with COVID-19. The literature review was provided to carry out a systematic review of the literature in these areas. In terms of the search strategy used, the use of Boolean queries was considered the best approach to identify pertinent studies concerning the neurocognitive mechanisms of mental fatigue and other forms of psychological manifestations. This technique helped in compiling the current practices and outputs from the research information regarding the subject.

Eligibility criteria

In the current review, we limited ourselves only to those sources that met the inclusion criteria, specifically for the quality and relevance of the research. When selecting papers, only those written in English, peer-reviewed and examined mental fatigue or other related psychological disorders in the context of COVID-19. Reporting on mental fatigue was preferred in studies that included biomedical, neurological or artificial intelligence approaches. The following studies were excluded: those that were published in duplicate, written in languages other than English, editorials, books, and those that did not fit the core theme of this review.

Search strategies

We have conducted a comprehensive literature search using multiple databases, including Elsevier, IEEE, Springer, ACM, Hindawi, MDPI, Frontiers, Wiley, Taylor & Francis, Nature, Google Scholar, Scopus, PubMed, and Web of Science. These databases were selected based on their relevance to psychological, bio-medical, and technological research. A bibliometric technique was used because a standardized search strategy was adopted for the review. As a result, all studies were considered

Table 1 Comparison between previous and present reviews based on different aspects

Reference	[27]	[28]	[29]	[30]	[31]	[32]	[33]	[34]	[35]	[36]	[37]	[38]	[39]	[40]	[41]	Our review
Introduction	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Research Question	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✓
Main Contributions	✗	✗	✗	✗	✓	✗	✗	✓	✓	✗	✗	✗	✓	✓	✓	✓
Comparison	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Method	✓	✓	✓	✗	✓	✓	✓	✗	✓	✓	✗	✓	✓	✗	✓	✓
Impact	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓
Association	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Psychological Disorder	✗	✗	✗	✗	✗	✓	✗	✗	✓	✓	✗	✗	✓	✓	✓	✓
Mental Stress	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Effect	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✓
COVID-19	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
AI	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓
Detection	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
ML Model	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓
DL Model	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Performance Metrics	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Feature Extraction	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Pre-Processing	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Bio-Signal	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓
EEG	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓
ECG	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
HRV	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
GSR	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
ST	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
fNIRS	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓
ECoG	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓

Table 1 (continued)

Reference	[27]	[28]	[29]	[30]	[31]	[32]	[33]	[34]	[35]	[36]	[37]	[38]	[39]	[40]	[41]	**Our review**
EOG	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Dataset	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Bibliometric Analysis	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Annual Production	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Citation	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Author Pattern	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Affiliation	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Publisher	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Three Field Plot	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Tree Map	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Word Cloud	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Closet Word	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Country	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Discussion	✓	✓	✓	✗	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✓
Funding Agency	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
Research Gap	✓	✗	✓	✗	✓	✓	✓	✗	✗	✗	✗	✓	✗	✗	✓	✓
Implication	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓	✗	✗	✓	✓
Application	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓
Future Prospects	✓	✓	✓	✓	✓	✗	✓	✗	✗	✗	✓	✗	✓	✓	✓	✓
Conclusion	✓	✓	✓	✗	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓

Table 2 Search strategies of the current study

No	Keywords
1	Mental fatigue" AND "COVID-19″ AND "psychological disorder"
2	"Mental fatigue" AND "bio-signal"
3	"Mental fatigue" AND "neurocognitive" AND "COVID-19"
4	"Mental fatigue" AND "AI" OR "artificial intelligence" AND "COVID-19"
5	"COVID-19" AND "stress" AND "fatigue" AND "diagnosis"

relevant to the topic based on their titles, abstracts, and keywords. The detailed search strategies are provided in Table 2.

Data selection

We summarized several important pieces of information for each of the selected articles, based on a predefined data extraction form: sample size, research design, outcome measures, and findings. From the start, we found 291 articles to be relevant, but excluding redundant articles and those that only described what was already known or did not go beyond conventional methods or at least usages, the number of articles to be considered was 182. The other papers were peer-reviewed for quality and risk of bias using set criteria for evaluation. Of these, the majority addressed the effect of mental fatigue on psychological disorders broadly about COVID-19 stressors [29–31].

Synthesis of the results

To systematically combine insights from the reviewed literature, a structured approach was used to synthesize both quantitative and qualitative findings related to mental fatigue. The studies were categorized based on their methodologies, outcomes, and practical application areas. Quantitative research offered measurable indicators—such as bio-signal patterns [44, 45] and performance metrics of AI models—while qualitative studies contributed deeper perspectives on user experiences, behavioral symptoms, and fatigue-related challenges. A consistent trend observed across studies was the disruption of cognitive functions, such as reduced attention and impaired executive control, often worsened during or after COVID-19. Research using artificial intelligence showed encouraging potential in detecting fatigue through physiological data, though many models lacked generalizability across diverse individuals and settings. There was also a noticeable increase in interdisciplinary work combining AI, psychology, and biomedical sciences to improve the accuracy and personal relevance of detection systems. However, several gaps remain, including limited use of explainable AI, a lack of real-world model validation, and inconsistencies in data collection protocols.

Understanding the mental fatigue with biomedical perspectives

In this section, the knowledge about mental fatigue from the biomedical point of view is explored by stressing the physiological and neurological roots of the phenomenon. Studying mental fatigue incorporated in the biomedical framework allows us to identify biological mechanisms and factors that play crucial roles in the occurrence and development of the mental fatigue phenomenon. It also helps in coming up with a correct diagnosis, but at the same time, helps in formulating effective intervention strategies.

Association between mental fatigue and psychological disorders

Cognitive load, on the other hand, is likely to be defined as the exhaustion that is likely to occur to individuals or during their working period or even in intervals of working time. These feelings are often experienced in routine contemporary life and include listlessness or fatigue, a desire to stop the current activity and lessened engagement in the current task [46]. Mental fatigue is a chronic psychophysiological condition which influences health and productivity negatively and has a sharp negative impact on the quality of life [47]. Mental fatigue manifests through decreased attention, impaired decision-making, and diminished motivation [34]. It is often the result of sustained cognitive effort, which depletes the brain's resources, leading to a state of mental exhaustion [46]. The underlying mechanisms involve neurotransmitter depletion, particularly dopamine and acetylcholine, which play key roles in cognitive processes and motivation [48]. This review aims to explore the association between mental fatigue and psychological disorders, specifically stress, anxiety, and depression. Understanding these relationships is central to developing effective interventions and therapeutic approaches.

Stress is a response to perceived threats or challenges, triggering physiological and psychological changes aimed at coping with the stressor [49]. Maintaining homeostasis in the presence of aversive stimuli (stressors) requires activation of a complex range of responses involving the endocrine, nervous, and immune systems, collectively known as the stress response. Chronic stress is linked to increased levels of mental fatigue. The hypothalamic–pituitary–adrenal (HPA) axis plays a critical role in this association, with prolonged stress leading to HPA axis dysregulation and subsequent mental fatigue [50]. Research indicates that individuals under chronic stress exhibit higher levels of mental fatigue, which impairs cognitive function and exacerbates stress-related symptoms [51]. For instance, a study by Jex and Gudanowski [52] demonstrated that job stress significantly predicted mental fatigue among employees, highlighting the impact of workplace stress on cognitive health.

Anxiety disorders, characterized by excessive worry and fear, are closely linked to mental fatigue. Anxiety results in increased arousal and a continuous stream of cognitions, which consume the attentional and associative capital of the individual and consequently causes a feeling of exhaustion [53]. A meta-analysis has revealed that there are changes in the way people with anxiety disorders use various networks in the brain, such as the attention and executive networks, which may cause mental tiredness [54]. The available literature provides evidence supporting this relationship. Wells, in his research [42], also observed that patients with Generalized anxiety disorder (GAD) experience higher levels of mental fatigue than normal healthy individuals. Stress and hyperarousal associated with anxiety disorder tends to deplete cognitive resources, hence results in tiredness. Depression is described by low mood, anhedonia and neurocognitive deficits as comprising of impaired attention, memory, and executive functioning [55]. The cognitive model of depression avers that negative beliefs and cognitive biases cause mental exhaustion in depressed people [56].

Depression is actually related to the imbalance of such key brain chemicals as serotonin or dopamine that influences cognition and energy [57, 58]. A similar study showed that the effects of MDD included mental fatigue that reduced the quality of life as well as cognitive productivity of patients. The presence of negative thoughts and the effort used to deal with negative thoughts are said to take a toll on mental energy in depression. It is also clear that mental fatigue and different kinds of psychological disorders influence each other. Thus, mental fatigue may worsen forms of stress, anxiety, and/or depression, participating in a continuous loop [59]. For example, when an individual becomes mentally exhausted, which is common when one is overloaded with work, he or she has minimal resources to cope with stress, hence becoming more prone to anxiety and depression-like symptoms. On the other hand, stress, anxiety or depression enhances cognitive loads, consequently resulting in increased mental exhaustion [60]. Hence, it is possible to state that psychological disorders like stress, anxiety, and depression are highly connected with mental fatigue. Mental fatigue results from prolonged cognitive activity and is exacerbated by chronic stress, anxiety, and depression. These disorders, in turn, increase cognitive demands, further depleting cognitive resources and perpetuating mental fatigue. Understanding these associations is vital for developing targeted interventions to alleviate mental fatigue and improve mental health outcomes.

Recent neurobiological research has identified several causal pathways underlying mental fatigue, particularly in relation to glutamate network dynamics and cortical connectivity changes [61]. Mental fatigue is associated with glutamate accumulation in the prefrontal cortex (PFC) and anterior cingulate cortex (ACC), impairing synaptic plasticity and leading to cognitive inefficiency [62]. Prolonged cognitive exertion disrupts the balance between glutamate release and reuptake, resulting in excitotoxicity and neural exhaustion. Additionally, changes in cortical connectivity have been observed, particularly in the default mode network (DMN) and central executive network (CEN). Fatigue leads to decreased functional connectivity between these networks, reducing the brain's ability to efficiently allocate cognitive resources [63]. Moreover, neurotransmitter imbalances, including dopamine, serotonin, and acetylcholine depletion, contribute to impaired motivation, attention, and cognitive flexibility. These neurochemical alterations explain why individuals experiencing mental fatigue often report reduced alertness, prolonged decision-making times, and diminished problem-solving abilities. The emerging evidence suggests the need for future research to employ multi-modal neuroimaging techniques, such as EEG, fMRI, and PET scans, to investigate the causal pathways and develop targeted interventions for mental fatigue in clinical and occupational settings.

Impact of COVID-19 on mental fatigue

The COVID-19 pandemic, caused by the SARS-CoV-2 virus, has deeply impacted global health, economies, and societies. Beyond the physical health implications, the pandemic significantly affected mental health, leading to a notable increase in mental

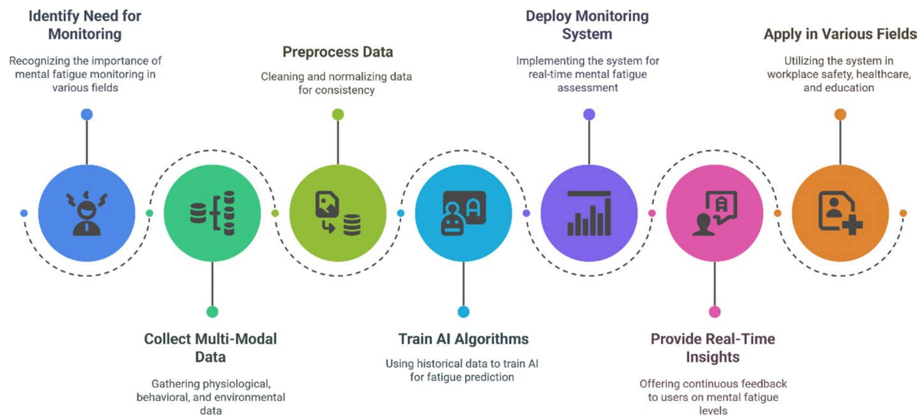

Fig. 1 An automatic mental fatigue classification system based on a multimodal dataset using AI

fatigue [64]. Mental fatigue, on the other hand, describes a feeling of exhaustion and decreased productivity, blunting of affect and cognitive impairment that may arise from sustained engagement in cognitive tasks or stress [65]. In this section, a literature review is conducted on the current research on the consequences of mental fatigue during the COVID-19 pandemic regarding its incidence, risk factors, and implications on the individual and society.

A recent cross-sectional survey revealed enhanced mental fatigue during the COVID-19 pandemic. During the peak of the COVID-19 outbreak, the American Psychological Association conducted a study in which 32% of Americans reported feeling so stressed by the coronavirus pandemic that they could not make any basic choices. In the study, the majority of the grown-ups were under stress due to the pandemic, and most of them complained of issues associated with mental exhaustion, including the inability to focus (American Psychological Association, 2021). However, a Kaiser Family Foundation (2021) study conducted among the population of the United States showed that 47% of the adults reported their mental health had worsened because of stress and worry caused by the coronavirus.

Artificial intelligence in the mental fatigue research

This section discusses various applications of machine learning [66–68] and deep learning [69–71] techniques within mental fatigue research. These techniques are remarkable tools for data analysis and discovering subtle patterns that the simplest approaches can overlook in Fig. 1. These technologies play a leading role in the progress of mental fatigue research, the improvement of diagnostic accuracy, and individualized therapy.

Recent advances in the detection of mental fatigue have employed a diverse variety of approaches, ranging from neurophysiological information to machine learning and deep learning techniques. For example, Yin et al. [72] demonstrated a task-independent model that utilized deep extreme learning machines and neurophysiological features. Along similar lines, Wang et al. [73] leveraged EEG signals and applying deep learning algorithms to identify fatigue in construction workers. Kalanadhabhatta et al. [74] introduced a wide-ranging multimodal dataset, FatigueSet, to aid in modeling fatigue. Ettahiri et al. [75] compared ML and DL approaches, eventually opting for deep learning methods. Zhang et al. [76] made use of a deep temporal model with fatigue detection particularly suited to detection in time-series data, while Yan et al. [77] established a contactless method involving several features for fatigue detection in space medicine scenarios. Xing et al. [78] focused on fatigue classification involving different tasks, and Zorzos et al. [79] utilized EEG time–frequency analysis with neural networks. In a separate investigation, Zhong et al. [80] employed ensemble deep belief networks for fatigue classification in different subjects. Monteiro et al. [81] combined deep learning and sensor technologies to track fatigue in ship pilots. Huang et al. [82] and Butkevičiūtė et al. [83] investigated ECG-based detection techniques with a special focus on wearables. Ansari et al. [84, 85] examined the analysis of head posture via advanced neural networks and unsupervised learning to identify fatigue in drivers. Qi et al. [86] utilized EEG connectivity as a predictor of behavioral degradation. Liu et al. [87, 88] examined machine learning models driven by EEG and utilized them for identifying fatigue. Wang et al. [89] recorded fatigue by detecting EEG entropy and rhythm. Qin et al. [90] integrated heart rate variability with eye tracking for application in aviation. Zhang et al. [91] improved EEG feature fusion techniques to better identify driver fatigue. Yao et al. [92, 93] investigated ECoG signals and biomarkers in the brain to determine how fatigue impacts task performance. Laurent et al. [94] demonstrated the benefit of combining multimodal data for improved detection. Zhang et al. [95] made use of numerous algorithms to process EEG data for fatigue detection, with Zhao et al. [96] utilizing autoregressive models for EEG-based classification. Goumopoulos et al. [47] made use of wearables to innovate a non-intrusive detection method, and Zhong et al. [97] investigated how brain networks shift with changes in tasks. Finally, Zeng et al. [98] produced a nonintrusive system for monitoring fatigue by applying epidermal electronics and machine learning in real-time. In total, these studies reflect increasing complexity and sophistication in mental fatigue detection by moving towards integration with physiological, behavioral, and computational advancements [99].

Automatic detection of mental fatigue

Automatic detection of mental fatigue is different from manual detection as it utilizes state-of-the-art sensor technologies and analytical algorithms to flag fatigue signs. This approach mainly involves physiological and behavioural parameters, including EEG [100, 101], electrooculogram (EOG), and ECG, to determine the level of fatigue. These data streams allow the utilization of neural networks and decision trees to predict fatigue in real time. This technology is useful where extended focus is important, such as when driving a car or handling a large piece of equipment. Through automating the detection process, appropriate measures can be instituted, thereby improving safety and increasing the productivity level. Table 3 represents an AI-based algorithm used in mental fatigue research. Furthermore, automatic detection systems may be embedded into the health monitoring devices which inform people how their mental health and how to prevent fatigue.

Dataset used in mental fatigue research

Decisions about the data in mental fatigue research are very important because they affect the generality or specificity of the findings. In Table 4, show the existing dataset

Table 3 AI-based algorithm used in the mental fatigue research

Ref	AI model	Performance Measure					Accuracy (%)
		Accuracy	Specificity	Recall	Precision	F1	
[72]	DD-ELM	✓	✗	✓	✗	✗	68.90
[2]	CNN	✓	✗	✗	✗	✗	88.85
[75]	CNN	✓	✗	✗	✗	✗	97.30
[76]	Deep Convolutional Autoencoding Memory network	✓	✗	✓	✓	✓	82.90
[77]	DCNN	✓	✗	✗	✗	✗	82.22
[78]	SVM	✓	✗	✗	✗	✗	84.50
[79]	TF + CNN	✓	✗	✓	✓	✓	97.00
[80]	KNN, NB, LR, SVM	✓	✗	✗	✗	✗	71.00
[81]	CNN, DBN, FFN	✓	✗	✗	✗	✗	–
[82]	KNN, NB, SVM, LR	✓	✗	✗	✗	✗	75.50
[84]	RT, CDT, SVM, KNN)	✓	✗	✓	✓	✓	99.20
[87]	LR	✓	✗	✗	✗	✗	72.70
[88]	LR, LDA, NN, SVM, NB	✓	✗	✗	✗	✗	93.45
[90]	SVM, DT, KNN	✓	✗	✓	✓	✓	91.80
[92]	LDA, SVM, XGB	✓	✗	✗	✗	✓	–
[95]	NN	✓	✗	✗	✗	✗	93.00
[96]	KPCA–SVM, PCA–SVM, SVM, KPCA–RF, KPCA–SVM	✓	✗	✗	✗	✗	81.64
[93]	LDA, SVM	✓	✓	✓	✗	✗	87.60
[47]	SVM, KNN, LR, PCA	✓	✗	✓	✓	✓	98.00
[97]	SVM, RF, KNN	✓	✗	✗	✗	✗	98.00
[98]	DT, SVM, KNN	✓	✗	✗	✗	✗	89.00

DD-ELM: Dynamical Deep Extreme Learning Machine; RT: RUS Boosted Trees; DCNN: Deep Convolutional Neural Network; CDT: Coarse Decision Tree; KNN: K-Nearest Neighbor; RF: Random Forest; LR: Linear Regression; LDA: Linear Discriminant Analysis; NN: Neural Network

used in the previous studies. These datasets usually include the subject's physiological, behavioral and self-report data, which is gathered under different conditions to obtain a broad picture of the antecedents and outcomes of mental fatigue.

AI algorithms used in mental fatigue research

This section describes the various machine learning algorithms that have been applied in mental fatigue studies, with emphasis on the studies and their contribution to the knowledge domain. These algorithms help researchers efficiently compute big data sets, explore patterns, and derive prediction equations for mental fatigue levels, essential for designing a better interventional plan and improving individual well-being.

In recent years, deep learning approaches have been adopted in mental fatigue studies because of the high capacity of modern DL to uncover non-linear relationships and temporal dynamics of the data, including EEG, ECG, and other behavioural data. The problem with identifying mental fatigue is that there are slight shifts in the pattern of EEG signals, which are non-stationary, which explains why deep learning approaches work with this kind of data. In this field, some current common

Table 4 The existing dataset used in the previous studies

Author	Dataset	Country	Sub-domain	Smart Device	Access
Yin et al. [72]	University of Shanghai for Science and Technology	China	Postgraduate students	–	Closed
Wang et al. [73]	Tsinghua University	China	Construction workers	BCI equipment	Closed
Kalanadhabhatta et al. [74]	University of Massachusetts Amherst	USA	Asthma	–	Open
Ettahiri et al. [75]	INRIA, SICOMO	Spain	Volunteers, Drivers	–	Closed
Zhang et al. [76]	Convolutional Autoencoding Memory network (CAEM)	China	Healthy young people	Microsoft Band2	Closed
Yan et al. [77]	China Astronaut Research and Training Center	China	Young men	–	Closed
Xing et al. [78]	Natural Science Foundation of Tianjin	China	Healthy, Intellectual	–	Closed
Zorzos et al. [79]	National Technical University of Athens	Greece	Hospital's doctors and staff	–	Closed
Zhong et al. [80]	University of Shanghai for Science and Technology	China	Postgraduate students	AutoCAMs	Closed
Monteiro et al. [81]	University of Sao Paulo	Brazil	Pilots	EEG headset Emotiv Epoc +	Closed
Huang et al. [82]	Shanghai Jiaotong University	China	Healthy students	LaPatch	Closed
Ansari et al. [84]	University of Wollongong	Australia	Drivers	MT sensors	Closed
Qi et al. [86]	Tongji University	China	Healthy university students	Brain Products GmbH, Germany	Closed
Liu et al. [87]	Nanyang Technological University	Singapore	Drivers	Quik-Cap	Closed
Liu et al. [88]	National Research Foundation, Prime Minister's Office, Singapore	Singapore	Male	Emotiv device	Closed
Wang et al. [89]	Northeastern University Shenyang	China	Drivers	wireless helmet Emotiv Inc	Closed
Qin et al. [90]	Southeast University	China	Flight simulation	HUD	Closed
Butkeviciute et al. [83]	Kaunas University of Technology	Lithuania	Healthy adults	CardioScout multi-device	Closed
Zhang et al. [91]	Xihua University	China	Drivers	–	Closed
Yao et al. [92]	Cornell University	USA	Monkeys	BioPac Systems Inc	Closed
Laurent et al. [94]	boulevard de l'Hôpital	France	Right-handed male	ActiCapTM, BrainAmpTM	Closed
Zhang et al. [95]	Beijing Union University	China	Students	–	Closed

Table 4 (continued)

Author	Dataset	Country	Sub-domain	Smart Device	Access
Zhao et al. [96]	Xi'an Jiaotong University	China	Male graduate students	Neruoscan system	Closed
Yao et al. [93]	Cornell University	USA	Monkeys	BioPac Systems Inc	Closed
Goumopoulos et al. [47]	Polytechnic School of the University of the Aegean	Greece	Healthy People	Zephyr HxM-BT sensor	Closed
Zhong et al. [97]	Zhejiang Normal University	China	Healthy young volunteers	–	Closed
Ansari et al. [85]	University of Wollongong	Australia	Drivers	MT sensors	Closed
Zeng et al. [98]	Huazhong University of Science and Technology	China	–	Arduino Uno system	
				ECG chip	Closed

MT: Motion Tracker; HUD: Head-up Display

deep learning architectures that include Convolutional Neural Networks CNNs, Recurrent Neural Networks RNNs and their modified types have been illustrated to have potential. They can capture temporal and spatial patterns of physiological signals, which enables the model to capture the temporal evolution of the mental fatigue indicators. Furthermore, mental fatigue can be detected with better accuracy when deep learning methods are coupled with feature extraction methods. The detail descriptions of the other methods are mentioned in Fig. 2 and Table 5.

Other methods used in mental fatigue research

These methodologies are indispensable for investigating mental fatigue and its impacts on people's performance and well-being since each provides a different perspective on the phenomenon. Figure 3 and Table 6 describe the other methods in detail.

Performance metrics used in mental fatigue

Performance measures are essential when studying mental fatigue because they help evaluate the implemented detection algorithms and interventions. These metrics enable one to determine the validity and reliability of some tools and methods that can be used to assess and combat mental fatigue. In other words, by developing such standardized measures, it will be possible to determine the effects of mental fatigue accumulated in various investigations and examine the influences of this phenomenon on cognition and physiology. The mathematical expression of the performance metrics is mentioned in Fig. 4 and Eqs. (1) to (6):

$$\text{Accuracy} = \frac{\text{Number of correctly classified instances}}{\text{Total number of instances}} \tag{1}$$

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{2}$$

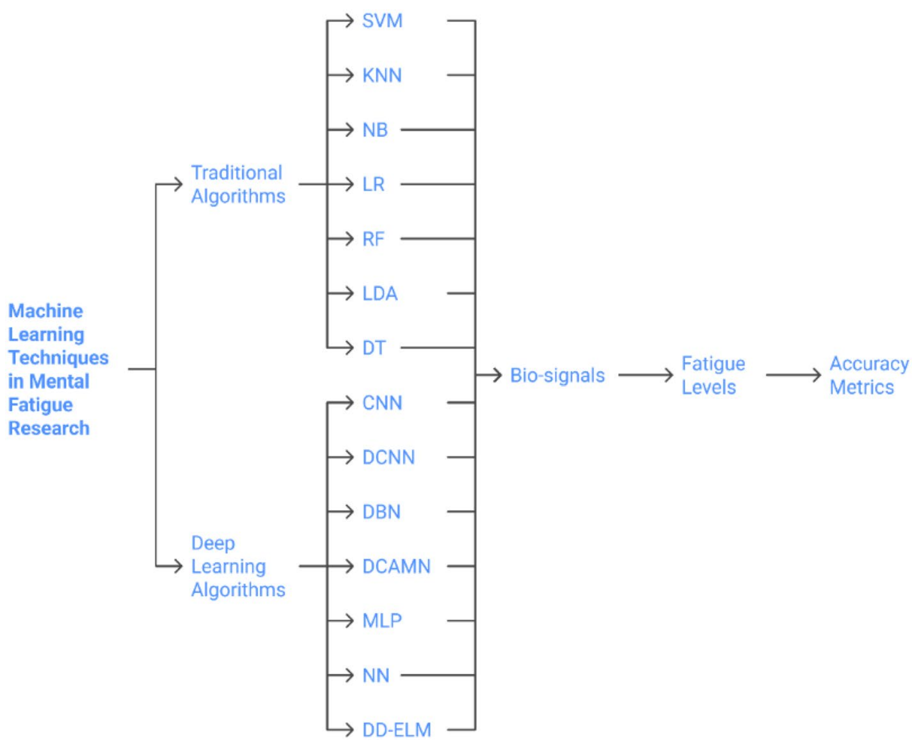

Fig. 2 Machine learning techniques are used in the mental fatigue research

$$\mathrm{F1} = \frac{2 \times \mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{3}$$

$$AUC = \int_0^1 TPR\left(f\right) d\, FPR\left(f\right) \tag{4}$$

TPR means true positive rate, which is sensitivity at threshold value f, and FPR means false positive rate, which is 1-specificity at value f.

$$\mathrm{Specificity} = \frac{\mathrm{True\ Negative}}{\mathrm{True\ Negative} + \mathrm{False\ Positive}} \tag{5}$$

$$\mathrm{Precision} = \frac{\mathrm{True\ Positive}}{\mathrm{True\ Positive} + \mathrm{False\ Positive}} \tag{6}$$

Bio-signals used in mental fatigue research

This section comprehensively explores the bio-signals often employed in mental fatigue studies since they are central to identifying the physiological process and neuro-physiological activities related to mental fatigue (Fig. 5). Bio-signals are the functional activity associated with reading values from a human being's body through functional means that are usually not invasive. They are essential in discovering and analyzing conditions, including mental fatigue; they give information about the body's functional state.

Table 5 Detail descriptions of the AI algorithm used in mental fatigue research

AI Algorithm	Descriptions	Limitation
AB	AB is an ensemble method that builds a strong classifier by iteratively combining weak learners, focusing on misclassified instances	Sensitive to noisy data and outliers
RT	RF builds each tree using a random subset of features, sampling from a uniformly distributed random vector to ensure diversity	Large datasets may require more computational resources
SVM	SVM typically uses binary classifiers, but multiclass SVMs are widely adopted to handle problems involving multiple classes	Its performance can be sensitive to the choice of kernel and parameter tuning
KNN	KNN stores all training examples and classifies new data based on similarity, which is mainly used in pattern recognition	Slow with large datasets due to high computational cost
NB	NB is a probabilistic classifier based on Bayes' Theorem, assuming feature independence for fast and efficient classification	It can perform poorly with correlated or insufficient data
LR	LR is used to classify mental fatigue levels by modelling the relationship between physiological or behavioural indicators and fatigue states	Sensitive to outliers and may underperform with high-dimensional or non-linear data
LDA	LDA distinguishes mental fatigue levels by finding a linear combination of features that best separates fatigue classes	Less effective when classes are not linearly separable or features are highly correlated
DT	DT classify mental fatigue by learning interpretable rules from physiological and behavioral data	Prove to overfitting, especially with noisy or small datasets
CNN	CNN are used to analyze and classify mental fatigue by extracting patterns from time-series or image data	Requires large amount of labeled data for effective training
DCNN	DCNN are employed to automatically learn hierarchical features from complex data to detect and classify mental fatigue	Requires large amount of high-quality labeled data for training
DBN	DBN are used to detect mental fatigue by learning deep, abstract features from physiological signals through unsupervised pertraining	Training is complex and time consuming due to layer-wise pretraining
DCAMN	DCAMN detects mental fatigue by integrating spatial–temporal features and attention mechanisms from dual-channel neural signals	High model complexity requires substantial computational resources
MLP	MLP is used to classify mental fatigue by learning complex, non-linear relationships from physiological or behavioral input data	Requires large datasets for effective generalization
NN	NN are applied to detect mental fatigue by modeling intricate patterns in physiological signals	Requires substantial data and computational power for training
DD-ELM	DD-ELM detects mental fatigue by rapidly learning complex temporal features from physiological data	May suffer from reduced accuracy with noisy or imbalanced data

Electroencephalography (EEG)

EEG is a type of neuroimaging technology that serves the healthcare profession in monitoring the electrical activity in the human brain without surgical intervention [102, 103].

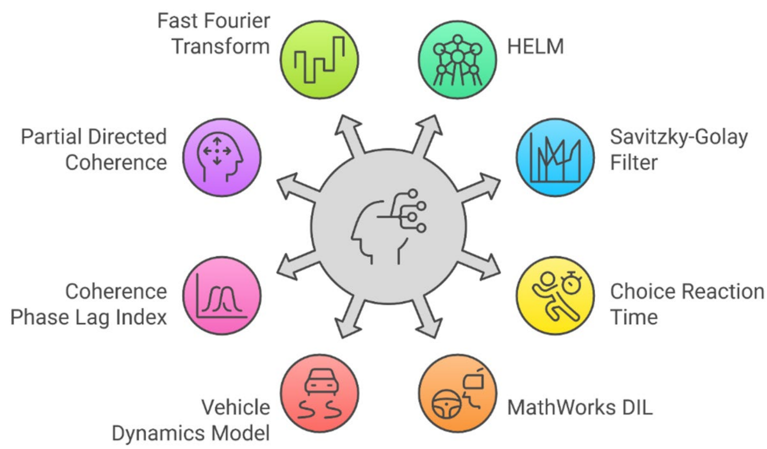

Fig. 3 Other methods used in the mental fatigue research

Table 6 Detail descriptions of the other methods used in mental fatigue research

Approaches	Descriptions	Limitation
FFT	FFT is used to analyse the frequency components of brain signals to identify patterns associated with mental fatigue	Assumes signal stationarity, which may not hold for dynamic mental states
HELM	HELM detects mental fatigue by hierarchically extracting deep features from physiological signals	Performance may degrade with noisy or limited data
Savitzky-Golay filter	Savitzky-Golay filter smooths physiological signals to reduce noise while preserving features critical for detecting mental fatigue	It may not effectively remove high-frequency noise in highly dynamic signals
CRT	CRT assesses mental fatigue by measuring the speed and accuracy of responses to multiple stimuli	External factors like distractions or motivation can influence it
Mathworks DIL	Mathworks DIL is used to design and train deep learning models for detecting mental fatigue from physiological data	It requires expertise in model design and parameter tuning
Vehicle dynamic model	Vehicle dynamic model can help to detect mental fatigue by analyzing deviations in driving behavior and control patters under fatigue conditions	External factors like road conditions and vehicle type can influence it
PLI	PLI measures the consistency of phase differences in EEG signals to assess functional brain connectivity changes linked to mental fatigue	It may overlook amplitude-related information in brain signals
PDC	PDC analyses directional information flow between brain regions in EEG data to identify connectivity changes due to mental fatigue	It requires high-quality, noise-free data and accurate model order selection

Hence, in connection with the studies of mental fatigue, EEG offers important possibilities for the investigation of cerebral processes and fatigue conditions. EEG signals and other physiological signals can be analyzed using different mathematical tools, and these tools can be classified into time-domain analysis, frequency-domain analysis, and time–frequency domain analysis. In time-domain analysis, the raw EEG signals are analyzed

Fig. 4 Performance metrics used in the mental fatigue research

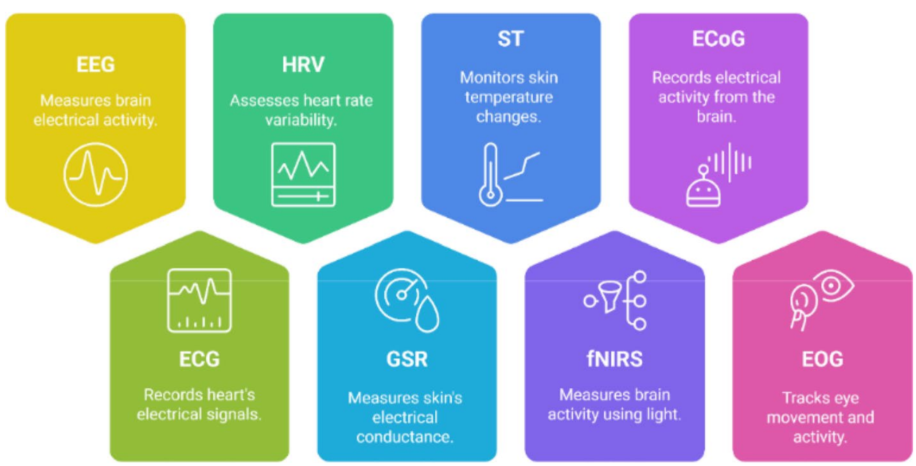

Fig. 5 Detailed description of the bio-signals used in mental fatigue research

directly in the time domain to qualify the signals' features like the amplitude, latency and duration of the components of signals like the event-related potentials (ERPs).

Alternatively, one can measure the electrical potential activity in the brain, referred to as EEG signals, which can be described as time-series data X(t), where t is time. Every X(t) represents the electrical potential of an electrode taken at some time t. Mathematically, EEG signals can be expressed in Eq. (7):

$$X(t) = \sum_{i=1}^{N} A_i(t)\sin\left(2\pi f_i t + \phi_i\right) + \varepsilon(t) \tag{7}$$

where, N is the number of the frequency component, $A_i(t)$ holds the amplitude of the ith frequency at time t, f_i is the frequency of the ith component, ϕ_i is the phase of the ith component, ϵ(t) denotes the noise or artifacts in Eq. (07).

Frequency domain analysis can be done on the obtained EEG signals by transforming them into their frequency components, for example, using the FFT or wavelet transform. It allows the researcher to explore the power spectral density of EEG signals, the actual distribution of power in the frequency bands. Mathematically, the PSD, denoted as P(f), quantifies the power of EEG signals as a function of frequency f. It provides valuable insights into how power is distributed across various frequency bands, which can vary in response to cognitive tasks and mental fatigue states and can be defined in Eq. (8):

$$P\left(f\right) = \lim_{T\to\infty} \frac{1}{T}\left|\int_{-\infty}^{\infty} X(t)e^{-2\pi ft}dt\right|^2 \tag{8}$$

where, T is the time duration for the conversion of EEG signal. This is evident from the PSD where information pertaining to distribution of power at various frequencies is presented including delta (0. 5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz) while gamma bands are above 30 Hz and which part of the brain is involved in each of them.

The time–frequency analysis is a useful tool for analyzing EEG data. The Signal Transformation techniques, such as STFT or wavelet transformation offer a time–frequency distribution of EEG signals. Mathematically, the STFT can be expressed in Eq. (9):

$$X\left(t,f\right) = \int_{-\infty}^{\infty} x(\tau)w(t-\tau)e^{-2\pi i f\tau}d\tau \tag{9}$$

where, $x(\tau)$ is the EEG signal, w(t − τ) is a window function, $X(t,f)$ represents the time–frequency representation of the signal.

The mathematical expressions described above are a good starting ground for analyzing EEG signals and allow for the analysis in time and frequency domain. This capability enables the researchers to discover enhanced features and explore the neural basis related to mental fatigue. In mental fatigue studies, EEG is considered the prerequisite tool widely used to analyze changes in brain waves associated with prolonged cognitive work, sleep loss, and other factors that affect fatigue. From the perspective of EEG signal processing, researchers can identify specific neural signatures of fatigue, estimate cognitive load, and develop strategies that would help minimize the negative effects of mental fatigue on productivity and health in general.

Electrocardiography (ECG)

ECG is a non-invasive technique used to record the electrical activity of the heart over time [42, 104]. In the context of mental fatigue research, ECG provides valuable insights into cardiac function and autonomic nervous system activity, which can be influenced by cognitive load and fatigue states. Mathematically, ECG signals can be represented as time-series data, denoted as Y(t), where t represents time. Each data point Y(t) corresponds to the electrical potential measured by electrodes placed on the skin surface, reflecting the depolarization and repolarization of cardiac muscle cells during each heartbeat. ECG signals exhibit characteristic waveforms, including the P wave, QRS complex, and T wave, which correspond to specific electrical events in the cardiac cycle. These waveforms can be analyzed to extract features such as heart rate, heart rate variability (HRV), and measures of cardiac autonomic function. Mathematically, heart rate (HR) can be calculated in Eq. (10):

$$HR = \frac{60}{\text{RR interval}} \tag{10}$$

where, the RR interval represents the time between consecutive R peaks in the QRS complex of the ECG waveform. Heart rate variability (HRV), a measure of the variation in the time interval between heartbeats, can be quantified using mathematical techniques such as the standard deviation of RR intervals (SDNN) or the root mean square of successive differences (RMSSD).

One common measure of HRV is the standard deviation of RR intervals (SDNN), which represents the overall variability of heart rate over a given time period. Mathematically, SDNN can be expressed in Eq. (11):

$$\text{SDNN} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(RR_i - \overline{RR}\right)^2} \tag{11}$$

where, RR_i represents the duration of the i$^{\text{th}}$ RR interval, $\overline{RR}$ is the average RR interval duration, and N is the total number of RR intervals. Another commonly used measure is the root mean square of successive differences (RMSSD), which reflects the short-term variability in heart rate. RMSSD can be calculated in Eq. (12):

$$\text{RMSSD} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2} \tag{12}$$

where, RR_i and RR_{i+1} represent successive RR intervals, and N is the total number of RR intervals. Concerning the assessment of mental fatigue, analysis of ECG can show changes in Cardiac response to cognitive tasks, stress and fatigue. Moreover, by analyzing ECG signal characteristics, researchers may discover that some of them are associated with changes in autonomic regulation. Therefore, it is possible to get some insights into the physiological basis of the mental fatigue phenomenon.

Heart rate variability (HRV)

HRV is closely related to physiological research, which assesses the variation of the time between two consecutive beats, the so-called RR intervals, or beat-to-beat intervals [105, 106]. In the case of mental fatigue assessment, HRV acts as an index of the activity of the ANS, being a measure of the relative interaction between the sympathetic and parasympathetic divisions in the regulation of the heart rate. In the assessment of the HRV, three main domains are most commonly used: the time domain, the frequency domain, and the nonlinear analysis, which gives insight into the modulation of the autonomic nervous system. In the time domain, the HRV parameters could be obtained by taking measurements on RR interval time series.

The frequency domain entails quantifying the PSD of RR interval time series. Power spectrum is often calculated with the help of specific mathematical tools like Fast Fourier Transform or autoregressive decomposition. Power spectrum density P(f) refers to power at the function of frequency f, which can be partitioned into frequency bands to purify specific components of the autonomic activity. For instance, power at the high frequency band, HF (0.15—0.4 Hz), is linked to the parasympathetic modulation, while the power at LF (0.04—0.15 Hz) is a measure of both sympathetic and parasympathetic tone. Nonlinear analysis of HRV includes calculating the features that measure the complexity or the randomness of the RR interval time series. For instance, approximate entropy (ApEn) is the logarithmic likelihood that similar patterns of a certain length remain identical on the subsequent data points in a tolerance level, r and embedding dimension, m. The mathematical expression is mention in Eq. (13).

$$\mathrm{ApEn}(m, r, N) = \phi(m, r) - \phi(m + 1, r) \tag{13}$$

The ϕ(m,r) is the logarithm of the conditional probability that two sequences of m consecutive data points will continue to remain similar to each other within a tolerance of r on the V^{th} data point overall. These mathematical expressions give a quantitative description of the HRV and facilitate feature selection that describes the autonomic nervous system activity and its change in response to cognitive load and mental fatigue.

Galvanic skin response (GSR)

GSR is defined as a physiological measure that assesses changes in the electrical conductance of skin owing to the activity of sweat glands [42, 107]. It usually employs the psychological or emotional activation index in different settings, including mental fatigue studies. In mathematical terms, GSR can be a time–series signal S(t) where t refers to time. Every data point S(t) refers to skin conductance level at a given time-stamped value t and is expressed as micro-Siemens (μS) or conductance per unit skin surface area. That is why GSR signals demonstrate specific oscillations when reacting to stimuli or changing the states of emotional responses. Such variations can be measured in terms of several particular features, such as the amplitude and the frequency of skin conductance responses or the tonic skin conductance level. There are several ways one can go about analyzing GSR signals, and one of the trends is SCR signaling, a technique that deals with the identification and measurement of response to stimuli that cause a temporary change in skin conductance. By definition, the amplitude of an SCR can be determined through the difference between the maximum and the minimum value of the GSR signal within a post-stimulus interval (Eq. (14)):

$$\mathrm{SCR}_{\mathrm{amplitude}} = \mathrm{S}_{\mathrm{max}} - \mathrm{S}_{\mathrm{min}} \tag{14}$$

The following formula determines the GSR signal's standard deviation within the time window where S_{max}—S_{min} denotes the maximum and minimum values. Moreover, the density of SCRs, which means the number of SCRs within a period, can also be calculated to provide an understanding of a dynamic aspect of electrodermal activity. In the case of mental fatigue studies, GSR analysis can be used to understand the fluctuations in the physiological activation levels correlated to cognitive demands, stress, and fatigue. Thus, looking at the features extracted from GSR signals, researchers are able to recognize those patterns that indicate the changed regulation of the autonomic nervous system and, so, shed light upon the psychological and physical aspects of mental fatigue.

Skin temperature (ST)

ST is an index of the skin's thermal status and depends on blood flow, skin metabolic activity, and environment temperature [78, 79]. Within the framework of investigations of mental fatigue, skin temperature measurements can provide important data on alterations in the functioning of the ANS and the amount of affective and stress stimuli experienced by the organism.

The skin temperature can be preferably expressed mathematically as T(t) where t stands for time. Skin temperature is normally sensed by the use of sensors, such as thermistors or infrared sensors, which are fixed in areas like the forehead, finger, or wrist. The position of the sensor depends on the type of research being carried out and the ease of accessing the measurement point. The relationship between the resistance of the sensor R and the skin temperature T can be described by the Steinhart-Hart equation, particularly for thermistor-based sensors, is mentioned in Eq. (15):

$$T = \frac{1}{A + B\ln(R) + C(\ln(R))^3} \tag{15}$$

where A, B and C are constants that are dependent upon the specific thermistor used to undergo the calibration process. Temperature detection on the skin surface is useful to researchers since it gives them insights into the regulation of heat of the body. Variations in skin temperature can denote shifts in sympathetic and parasympathetic tone regarding mental demand, stress and fatigue. For instance, an increase in the skin temperature might be indicative of augmented sympathetic activity arising from excitement or stress, while a decrease might point to relaxation or reduced sympathetic modulation. Studying the changes in skin temperature at the same or different time points makes it possible to reveal the physiological effects of mental fatigue. When skin temperature information is combined with other autonomic variables like HRV or EDA, a researcher is then in a position to explore the relationship between physiological activation, cognitive demand and mental fatigue.

Functional near-infrared spectroscopy (fNIRS)

fNIRS is a portable and non-invasive optical brain imaging methodology which is used to quantify the variations in the concentration of oxygenated blood in the brain laminar level with reference to neural activity [108]. The study of mental fatigue benefits from fNIRS as a technique for analyzing neural effects on performance or fatigue-related states. Federally, fNIRS is biochemical in nature, and it uses spectroscopy to identify variations in the absorbance of near-infrared light by the hemoglobin in circulating blood. The modified Beer-Lambert law is commonly used to relate the changes in light attenuation to changes in hemoglobin concentration. The mathematical expressions are mentioned in Eq. (16):

$$\Delta C = -\ln\left(\frac{I}{I_0}\right) \times \frac{1}{\varepsilon d} \tag{16}$$

The ΔC represents the change in hemoglobin concentration, I is the intensity of the transmitted light, I_0 is the initial intensity of the incident light, ϵ is the molar extinction coefficient of hemoglobin, and d is the distance between the light source and detector.

This ability results from deploying near-infrared light at various wavelengths, which enables the differentiation of oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) in fNIRS systems. These changes in these species of hemoglobin can, therefore, be used to decipher flow in the cerebral blood as well as oxygen metabolism of the neural activity. fNIRS sensors are made of optodes, which are used to launch and receive near-infrared light using the scalp over the desired cortex regions. The detected signals are then used to generate hemodynamic response curves that depict the time course of the neural response to cognitive tasks or stimulus. As mentioned earlier, fNIRS has several benefits, especially when it comes to the assessment of mental fatigue: 1) It is mobile, 2) It fits natural settings, and 3) It is suitable for long-term tracking. Thus, fNIRS studies would allow the identification of the neural biomarkers of mental fatigue, the estimation of an individual's cognitive workload and the creation of countermeasures against the deteriorations in efficiency and subjective states due to fatigue.

Electrocorticography (ECoG)

ECoG is another type of neuroimaging which is more invasive in nature because it requires the placement of electrodes directly on the exposed surface of the brain [93]. As a research method, ECoG allows studying the brain activity linked with cognitive processes and fatigue states with high spatial and temporal resolution. ECoG depicted as voltage signals captured in time at defined electrode contacts placed on the cortical surface. The voltage signal recorded by an electrode at time t is represented by V(t) electrical activity observed in ECoG signals due to the massive synchronous discharge of cortical neurons of the underlying regions.

ECoG electrodes are most often placed subdural or epidurals on the brain's cortex; therefore, the activity can be recorded directly from the cortex of interest. With the help of the positioning of the electrodes, investigators are able to pinpoint the reaction to cognitive tasks or stimuli with great accuracy, thereby contributing to the understanding of the functional architecture of the brain. There are a number of methods in ECoG analysis – time-domain analysis, frequency-domain analysis, and event-related potential (ERP) analysis. Hence, time-domain analysis deals with the characterization of temporal features of the neuronal activity, whereas frequency-domain analysis, including the Fourier transform, deals with a power density of oscillations.

Many derived measures are extracted from ECoG signals, but the most popular one is event-related desynchronization/synchronization (ERD/ERS), which reflects changes in oscillatory activity in response to a certain event or cognitive task.

Quantitative descriptions of ERD/ERS can be formulated as the percentage of alterations in the power of the frequencies within certain frequency bands compared to a baseline timed are mentioned in Eq. (17):

$$ERD/ERS(\%) = \frac{P_{task} - P_{baseline}}{P_{baseline}} \times 100 \tag{17}$$

where P_{task} is the power spectral density during the task and $P_{baseline}$ is the power during the baseline period. Using ECoG, it is possible to study cortical network states by applying connectivity analysis methods such as coherence, phase locking value, or Granger causality. These measures help to understand the relations between the brain areas during different cognitive tasks and how these relationships might be altered at the state of mental exhaustion.

Electrooculography (EOG)

EOG is an electrical recording technique that is surface recorded and used to record the eye movement potentials [109]. As for the usefulness of EOG in the context of mental fatigue, it is necessary to comprehend that EOG provides information about oculomotor activity, which may be affected by load and fatigue states. Regarding measurement technique, EOG is normally elicited by placing electrodes around the eyes to pick up electrical differences relating to eye movement. Let V(t) denote the voltage signal given by the EOG electrode at time t; levels of amplitude and direction of eye movement can be identified from the waveform of this EOG signal.

EOG signals also show specific waveforms depending on the type of eye movements, which include Saccadic movements, pursuits, and blinks. It is possible to extract waveforms containing information about such measures as saccade velocity, blink frequency, and fixation time, which can help investigate oculomotor activity during different cognitive tasks. Among the derived measures of EOG signals, the most frequently used one is the peak velocity of saccades, which reflects the rate of a fast eye movement. Mathematically, the peak velocity V_{peak} can be calculated using the Eq. (18):

$$V_{peak} = \frac{\Delta\theta}{\Delta t} \tag{18}$$

where $\Delta\theta$ is the angular displacement of the eye during a saccade, and Δt is the saccade duration. EOG signals can help identify artifacts such as eye blinks and muscular activity that may contaminate the recordings of cognitive task execution. Artifact removal algorithms and baseline correction methodology are used to pre-process the EOG signal to enhance its quality. Additionally, EOG signals can also be combined with other physiological indices, including EEG and heart rate variability (HRV), to form a more holistic index of cognitive load and mental fatigue. In Table 7, signals used in the mental fatigue research are presented. By using more than one modality, we can comprehensively understand changes going through the body and mind when it is fatigued and how we can manage this state in different settings.

Table 7 Bio-signals used in the mental fatigue research

Ref	Objective	Part	Methods	Signal	Channels
[72]	Recognition	14	Hierarchical ELM	EEG	11
[2]	Identify	16	–	EEG	–
[75]	Detection	20	–	EEG	–
[76]	Detection	06	Savitzky–Golay filter	GSR, HR, ST	–
[74]	Impact	12	CRT	EEG, ECG, ST	–
[77]	Detection	36	–	–	–
[78]	–	08	Fuzzy Entropy	EEG	–
[79]	Detection	22	–	EEG	64
[80]	–	08	–	EEG	–
[81]	Detection	09	–	EEG	14
[82]	Detection	35	–	ECG, HRV	–
[84]	Detection	15	DIL	EEG	–
[86]	Predict	40	Coherence PLI, PDC, ANOVA	EEG	–
[87]	Recognition	27	FFT; FIR filter	EEG	30
[88]	Evaluation	07	–	EEG	14
[89]	Assessment	03	Entropy, Wavelet Transform	EEG	14
[90]	Detection	11	ANOVA, TICC	ECG, EEG, fNIRS	–
[83]	Recognition	60	–	ECG	–
[91]	Recognition	–	ANOVA, Entropy	EEG	60
[92]	Prediction	2	ANOVA	ECoG	10
[94]	Detection	13	ANOVA	EEG, ECG, EOG	32
[95]	Recognition	10	Power spectrum, Wavelet entropy	EEG	04
[96]	Classification	13	MVAR model	EEG	32
[93]	Prediction	2	Wavelet entropy, ANOVA	ECoG	10
[47]	Detection	32	PCA, HRV	ECG	–
[97]	Reorganization	20	PLI	EEG	–
[85]	Monitor	10	EM	–	–

ST: Skin Temperature; HR: Heart Rate; GSR: Galvanic Skin Response; FFT: Fast Fourier Transform; CRT: Choice Reaction Time; DIL: Driver-in-Loop; PDC: Partial Directed Coherence; ECoG: Electrocorticography; TICC: Toeplitz Inverse Covariance-Based Clustering; MVAR: Multivariate Autoregressive; PLI: Phase Lag Index; EM: Expectation–Maximization

Bibliometric analysis on mental fatigue research

In this section, we proceed with the bibliometric analysis of the systematically screened studies on mental fatigue. Bibliometric analysis provides a measurable view of a given subject field, showing its evolution, areas of concentration, and significant researchers and works. This method applies statistical methods to examine the quantitative elements of academic literature to understand the trends of research dynamics and identify key research articles.

Data on mental fatigue used in bibliometric analysis

The information about studies conducted between 2020 and 2024 on mental fatigue is mentioned in Table 8. The analysis includes 2,725 documents and is based on 829 sources, including books and periodicals. With an annual negative growth rate of 40.12% over period under review, research on this topic has declined, showing a reduction in

Table 8 Description of the mental fatigue data used in bibliometric analysis

Description	Results
Main Information about Data	
Timespan	2020:2024
Sources (Journals, Books, etc.)	829
Documents	2725
Annual Growth Rate %	−40.12
Document Average Age	2.34
Average citations per doc	17.91
References	76,534
Document Contents	
Keywords Plus (ID)	3324
Author's Keywords (DE)	4161
Authors	
Authors	8071
Authors of single-authored docs	55
Authors Collaboration	
Single-authored docs	93
Co-Authors per Doc	6.26
International co-authorships %	26.94
Document Types	
Article	1986
Review	739

the number of new publications. Despite this, the surviving texts are well-cited, with an average of 17.91 citations per document, and they are relatively recent, averaging 2.34 years. The content contains 3,324 Keywords Plus (ID) and 4,161 Author's Keywords (DE), emphasizing the themes covered. The research is widely referenced, with a total of 76,534 references. Only 55 of the 8,071 authors in the research contributed to single-authored publications, showing a clear tendency towards collaboration and joint authorship. Significant worldwide collaboration in this field of study is demonstrated by the average of 6.26 co-authors per document and the international co-authorship rate of 26.94%. Regarding document types, articles (1,986) make up the majority of contributions, with reviews coming in second (739). Even though the number of new papers is decreasing, the data shows how active and cooperative medical intelligence research is regarding mental tiredness.

Annual production

Figure 6 shows the total number of publications (TP) on the subject of"Medical Intelligence (Medical + AI) in Mental Fatigue Research"throughout a range of years (Publish Year (PY)). The statistics shown began in 2020, when 560 papers were published. In 2021, the number of publications rose steadily to 637, indicating the growing interest and progress in this field.

The upward trend persisted until 2022, when there was a notable increase to 780 articles, suggesting increased research activity and potential discoveries or new directions in medical intelligence and mental weariness. However, the number of publications

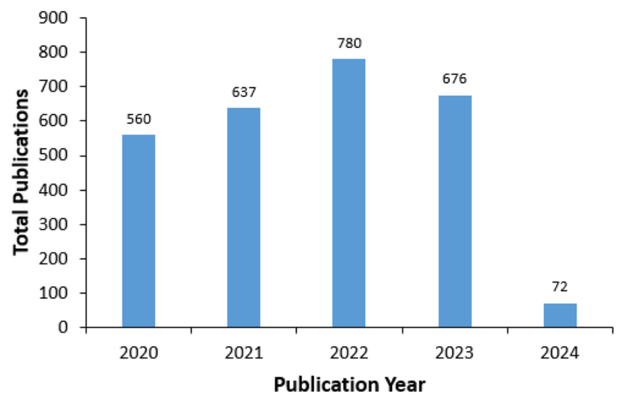

Fig. 6 Annual research output based on publication and their respective years

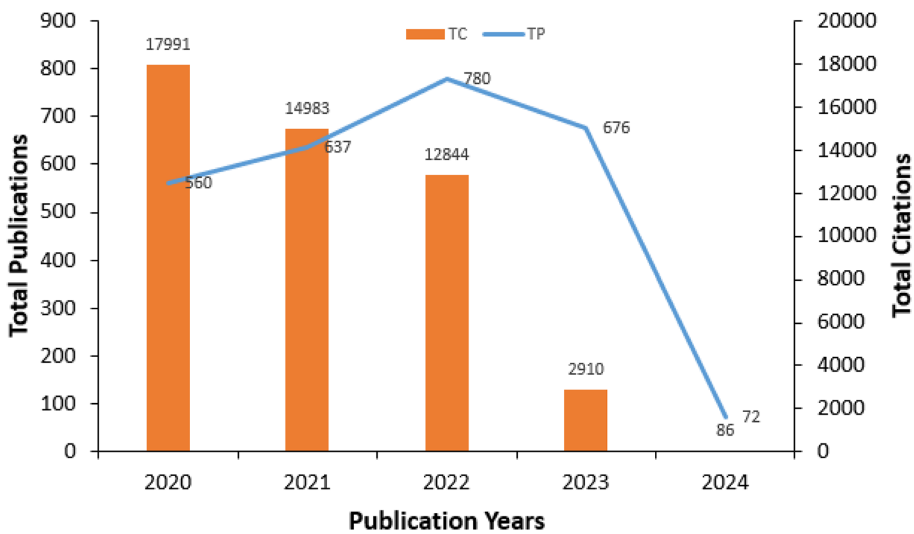

Fig. 7 Annual research output on AI applications in mental fatigue, illustrating total publications (TP) and total citations (TC) from 2020 to 2024

dropped to 676 in 2023, indicating either a possible stabilization of research production or a change in the field's focus. This decline can also indicate difficulties or a reallocation of funds and research efforts. Notably, the data for 2024 reveals a sharp fall to just 72 articles.

Brust citations

For the years 2020 through 2024, Fig. 7 represents publication and citation, emphasizing studies on"Medical Intelligence in Mental Fatigue."The table shows each year's total citations (TC) and publications (TP). 17,991 citations were obtained from 560 publications on this topic in 2020, demonstrating the high impact and importance of the research conducted in that year. In 2021, there was a rise in publications to 637, but there was a decrease in total citations to 14,983. In contrast to the rise in publications, the observed

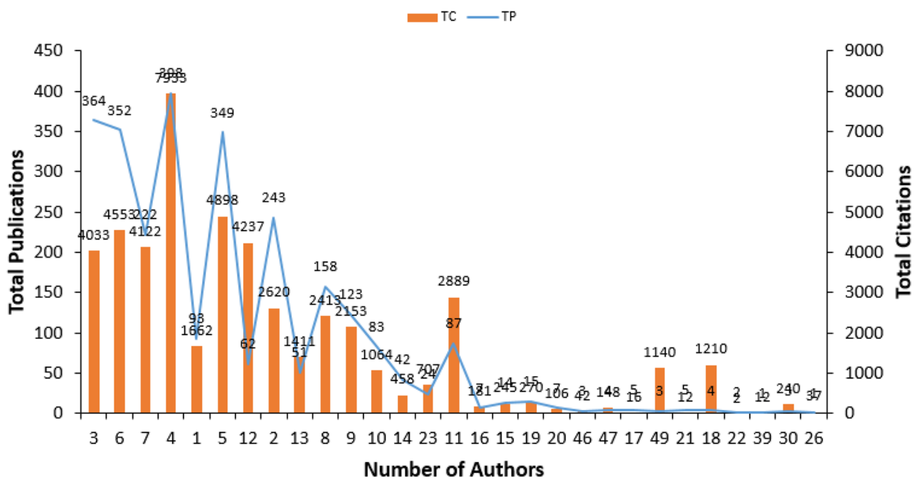

Fig. 8 Impact of authors based on a number of contributions and their total publications

decrease in citations indicates that although the research output was substantial, the total impact or adoption of these studies was lower compared to 2020.

Publications reached 780 in 2022 as the number kept rising. However, the overall number of citations fell to 12,844, a more noticeable decrease. This pattern could indicate a dilution effect, in which more research was conducted, but fewer citations were obtained. This could be because the studies' various degrees of quality or their narrower scope had less impact. In 2023, the situation was different; while there were 676 fewer articles overall, there were 2,910 fewer citations overall. There are several possible reasons for this dramatic drop in citations, including changes in the academic community's interest in mental exhaustion, the rise of other, more pertinent issues, or changes in the focus of the studies. Ultimately, the data reveals a sharp decline in publications and citations in 2024—just 72 and 86 were registered. This sharp fall implies that either the topic has matured and fewer new studies or attention from the academic community is coming from it, making research on"Medical Intelligence in Mental Fatigue"less critical.

Author pattern

Regarding medical Intelligence connected to Mental Fatigue Research, Fig. 8 thoroughly summarizes the author's contributions and the impact of matching citations. For different authors, the information comprises the total number of publications (TP) and total citations (TC). It shows a wide range of influence and research activity in this field. Authors who have published more frequently, like those with six or seven publications, for example, have received a significant number of citations—4,553 and 4,122, to be exact. This implies a direct relationship between the amount of research produced and the impact determined by citations.

On the other hand, writers who have fewer publications—for example, just one or two—have much lower citation counts, which may indicate that their influence is more limited or that their contributions are more recent and have not yet received widespread recognition and an increase in publications only sometimes translates into an increase in citations. For instance, the author with four publications has a remarkable number of citations (7,933), suggesting that their work has been especially significant or innovative

Table 9 Most relevant institutions working in mental fatigue

Institutions	TP	Percentage	Country
University of Macau	134	5	China
University of Oxford	97	4	U. K
University of Toronto	84	3	Canada
Huazhong University of Science and Technology	74	3	China
King's College London	71	2	U. K
Sichuan University	70	2	China
Capital Medical University	68	2	China
Melbourne University	67	2	Australia
Hong Kong Polytechnic University	58	2	Hong Kong
University of Washington	54	5	U.S. A

in the field. However, there are instances in which writers with comparable numbers of publications have different numbers of citations, indicating variations in the caliber, applicability, or originality of their work.

Most relevant affiliations, authors and journals

The organizations in Table 9 have significantly contributed to medical intelligence and mental fatigue research. With a 5% contribution, the University of Macau stands out and demonstrates leadership in this field. This is probably because of its strong emphasis on multidisciplinary research that combines AI with healthcare. Important British universities with a reputation for breaking new ground in medical research and cognitive neuroscience—two fields closely related to studies on mental fatigue—are the University of Oxford (4%) and King's College London (2%). China's Huazhong University of Science and Technology (3%) and Sichuan University (2%) have also made significant contributions, highlighting the country's expanding prominence in AI-driven health research. The understanding of mental weariness has been further enhanced by other universities, such as the University of Toronto and the University of Washington, renowned for their developments in AI applications in healthcare.

In Table 10, authors are ranked by total publications (TP), total citations (TC), citation impact (CI), and active years (AY) about their contributions to medical intelligence in the field of mental fatigue research. In terms of publications (31) and citations (397),"Xiang YT"is first. Notwithstanding the recent past four active years, her citation impact has been significantly lower (13). Conversely,"Fares K"and"Haddad C"have had the most significant citation impact (28) while having fewer publications (12) and shorter active duration (2 years)."Cheung T"sticks out even more, with 26 articles and 381 citations during four active years. The data shows that while specific authors, like"Xiang YT"and"Cheung T,"publish a lot, other authors, like"Fares K"and"Haddad C,"have made a name for themselves with fewer but highly cited works. The authors' main active periods are 2020–2024, highlighting the recent and rapidly growing interest in this area of research.

Table 11 displays the standing of journals supporting medical intelligence on mental fatigue based on several metrics, including impact factor (IF), country of publication

Table 10 Most relevant authors

Rank	Authors	TP	TC	CI	Starting Year	Ending Year	AY
1	Akel M	14	362	26	2020	2021	2
2	Hallit S	17	374	22	2020	2022	3
3	Sacre H	14	362	26	2020	2021	2
4	Salameh P	14	362	26	2020	2021	2
5	Cheung T	26	381	15	2021	2024	4
6	Fares K	12	332	28	2020	2021	2
7	Haddad C	12	332	28	2020	2021	2
8	Obeid S	15	344	223	2020	2022	3
9	Xiang Yt	31	397	13	2021	2024	4
10	Cai H	17	299	18	2021	2023	3

Table 11 Most relevant journals related to mental fatigue research

Rank	Source	TP	TC	CI	CU	Q	IF	Publisher
1	International Journal of Environmental Research and Public Health	59	2413	40	Switzerland	Q2	4.5	MDPI
2	Journal of Affective Disorders	44	2252	56	Netherlands	Q1	6.7	Elsevier
3	Frontiers in Psychology	42	732	17	Switzerland	Q2	3.9	Frontiers
4	Brain Behavior and Immunity	18	2414	134	U. S. A	Q1	12.0	Elsevier
5	Journal of Medical Internet Research	21	450	21	Canada	Q1	8.0	JMIR
6	Journal of Psychosomatic Research	26	802	30	U. S. A	Q1	4.0	Elsevier
7	Healthcare	20	569	28	Switzerland	Q1	2.7	MDPI
8	Journal of Psychiatric Research	19	470	24	U. K	Q1	4.9	Elsevier
9	Nutrients	19	331	17	Switzerland	Q1	5.0	MDPI
10	Multiple Sclerosis and Related Disorders	45	255	5	U. S. A	Q1	3.2	Elsevier

(CU), citation impact (CI), total publications (TP), and total citations (TC). Despite having a moderate impact factor (IF =4.5), the Swiss based MDPI publishing journal “International Journal of Environmental Research and Public Health"ranks

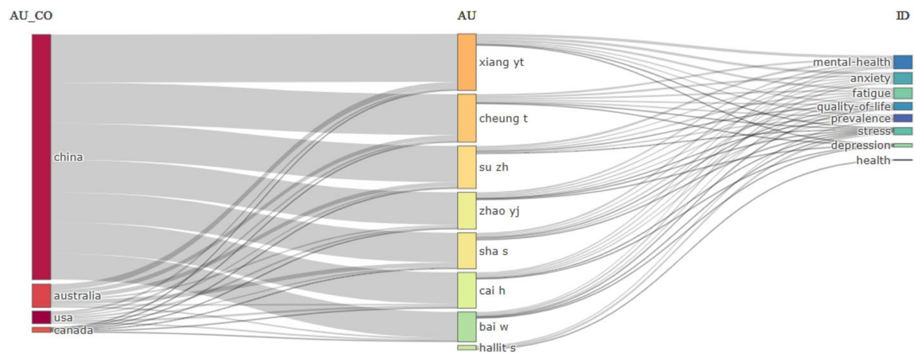

Fig. 9 Sankey diagram showing the relationship between author countries (AU_CO), authors (AU), and research topics (ID). China has the highest contribution, followed by Australia, the USA, and Canada. The diagram highlights key authors and their focus areas, including mental health, anxiety, depression, and quality of life

highest with the most publications (59) and a strong citation impact (CI =40)."Journal of Affective Disorders"is ranked second with 44 publications, but it has the highest impact factor (IF =6.7) and citation impact (CI =56), indicating its substantial importance in the field. Despite having the fourth-highest number of publications,"Brain Behaviour and Immunity"has the highest impact factor (IF =12) and citation impact (CI =134), demonstrating its importance in high-impact research. The top-ranked journals published in Switzerland and the US, with Elsevier being a well-known publisher, strongly represent high-quality research outputs in this field.

Three field plot

In the area of medical intelligence, with an emphasis on research on mental tiredness, the relationships between author countries (AU_CO), individual authors (AU), and study issues (ID) are visualized in Fig. 9, a three-field plot. The countries are represented on the left side (AU_CO), with China occupying the most prominent position, followed by Australia, the United States, and Canada. The authors are listed in the middle part (AU), with"Xiang YT"and"Cheung T"being the most notable. They have contributed to a variety of themes."Mental health,""anxiety,"and"fatigue"are the main research areas highlighted on the right side (ID) of the diagram. The plot highlights the productive relationships that Chinese writers have with these research subjects, with notable contributions from Australian and American scholars as well. The overall flow suggests a focused research effort in mental health and related diseases, led mainly by Australian and Chinese academics.

Tree map related to medical intelligence in mental fatigue

Figure 10 displays a tree map of the essential study subjects related to medical intelligence in mental fatigue research. The size of each rectangle, which represents a specific issue, is correlated with the number of publications on the topic.

The largest rectangle,"COVID-19,"appears in 15% of the papers (552), suggesting that the pandemic has been the discipline’s primary focus. Other common themes that show how significant these subjects are to the field of mental fatigue research are"mental health"(501 publications, 13%),"depression"(451 publications, 12%), and"fatigue"(392

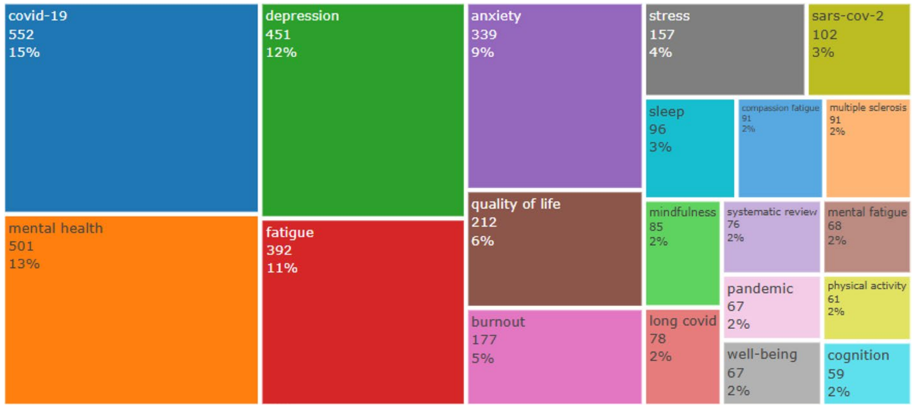

Fig. 10 Research distribution on mental fatigue and related topics, highlighting key areas such as COVID-19, mental health, depression, fatigue, anxiety, and quality of life, along with their relative contribution to the field

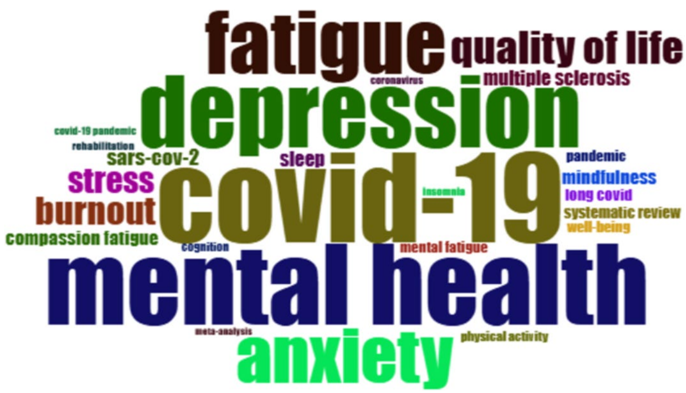

Fig. 11 Word cloud visualization of key research topics in our study. Larger words represent more frequently occurring terms, with"COVID-19,""mental health,""depression,""fatigue,"and"anxiety"being the most prominent

publications, 11%). Distinguished topics comprising 5% to 9% of the overall research output are"anxiety,"and"burnout."The data indicates a strong association between general mental health issues and mental tiredness, particularly in the context of the COVID-19 pandemic.

Word cloud related to medical intelligence in mental fatigue

Figure 11 displays a word cloud of essential terms linked to medical intelligence in studies on mental fatigue. The focus of the study is mainly on the effects of the COVID-19 pandemic on mental health. Critical phrases like"mental health,""COVID-19,"and"depression"are used, demonstrating how important it was to take people's mental health seriously both during and after the pandemic. Other notable terms are"fatigue ,""anxiety,"and"stress,"which are often associated with mental depletion. It draws attention to how terms like"burnout,""compassion fatigue,"and"quality of life"have wider societal and psychological ramifications. Phrases like"long COVID,""sleep,"and"rehabilitatio n"also imply that a study is ongoing to determine the long-term effects of the virus and

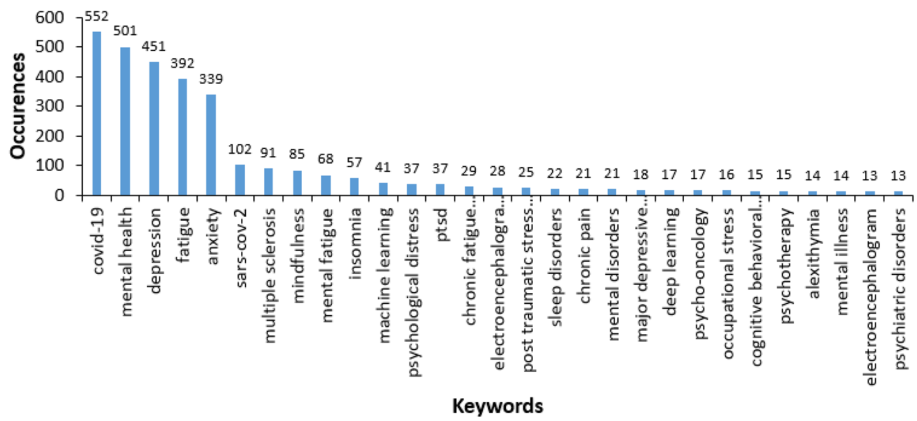

Fig. 12 Keyword distribution based on occurrence, highlighting the most frequently used terms in mental fatigue research, including COVID-19, mental health, depression, fatigue, and anxiety

how it impacts mental and physical health. The word cloud provides a comprehensive analysis of the pandemic's effects, both immediate and long-term, on mental health.

Author keywords related to related to medical intelligence in mental fatigue

The author's keywords and their occurrences from an extensive survey on medical intelligence in mental fatigue research are shown in Fig. 12."COVID-19,"which appears 552 times, is the most often referenced term, suggesting a heavy emphasis on the pandemic's effects on mental health. With 501 mentions,"mental health"comes in second, emphasizing its crucial relevance in the study. Related mental health conditions such as"anxiety"(with 339 and 451 occurrences, respectively) are also common, indicating the importance of mental exhaustion. With 392 occurrences, the term"fatigue"is significant and suggests that the survey strongly prioritized comprehending this condition.

The 102 appearances of the virus"SARS-CoV-2,"directly related to COVID-19, highlight the pandemic. Notable terms include"multiple sclerosis,""mindfulness,"and"mental fatigue."Occurrences of these terms range from 91 to 68, indicating that certain conditions and interventions related to mental fatigue may be investigated. Terms like"insomnia,""machine learning,"and"psychological distress,"which are less commonly used but significant, reflect a combination of clinical conditions and technology methods in the research. Additional terms like"chronic fatigue syndrome,""PTSD,"and"electro encephalography"demonstrate the wide variety of subjects addressed in the poll. Overall, the chart highlights how sophisticated technical tools, medical issues, and mental health all connect with the research on mental health.

All keywords related to medical intelligence in mental fatigue

Figure 13 details the keywords essential to the investigation of medical intelligence in mental fatigue research and shows how frequently these terms appear in the literature. With 639 occurrences, the most common term is"depression,"indicating its substantial relevance to the subject. Terms like"fatigue,""stress,"and"anxiety,"which are all linked to both bodily and mental weariness, are closely followed, indicating their crucial function in the context of mental fatigue. With 351 and 108 instances, respectively,"mental

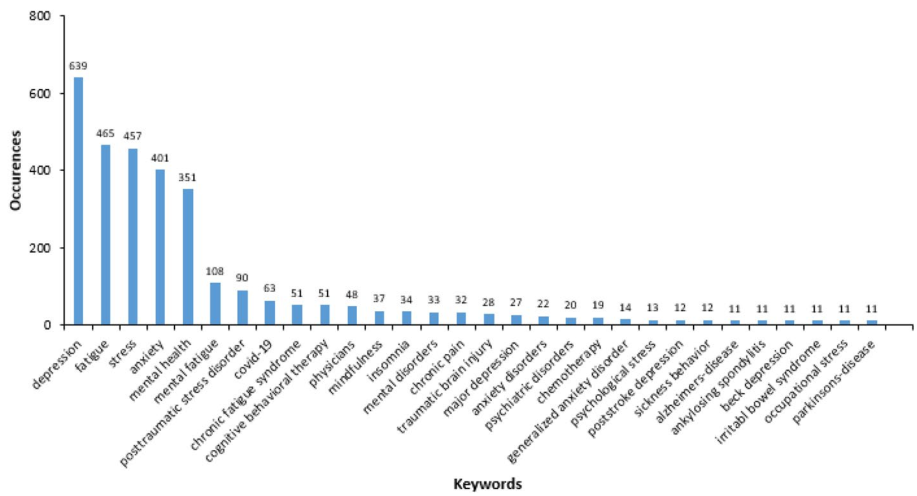

Fig. 13 Bar chart showing the frequency of keyword occurrences in our study."Depression"is the most frequently occurring term, followed by"fatigue,""stress,""anxiety,"and"mental health

health"and"mental fatigue"are also heavily featured, highlighting the study's emphasis on psychological well-being and the particular condition of mental exhaustion. Ninety times, the term"posttraumatic stress disorder"(PTSD) is used, indicating a possible connection between PTSD and mental exhaustion because of the chronic tension and worry it might induce.

The impact of"COVID-19,"which appears 63 times in the figure, is another indicator of the pandemic's effects on weariness and mental health. Fifty-one occurrences of the terms"chronic fatigue syndrome"and"cognitive behavioral therapy"indicate the importance of both the syndrome and its therapeutic modalities in this area. Related phrases like"mental disorders,""mindfulness,""insomnia,"and"physicians"highlight the variety of variables and treatments under investigation. Further broadening the scope of the research are specific illnesses like"chronic pain,""traumatic brain injury,"and"major depression"that are recognized. The existence of keywords like"chemotherapy,""generalized anxiety disorder,"and"psychological stress,"in addition to less common terms like"Parkinson's disease,""Alzheimer's disease,"and"irritable bowel syndrome,"highlights the variety of medical conditions that can cause or worsen mental fatigue, demonstrating the intricate and multidisciplinary nature of this field of study.

Network Co-citations of authors, countries and sources

The linkages and connections between different writers who have been referenced together in the field are depicted in Fig. 14. The lines (edges) that join each node to represent an author show the frequency of co-citation, or how frequently certain authors are quoted together in other works. Stronger ties are shown by the thickness and density of the connections; closely connected nodes indicate writers who are frequently mentioned together, which may indicate a collaborative effort or a common area of study. Scholars such as Chen Shubao, Yang Winson Fuzun, and Tang Jinsong seem to be central figures, indicating that they are important players in this field of study and have probably

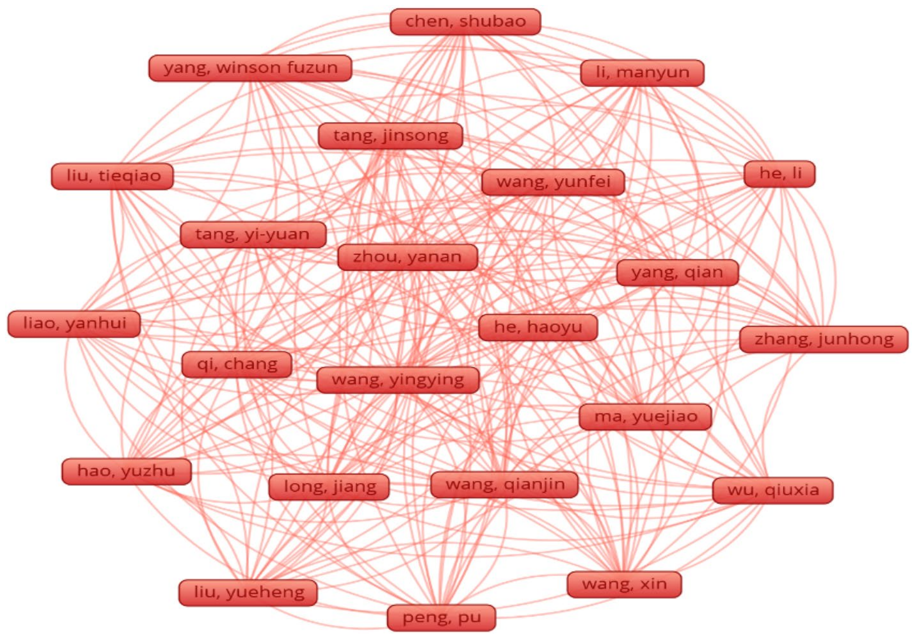

Fig. 14 Co-authorship network visualization, illustrating collaborative relationships among researchers based on co-citation analysis

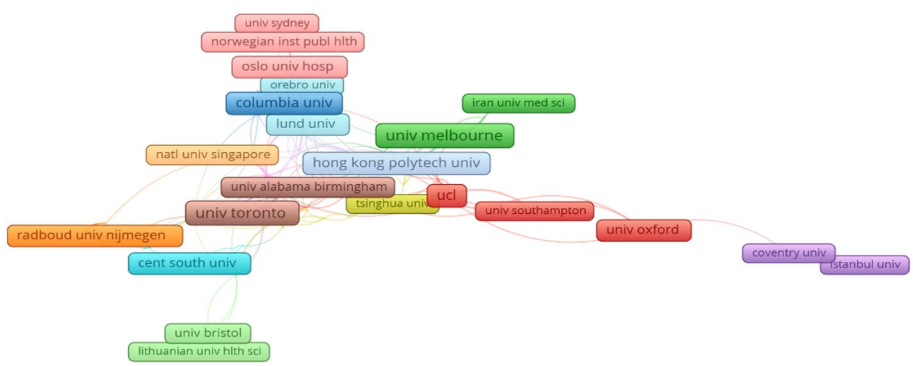

Fig. 15 Institutional collaboration network, illustrating co-citation relationships among universities and research institutions

produced seminal or well-known works. A highly collaborative and linked field of study is shown by the overall network structure's tight interconnection.

An affiliation network co-citation analysis of clusters associated with medical intelligence in mental fatigue research is shown in Fig. 15. The network indicates a collaborative research landscape because of the significant connections between universities. The University of Oxford, University of Southampton, University of Toronto, University of Melbourne, and University of Alabama Birmingham are meaningful clusters that are central hubs in this discipline. Numerous connections among these establishments suggest regular cooperation and exchange of knowledge. The network also emphasizes the participation of organizations from various geographic locations, such as the University of Sydney, the Norwegian Institute of Public Health, Oslo University Hospital, and the

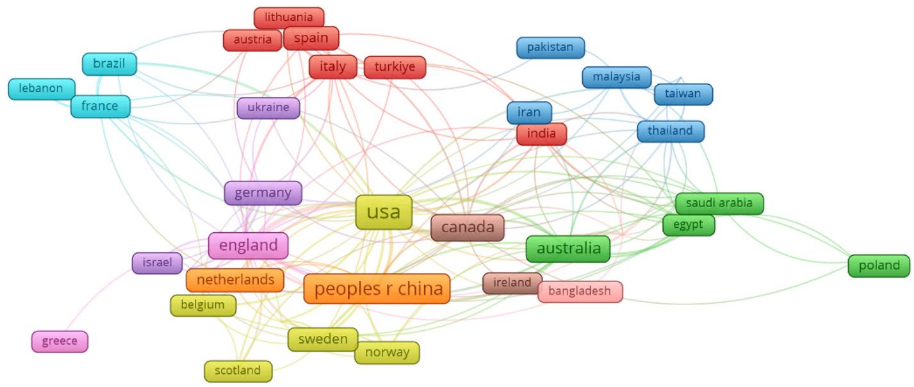

Fig. 16 Global research collaboration network, depicting co-citation relationships among countries in mental fatigue studies

University of Tehran, indicating a worldwide scope in this field of study. The affiliation network co-citation analysis offers insightful information on the institutional environment and collaborative dynamics surrounding medical intelligence in mental fatigue research.

Each node represents a country, and the edges between them show how frequently research from these countries is mentioned together in Fig. 16. The colour-coding of the nations into clusters suggests that some groups of nations have stronger ties to one another when it comes to their scientific endeavours. China, the USA, and England are prominent contributors to this field of study, as evidenced by their appearance as central nodes with numerous connections. The close ties forged between these nations suggest strong cooperation or considerable impact in the field. Other clusters exhibit regional or theme partnerships, such as those comprising nations like Australia, Canada, and Germany. Poland and Greece, for example, are peripheral nations; this suggests that their cooperation may be more specialized or infrequent. The entire network shows the worldwide terrain of medical intelligence and mental fatigue research, with significant centers in North America, Europe, and Asia, as well as wide-ranging international partnerships that propel the field's advancement.

Discussion

This section presents a comprehensive discussion of the study, systematically integrating current knowledge on mental fatigue, with particular emphasis on its onset and exacerbation during the COVID-19 pandemic. The findings reinforce the multifaceted nature of mental fatigue and its established links to psychological disorders such as stress, anxiety, and depression. Persistent cognitive strain and neurochemical dysfunctions—particularly involving glutamate signaling and cortical connectivity—are identified as key neurological underpinnings of the condition.

AI has emerged as a powerful tool for the detection and analysis of mental fatigue via bio-signals. Machine learning and deep learning models have demonstrated high accuracy and real-time monitoring capabilities. Despite these advancements, significant challenges remain, including limited model generalizability, lack of standardized datasets, and minimal application of explainable AI in practical settings. Addressing these

Fig. 17 Role of AI in fatigue research, including research gap and its solutions

gaps requires robust interdisciplinary collaboration among neuroscience, psychology, and data science domains to develop personalized and adaptive approaches to fatigue management. To support this, Fig. 17 presents a structured framework of AI-driven fatigue research, encompassing four critical dimensions—research gaps, proposed directions, testable hypotheses, and potential application areas—all anchored around the central concept of AI-enabled fatigue detection.

The COVID-19 pandemic served as a global stressor that markedly intensified mental fatigue across populations, with widespread reports of heightened stress and decision fatigue. These observations underscore the urgent need for effective, scalable detection and intervention strategies, particularly within healthcare, education, and workplace environments.

Bibliometric analysis indicates increasing international collaboration [110, 111] and a rising focus on mental fatigue research in the post-2020 era. However, a recent slowdown in publication volume suggests that the field is evolving toward more mature, in-depth investigations. Notable research gaps persist, including insufficient dataset diversity, a lack of longitudinal assessments, and limited real-world validation of AI-based tools. Moving forward, it is essential to enhance the transparency and interpretability of AI models, broaden the diversity and quality of datasets, and strengthen transdisciplinary collaborations to ensure the successful translation of research into real-world impact.

Funding agencies related to mental fatigue research

This section discusses the details of funding agencies that support mental fatigue research (Table 12). These agencies are very useful for supporting such research activities, which are aimed at exploring, assessing, and preventing mental fatigue by providing funds for Research and development programs that foster public participation. They are great at ensuring further enhancement of understanding in science and providing usable solutions, as embraced by mental fatigue across these different platforms.

Research gap in mental fatigue

In this subsection, we assess the existing knowledge gaps within the mental fatigue area of study. These overlaps outline areas that have had minor development or lack data, serving as a proposal for future research that can offer more penetration and enhanced understanding. By filling these gaps, researchers can improve the knowledge of mental fatigue, enhance diagnostic instruments, and enhance treatment methods used in our society.

Limited dataset size and diversity

A major concern of the current literature on mental fatigue detection through IoMT [20, 110, 112] and AI is the scarcity and the relatively small variety of datasets employed in the studies. Most of the research has used small sample size because it is expensive to conduct research and recruit participants. For example, certain studies included as few as several subjects, which is clinically insufficient to train deep learning models that need plenty of data to provide generalisation capabilities across populations and various conditions. Furthermore, these datasets are not fully diverse in terms of demographic variables and types of factors of mental fatigue; thus, the resulting models could be more solid and versatile.

Laboratory vs. real-world conditions

The second major problem is between the laboratory and the standard conditions of the environment in which the product is released into the market. Most experiments are performed in artificial settings far from the real working conditions. This type of environment disparity can create superb models when trained in a controlled condition but utterly unworkable when the constraints of real-world application are considered, whether in a construction site or a medical facility, where mental fatigue is a significant factor to consider. The failure to build and test these models on actual data restrains their significance and feasibility in daily life conditions.

Equipment and sensor limitations

These include calibrating the data collected from homemade or low-cost EEG equipment and noise reduction in the signals. Some of these limitations include: In the case

Table 12 Funding agencies used in mental fatigue research

Ref	Funding	Publisher	Journal	Used Ref
[72]	National Natural Science Foundation of China, Shanghai Sailing Program	Elsevier	Neurocomputing	44
[2]	Natural Science Foundation of Beijing Municipality, National Natural Science Foundation of China, Institute for Guo Qiang, Tsinghua University	Elsevier	Automation in Construction	71
[76]	European Union, European Union Next Generation EU/PRTR	IEEE	IEEE International Conference on Systems, Man, and Cybernetics	14
[74]	National Key Research & Development Program of China, Beijing Municipal Science & Technology Commission	IEEE	IEEE International Conference on Systems, Man, and Cybernetics	23
[77]	China Manned Space Advanced Research Project ES-2-NO.0030	IEEE	IEEE International Conferences on Internet of Things	38
[78]	Natural Science Foundation of Tianjin, National Key Research and Development Program of China, National Natural Science Foundation of China, Tianjin Natural Science Foundation for Distinguished Young Scholars	IEEE	IEEE International Conference on Mechatronics and Automation	22
[80]	Shanghai Sailing Program, National Natural Science Foundation of China	–	36 th Chinese Control Conference	22
[81]	SFI Offshore Mechatronics, Norway Research Council, INTPART Subsea—Subproject USP/NTNU, SFI Marine Operations, Norway Research Council	IEEE	IEEE 15 th International Conference on Control and Automation	20
[82]	National Natural Science Foundation of China	Elsevier	International Journal of Medical Informatics	62

Table 12 (continued)

Ref	Funding	Publisher	Journal	Used Ref
[86]	National Natural Science Foundation of China, Hundred Talents Program of Zhejiang University, Central Universities, Zhejiang Lab, National University of Singapore, Ministry of Education of Singapore, Natural Science Foundation of Shanghai, National Natural Science Foundation of China	IEEE	IEEE Transactions on Neural Systems and Rehabilitation Engineering	60
[87]	National Research Foundation, Prime Minister's Office, Singapore	–	International Conference on Cyberworlds	31
[88]	National Research Foundation, Prime Minister's Office, Singapore, International Research Centre	–	International Conference on Cyberworlds	33
[89]	Liaoning Provincial Natural Science Foundation of China	IEEE	The 5 th Annual IEEE International Conference	21
[90]	National Natural Science Foundation of China	WILEY	Human Factors and Ergonomics in Manufacturing & Service Industries	97
[91]	Chinese National Natural Science Foundation	Elsevier	Biomedical Signal Processing and Control	52
[92]	National Institute of Neurological Disorders and Stroke	–	ICASSP 2020	22
[94]	French Direction Générale de l'Armement	Elsevier	Biomedical Signal Processing and Control	39
[95]	Beijing Municipal Education Commission, Beijing University	IEEE	IEEE fifth International Conference on Advanced Computational Intelligence	05
[96]	National Science Foundation of China	Elsevier	Expert Systems with Applications	22
[93]	National Institute of Neurological Disorders and Stroke, Cornell University, EPFL, National Key R&D Program of China, Zhejiang Lab	IOP	Journal of Neural Engineering	71
[97]	National Natural Science Foundation of China, Zhejiang Provincial Natural Science Foundation of China, Key Project of Natural Science Foundation of Zhejiang Province, Key Research and Development Program of Zhejiang Province	MDPI	Sensors	66
[85]	University of Wollongong, Higher Education Commission Pakistan	IEEE	IEEE Symposium Series on Computational Intelligence	24

Table 12 (continued)

Ref	Funding	Publisher	Journal	Used Ref
[98]	National Key Research and Development Program of China, National Natural Science Foundation of China	ACS	Sensors	39

of using these platforms for data mining, it can lead to the gathering of compromised quality or unreliable data, which in turn affects the outcome of the artificial intelligence models. Also, there are challenges in managing and synchronizing multiple kinds of physiological and behavioral data, which is necessary to build an overall picture of mental fatigue. These problems have to be addressed, and new strain sensors and higher-level signal acquisition techniques are required.

Cross-task and cross-subject variability

Modern research mostly focuses on within-task and within-subject volatility as one of the key issues. In general, the functional models trained on some particular jobs or topics cannot yield good results when undertaken in other jobs or while working on other topics, suggesting a huge void in building generalized models. This variability is important in real-world applications where models have to be effective in a variety of contexts and also when dealing with individual users. It is necessary to perform another study to determine how it is possible to develop models that can adequately work under these conditions.

Understanding mechanisms of mental fatigue

Very little is known about how the relationship between mental fatigue and behavioural performance is mediated. These mechanisms are essential for designing new interventions or enhancing models. However, many researchers have not conducted detailed investigations of these factors and their relationships. It is almost impossible to develop detection and prevention methods for mental fatigue if one does not analyze how it builds up and shows itself. Future studies should, therefore, endeavor to examine the mechanisms above more exhaustively.

Feature selection and model optimization

Feature selection remains a significant challenge due to the high dimensionality of EEG data and other physiological signals. This complexity can make model training and interpretation difficult. Current studies indicate that there is considerable room for improvement in selecting and optimizing features to enhance model performance. Advanced feature selection techniques and optimization of hyperparameters are needed to improve classification accuracy and robustness.

Implications in mental fatigue research

This section elaborates on the policy implications of the research findings for areas such as health care, workplaces, or schools and explains how the research can be applied. Studying and comprehending the concept of mental exhaustion has broad applications

Table 13 Implications in mental fatigue research

Field	Implications
Healthcare	Early detection and management of mental fatigue to prevent burnout and improve patient care
Workplace	Enhancing employee well-being and productivity through fatigue management strategies, reducing errors and improving efficiency
Education	Developing interventions to improve student concentration and learning outcomes by managing mental fatigue
Transportation	Improving safety by monitoring driver fatigue and implementing rest protocols to prevent accidents
Military	Enhancing performance and decision-making by managing mental fatigue in high-stress environments
Sports	Optimizing athlete performance by understanding and managing mental fatigue during training and competitions
Research Trends	Bibliometric analysis can identify evolving trends, pivotal research gaps, and emerging themes in mental fatigue studies across all fields, guiding future inquiries

ranging from healthcare to productivity within workplaces, learning facilities, and driving. The implications of mental fatigue research include the development of practical recommendations on the best way to fight mental health disorders, the best way to improve safety measures, and the best way to record people's performance in different settings. For instance, in the healthcare system, understanding early symptoms of mental fatigue can assist in avoiding half-burnt carcasses of workers and enhance patient outcomes. Table 13 presents the implications of mental fatigue research.

Mental fatigue research in clinical and occupational applications

In modern healthcare, AI-driven mental fatigue detection offers transformative potential for neurodegenerative, psychiatric, and post-viral conditions such as long-term COVID-19. Innovative approaches like wearable biosensors, bio-signals-based AI models, and HRV monitoring systems allow us to move to real-time, objective fatigue measures beyond self-reported assessments. AI-powered tools enhance diagnosis and treatment personalization by integrating physiological signals with predictive analytics, improving management strategies for depression, anxiety, neurodegenerative diseases, and chronic fatigue syndrome. Moreover, AI-driven CBT, neurofeedback, and similar digital health platforms enable tailored interventions that adapt treatment based on real-time fatigue fluctuations.

In high-stakes areas like healthcare, aviation, and transportation, AI-based fatigue monitoring solutions improve safety and productivity by detecting cognitive decline and minimizing errors. Machine learning models and smart wearable sensors help optimize workload distribution, monitor burnout, and improve employees' health. Conversational AI tools like fatigue risk assessment can use real-time data to adjust the schedule and task allocations to minimize mental fatigue, which is particularly beneficial in high-stakes environments such as hospitals, manufacturing plants, and emergency rescue units. Nonetheless, data privacy, AI validation, and regulatory compliance are fundamental for real-world adoption challenges. Additional innovations will require the integration of AI, neurotechnology and human-centered design for more effective fatigue management across clinical and occupational settings.

Table 14 Contribution to Mental Fatigue Research

Discipline	Contributions
Neuroscience	Understanding the neural mechanisms underlying mental fatigue and identifying biomarkers for early detection
Psychology	Providing insights into cognitive and emotional aspects of mental fatigue and informing intervention strategies
Engineering	Developing wearable technologies and sensors for real-time monitoring and assessment of mental fatigue
Computer Science	Applying AI and machine learning techniques to predict and analyze mental fatigue patterns and outcomes
Biomedical Science	Investigating the physiological changes associated with mental fatigue and exploring potential pharmacological interventions
Human Factors	Examining the impact of mental fatigue on human performance and designing environments and tasks to minimize fatigue-related errors and accidents
Public Health	Analyzing the broader impacts of mental fatigue on community health, workplace safety, and quality of life, while developing public health initiatives to address these issues

Interdisciplinary approaches in mental fatigue research

Depending on the findings of previous or current literature, this section provides a brief overview of how this analytical approach could be advanced through the use of neuroscience and psychology along with technology integration. Mental fatigue research is multi-disciplinary research in which knowledge from neuroscience, psychology, engineering, and computer science is embraced. Such a collaboration can result in the creation of more complex models regarding mental fatigue which in turn will necessitate a search for a variety of new and effective solutions. For example, applying neuroscience and artificial intelligence can complement each other in the improvement of diagnostic assessments concerning mental fatigue, as well as applying psychological knowledge in designing possible prevention strategies at a behavioral level. Table 14 presents the contribution in mental fatigue research. Further, the publishing of engineering as well as computer science speed up the potential methods for signal processors and wearable devices meant for monitoring mental fatigue in a real-time fashion.

Future prospects

In this section, we explore the prospects of mental fatigue research, highlighting potential advancements and directions that could significantly impact the field (Fig. 18). This forward-looking analysis aims to inspire new research initiatives, guide funding priorities, and foster the development of innovative technologies and methodologies. By identifying promising areas of future exploration, we can better position the scientific community to address the challenges posed by mental fatigue and enhance both preventive and therapeutic strategies.

Expanding data collection efforts

Future research should focus on collecting larger and more diverse datasets to address the limited dataset size and diversity issue. This includes recruiting participants from

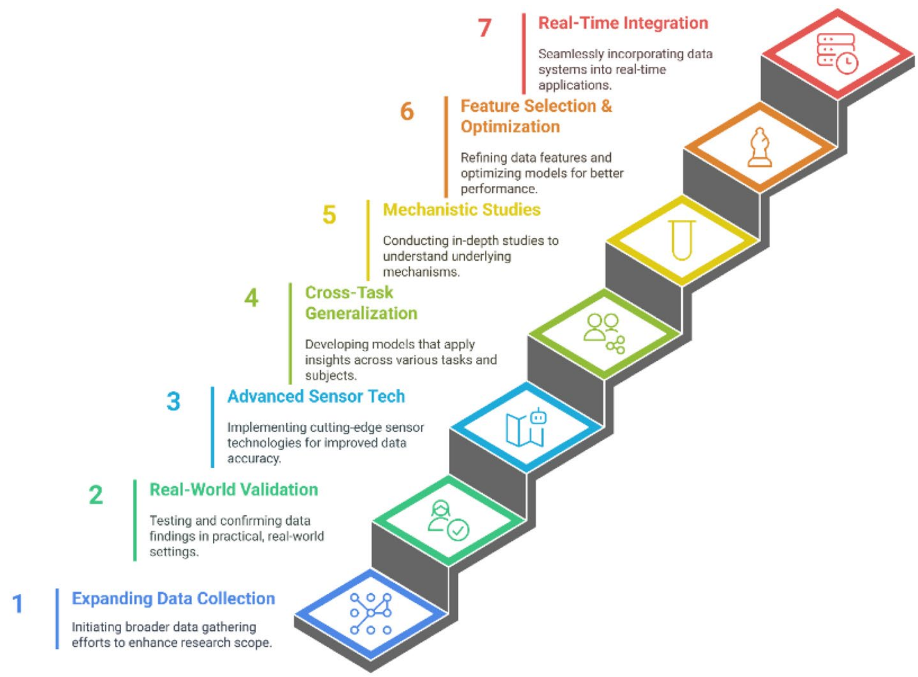

Fig. 18 Future prospects of the mental fatigue research

various demographic backgrounds and incorporating multiple types of fatigue-inducing tasks. By enriching the participant pool and task diversity, researchers can develop models that generalize better across different scenarios and populations. Additionally, increasing the dataset size will allow deep learning techniques to fully leverage their capabilities, which thrive on large amounts of data.

Real-world validation and deployment

There is a pressing need to validate and refine mental fatigue detection models in real-world environments. Future studies should prioritize deploying these models in actual work settings, such as construction sites, healthcare facilities, and other high-stress environments, to assess their performance and practicality. Since the data for the models will be gathered in real-world conditions, various restrictions and the sets of options that can be improved will be defined while using the models. This is important as the documented information will enable the development to move from laboratory work to practical development.

Incorporating advanced sensor technologies

There is a problem with homemade EEG equipment, and to overcome that, the integration of advanced and more reliable sensor technology is important. Further studies should focus on, for instance, the application of accurate, high-fidelity wearable sensors that would not give noisy data when used in different settings. Furthermore, integrating a combination of EEG, ECG, and behavioral sensors, for instance, can provide a better perspective on mental fatigue. This wearables approach can improve the validity and reliability of detection systems for fatigued performers.

Enhancing cross-task and cross-subject generalization

The practicality of the models also comes into play since the models should be generalized to other tasks and subjects. The next studies should be aimed at developing models with higher variability of tasks and inter-individual differences. This goal may be addressed through transfer learning, domain adaptation, or data collection from a more diverse population. The ability to make models generalize will ensure that such models are useful in as many scenarios as possible since real-life environments are diverse.

In-depth mechanistic studies

There are directions for future research, such as better feature selection methodologies and better feature optimization techniques. They include applying new descriptive techniques for feature extraction and selection and tuning of model parameters to improve the function. Researchers should also study the combination methods or meta-models that enhance various algorithms' performance characteristics and increase the generalization. This means that when sophisticated feature selection methods are used, one is able to settle for the features that make sense in the smallest number of models possible, hence resulting in smaller model complexities but better interpretability and improved accuracy.

Advanced feature selection and model optimization

The areas that need to be focused on in the future include enhancing feature selection and model optimization components. This involves the search for better algorithms for feature extraction and selection and determining the best parameters to apply to come up with the best prediction model. This requires learning whether researchers have attempted to use ensembles and hybrid models where two or more algorithms are combined to arrive at good levels of accuracy and generalization. The enhanced methods for selecting important features can help to choose the best ones, thus simplifying the models and increasing the possibility of their interpretation and effectiveness.

Integration with real-time systems

Further works should be directed towards linking the detection of mental fatigue to other systems that both monitor and intervene in real-time. This depends on creating algorithms that can help analyze the data and feedback systems that can feed back current results in real-time so that some action can be taken to counter this problem. Real-time systems may have benefits, especially in aviation, health care, and industrial applications, which require continuous high attention due to fatigue. The use of such systems comes in handy when it comes to early detection and mitigation of mental fatigue, hence improving safety and performance.

Conclusion

This review highlights the multifaceted nature of mental fatigue, emphasizing its neurological, psychological, and AI-driven detection mechanisms. The finding indicates that while AI model and bio-signal analysis offer promising advancements, challenges remain in dataset generalization, real-world validation, and interdisciplinary integration. The lack of standardized definitions and evaluation criteria further complicates the development of reliable diagnostic tools. Additionally, current machine learning models often suffer from limited scalability and variability in bio-signal responses across individuals. Further research should focus on improving model robustness, integrating real-time monitoring systems, and exploring novel interventions tailored to individual cognitive needs. Incorporating multimodal data fusion techniques and hybrid AI models could significantly enhance detection accuracy and personalization. Furthermore, ethical considerations, such as data privacy and bias in AI-driven diagnostics, must be addressed to ensure fairness and reliability in practical applications. By addressing these gaps, the scientific community can advance both diagnostic accuracy and intervention strategies, ultimately enhancing cognitive well-being and performance across various sectors. Future work should also explore AI-assisted cognitive training programs and adaptive workload management systems to mitigate mental fatigue in high-risk professions.

Author contributions

SP: conceptualization, data curation, validation, visualization, formal analysis, investigation, and writing-original draft; MBBH: conceptualization, data curation, validation, visualization, formal analysis, investigation, project administration, and writing-original draft; UT and FA: data curation, formal analysis, validation, software, and writing-original draft; HMZ and SCYA: conceptualization, funding acquisition, supervision, investigation, and writing-original draft; SMZ and HL: data curation, resources, supervision, investigation, and writing – review & editing. All authors read and agreed for the publication.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Competing interests

The authors declare no competing interests.

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