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Review Article

Cognitive Workload Assessment: A Comprehensive Review

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Abstract: Mental workload during high-effort tasks is a crucial measure of effective task performance. Maintaining cognitive demands within an individual's capacity enables the effective performance of complex multi-tasking. Conversely, surpassing this margin may lead to unpredictable and suboptimal performance. This review explores human mental workload assessment across real-world tasks like aircraft piloting, vehicle driving under challenging conditions, and automated power plant monitoring. Both subjective and objective monitoring methods are examined: subjective methods include the widely used NASA-TLX, while objective methods cover EEG and eye-tracking measures during task execution. Findings from these methods are correlated with overall task performance outcomes. Real-time workload monitoring provides distinct advantages in critical settings; for instance, if an operator's cognitive capacity is reached, alerts could be triggered, or task demands adjusted to alleviate overload. Finally, a multi-modal analysis of the literature is presented, comparing the effectiveness of various monitoring technologies across different task domains to guide future research directions.

Keywords: Cognitive Workload, EEG, Physiological Measures, Performance Metrics, NASA-TLX, Multimodal Assessment, Real-Time Monitoring

Introduction

Mental Workload (MWL) is the cognitive effort expended to meet the demands of a specific task. The assessment of mental workload is vital for accurately predicting operator performance and the resulting system outcomes. Understanding mental workload is essential for enhancing human-machine interactions and detecting factors contributing to elevated mental workload. MWL assessment information can be used to enhance performance by mitigating stress, fatigue and performance declines caused by excessive MWL. Neuroergonomics (Safari *et al.*, 2024) combines neuroscience, cognitive psychology and human factors to investigate brain activity within workplace settings (Di Flumeri *et al.*, 2019). Cognition fulfills a vital role in in reasoning and problem-solving, involves billions of neurons communicating through synapses in the brain (Sweller, 2011; Sporns *et al.*, 2000). MWL, influenced by task complexity, time constraints and distractions, affects task performance (Dyke *et al.*, 2015). Maintaining an optimal cognitive workload, a level of workload that can be managed by a human is vital for efficiency in real-world tasks (Paas and Van Merriënboer, 1994; Parasuraman, 2003). varying with tasks such as numerical operations or reading, which challenge working memory (Ladekar *et al.*, 2021). MWL Plays a critical role in human-machine interaction and scales with information presented, available processing time and other tasks (Ramakrishnan *et al.*, 2021; Paas *et al.*, 2003). Assessing cognitive workload would be beneficial in tasks such as military operations (Diaz-Piedra *et al.*, 2020; Wu *et al.*, 2022), air traffic control (Aricò *et al.*, 2016; Izadi Laybidi *et al.*, 2022; Li *et al.*, 2023) and vehicle driving (Abd Rahman *et al.*, 2020; Yang *et al.*, 2020; Low *et al.*, 2021), where excessive workload can lead to errors. Tasks vary in cognitively demanding contexts. For instance, visual tasks require more MWL compared to auditory tasks (Amon and Bertenthal, 2018). Short-term information processing relies on working memory, while long-term memory supports extended information retention, retrieval and use (Burgess and Hitch, 2005). The varying task cognitive demand presents challenges to assess MWL effectively.

Automation in the workplace heightens the need for real-time MWL assessment. As automation increases, human operators are faced with MWL-intensive roles like system monitoring and troubleshooting (Mouloua and Hancock, 2019). The shift in task focus resulting from automation often involves continuous passive monitoring, with human intervention triggered only by exceptional conditions. Despite or perhaps due to automation, environments with high levels of automation continue to encounter performance variability and human error owing to limitations in cognitive resources (Borghini *et al.*, 2014; Zanetti *et al.*, 2022). This review paper examines current practices in cognitive workload assessment and integrates insights from psychology, neuroscience, engineering and computer science, aiming to provide a holistic understanding that will benefit future studies and practice. The review identified significant contributions by using PRISMA guidelines. As a result, this review synthesizes existing research, explores methodologies and delves into the definitions and assessment mechanisms for MWL. Applications across diverse domains such as military operations and air traffic control are analyzed, highlighting the critical role of workload assessment in enhancing human performance and reducing errors in automated environments. By considering various approaches from existing literature, this review seeks to advance understanding and practices in cognitive workload management for real-world applications. The use brain activity data, as measured with ElectroEncephaloGraphy (EEG) figures prominently in MWL assessment. EEG-based approaches may be augmented with other physiological measures, as outlined below.

Materials and Methods

This review is based on a comprehensive survey of peer-reviewed literature retrieved from reputable academic databases and digital libraries. The selected sources span a range of disciplines relevant to mental workload, ensuring both foundational research and recent developments are included. Studies were chosen to reflect diverse methodologies and perspectives in cognitive workload assessment, allowing for a thorough and interdisciplinary understanding of the topic.

Selection Process and Scope

The review aimed to capture the breadth and depth of the field of cognitive workload monitoring and assessment, accommodating its inherently interdisciplinary nature. To achieve this, the following steps were taken:

Data Collection Strategy

Relevant studies were identified using targeted search terms, such as cognitive workload, mental workload assessment, neuroergonomics, EEG-based workload monitoring and workload in aviation and aerospace. Boolean operators were applied to refine searches, ensuring the inclusion of highly relevant literature.

Time Frame

The primary focus was on research published in the past decade to highlight contemporary advancements. However, seminal contributions published before this period were also incorporated where they provided foundational insights or historical context.

Inclusion and Exclusion Criteria

Studies were included if they explicitly addressed methodologies for monitoring or assessing cognitive workload, offered experimental evidence, or explored interdisciplinary applications. Papers were excluded if they lacked sufficient methodological detail, were not peer-reviewed, or presented duplicate findings.

Data Evaluation and Methodology

The material selected emphasizes the impact and significance of published research in this field, considering both theoretical advancements and practical applications. A high-level summary of the scope, data and methodologies is provided to guide readers through the contributions of the reviewed studies. Special attention was given to identifying and discussing cross-disciplinary approaches that integrate neuroscience, human factors, ergonomics and engineering perspectives.

PRISMA Chart Overview

To ensure transparency and reproducibility, the review process is detailed in a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) chart, shown in Figure (1).

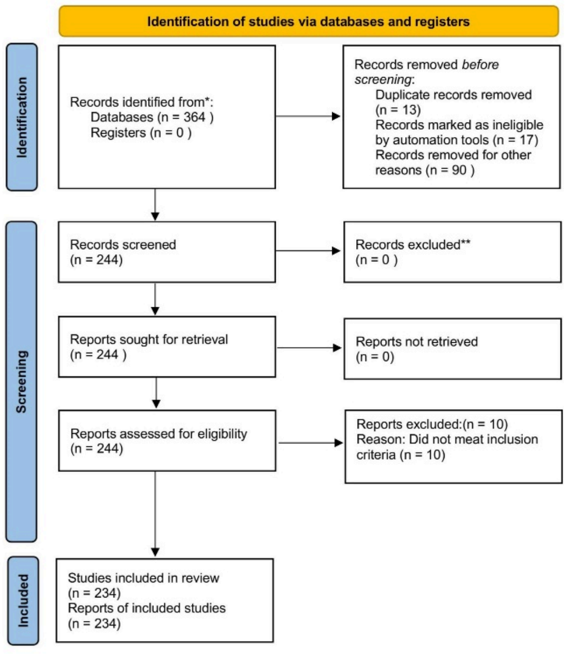

Fig. 1: The PRISMA Chart for the Current Review Paper

This chart illustrates the workflow for paper selection, including:

- The total number of studies identified through initial searches
- The screening process based on titles and abstracts
- Excluded papers with reasons for exclusion
- The final set of studies included after a full-text review

By combining systematic searching with rigorous selection criteria, this review offers a comprehensive exploration of cognitive workload monitoring and assessment methods, providing valuable insights into this rapidly evolving field.

Defining Mental Workload

Mental workload (MWL) refers to the cognitive resources utilized during task performance (O'Donnell, 1986). Insufficient resources can cause stress and hinder performance (Paxion *et al.*, 2014; Heard *et al.*, 2018). Tasks involving potentially risky human-machine interaction, like piloting aircraft or operating unmanned vehicles, exhibit particularly high MWL potentially compromising safety (Jaquess *et al.*, 2018). Of note, research shows performance declines with both high (overload) and low (underload) MWL levels (Zarjam *et al.*, 2013; Yi *et al.*, 2019; Bagheri and Power, 2020; Sammer *et al.*, 2007; Brookhuis and De Waard, 2010; Ryu and Myung, 2005; Calabrese, 2008). Assessing MWL is crucial for optimizing user interface design to maintain an appropriate workload balance (Borghini *et al.*, 2016).

Assessing Mental Workload

Interdisciplinary methods of assessing MWL are crucial for characterizing and predicting human performance (Young *et al.*, 2015; Parasuraman *et al.*, 2008), impacting high-risk task environments (Jou *et al.*, 2009) and task environments requiring sustained reliability (Carswell *et al.*, 2005; Yurko *et al.*, 2010). MWL in this review refers to the cognitive effort subjectively perceived by subjects, usually augmented by EEG and other physiological information (Noyes *et al.*, 2004; Luximon and Goonetilleke, 2001; Orlandi and Brooks, 2018). MWL can be assessed using various methods (Heine *et al.*, 2017; Averty *et al.*, 2004; da Silva, 2014):

1. Subjective measures like the NASA Task Load Index (NASA TLX) (Wang *et al.*, 2005; Hernández-Sabaté *et al.*, 2022) and Subjective Workload Assessment Technique (SWAT) (Hart and Staveland, 1988)
2. Objective measures based on physiological responses such as EEG and ElectroCardioGram (ECG) (Rim *et al.*, 2020)
3. Task performance measures like response time and task accuracy (Astrand, 2018; Hogervorst *et al.*, 2014; Zhang *et al.*, 2017)

Qualitative vs. Quantitative Measures of Mental Workload

Qualitative methods evaluate mental workload by exploring distinct characteristics without relying on objective numerical quantification (Bernard, 2017). These approaches offer depth and context, helping to interpret quantitative findings and describe phenomena across diverse settings often at the expense of reproducibility (Sofaer, 1999; Palinkas *et al.*, 2011). By allowing individuals to express their experiences freely, without being confined to predefined categories or terminologies, qualitative methods offer a nuanced understanding of mental workload. Qualitative research addressing MWL-related phenomena is typically flexible, unstructured, and subjective, whereas quantitative research aimed at testing specific hypotheses tends to be more stable, structured, and objective (Longo *et al.*, 2022).

Subjective Measurements

Conventional methods for evaluating cognitive workload often use subjective techniques (Reid and Nygren, 1988), such as questionnaires or interviews. In such scenarios, participants assess the mental effort required for tasks (Kruger and Doherty, 2016). These tools combine subjective and objective measures to monitor MWL. Subjective assessment typically involves participants completing questionnaires based on stimuli or time intervals (Balta *et al.*, 2024). However, reliance on subjective participant opinions can yield unreliable and non-repeatable results (Hancock and Chignell, 1988). To address these issues, multidimensional approaches like the NASA TLX and SWAT (Roca-González *et al.*, 2024) have been developed for comprehensive mental workload assessment.

National Aeronautics and Space Administration Task Load Index

The NASA-TLX tool is widely used for subjective workload assessment (Hart, 2006). NASA-TLX includes six subscales: mental demand, physical demand, temporal demand, own performance, effort and frustration, each assessed on a scale (Wang *et al.*, 2019; Wu *et al.*, 2021; Lau-Zhu *et al.*, 2019). Scores range from 0 to 100, with higher scores indicating higher workload (Diaz-Piedra *et al.*, 2019), derived from ratings on a 0-10 visual scale. The effort subscale assesses consistency in engagement (Yu *et al.*, 2015; Venables and Fairclough, 2009). Weighted averages across dimensions provide an overall workload score (Guan *et al.*, 2022). ANOVA with repeated measurements identified cognitive load as a primary factor influencing NASA-TLX scores (Qu *et al.*, 2020). The NASA-TLX has been employed to gauge pilot mental workload and correlatation with task performance scores under different workload conditions, revealing insights into performance, attention and working memory strategies (Mohanavelu *et al.*, 2020). Pilots consistently reported higher workload under high-difficulty compared to low-difficulty conditions when using the NASA-TLX (Verdière *et al.*, 2019). Subjective assessments of task difficulty and performance usually follow task performance. As a result, such assessments lack temporal resolution, limiting the capture of dynamic or transitory features in mental workload (Drouin-Picaro *et al.*, 2017).

Subjective Workload Assessment Technique (SWAT)

The Subjective Workload Assessment Technique (SWAT) captures the multidimensional aspects of Mental Work Load (MWL) by having individuals rate the time, mental effort and emotional stress required for a task. Similar techniques, such as NASA-TLX, also assess MWL using multidimensional approaches. While these tools provide valuable diagnostic information about overall mental workload, they do not offer detailed insights into the specific attentional resources needed for different task levels (Alotaibi *et al.*, 2024).

Objective Measurements

Objective measurements provide useful augementation to subjective methods for continuous and objective MWL assessment. Examples of objective measurements include ECG for heart activity (Chen *et al.*, 2017), electromyography for muscle activity, respiration (Gagnon *et al.*, 2016; Kroupi *et al.*, 2014; Aydemir, 2017; Hou *et al.*, 2020), eye tracking (Glaholt, 2014) and EEG for brain activity (Lee *et al.*, 2020), among others (Rim *et al.*, 2020). These measurements can provide insight to subject's physiological state and may be used to predict sustained or instantaneous MWL. Heart Rate Variability (HRV), another orjective measurement, is correlated to MWL (Fairclough *et al.*, 2005). Ocular features also respond to changes in workload (Van Orden *et al.*, 2001).

EEG is particularly valuable for its direct measurement of brain activity, offering accurate workload assessments with lower reaction times (Reinerman-Jones *et al.*, 2014; Matthews *et al.*, 2015). EEG headsets, though sensitive to movement artifacts, are preferred for their practicality and high temporal resolution (Cassani *et al.*, 2014). Despite technical challenges collecting "clean" EEG data, EEG remains the most popular physiological method for assessing mental workload (Suk and Lee, 2013; Liu *et al.*, 2017). EEG measures brain electrical activity via scalp electrodes, with brain activity analyzed across frequency bands. The high temporal resolution of EEG captures subtle variations in mental states, such as vigilance and cognitive workload (Zarjam *et al.*, 2013). EEG is a key method for measuring the brain's electrical activity through electrodes placed on the scalp (Mihajlovicet al., 2015; Hoppe *et al.*, 2015).

Studies have shown that EEG power in various frequency bands are sensitive to fluctuations in cognitive demand (Petkar *et al.*, 2009; Antonenko *et al.*, 2010; Pavlov and Kotchoubey, 2017; Friedman *et al.*, 2019). For instance, Cheng and Hsu (2011) used EEG data to estimate workers' fatigue, finding that increased theta band activity indicates decreased attention levels. Borghini *et al.* (2012) developed an EEG-based cerebral workload index to assess drivers' mental efforts under varying task difficulties, based on EEG power spectra increases. Schrauf *et al.* (2011) identified EEG alpha spindles and alpha band power as indicators of task performance during secondary auditory tasks, suggesting that EEG power levels are strong indicators of cognitive workload variations (Hebbar *et al.*, 2021).

EEG bands included delta (0-4 Hz), theta (4-7 Hz), alpha (8-12 Hz), beta (13-30 Hz) and gamma (30-100 Hz) (Saby and Marshall, 2012). Alpha and theta band activity is commonly used to measure cognitive load, with alpha activity linked to idling, arousal and workload. Decreased alpha activity correlates with increased mental load, stress and anxiety (Sauseng *et al.*, 2009; Iqbal *et al.*, 2019). Alpha waves increase during relaxation and enhance autonomic responses to stimuli while theta waves play a role in daydreaming and sleep, enhancing creativity and reducing pre-performance anxiety (Choi *et al.*, 2018). Beta waves are linked to attention-related mental activities (Engel and Fries, 2010; Howells *et al.*, 2010; Murata, 2005), Gamma waves are involved in cognitive processing, learning and memory (Wang and Wang, 2013). EEG is an effective tool for measuring mental workload and monitoring cognitive states by capturing the brain's electrical activity directly (Seppänen and Fisk, 2006). Changes in theta and alpha activity are associated with higher brain functions, such as working memory and executive control (Fink *et al.*, 2005; Stipacek *et al.*, 2003; Morton *et al.*, 2022). As mental workload increases, theta band activity in the frontal lobe rises, while alpha band activity in the parietal lobe declines (Holm *et al.*, 2009; Lean and Shan, 2012). EEG signals across different frequency bands offer valuable insights into various cognitive states and task conditions. Increased theta band power is linked to greater working memory demands (De Smedt *et al.*, 2009; Liu *et al.*, 2019), while beta band activity relates to task-specific cognitive effects, including sensory and language processing, as well as motor effects (Ghosh Hajra *et al.*, 2018). Conversely, alpha band activity represents inhibitory mechanisms in the brain, with reduced alpha activity indicating increased neuronal excitability and active information processing (Klimesch, 2012). Task-relevant brain regions show decreased alpha power, while non-essential regions exhibit increased alpha activity, especially as task difficulty rises (Sauseng *et al.*, 2009; Hajra *et al.*, 2020).

Using EEG for Assessing Mental Workload

Electroencephalography (EEG) offers several advantages, such as versatility, non-invasiveness and ease of setup, making it a widely used method for monitoring brain activity (Ding and Lee, 2013; Kwak and Lee, 2019). Despite these benefits, EEG is limited by a low signal-to-noise ratio, as signals can be contaminated by eye blinks, muscle contractions and electronic devices (Kwak *et al.*, 2015; Górecka and Walerjan, 2011). Additionally, individual differences in EEG characteristics can affect reliability (Lee *et al.*, 2019). To mitigate these issues, studies often combine EEG with Peripheral Physiological Measures (PPMs) such as ECG, respiration and EDA, enhancing accuracy and reliability (Aarsland *et al.*, 2017; Kamei *et al.*, 2010; Ahn *et al.*, 2016). High mental workload is associated with increased EEG power in the theta band and decreased power in the alpha band. As mental fatigue sets in, increases in theta, delta and alpha bands can be observed. While EEG has broad applications, its potential in improving aircraft operations has been less explored (Borghini *et al.*, 2014). Effective analysis of EEG signals involves time-frequency analysis to identify power distribution across different frequencies and cortical locations. The proposed analysis pipeline focuses on delta, theta, alpha, beta and gamma bands (Nunez and Srinivasan, 2006). Low-cost and wireless EEG devices have made the technology more accessible, yet its application remains largely within laboratory settings. Tight clamping of headsets can cause discomfort, limiting continuous measurement of mental workload (Wang *et al.*, 2019). Changes in 141 mental workloads are effectively measured by spectral power analysis of theta and alpha bands (Iqbal *et al.*, 2020). However, individual differences in thoughts and emotions can complicate cross-task classification, necessitating a robust approach for reliable analysis (Ladekar *et al.*, 2021).

Types of EEG Devices in Mental Workload Studies

EEG technology is categorized into four types by Bleichner and Debener, 2017; Mihajlovic *et al.*, 2015:

- Mobile EEG: Allows for movement during signal acquisition, suitable for naturalistic settings and ambulatory monitoring
- Portable EEG: Can be easily carried but may not tolerate movement as well as mobile EEG
- Wearable EEG: Self-applied and worn with regular clothing, emphasizing convenience and everyday use
- Transparent EEG: Highly unobtrusive, nearly invisible and comfortable, combining portability with motion tolerance for prolonged use

Wireless EEG refers to devices utilizing wireless protocols for signal acquisition, applicable across mobile, portable, wearable, or transparent EEG categories (Suk and Lee, 2013). Recent advancements in mobile EEG systems, such as Neurosky's Mindwave and InteraXon's Muse, have enhanced accessibility but face challenges like comfort and integration into ergonomic designs. These devices, often employing dry electrodes and wireless transmission, are suitable for non-clinical studies requiring ecological validity despite limitations in electrode count and signal quality compared to traditional EEG setups (Petkar *et al.*, 2009; Iqbal *et al.*, 2020). Emerging System-On-a-Chip (SoC) technologies are furthering the development of wearable EEG devices for commercial applications, promoting user-friendly interfaces and passive Brain-Computer Interface (BCI) applications (Suk and Lee, 2013).

Scientific Domains That Can Benefit from Mental Workload Assessment

Mental workload assessment is crucial in high-demanding fields such as military operations, nuclear power plant monitoring, air traffic control and driving to optimize user performance and prevent critical errors (Guan *et al.*, 2022).

Measuring Mental Workload in Aerospace

Challenging flight conditions can significantly impact pilots' cognitive levels and their ability to control flights, evidenced by changes in multiple physiological measures (Gentili *et al.*, 2014). Pilots face increased cognitive load due to complex environmental factors and rapid processing of visual information, which can impair task performance (Wanyan *et al.*, 2014). Experiments utilizing high-fidelity 6-degree-of-freedom flight simulators provide insights into pilots' physiological responses during flight simulations, offering a realistic environment for research and training purposes (Wu *et al.*, 2022). Traditionally, pilots' workload during flights is evaluated using expert interviews and subjective questionnaires like rating scales. However, these methods are problematic: questionnaire assessments vary subjectively among individuals and interrupt flight operations, impractical in real-time. Moreover, they only capture workload at specific times, missing continuous task-related workload changes and physiological states (Li *et al.*, 2022).

To address these challenges, psychophysiological measurements such as electrocardiogram-derived heart rate variability, electrodermal activity, pupil size and blink rates offer more objective and real-time insights into pilots' workload and cognitive states during flight operations (Wilson, 2002; Fritz *et al.*, 2014).

Psychophysiological measures are extensively studied for assessing workload in operational environments (Hajra *et al.*, 2020; Gateau *et al.*, 2018). These measures encompass brain-related metrics like EEG, ERP, MEG and brain metabolism, ocular measures such as fixations, scan path, blinks and pupil diameter, cardiac measures including HRV and facial expression analysis. These metrics offer objective and time-sensitive insights into pilots' cognitive and physiological states. However, integrating these measures with performance-based parameters in pilot studies remains underexplored (Hebbar *et al.*, 2021).

Recent advancements include minimally invasive sensors like screen-mounted and head-mounted eye trackers, watch-type blood pressure monitors (Carmen *et al.*, 2006), necklace-type devices for cardiac monitoring (Penders *et al.*, 2011), wearable devices for heart rate and blood pressure monitoring (Gu *et al.*, 2009) and ring-type devices for heart rate and temperature measurements (Wu *et al.*, 2011). These technologies enable continuous monitoring of cognitive workload in safety-critical domains (Iqbal *et al.*, 2020). Studies utilizing physiological measures have gained popularity for their ability to objectively track autonomic and central nervous system changes associated with cognitive workload, moving beyond subjective assessments (Wilson, 2000). Changes in EEG frequency bands, particularly theta (4-8 Hz) and alpha (8-11 Hz), correlate with higher cognitive functions such as working memory and executive control, providing valuable insights into workload dynamics (Sauseng *et al.*, 2010; Herweg *et al.*, 2020; Wu *et al.*, 2021).

Iqbal *et al.* (2020) presented an innovative EEG-based approach to evaluate cognitive workload among control room operators by examining the alignment between operators' mental models and actual system behavior. This study introduces a technique utilizing S ϴ(ω) to measure the degree to which participants' mental models correspond with real-time process behaviors during control tasks. Results indicate that lower S ϴ(ω)values correspond to effective task management and reduced cognitive workload when mental models align closely with process dynamics. Conversely, higher S ϴ(ω)values point to mismatches and increased workload. This method achieved 83.9% accuracy in population studies for identifying task outcomes, underscoring its effectiveness in assessing cognitive workload within control room settings. Similarly, Ke *et al.* (2021) investigated the impact of ambient noise on cognitive and task performance using portable EEG devices, focusing on safety-critical tasks like hazardous hole identification under different noise conditions. The research processed EEG data to mitigate artifacts through filtering and independent component analysis.

Wavelet decomposition extracted alpha band energy and asymmetry indices for stress assessment. Statistical analysis with Kruskal-Wallis ANOVA revealed significant noise effects on cognitive indicators. Meta-analysis synthesized EEG and behavioral metrics across noise conditions, while meta-regression identified predictors of cognitive workload and stress responses, highlighting noise's nuanced impact and suggesting strategies for optimal noise management in real-world contexts (Ke *et al.*, 2021*).*

Application of Mental Workload in Psychology

Ladekar *et al.* (2021) developed a method using EEG signals from dry electrodes to classify visual cognitive workload. Participants engaged in tasks involving counting colored balloons to assess four levels of workload intensity. Gupta *et al.* (2021) estimated cognitive load during cross-task performance using custom visual tasks involving geometric shapes and colored balloons, analyzing EEG signals through time windowing and smoothing techniques. Shaw *et al.* (2018) explored ERP and spectral changes as indices of cognitive workload during locomotion tasks of varying difficulty (easy vs. hard) and conditions (seated vs. walking). Yim *et al.* (2022) developed a model combining EEG data and NASA-TLX scores to estimate mental workload during visualization tasks. Roy *et al.* (2016) compared EEG markers for workload estimation using tasks like the Sternberg task, emphasizing spectral measures and ERPs. Radüntz (2020) investigated workload across cognitive tasks like the Grooved Pegboard Test (GPT) and Tower of Hanoi (TOH), highlighting workload variations based on task complexity and individual factors like handedness and working memory capacity. Belkhiria and Peysakhovich (2021) proposed using EEG-EOG headsets to objectively measure workload via eye movements and brain activity, assessing complexity levels across auditory, memory and counting tasks. Taori *et al.* (2022) classified workload using EEG temporal dynamics with methods like AR modeling and HMM, showing promise for continuous engagement assessment. These studies underscore the diverse applications of EEG and psychophysiological measures in psychology, offering insights into cognitive workload assessment across various tasks and conditions. This section reviews diverse methodologies utilizing EEG and psychophysiological measures to assess cognitive workload in psychology. Studies range from classifying workload levels during visual tasks using EEG signals to analyzing ERP and spectral changes during locomotion tasks of varying difficulty. These studies underscore the diverse applications of EEG and psychophysiological measures in psychology, offering insights into cognitive workload assessment across various tasks and conditions. Table (1) describes the information of mental workload assessment in psychology.

Yin *et al.* (2019) developed the Transfer Dynamical AutoEncoder (TDAE), a novel autoencoder designed to capture dynamic EEG features and individual differences. TDAE utilizes transfer learning across datasets from process control tasks and emotional stimuli responses. In tasks involving Auto CAMS, managing cabin air quality, TDAE significantly outperformed existing machine learning models, demonstrating superior classification accuracy when optimized with appropriate hyper parameters. Puma *et al.* (2018) studied cognitive workload in multitasking environments using EEG. They observed increased theta and alpha rhythms correlating with higher task engagement, plateauing with three to four tasks. EEG, along with HEOG, VEOG and pupil size, assessed tasks like gauge monitoring, tracking, letter detection and mental arithmetic. The study used EEG signal processing and meta-analytic methods to assess cognitive workload during multitasking, finding significant increases in Nasa-Tlx scores ($F(3,57) = 74.56$, $p < 0.001$) and pupil size ($F(3,57) = 21.57$, $p < 0.001$) with task complexity. Performance scores ($F(3,57) = 22.24$, $p < 0.001$) varied significantly, grouped into three distinct categories by cluster analysis. Theta power increased with task demands, plateauing, while alpha power unexpectedly rose with task complexity, emphasizing EEG's role in understanding multitasking cognitive workload and performance. Choi *et al.* (2018) proposed EEG-based Workload Index (EWI) for measuring mental workload in digitalized control rooms, such as nuclear power plants. Their findings validated EWI's efficacy over subjective methods during scenarios like PRZ safety valve malfunctions. Li *et al.* (2019) introduced a wearable EEG method to screen mental fatigue in construction workers, using spectral parameters and Stroop tests to quantify fatigue levels based on reaction times and performance metrics. Xing *et al.* (2020) investigated physical and mental fatigue induction in construction workers, finding that high physical fatigue accelerates mental fatigue onset. Wearable EEG monitored tasks involving manual handling and mental fatigue induction through picture identification tasks. Fan *et al.* (2020) studied EEG and ECG responses to varying task difficulty levels in visual monitoring tasks, developing a model that correlates task complexity with mental workload indicators like reaction times and accuracy. Argyle *et al.* (2021) studied the effects of task demand, fatigue and attention degradation on physiological responses such as heart rate, breathing rate, nose temperature and hemodynamic activity in the prefrontal cortex and middle temporal gyrus. They found that fatigue significantly influenced heart rate, breathing rate and hemodynamic response compared to baseline during a visual search task. However, task demand only showed slight effects on breathing rate and nose temperature, with no significant impact on heart rate or hemodynamic response. Tang *et al.* (2021) explored the precision of mental workload classification using Riemannian log map of spatial covariance combined with event-related potentials (ERPs) from a single-stimulus paradigm. Participants controlled a drone in a flight simulator, adjusting mental workload levels by varying simulator difficulty. Dehais *et al.* (2019) investigated the use of a portable EEG system with six dry electrodes to estimate pilot workload during real flight conditions. They observed decreased P300 amplitude as task difficulty increased, suggesting reduced auditory processing capacity during critical flight phases. Statistical analyses included a 3-way repeated measure ANOVA for ERPs with factors load (Low, High), Type of sound (Frequent, Target) and Electrodes (Fz, Cz, Pz, P3, P4, Oz) and a 2-way ANOVA for spectral band powers across delta, theta, alpha and beta bands at electrodes Fz, Cz, Pz, P3, P4 and Oz. EEGlab bootstrap test (10,000 iterations) was employed, offering robustness without assuming normal distribution or homoscedasticity.

Table 1: Describes the information of mental workload assessment in psychology

References	Country	Simulation Section	Participants	Type of Measurement	Type of EEG Device
Guan *et al*. (2022)	China	N-Back	16	EEG	NeuroScan system
Drouin-Picaro *et al*. (2017)	Canada	Mental Rotation, N-Back, Visual Search	16	EEG, ECG	The Muse (InteraXon, Canada)
Liu *et al*. (2017)	USA	N-Back	21	EEG EOG	Neuroscan Nuamp
Hebbar *et al*. (2021)	India	Auditory N-back, Visual N-back, Auditory Arithmetic Test	33	EEG	Emotive Inc
Radüntz (2017)	Germany	Back, Sternberg, Stroop, AOSPAN	54	EEG	EMOTIV EPOC+
Liu *et al*. (2017)	USA	N-Back	13	EEG	Neuroscan Nuamp
Samima and Sarma (2023)	India	N-Back	10	EEG	Ag/AgCl, RMS, India
Mun *et al*. (2017)	Korea	N-Back	16	EEG	BIOPAC Systems Inc
Sadeghian *et al*. (2022)	Iran	N-Back	120	EEG	Portable g-Tec Signal
Pergher *et al*. (2019)	Belgium	N-Back	38	EEG	SynAmpsRT device
Dimitrakopoulos *et al*. (2017)	Singapore	N-Back	20	EEG	ANT waveguard system
Aghajani *et al*. (2017)	USA	N-Back	17	EEG	Bio-Signal Group Inc. (Brooklyn, New York)
Kutafina *et al*. (2021)	Germany/Poland	Fixed-base, Go/No-go task	23	EEG	EMOTIV Inc.
Zhang *et al*. (2019)	China	Spatial N-back, Arithmetic Tasks		EEG	SYMTOP Instrument Co. Ltd.

Gu *et al*., 2022; Roca-González *et al*., 2024 developed a theoretical framework linking mental schema evolution and cognitive workload using EEG metrics. Their research employed a simulated UAV flight task and demonstrated that highlighted changes in frontal theta, parietal alpha and central beta power spectral

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density corresponding to varying mental workload stages. Statistical analysis was performed using MATLAB R2018b with EEGLAB 2020, validated in RStudio (version 1.4). A two-way repeated-measures ANOVA analyzed frontal theta, parietal alpha, central beta PSD, subjective and behavioral data, with Geisser-Greenhouse corrections for sphericity violations. Paired t-tests with Bonferroni corrections identified the main effects. Li *et al.* (2023) proposed a methodology to analyze neurophysiological patterns related to Situation Awareness (SA) and detect instances of SA loss in air traffic control operators (ATCOs) under different workload conditions. Their findings underscored distinct neurophysiological responses during normal and high workload scenarios.

Plechawska-Wójcik *et al.* (2019) utilized machine learning and EEG features to estimate cognitive workload during arithmetic tasks. They identified significant correlations between workload levels and Beta wave power across central and parietal brain regions. Statistical analysis was performed using Statistica 13, Matlab and R, with a significance level of 5%. A repeated-measures ANOVA analyzed 285 EEG features across 19 electrodes, 5 frequencies and 3 cognitive workload levels in 11 subjects. Spearman correlation coefficients determined relationships between EEG features and cognitive workload, revealing significant effects for workload, location and frequency. Post hoc tests confirmed stronger EEG wave power during cognitive tasks than relaxation. Bagheri and Power (2020) investigated the impact of mental workload and stress on EEG-based detection accuracy. Their findings emphasized reduced classification performance when training and testing data differed in workload and stress levels. Wang *et al.* (2019) explored the use of facial infrared thermography to detect mental workload during cognitive tasks. They identified moderate correlations between facial skin temperature and mental workload, varying across facial regions. This study used facial skin temperature and random forest classifiers to predict mental workload across six facial regions, optimizing hyper-parameters via grid search and assessing performance with leave-one-out cross-validation. Results showed prediction accuracies of 45% ± 9% (slightly cool), 57% ± 9% (neutral) and 44% ± 9% (slightly warm), indicating moderate accuracy compared to EEG-measured workload. Discussion noted challenges like short tasks, small datasets and task variability influencing facial thermography. Future work should focus on extending task durations, increasing task difficulty and improving camera capabilities for more reliable predictions. Kosti *et al.* (2018) examined the potential of mobile EEG scanners to monitor mental workload in programmers during task performance. Results suggested applications in improving training and performance in software development. Wu *et al.* (2021) investigated how design principles of online courses affect mental workload using physiological measures and machine learning techniques. Their findings highlighted the role of multimodal physiological features in accurately classifying workload induced by different course designs. Andreessen *et al.* (2021) explored a passive brain-computer interface's ability to predict mental workload based on EEG signals during tasks of varying difficulty and presentation speeds. Their study suggested promising applications for personalized user models. So *et al.* (2017) investigated frontal theta activity as a potential biomarker for mental workload using a mobile EEG system across multiple cognitive tasks. Findings suggested this is a consistent indicator of workload across different task types.

To summarize, the application of EEG and psychophysiological measures in psychology spans various methodologies to assess cognitive workload. Studies utilize EEG signals for tasks like visual cognitive workload classification, cross-task performance analysis and ERP exploration during locomotion tasks. These approaches underscore EEG's versatility in capturing workload variations across diverse psychological tasks, enhancing understanding and measurement precision in cognitive workload assessment across different conditions and applications.

Application of Mental Workload in Healthcare

Wang *et al.* (2019) investigated assessing cognitive and behavioral states in surgical trainees during robotic surgeon training using the da Vinci Skill Simulator. Results indicated that monitoring cognitive states during training could enhance surgical performance and reduce errors during surgeries. Watson *et al.* (2019) explored the effects of acute consumption of blackcurrant juice on mood and attention using EEG. They found that polyphenols in the juice modulated prefrontal cortex activity in young adults, influencing cognitive performance. Murugesan *et al.* (2022) assessed mental workload in depressive disorder patients using single-channel EEG during visual-motor tasks. Their findings highlighted differences in frontal brain activity related to task complexity and perceived difficulty in patients. Shafiei *et al.* (2020) developed an EEG-based method to objectively evaluate mental workload during Robot-assisted Surgery (RAS) training. Their model outperformed traditional methods, offering a more accurate assessment of workload for surgical trainees.

Morales *et al.* (2019) studied prefrontal beta power as an indicator of surgical workload complexity in laparoscopic surgery. Their research underscored the utility of EEG in assessing cognitive demands during surgical procedures. Liu *et al.* (2020) investigated EEG markers for Visually Induced Motion Sickness (VIMS) using a driving simulator. Their findings suggested varying susceptibility to VIMS among individuals, emphasizing the need for personalized assessment approaches. Blackburn *et al.* (2018) used a quantitative EEG method to detect abnormalities in Alzheimer's

Disease (AD) patients. Their study revealed significant differences in brain synchronization patterns between AD patients and healthy controls, particularly during different states of rest. Kutafina *et al.* (2021) examined mobile EEG's ability to track mental workload during cognitive tasks. They demonstrated its effectiveness in distinguishing workload levels and capturing task-induced variations in EEG data, suggesting its potential for evaluating cognitive training interventions. The application of EEG in healthcare reveals its diverse utility in assessing mental workload across clinical contexts. Studies highlight EEG's effectiveness in enhancing surgical training by monitoring cognitive states and performance during robotic surgery simulations. Additionally, EEG proves valuable in evaluating mental workload in depressive disorder patients and assessing cognitive demands during laparoscopic surgery, underscoring its potential for personalized healthcare interventions and diagnostic applications in conditions like Alzheimer's Disease and Visually Induced Motion Sickness.

Application of Mental Workload in Aviation and Transportation

Liu *et al.* (2020) compared physiological signals and vibration artifacts in response to task difficulty using the NRC Bell 205 helicopter's fly-by-wire system. ECG-based regressors showed stronger correlations with task parameters, suggesting ECG as a reliable indicator of physiological response. Abd Rahman *et al.* (2020) developed a system to monitor ental workload in aging drivers during real road conditions. EEG data revealed significant changes in theta and alpha activity, indicating workload variations with driving complexity. The study used repeated measures ANOVA to analyze EEG and driving performance across different complexities. Pearson correlation explored relationships between NASA-TLX scores, EEG and Overall Driving Performance Scores (ODPS). Multiple linear regression predicted ODPS from NASA-TLX and EEG, revealing workload effects on aging drivers' performance. Fan *et al.* (2018) used a driving simulator to study mental workload in individuals with Autism Spectrum Disorder (ASD). EEG data highlighted power features as effective indicators of engagement during driving tasks. Di Di Flumeri *et al.* (2019) assessed mental workload in car drivers using EEG, demonstrating real-time workload measurement feasibility for adaptive automation systems. Choe *et al.* (2016) explored transcranial Direct Current Stimulation (tDCS) effects on flight simulator training, emphasizing timing's role in enhancing learning and performance. Yang *et al.* (2020) studied the impact of directional road signs on driver workload using a driving simulation system, revealing differential effects based on sign complexity. Liu *et al.* (2020) developed an EEG-based evaluation system for seafarers in maritime simulators, showing varied performance outcomes based on EEG assessments. Wanyan *et al.* (2018) investigated mental workload's effects on pilots' information processing using flight simulator data, highlighting changes in pre-attentive processing and blink rates.

Jaquess *et al.* (2018) monitored cortical dynamics during flight simulator tasks, observing changes in mental workload indicators with task practice. Orlandi and Brooks (2018) analyzed ship handling maneuvers' effects on mental workload and physiological responses in marine pilots using simulators. Cui *et al.* (2021) evaluated pilot competency using EEG signals during flight simulations with abnormal events, demonstrating EEG's potential in assessing pilot performance. Scholl *et al.* (2016) investigated PIO detection using EEG during flight maneuvers, highlighting EEG's role in identifying critical pilot-induced oscillations. This study used Cognionics dry electrode sensor data filtered between 1-50 Hz and down-sampled to 250 Hz for PIO classification using HDCA. Spectral power features in ten frequency bins were analyzed, with Fisher Linear Discriminant classifiers determining spatial electrode weights. Training and testing trials were balanced, yielding PIO classification Az of 0.70 and prePIO Az of 0.69. Artifact Subspace Reconstruction (ASR) improved PIO classification to Az of 0.79, with minimal score variation across ASR thresholds (0.79-0.80). Tables (2-3) summarize research findings on mental workload assessments in aviation and transportation contexts. The application of EEG to aviation and transportation tasks suggests it can be used to assess mental workload across diverse operational scenarios. Studies reveal EEG's efficacy in monitoring pilot and driver performance, detecting workload variations during flight maneuvers and driving tasks. EEG data analysis, including spectral power features and regression models, proves instrumental in evaluating cognitive engagement and performance outcomes in real-time settings such as flight simulators and driving simulations. These findings underscore EEG's potential for enhancing safety and efficiency in aviation and transportation through tailored workload management strategies and adaptive automation systems.

Application of Mental Workload in Military and Defense

Diaz-Piedra *et al.* (2020) investigated the impact of diverse road environments on mental workload among Spanish Army drivers during combat and non-combat scenarios using a sophisticated military LMV driving simulator. EEG recordings were used to objectively measure variations in mental workload during real training and operational settings. Findings underscored the utility of EEG in discerning workload fluctuations, even in high-stress situations such as combat scenarios. Mohanavelu *et al.* (2020) analyzed the dynamic workload of fighter pilots across various conditions using a high-fidelity flight simulator. Their study encompassed normal and low visibility scenarios with

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and without secondary tasks during take-off, cruise and landing maneuvers. Results indicated that heightened workload detrimentally affected pilot performance across all flight phases, with an observable increase in sympathetic nervous system activity under demanding cognitive tasks. The study used non-parametric tests (Friedman and Wilcoxon signed-rank) to analyze HRV features across flight segments and workload conditions, due to non-normal distributions. Significant differences were found, highlighting distinct HRV patterns and performance challenges during critical flight phases, particularly in high workload conditions such as take-off and landing. Wu *et al.* (2022) developed an adversarial Bayesian deep network to detect pilot fatigue based on EEG signals collected during military flight simulations. Employing a 6-degree-of-freedom full flight simulator, they achieved significant accuracy in cognitive state detection, enhancing their method's performance through data augmentation and brain power map analysis. The application of EEG in military and defense settings demonstrates its critical role in monitoring and managing mental workload under high-stress conditions. Studies employing EEG to assess Army drivers and fighter pilots reveal its effectiveness in detecting workload variations during combat simulations and flight maneuvers. EEG-based methodologies offer real-time insights into cognitive states, enhancing operational readiness and performance assessment in dynamic military environments. These findings underscore EEG's potential as a valuable tool for mitigating fatigue, optimizing decision-making and improving mission outcomes in military and defense applications.

Table 2: Information of Mental Workload Assessments in Aviation

References	Country	Simulation Section	Participants	Type of Measurement	Type of EEG Device
Wu *et al*. (2022)	China	C919/military simulators		EEG, Eye-tracking	BCI200 system
Aricò *et al*. (2016)	Italy	ATM scenario	12	EEG	BioSemi ActiveTwo
Izadi Laybidi *et al*. (2022)	Iran	N-Back	20	EEG	Mind Media Nexus-10 MKII system
Zanetti *et al*. (2022)	Switzerland, Sweden	simulated search with drones and rescue	24	EEG	Emotiv EPOC
Jaquess *et al*. (2018)	USA	Control an airplane (Beechcraft T-6 Texan II)	36	EEG	Brain Products GmbH
Hernández-Sabaté *et al*. (2022)	Spain	N-Back, flight scenario in A320 simulator	20	EEG	EMOTIV EPOC+
Diaz-Piedra *et al*. (2019)	Spain	High-fidelity fixed-base Armed Reconnaissance Helicopter Simulator	15	EEG, Eye-tracking	SOMNOwatch+EEG-6 (Somnomedics, Germany)
Guan *et al*. (2022)	Australia, USA	MATB	29	EEG, EOG, Eye-tracking	ActiCAP Xpress
Qu *et al*. (2020)	China	MATB-II	10	EEG	Neuroscan Neuamps
Verdière *et al*. (2019)	France	MATB-II	20	EEG	BioSemi ActiveTwo
Causse *et al*. (2015)	Canada	Armchair and Computer	15	EEG, ERP, EOG	ctiveTwo BioSemi System
Lee *et al*. (2020)	Korea	Cessna 172 aircraft	7	EEG, EOG	BrainAmp

Table 3: Information on Mental workload assessments in Transportation

References	Country	Simulation Section	Participants	Type of Measurement	Type of EEG Device
Di Flumeri *et al*. (2019)	Italy	Real Driving a Fiat 500L	8	EEG	BEmicro system
Diaz-Piedra *et al*. (2020)	Spain	Combat Military LMV Driving Simulator	41	EEG	SOMNOwatch
Abd Rahman *et al*. (2020)	Malaysia	Sedan Car Driving	20	EEG, EOG	BIOPAC EEG100C
Yang *et al*. (2020)	China, USA, Canada	riving simulation system (DSR-1000TS2.0)	32	EEG	-----
Low *et al*. (2021)	Australia	Logitech G25 Racing Simulator	45	EEG	Advanced Brain Monitoring (ABM Inc.)
Liu *et al*. (2020)	China	Wide Field Driving Simulator (DE-1500, FAAC Inc.)	8	EEG	The MuseTM (InteraXon Inc.)
Fan *et al*. (2018)	USA	Virtual Driving Environment	20	EEG	Emotiv EPOC

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EEG-Based Mental Workload Study Design

Experiment Design for an EEG-based Mental Workload Assessment Study Scientific inquiry in brain-based studies begins with a research question, such as identifying EEG bands associated with depression or stress. This drives the formulation of a research hypothesis, describing how specific conditions may influence measured outcomes. EEG research demands substantial resources equipment, time and human effort including participants and research assistants. Participant sample size and trial counts effect size and trial requirements. Moreover, rigorous experimental design is crucial to mitigate unwanted artifacts in raw EEG data, ensuring the reliability and interpretability of study outcomes. Researchers must plan every aspect, from participant recruitment to data analysis, accounting for potential risks, confounders and resource constraints (Malik and Amin, 2017).

Real-Time vs. Controlled Experiment Design

Real-time analysis involves immediate problem-solving with limited resources, allowing for adaptation to evolving conditions, such as routine analysis, control and nondestructive evaluation/parameter estimation (Yondo *et al.*, 2018). In contrast, controlled experiments, derived from psychology research methods, are crucial in Human-Computer Interaction (HCI) studies. The HCI serves a crucial role in human-computer-environment systems, facilitating efficient task completion with features like simplicity, ease of operation and low cognitive load. Therefore, ensuring the scientific rigor and validity of evaluation processes has become a critical concern in contemporary HCI research (Song *et al.*, 2023)

Experimental Designs for Mental Workload Studies

Tasks like mental arithmetic and the n-back task are effective in manipulating cognitive workload levels reliably. The n-back task assesses working memory by requiring participants to recall whether current stimuli match those seen n steps earlier. Variants like the 0-back task serve as baselines, while higher n-back levels increase workload demands (Kane *et al.*, 2007; Brouwer *et al.*, 2012; Walter *et al.*, 2013; Baldwin and Penaranda, 2012). Mental arithmetic tasks, involving solving arithmetic problems under time constraints without external aids, also correlate closely with working memory performance (Wang and Sourina, 2013; Hwang *et al.*, 2014). The Stroop color-naming task, a classic in attention research, illustrates how word meanings interfere with identifying ink colors. It probes the brain's ability to manage conflicting stimuli, contributing significantly to theoretical models of attention and cognitive control (Stroop, 1935; Cohen *et al.*, 1990; MacLeod, 1991; Sharma and McKenna, 2001). Cognitive control involves directing attention, memory retention and response selection to achieve goals, as seen in studies on response inhibition and error correction (Rietschel *et al.*, 2014; Bustamante *et al.*, 2021; Miller and Cohen, 2001; Schumacher *et al.*, 2003; Wager *et al.*, 2005; Goghari and MacDonald, 2009). The Sternberg task evaluates working memory capacity by presenting sequences of digits for memorization and subsequent retrieval. Dual-task paradigms, involving simultaneous performance of primary and secondary tasks, assess cognitive load and resource allocation during learning processes (Sternberg, 1966; Whitney and Hinson, 2010; Klabes *et al.*, 2021; Esmaeili Bijarsari, 2021). Such designs illuminate how cognitive processes manage multiple tasks and allocate attention resources effectively (Brünken *et al.*, 2002; Klepsch *et al.*, 2017; Park and Brünken, 2015; Sun and Shea, 2016).

Conclusion

This review emphasizes the critical impact of mental workload (MWL) on task performance, particularly in complex operational environments such as piloting aircraft and maritime vessels. Several methods, including EEG, eye-tracking and subjective evaluations, have been explored for MWL assessment, highlighting their potential and associated challenges. Future research should prioritize less intrusive technologies and standardized methodologies to improve the accuracy and applicability of cognitive workload assessments.

Advancements in EEG technology and machine learning have significantly enhanced the granularity and reliability of cognitive workload assessments. However, challenges persist, including variability in signal interpretation and the integration of multimodal data sources. Addressing these challenges is essential for advancing the field and developing effective tools to optimize human performance and safety across diverse domains.

Implications for Research and Practice

A multimodal approach integrating physiological, subjective and performance-based measures is crucial for comprehensive cognitive workload assessment. Standardizing protocols and leveraging technological advancements, such as machine learning and AI, can enhance assessment accuracy and enable real-time interventions. Future research should expand into diverse application domains and conduct longitudinal studies to validate findings and enhance generalizability.

Future Research Directions

1. Standardization of Protocols: Develop and implement standardized protocols for physiological measurements and data analysis to improve comparability and reproducibility
2. Integration of Multi-Modal Measures: Investigate the integrated use of physiological, subjective and

performance based measures for holistic workload assessment
3. Advancements in Technology: Utilize machine learning and AI to develop adaptive systems for real-time workload assessment
4. Application to Diverse Domains: Extend research to diverse operational settings to broaden applicability
5. Longitudinal Studies: Conduct longitudinal studies to understand the long-term effects of cognitive workload on performance and well-being

Limitations

While this review provides valuable insights, differences in experimental methodologies and rapid technological advancements pose challenges. Continuous updates and rigorous synthesis of literature are necessary to keep pace with evolving methodologies and technologies.

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Author's Contributions

Negin Ozve Aminian: Conceived the idea for the review on mental workload, led the selection and synthesis of relevant literature, and was responsible for drafting and critically revising the manuscript.

William Michael: Contributed to the analytical interpretation of the literature, enhanced the theoreti-cal framing of the manuscript, and supported the refinement of the structure and clarity.

Mehdi Ghoreyshi: Conducted an in-depth literature search on mental workload assessment methods, organized and managed references, and contributed to writing specific sections, including methodology and assessment tools.

Ethics

This article is a review of previously published work and does not involve human participants or animal studies. Therefore, ethical approval was not required.gy and assessment tools.

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