# Mental Workload: A Review of the Definition and Measurement

**Abstract.** The assessment of mental workload (MWL) is pivotal for understanding human performance limitations, optimizing task design, and enhancing overall system efficiency and safety across various domains, including aviation, healthcare, and technology interfaces. However, reaching agreement on its definition, whether in technical or philosophical terms, is highly challenging. This paper aims to critically examine the theories of MWL and offer a conceptual and operational definition for future researcher in the field. This paper also provides a review of the MWL measurement by exploring the progress made in measuring MWL, including the development of novel techniques. We searched literatures from scientific database covering the topic of limited and multiple resource theories, along with the measurement of MWL, covering the topics of performance, psychophysiological, and subjective techniques. A narrative review was applied to appraise the literature, particularly using theoretical integrative reviews (TIR) approach. Based on our review, MWL definition consists of four elements: cognitive processing, task demand, performance and physiological changes, and subjective experience. Furthermore, our review provides a framework for measuring mental workload that encompasses the interplay between performance and psychological changes, demands, and subjective measures. Several theoretical and practical issues regarding the measurement approach are also discussed.

*Keywords:* Mental workload; Limited resource theory; Multiple resource theory; Definition; Measurement

## 1. Introduction

Mental workload (MWL) has been a concern in many modern work environments as automated jobs has replaced physical demand with mental demand (Young et al., 2015). It has a significant contribution to mental fatigue by increased workload (Nealley and Gawron, 2015) or prolonged time-on-task (Zhang et al., 2017). Furthermore, the relation between MWL and fatigue is complex, where these two constructs can influence each other in a feedback loop. Increased mental workload can lead to increased mental fatigue (Fallahi et al., 2016b), while increased fatigue can affect MWL (Fan and Smith, 2020). The most notable consequence of suboptimal workload and fatigue is performance and safety deterioration (Jalali et al., 2023). When such performance is not maintained at an acceptable level, it poses a risk, particularly to individuals employed in safety-critical positions. The primary objective of measuring MWL is therefore to quantify the mental cost associated with task completion in order to anticipate the responses of operators and systems (Longo et al., 2022).

However, the idea of MWL is often criticized due to its inherent complexity and subjective nature. Critics argue that establishing a universal definition of MWL is difficult due to its complex nature, which includes cognitive, emotional, and physiological elements (Young et al., 2015). In numerous studies, MWL is frequently defined in operational terms as the cognitive demands or effort encountered during tasks (Mohammadian et al., 2022; Piranveyseh et al., 2022; Safari et al., 2024, 2024), with additional variables of interest such as emotional/psychological aspect (López-López et al., 2018; Piranveyseh et al., 2022) or individual factors (Nino et al., 2023; Van Acker et al., 2018). This diversity in definitions arises from varied research objectives, and it has consequences on the way the concept is measured. Due to its subjective nature of cognitive demands, most of MWL studies utilise subjective measurements, such as NASA-TLX (Galy et al., 2018; Mohammadian et al., 2022; Safari et al., 2024). In addition, behavioural measurement is also employed in most studies due to the presumed connection between cognitive demands and performance (Fallahi et al., 2016b; Lobjois et al., 2021; Zakeri et al., 2023), and to minimise potential bias and poor reliability arising from subjective measurements (Fista et al., 2019). Furthermore, recent studies in MWL have included physiological changes as indicators for MWL changes using various sensors, such as electroencephalogram/EEG (Aghajani et al., 2017; Ahn et al., 2016; Cabañero et al., 2019), functional near-infrared spectroscopy/fNIRS (Aghajani et al., 2017; Foy et al., 2016; Verdière et al., 2018), electrocardiogram/ECG (Ahn et al., 2019; Mansikka et al., 2016; Tjolleng et al., 2017), or eye-tracker (Appel et al., 2018; Rodemer et al., 2023; Zhang et al., 2017). The interplay between cognitive activation and physiological responses from the autonomous nervous system facilitates this measurement (Ben Mrad et al., 2021; Eckstein et al., 2017). These show that both conceptual and operational definition of MWL vary among researchers.

The authors propose that the diverse measurement techniques for MWL fundamentally seek to quantify cognitive demands by including multiple dimensions for its measurement. Nonetheless, existing framework in the literature inadequately encompass these dimensions. The unavailability of universal MWL definition may lead to a dilemma. It may generate flexibility in applying and measuring the concept in various work environments, however, it can also create confusion and unclarity of the concept. Past reviews have attempted to clarify the concept definition, but they are either limited to a certain field (Pearson et al., 2006) or they concentrate on a singular facet of MWL measurement (Charles and Nixon, 2019). This paper therefore aims to review the concept of MWL more comprehensively and provide theoretical framework for future researcher in the field. By articulating a comprehensive definition of mental workload, one can facilitate the development of more efficient methodologies for the management of workload, in addition to the establishment of standardised measurement and conceptual frameworks.

## 2. Methodology

A paper review would often employ systematic literature review (SLR), which relies on a systematic approach to identify, evaluate, and integrate evidence from prior investigations to address a precisely articulated and focused inquiry. In this review, however, a narrative review approach was deemed more suitable. Unlike the SLR method, the narrative review can better describe information in a more qualitative manner (Bui and Deakin, 2021). The theoretical integrative reviews (TIR) (Sukhera, 2022), a technique within the narrative review approach, was employed in this investigation. Theoretical integrative reviews (TIRs) function as an essential approach for the synthesis and advancement of theoretical constructs pertinent to phenomena. In contrast to conventional literature reviews, TIRs incorporate an array of theoretical perspectives, fostering a discourse that has the potential to enhance established theories or to engender the development of novel theoretical frameworks (Battistone et al., 2023).

As the first step, we identified two foundational theories that arguably form the basis of the mental workload construct: Limited Resource Theory (LRT) and Multiple Resource Theory (MRT). This is attributable to the fact that both theoretical frameworks concentrate on comprehending the mechanisms by which cognitive resources are distributed and regulated throughout the execution of tasks (Chen et al., 2018; Pei et al., 2023). A systematic search of the literature was then conducted in Science Direct database, covering publications from conception to 2023. Search terms included (1) “limited resource theory” AND "mental workload"; (2) “multiple resource theory” AND "mental workload"; (3)

”performance measurement" AND "mental workload"; (4) “subjective measurement” AND "mental workload"; and (5) “psychophysiological measurement” AND "mental workload”.

The next phase encompassed a detailed analysis of the manuscripts that conform to the inclusion criteria. To be included in the review, sources had to meet the following criteria: (1) peer-reviewed articles, proceedings, textbooks, or book chapters, (2) publications in English, (3) publications supporting theoretical concept in relation to limited or multiple resource of MWL, and (4) publications discussing about the measurement of MWL. The final step of this search strategy was to review abstract and articles to ensure that they align with our objective. It is important to note that, with narrative review, it is not necessary to encompass all publications pertaining to a subject (Demiris et al., 2019). The synthesis approach employed thematic analysis grounded in the following themes: LRT and MRT as the fundamental theories along with the relevant measurement methodologies. The summary of the search is shown in Table 1.

Table 1. Search strings and results

| No. | Search string | Initial results | Inclusion criteria fulfilled | Abstract and article screened |
|---|---|---|---|---|
| 1 | "limited resource theory" AND "mental workload" | 1 | 1 | 1 |
| 2 | "multiple resource theory" AND "mental workload" | 93 | 93 | 37 |
| 3 | "performance measurement" AND "mental workload" | 138 | 130 | 26 |
| 4 | "subjective measurement" AND "mental workload" | 129 | 125 | 21 |
| 5 | "psychophysiological measurement" AND "mental workload" | 48 | 45 | 25 |

## 3. Results

### *3.1. Limited Resource Theory (LRT)*

The underlying assumption behind LRT is that all cognitive tasks compete for the single central attentional resource. Primarily focused on comprehending attention, the theory may also be expanded to encompass the knowledge of MWL. Kahneman (1973) suggested that when presented with several stimuli, the core attentional resource is required to handle the demands, leading the operator to make strategic choices and allocate attentional capacity accordingly. The theory considers the level of demand generated by the task at hand or stimuli, including mental rehearsing, timed activities, mental arithmetic, or activities that require the use of working memory (Oberauer, 2019). These tasks can place certain level of demands on attentional resource, which has limited resource capacity. Furthermore, human operators could regulate the distribution of the resources, that is, the strategies to allocate the limited capacity of attentional resources. Wickens et al. (2012) asserted that individuals tend to prefer heuristic-based methods that provide satisfactory results requiring little effort. Moreover, individual preferences influence the demands placed on resources, particularly in terms of perceived acceptable degree of effort and performance. The allocation approach may include task complexity, as it is linked to the perceived effort expenditure (Pickup et al., 2005).

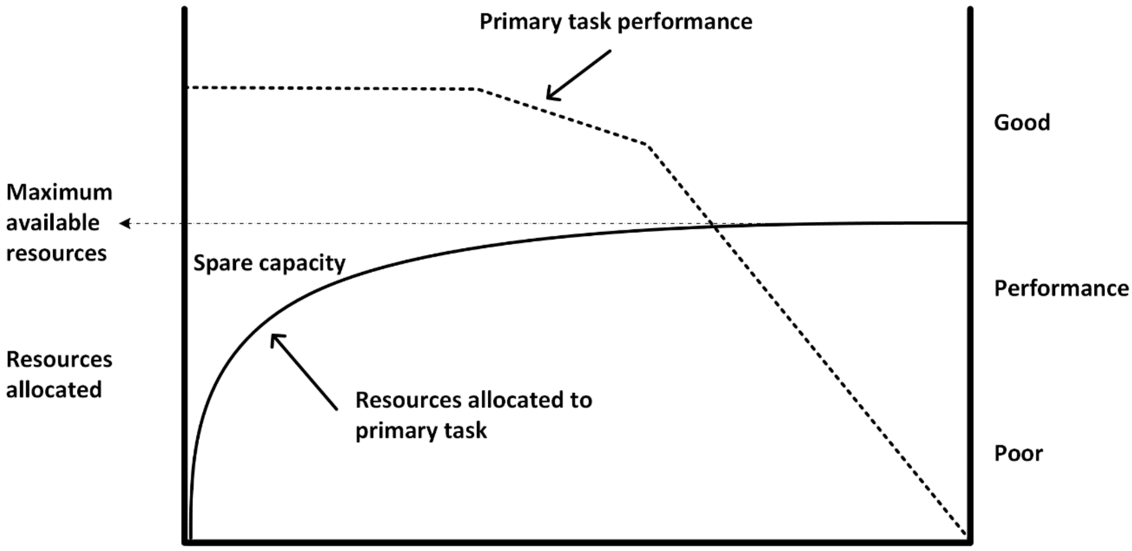


**Figure 1** The graphical representation of LRT

According to this theory, the basic concept of MWL can be viewed as the interaction between demands placed by the task and the information processing resource allocated to the completion of the task. The more resource allocated to complete the task, the higher the MWL will be. Figure 1 shows a visual depiction of the LRT (Wickens et al., 2012). As depicted in Figure 1, the left vertical axis reflects the number of resources used to complete the task and the maximum quantity of resources available. Meanwhile, the performance in the primary task is shown as a dashed line on the right vertical axis. The left portion of the image exhibits acceptable task performance due to a surplus of resources exceeding the demands of the task. This region also contains spare capacity or attentional resources. The MWL is negatively correlated with the amount of available spare resource capacity in this area, indicating situations where task demands are minimal. The right portion of the image depicts a region where the available resources are not enough to meet the requirements of the task, since the maximum resource capacity has been achieved. This is a domain characterized by high demands, where performance of primary task and MWL exhibit an inverse relationship. Therefore, in this area, a measure of primary task performance can determine the MWL level.

*3.2. Multiple Resource Theory (MRT)*

In contrast to the LRT, the primary proposition of MRT is that a person possesses various or distinct resources for processing information. The idea was not specifically formulated for the purpose of addressing MWL. However, it may be employed to comprehend MWL by examining how individuals perform many activities, especially in terms of their capacity to allocate time (Wickens et al., 2012). At first, there were three distinct stages related to information processing. These stages described the various phases of cognitive processing, the process of encoding information, and the diverse ways in which information is received. Later, the model was expanded to include the fourth element, which is the visual channel. Figure 2 depicts the 'cube' that represents the model.

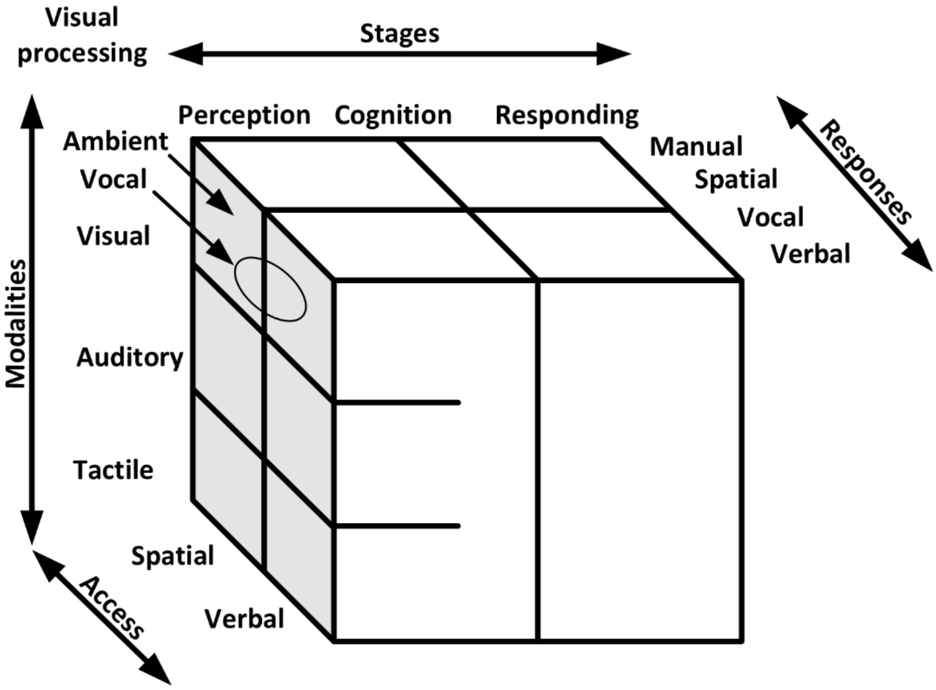


**Figure 2** The graphical representation of MRT

As posited by this theory, information processing occurs in three distinct phases. Cognitive and perceptual activities are two distinct types of mental processes. Perceptual activities, such as visual search, are often less difficult than cognitive activities that include intricate tasks such as decision-making. However, both types of activities need the use of working memory and rely on a shared resource for processing information (Oberauer, 2019). Another component is the utilization of its resources for processing information in selection and response tasks, such as speech production (Serences et al., 2009). The separation of resources has an impact on performance (Grinschgl et al., 2023). Specifically, if two activities differ in their processing phases (perceptual-cognitive versus response/selection), the performance of both tasks will not decline simultaneously. However, the performance of dual activities that involve separate phases but rely on the same perceptual and cognitive resources may be negatively impacted by interference. Engaging in a phone call while driving can impair performance since both activities need the same mental and sensory resources (Horrey and Wickens, 2006).

When it comes to processing encoding, MRT model delineates a distinction between analogue-spatial and categorical-symbolic processing, namely in the domains of language or verbal communication. According to the theory, spatial and linguistic processes, also known as codes, depend on distinct resources when they are utilized in the stages of perceiving, thinking, or responding during information processing. Driving (spatial) and listening to an unfamiliar voices (verbal) simultaneously might be challenging due to the distinct processing codes involved in spatial and linguistic tasks (Rann and Almor, 2022).

Another crucial aspect of this model is the variation of perceptual modalities, which refers to the way our sensory organs receive information. The two predominant modalities of task presentation are visual (the eyes) and auditory (the ears). According to this model, allocating attentional resource to both visual and auditory modalities lead to superior performance compared to allocating attention to either auditory or visual modalities (Atkin et al., 2023). This might be attributed to the fact that tasks utilising identical modalities would deplete the resource more rapidly compared to activities that utilise distinct modalities. Using a navigation device (visual) while driving (visual) would have a greater negative impact on driving performance compared to listening to the radio (auditory). However, in addition to visual and auditory senses, the sense of touch, or tactile perception, is also being recognized as additional pathway for gathering sensory information (Scott and Gray, 2008). Stick-shakers in contemporary aircraft cockpits, which alert pilots to stall situations, exemplify this aspect of the theory.

The last aspect of this theory pertains to the different forms of visual processing: focused and ambient. Focal vision is responsible for seeing tiny details, such as reading text. On the other hand, ambient vision mostly includes peripheral vision and is used for sensing direction. The example of this aspect is a driver maintaining the vehicle's position on the correct lane (ambient) while simultaneously comprehending a traffic sign (focal). The utilization of distinct resources within the visual modality channel enhances the probability of successful completion of these tasks (Lenneman and Backs, 2018).

### *3.3. Measurement Techniques*

#### 3.3.1. Performance techniques

Performance or empirical approaches aim to comprehend MWL by immersing an operator in an actual task. By imposing task, demand will be placed in operator's cognitive processing system. There are two distinct techniques under this category: primary and secondary task evaluations. Primary task measurements are derived from the direct evaluation of variables that are associated with the main task. For example, one way to measure an aircraft pilot's MWL is by evaluating their proficiency in controlling the airplane during flight, utilizing pertinent indications such as altitude, speed, and horizontal position. The core concept of the main task measurement approach may be summarized as follows: when the difficulty of the task increases (such as flying into adverse weather conditions), the performance indicators will diverge farther from their desired objective. Therefore, MWL may be deduced from these objective indices, meaning that a greater divergence from the ideal aim may suggest a larger MWL. A potential drawback of primary task approaches is that performance may not decline even as demands grow if the demands remain within the operator's total resource capacity (Young et al., 2015).

To address the problem, the secondary task strategy is employed. The fundamental principle of the secondary task strategy is to provide a task that can compete the primary task for the same attentional resources. The measurements obtained from the secondary task have the potential to be utilized to ascertain the level of MWL generated by the primary task. In this scenario, the secondary task might serve as a proxy for the remaining spare resource capacity of the primary task. Hence, if the primary task demand increases, spare capacity will diminish, leading to a decline in performance in the secondary task (Hart and Staveland, 1988). For instance, drivers must prioritize the main objective of driving, such as staying in their lane, even when they are requested to configure a satellite navigation system (satnav) if it is feasible. The variability in the precision of establishing a satnav, for example, might serve as an indicator of the MWL needed for the main driving task. However, the key issue with secondary tasks is the lack of experimental control over the allocation of attentional capacity to them, resulting in their interference with the primary task that is being used to evaluate workload.

#### 3.3.2. Subjective techniques

As previously stated, the experience of operator MWL is highly subjective. Consequently, the assessment of MWL frequently involves inquiring about the subjective experience of operators during or after task completion. The NASA Task Load Index (NASA-

TLX) (Hart, 2006; Hart and Staveland, 1988), is a highly used measure for measuring MWL. Many studies have utilized the NASA-TLX to assess the amount of operator workload associated with specific tasks. This instrument is commonly used to identify the level of MWL in a preliminary investigation (Fairclough et al., 2005; Hsu et al., 2015) or to serve as a main measure for a dependent variable (Takae et al., 2010). Other popular subjective scales of MWL includes The Subjective Workload Assessment Technique (SWAT) (Reid and Nygren, 1988) or Workload Profile (Tsang and Velazquez, 1996).

These subjective scales are typically administered after the completion of the task. Although it is possible to administer during the completion of the task, it appears unsuitable because the scale consists of questions that need to be responded, which might potentially disrupt the continuity of the task. The practical alternative for this issue is provided by the Instantaneous Self-Assessment of Workload instrument (ISA) (Brennan, 1992), which appears to be suitable for monitoring subjective MWL changes while completing tasks. The ISA is a method used to promptly evaluate the MWL experienced *during* a task. It was initially designed to measure the workload of air traffic controllers (ATC). The scale's instantaneity makes it less obtrusive and more suitable for real-time evaluation. The scale employs a five-point rating system to assess the perceived workload of the operator, with "1" indicating low workload and "5" indicating high workload. The scale is delivered at different intervals during a task, such as every 45 seconds (Marinescu et al., 2018) or every two minutes (Kirwan et al., 1997).

#### 3.3.3. Psychophysiological techniques

As mentioned earlier, the rationale for the psychophysiological measurement of MWL is clear: an increase in MWL leads to an increase in arousal, which is reflected in the activity of the ANS. The purpose of developing these techniques is to enable the continuous assessment of MWL in actual work settings. Prior to the emergence of psychophysiological measurements, subjective methods, particularly NASA-TLX, have gained widespread popularity as the primary instruments in MWL studies. As stated before, like other subjective methods, NASA-TLX is inherently retrospective, meaning that the tool is used after the task has been completed. Administering it during a task might be challenging due to potential operator distractions. Subjective measuring tools are sometimes impracticable and might compromise safety in operational contexts, such as while driving a car or flying an aircraft.

As a result, psychophysiological measurements appear to be gaining prominence in MWL research. The advancement of more sophisticated and practical measuring instruments has facilitated this tendency. Various prominent psychophysiological indicators have been employed to measure changes in MWL, including heart rate variability from electrocardiography (ECG) signals (Chowdhury et al., 2018; Mansikka et al., 2016; Puspita et al., 2015), brain activation derived from fMRI (Causse et al., 2022), EEG (Dahlstrom et al., 2011; Wanyan et al., 2018; Wilson, 2002), or fNIRS (Ayaz et al., 2012; Causse et al., 2017; Foy et al., 2016; Verdière et al., 2018), eye-gaze behaviour using eye-tracker (Di Nocera et al., 2007; He et al., 2022; Rodemer et al., 2023; Widyanti et al., 2017), and facial thermography (Marinescu et al., 2018). Nevertheless, the performance of these physiological measurements is subject to debate. For example, fNIRS is not sufficiently sensitive for tasks with small demand variations, such as office works or tasks with great number of elements (Argyle et al., 2021). With respect to heart-rate variability parameters, an increase in low frequency (LF) and high frequency (HF) ratio (LF/HF ratio) is commonly considered as indicators of increased MWL (Li et al., 2021), although findings from Tao et al. (2019) demonstrated that decrease in both LF and HF reflects an increase in MWL.

## 4. Discussions

### *4.1. The Conceptual and Operational Definition of MWL*

Based on the two previously reviewed theories, there are four elements that should be included in defining MWL conceptually. The first element concerns to the cognitive ability to process information. It is essential as there is a claim that humans possess a finite amount of resources for the purpose of information processing, from the classical hypothesis of "the magic number seven plus or minus two" (Miller, 1956) to more contemporary hypothesis stating that the number of information piece humans can retain is around three to four (Gilchrist et al., 2008) or five (Halford et al., 2007). Although there is ongoing discussion over the precise quantity of information that may be stored in a person's working memory, these experiments demonstrate that our cognitive processing ability is limited. This restriction is intended to either save energy or facilitate the retrieval of information in the future (Cowan, 2010). Due to its restricted capacity, individuals must choose which information they need to be conscious of to execute certain behaviour effectively. Attention plays a crucial role in the selection of information through three distinct processes: "input selection" guides processing toward particular information, "executive control" oversees ongoing tasks, and "alerting" interrupts ongoing tasks to concentrate on new information (Remington and Loft, 2015). Recent studies also connect cognitive activities with changes in physiological activities. An increase in MWL leads to an increase in arousal, which is reflected in the activity of the autonomous nervous system (ANS). The ANS controls involuntary physiological functions such as heart rate, blood pressure, and digestion through the parasympathetic nervous system (PNS) and the sympathetic nervous system (SNS). Simply put, the sympathetic nervous system (SNS) helps the body prepare to deal with stress by triggering the 'fight-or-flight' reaction, which can result in elevated heart rate and blood pressure. In contrast, the parasympathetic nervous system (PNS) promotes the activation of the "rest and digest" processes, such as heart relaxation (Waxenbaum et al., 2021).

The second element is the level of task demand. Task is a significant focus of human factors and ergonomics study, as they are closely linked to humans. A significant amount of endeavour in this field is focused on comprehending how individuals successfully accomplish desired goals, especially in their professional or everyday activities. According to Hollnagel (2021), tasks are defined as specific pieces of work that must be completed in order to achieve a desired outcome. This definition encompasses the actions and functions that are necessary to accomplish the intended goal. Tasks and humans engage in an interaction, by imposing physical and/or mental demands on humans, and humans must fulfil these demands to complete the tasks. Given the increasing cognitive demands of contemporary work (Young et al., 2015), comprehending task is crucial in the field of MWL. In an MWL study, tasks are the elements that are often altered by adjusting the amount of demand (Devlin et al., 2020). This allows for the observation and measurement of changes in MWL.

The third element focuses on the task performance. The third attribute of the definition is task performance. Although a particular task consistently creates specific demands, the way in which a human operator accomplish the task might vary. It may be inferred that when the demands of a task are high, the performance of the operator would decline. Nevertheless, according to Sharples and Megaw (2015), this assertion is not universally true. Performance and task demands do not necessarily have a negative correlation, since operators prefer to actively check their performance and system's feedback, such as via instruments and relevant indicators. This may subsequently influence their approach to completing the task, their comprehension of the task at hand, and their motivation to engage in the task; hence, ultimately changing their workload. Performance results might modify subsequent expectations by altering the task. For instance, if a pilot fails to execute their landing process correctly, they must carry out additional task to retake the landing operations from the initial stage. This undoubtedly amplifies their workload. In conclusion, performance must be included in defining MWL.

The fourth attribute is the subjective experience. MWL encompasses the subjective evaluation of the demands imposed by a task. Although the activity or job may be identical, various human operators may have varying perceptions of their experiences regarding MWL and situation appraisal. This unconscious process aims to assess the present levels of arousal, emotional reactions, and performance, and then adapts the allocation of effort to cognitive processing resources (Van Acker et al., 2018). These psychological elements are inevitable since most activities or occupations occur in a work environment, where external factors including job type, support, and culture are critical (Sharples and Megaw, 2015). In addition to external factors, internal factors such as skill and motivation (Smith and Hess, 2015) can also influence how operators perceive workload and adapt their strategies to meet task demands, ultimately impacting their experienced workload.

Based on these elements, we proposed the conceptual definition of MWL as changes in cognitive activities in response to changes in task demands, and this can be indicated by changes in particular physiological indices, performance, or subjective experience. More operationally, higher MWL can be concluded by tendency to have poorer performance or higher score in subjective experience measurement, along with changes in various physiological indices, such as increased heart rate and decreased heart rate variability (Gullett et al., 2023; Tjolleng et al., 2017), increased oxygenation in prefrontal areas (Ayaz et al., 2012; Causse et al., 2017; Galoyan et al., 2021), or increased pupil diameter (Appel et al., 2018).

### *4.2. Measurement Framework*

Based on the review, a framework for measuring MWL can be utilised based on the components involved in the formation of MWL. Figure 3 depicts the components and their interplay. Operator workload refers to the level of effort or strain that an operator experiences while carrying out a task. This aspect is mostly subjective but can also be deduced from physiological or behavioural indicators. The cognitive and physical demands might be conceptualized as “the work” that the operator must perform. These factors explicitly encompass both the physical and psychological aspects of the task(s) that are highly probable to coexist during task completion, and they will influence the operator's experience with the work (Astin and Nussbaum, 2002). Operators will have the ability to observe the outcomes of their tasks, namely the performance feedback (Vitense et al., 2003). Typically, an objective metric, such as reaction times (Makishita and Matsunaga, 2008) or number of mistakes/error (Louis et al., 2023), is used to quantify this element. External factors, such as organizational culture, and internal factors, such as motivation, are unavoidable in today's work environment, which is mostly social in nature (Sweller, 1994). This factor, to a certain degree, is crucial in the construction of MWL. This framework, however, lacks an explanation about physiological changes and mechanisms. We argue that this element could be placed alongside with performance, as changes in this element occur immediately in response to demand, and thus MWL, changes (Puusepp et al., 2024).

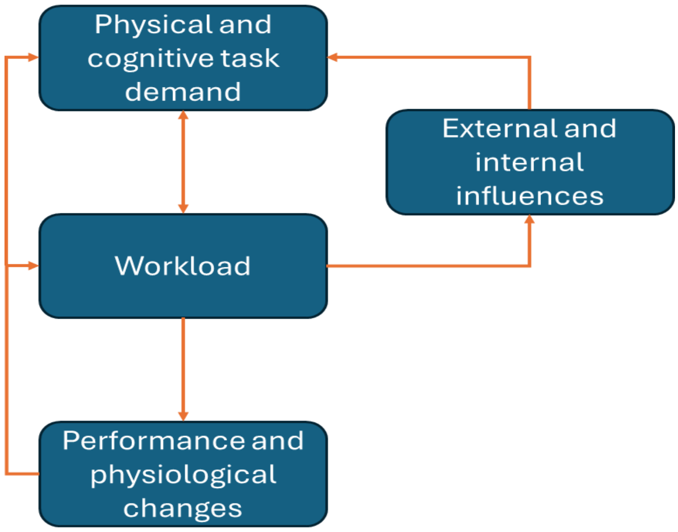

**Figure 3** A dynamic framework for measuring MWL

The interplay between these components is also distinctive. It is not as straightforward as deducing that, for instance, a heavy workload would inevitably lead to poor performance. The operator's workload can be attributed to the direct consequences of both physical and cognitive demands. However, the framework proposes that external and internal factors should be considered as they might define the magnitude of the demands. For instance, a task that is identical might result in varying demands for novice and expert operators (Byrne et al., 2013; Lassiter et al., 1996). Performance and physiological changes, on the other hand, is a direct result of MWL. Nevertheless, the connection may not always follow a linear pattern. The outcome of a challenging task might be superior if operators apply strategies to effectively maintain their performance (Gathmann et al., 2015). Operators can frequently get feedback of their performance by utilising self-assessment or by observing indicators or displays. Performance feedback might subsequently impact an operator's assessment of their workload, and has the potential to not only impact how heavy the task is perceived to be, but also to alter the level of expectations (Maior et al., 2018). Inadequate performance might lead to the emergence of additional unforeseen tasks aimed at restoring performance to the intended standard. As mentioned earlier, the perceived MWL can be influenced by internal and external factors, such as the selection of behavioural strategies, which can in turn affect task demands.

*4.3. Limitations and Challenges*

It is noteworthy that this review is not without limitations. The primary limitation of our analysis may be attributed to the implementation of a non-systematic review approach, specifically the narrative review methodology. While it allows for a broad exploration of topics, the narrative review (including TIRs) approach possesses some challenges, such as potential biases and variability in interpretation (Sukhera, 2022). Nonetheless, these challenges have been alleviated through the establishment of transparent methodological selections, encompassing the criteria for literature inclusion and the approach to synthesis. This review further employs structured frameworks and guidelines designed to reduce bias and enhance the reproducibility of the findings, including a clear delineation of the scope, boundaries, and pertinent terminology of the review.

There are several challenges and issues that continue to surround MWL research. One of which is that most research on MWL are conducted in controlled laboratory settings (often using simulators) that can limit external validity. Nevertheless, the utilisation of

MWL assessment is undeniably beneficial in practical situations. Given the progress made in psychophysiological theory and the development of methodologies to assess MWL, it is necessary to conduct research that applies these measures in actual work environments (Midha et al., 2021). The primary goal of real-time MWL monitoring is to offer operators immediate alerts and feedback regarding their existing workload. It is arguably advantageous for aiding an operator in handling their tasks. In a situation of excessive workload, the provision of feedback and warnings can prove beneficial in indicating the status of one's workload and identifying potential steps to address the problem (Maior et al., 2018).

Furthermore, over the past decade, several studies have endeavoured to quantify MWL by employing diverse psychophysiological methods in actual work environments, including traffic control centres (Fallahi et al., 2016a), driving (Lei et al., 2017; Sahaï et al., 2021; Schoedel et al., 2018), and electric bike riding (Boele-Vos et al., 2017). However, the studies lacked the capability to offer immediate feedback and notifications regarding MWL, as demonstrated in Maior et al. (2018) research conducted within a controlled laboratory environment. These studies eventually can provide insights into the feasibility of implementing MWL measurement, particularly utilising psychophysiological approaches, in specific real-world work environments. Virtual reality (VR) can also be employed to provide a more realistic simulated environment in measuring operator's MWL and performance (Sudiarno et al., 2024). Moreover, gaining insights into the perspective of operators or subject-matter experts/SMEs on MWL sensors and its implementation in actual workplaces is essential as it can predict the acceptance of the technologies (Salma et al., 2024). Additionally, incorporating MWL into brain-machine interfaces (BMIs) (Whulanza et al., 2024) is also potential to enhance the development and implementation of neurofeedback in workplace setting.

### *4.4. Implications and Significance*

The outcomes of this review could function as a reference for the definition of mental workload. This can subsequently provide a framework for research, evaluation, and intervention across diverse disciplines. In the absence of a standardized definition, studies may yield contradictory results, as researchers may conceptualise mental workload differently based on their respective domains, such as psychology, engineering, or medicine. Furthermore, by looking at various measurement instruments—subjective scales, psychophysiological metrics, and performance indicators—this review directs forthcoming research towards the establishment of reliable, standardised methodologies, ultimately enhancing safer, more effective task design and promoting improved well-being within occupational environments.

## 5. Conclusions

This paper reviewed the definition and measurement of MWL. We approached the definition from two foundational theories: LRT and MRT. From our review, we proposed that the conceptual definition should consider four elements, i.e. limited cognitive processing capacity, task demand variations, performance and physiological changes, and subjective experience. In more operational term, one could indicate higher MWL, as the function of high task demands, by observing tendency to have poorer performance, higher score in subjective measurement, and various changes in physiological measurement. Concerning the measurement of MWL, it usually involves a variety of approaches, with psychophysiological techniques currently being the primary indicators. This is because these techniques offer an objective measure of changes in MWL and can be implemented during the completion of tasks. Despite its potential, several theoretical and practical concerns with this approach still exist and require further research.

**Acknowledgement**

This research has received no external funding.

**Conflict of Interest**

The authors declare no conflicts of interest.

## References

Aghajani, H., Garbey, M., Omurtag, A., 2017. Measuring Mental Workload with EEG+fNIRS. Front Hum Neurosci 11. https://doi.org/10.3389/fnhum.2017.00359

Ahn, J.W., Ku, Y., Kim, H.C., 2019. A Novel Wearable EEG and ECG Recording System for Stress Assessment. Sensors 19, 1991. https://doi.org/10.3390/s19091991

Ahn, S., Nguyen, T., Jang, H., Kim, J.G., Jun, S.C., 2016. Exploring Neuro-Physiological Correlates of Drivers' Mental Fatigue Caused by Sleep Deprivation Using Simultaneous EEG, ECG, and fNIRS Data. Frontiers in Human Neuroscience 10, 219. https://doi.org/10.3389/fnhum.2016.00219

Appel, T., Scharinger, C., Gerjets, P., Kasneci, E., 2018. Cross-subject workload classification using pupil-related measures, in: Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications, ETRA '18. Association for Computing Machinery, New York, NY, USA, pp. 1–8. https://doi.org/10.1145/3204493.3204531

Argyle, E.M., Marinescu, A., Wilson, M.L., Lawson, G., Sharples, S., 2021. Physiological indicators of task demand, fatigue, and cognition in future digital manufacturing environments. International Journal of Human-Computer Studies 145, 102522. https://doi.org/10.1016/j.ijhcs.2020.102522

Astin, A., Nussbaum, M.A., 2002. Interactive Effects of Physical and Mental Workload on Subjective Workload Assessment. Proceedings of the Human Factors and Ergonomics Society Annual Meeting 46, 1100–1104. https://doi.org/10.1177/154193120204601320

Atkin, C., Stacey, J.E., Roberts, K.L., Allen, H.A., Henshaw, H., Badham, S.P., 2023. The effect of unisensory and multisensory information on lexical decision and free recall in young and older adults. Sci Rep 13, 16575. https://doi.org/10.1038/s41598-023-41791-1

Ayaz, H., Shewokis, P.A., Bunce, S., Izzetoglu, K., Willems, B., Onaral, B., 2012. Optical brain monitoring for operator training and mental workload assessment. NeuroImage, Neuroergonomics: The human brain in action and at work 59, 36–47. https://doi.org/10.1016/j.neuroimage.2011.06.023

Battistone, M.J., Kemeyou, L., Varpio, L., 2023. The Theoretical Integrative Review—A Researcher's Guide. J Grad Med Educ 15, 453–455. https://doi.org/10.4300/JGME-D-23-00266.1

Ben Mrad, I., Ben Mrad, M., Besbes, B., Zairi, I., Ben Kahla, N., Kamoun, S., Mzoughi, K., Kraiem, S., 2021. Heart Rate Variability as an Indicator of Autonomic Nervous System Disturbance in Behcet's Disease. IJGM Volume 14, 4877–4886. https://doi.org/10.2147/IJGM.S326549

Boele-Vos, M.J., Commandeur, J.J.F., Twisk, D.A.M., 2017. Effect of physical effort on mental workload of cyclists in real traffic in relation to age and use of pedelecs. Accident Analysis & Prevention, Improving cyclist safety through scientific research, ICSC2015. 105, 84–94. https://doi.org/10.1016/j.aap.2016.11.025

Brennan, S., 1992. An experimental report on rating scale descriptior sets for the instantaneous self assessment (ISA) recorder (No. DRA Technical Memorandum (CAD5) 92017). DRA Maritime Command and Control Division, Portsmouth.

Bui, L., Deakin, J., 2021. What we talk about when we talk about vulnerability and youth crime: A narrative review. Aggression and Violent Behavior 58, 101605. https://doi.org/10.1016/j.avb.2021.101605

Byrne, A.J., Murphy, A., McIntyre, O., Tweed, N., 2013. The relationship between experience and mental workload in anaesthetic practice: an observational study. Anaesthesia 68, 1266–1272. https://doi.org/10.1111/anae.12455

Cabañero, L., Hervás, R., González, I., Fontecha, J., Mondéjar, T., Bravo, J., 2019. Analysis of Cognitive Load Using EEG when Interacting with Mobile Devices, in: 13th International Conference on Ubiquitous Computing and Ambient Intelligence UCAmI 2019. Presented at the UCAml 2019, MDPI, p. 70. https://doi.org/10.3390/proceedings2019031070

Causse, M., Chua, Z., Peysakhovich, V., Campo, N.D., Matton, N., 2017. Mental workload and neural efficiency quantified in the prefrontal cortex using fNIRS. Scientific Reports 7, 5222. https://doi.org/10.1038/s41598-017-05378-x

Causse, M., Lepron, E., Mandrick, K., Peysakhovich, V., Berry, I., Callan, D., Rémy, F., 2022. Facing successfully high mental workload and stressors: An fMRI study. Hum Brain Mapp 43, 1011–1031. https://doi.org/10.1002/hbm.25703

Charles, R.L., Nixon, J., 2019. Measuring mental workload using physiological measures: A systematic review. Appl Ergon 74, 221–232. https://doi.org/10.1016/j.apergo.2018.08.028

Chen, O., Castro-Alonso, J.C., Paas, F., Sweller, J., 2018. Extending Cognitive Load Theory to Incorporate Working Memory Resource Depletion: Evidence from the Spacing Effect. Educ Psychol Rev 30, 483–501. https://doi.org/10.1007/s10648-017-9426-2

Chowdhury, A., Shankaran, R., Kavakli, M., Haque, Md.M., 2018. Sensor Applications and Physiological Features in Drivers' Drowsiness Detection: A Review. IEEE Sensors J. 18, 3055–3067. https://doi.org/10.1109/JSEN.2018.2807245

Cowan, N., 2010. The Magical Mystery Four: How is Working Memory Capacity Limited, and Why? Curr Dir Psychol Sci 19, 51–57. https://doi.org/10.1177/0963721409359277

Dahlstrom, N., Nahlinder, S., Wilson, G.F., Svensson, E., 2011. Recording of Psychophysiological Data During Aerobatic Training. The International Journal of Aviation Psychology 21, 105–122. https://doi.org/10.1080/10508414.2011.556443

Demiris, G., Oliver, D.P., Washington, K.T., 2019. Defining and Analyzing the Problem, in: Behavioral Intervention Research in Hospice and Palliative Care. Elsevier, pp. 27–39. https://doi.org/10.1016/B978-0-12-814449-7.00003-X

Devlin, S.P., Moacdieh, N.M., Wickens, C.D., Riggs, S.L., 2020. Transitions Between Low and High Levels of Mental Workload can Improve Multitasking Performance. IISE Transactions on Occupational Ergonomics and Human Factors 8, 72–87. https://doi.org/10.1080/24725838.2020.1770898

Di Nocera, F., Camilli, M., Terenzi, M., 2007. A Random Glance at the Flight Deck: Pilots' Scanning Strategies and the Real-Time Assessment of Mental Workload. Journal of Cognitive Engineering and Decision Making 1, 271–285. https://doi.org/10.1518/155534307X255627

Eckstein, M.K., Guerra-Carrillo, B., Miller Singley, A.T., Bunge, S.A., 2017. Beyond eye gaze: What else can eyetracking reveal about cognition and cognitive development? Developmental Cognitive Neuroscience, Sensitive periods across development 25, 69–91. https://doi.org/10.1016/j.dcn.2016.11.001

Fairclough, S.H., Venables, L., Tattersall, A., 2005. The influence of task demand and learning on the psychophysiological response. International Journal of Psychophysiology 56, 171–184. https://doi.org/10.1016/j.ijpsycho.2004.11.003

Fallahi, M., Motamedzade, M., Heidarimoghadam, R., Soltanian, A.R., Farhadian, M., Miyake, S., 2016a. Analysis of the mental workload of city traffic control operators while monitoring traffic density: A field study. International Journal of Industrial Ergonomics 54, 170–177. https://doi.org/10.1016/j.ergon.2016.06.005

Fallahi, M., Motamedzade, M., Heidarimoghadam, R., Soltanian, A.R., Miyake, S., 2016b. Effects of mental workload on physiological and subjective responses during traffic density monitoring: A field study. Appl Ergon 52, 95–103. https://doi.org/10.1016/j.apergo.2015.07.009

Fan, J., Smith, A.P., 2020. Effects of Occupational Fatigue on Cognitive Performance of Staff From a Train Operating Company: A Field Study. Front Psychol 11, 558520. https://doi.org/10.3389/fpsyg.2020.558520

Fista, B., Azis, H.A., Aprilya, T., Saidatul, S., Sinaga, M.K., Pratama, J., Syalfinaf, F.A., Steven, Amalia, S., 2019. Review of Cognitive Ergonomic Measurement Tools. IOP Conf. Ser.: Mater. Sci. Eng. 598, 012131. https://doi.org/10.1088/1757-899X/598/1/012131

Foy, H.J., Runham, P., Chapman, P., 2016. Prefrontal Cortex Activation and Young Driver Behaviour: A fNIRS Study. PLOS ONE 11, 1–18. https://doi.org/10.1371/journal.pone.0156512

Galoyan, T., Betts, K., Abramian, H., Reddy, P., Izzetoglu, K., Shewokis, P.A., 2021. Examining Mental Workload in a Spatial Navigation Transfer Game via Functional near Infrared Spectroscopy. Brain Sciences 11, 45. https://doi.org/10.3390/brainsci11010045
Galy, E., Paxion, J., Berthelon, C., 2018. Measuring mental workload with the NASA-TLX needs to examine each dimension rather than relying on the global score: an example with driving. Ergonomics 61, 517–527. https://doi.org/10.1080/00140139.2017.1369583
Gathmann, B., Schiebener, J., Wolf, O.T., Brand, M., 2015. Monitoring supports performance in a dual-task paradigm involving a risky decision-making task and a working memory task. Front Psychol 6, 142. https://doi.org/10.3389/fpsyg.2015.00142
Gilchrist, A.L., Cowan, N., Naveh-Benjamin, M., 2008. Working Memory Capacity for Spoken Sentences Decreases with Adult Aging: Recall of Fewer, but not Smaller Chunks in Older Adults. Memory 16, 773–787. https://doi.org/10.1080/09658210802261124
Grinschgl, S., Papenmeier, F., Meyerhoff, H.S., 2023. Mutual interplay between cognitive offloading and secondary task performance. Psychon Bull Rev 30, 2250–2261. https://doi.org/10.3758/s13423-023-02312-3
Gullett, N., Zajkowska, Z., Walsh, A., Harper, R., Mondelli, V., 2023. Heart rate variability (HRV) as a way to understand associations between the autonomic nervous system (ANS) and affective states: A critical review of the literature. International Journal of Psychophysiology 192, 35–42. https://doi.org/10.1016/j.ijpsycho.2023.08.001
Halford, G.S., Cowan, N., Andrews, G., 2007. Separating Cognitive Capacity from Knowledge: A New Hypothesis. Trends Cogn Sci 11, 236–242. https://doi.org/10.1016/j.tics.2007.04.001
Hart, S.G., 2006. Nasa-Task Load Index (NASA-TLX); 20 Years Later. Proceedings of the Human Factors and Ergonomics Society Annual Meeting 50, 904–908. https://doi.org/10.1177/154193120605000909
Hart, S.G., Staveland, L.E., 1988. Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research, in: Hancock, P.A., Meshkati, N. (Eds.), Human Mental Workload. North-Holland Press, Oxford, pp. 139–183.
He, D., Wang, Z., Khalil, E.B., Donmez, B., Qiao, G., Kumar, S., 2022. Classification of Driver Cognitive Load: Exploring the Benefits of Fusing Eye-Tracking and Physiological Measures. Transportation Research Record: Journal of the Transportation Research Board 2676, 670–681. https://doi.org/10.1177/03611981221090937
Hollnagel, E., 2021. The Changing Nature of Task Analysis, in: Salvendy, G., Karwowski, W. (Eds.), Handbook of Human Factors and Ergonomics. John Wiley & Sons, Ltd, Hoboken, NJ, pp. 358–367.
Horrey, W.J., Wickens, C.D., 2006. Examining the Impact of Cell Phone Conversations on Driving Using Meta-Analytic Techniques. Hum Factors 48, 196–205. https://doi.org/10.1518/001872006776412135
Hsu, B.-W., Wang, M.-J.J., Chen, C.-Y., Chen, F., 2015. Effective Indices for Monitoring Mental Workload While Performing Multiple Tasks. Perceptual and Motor Skills 121, 94–117. https://doi.org/10.2466/22.PMS.121c12x5
Jalali, M., Esmaeili, R., Habibi, E., Alizadeh, M., Karimi, A., 2023. Mental workload profile and its relationship with presenteeism, absenteeism and job performance among surgeons: The mediating role of occupational fatigue. Heliyon 9, e19258. https://doi.org/10.1016/j.heliyon.2023.e19258
Kahneman, D., 1973. Attention and Effort. Prentice-Hall Inc., Englewood Cliffs, NJ.
Kirwan, B., Evans, A., Donohoe, L., Kilner, A., Lamoureux, T., Atkinson, T., MacKendrick, H., 1997. Human Factors in the ATM System Design Life Cycle, in: Human Factors in the ATM System Design Life Cycle Report. Presented at the FAA/Eurocontrol ATM R&D Seminar, Paris.
Lassiter, D.L., Morrow, D.G., Hinson, G.E., Miller, M., Hambrick, D.Z., 1996. Expertise and Age Effects on Pilot Mental Workload in a Simulated Aviation Task. Proceedings of the Human Factors and Ergonomics Society Annual Meeting 40, 133–137. https://doi.org/10.1177/154193129604000306
Lei, S., Toriizuka, T., Roetting, M., 2017. Driver adaptive task allocation: A field driving study. Le Travail Humain 80, 93–112.
Lenneman, J.K., Backs, R.W., 2018. A psychophysiological and driving performance evaluation of focal and ambient visual processing demands in simulated driving. Transportation Research Part F: Traffic Psychology and Behaviour 57, 84–96. https://doi.org/10.1016/j.trf.2017.11.001

Li, X., Zhu, W., Sui, X., Zhang, A., Chi, L., Lv, L., 2021. Assessing Workplace Stress Among Nurses Using Heart Rate Variability Analysis With Wearable ECG Device-A Pilot Study. Front Public Health 9, 810577. https://doi.org/10.3389/fpubh.2021.810577

Lobjois, R., Faure, V., Désiré, L., Benguigui, N., 2021. Behavioral and workload measures in real and simulated driving: Do they tell us the same thing about the validity of driving simulation? Safety Science 134, 105046. https://doi.org/10.1016/j.ssci.2020.105046

Longo, L., Wickens, C.D., Hancock, G., Hancock, P.A., 2022. Human Mental Workload: A Survey and a Novel Inclusive Definition. Front Psychol 13, 883321. https://doi.org/10.3389/fpsyg.2022.883321

López-López, M.L., Balanza-Galindo, S., Vera-Catalán, T., Gallego-Gómez, J.I., González-Moro, M.T.R., Rivera-Caravaca, J.M., Simonelli-Muñoz, A.J., 2018. Risk factors for mental workload: influence of the working environment, cardiovascular health and lifestyle. A cross-sectional study. BMJ Open 8, e022255. https://doi.org/10.1136/bmjopen-2018-022255

Louis, L.-E.L., Moussaoui, S., Van Langhenhove, A., Ravoux, S., Le Jan, T., Roualdes, V., Milleville-Pennel, I., 2023. Cognitive tasks and combined statistical methods to evaluate, model, and predict mental workload. Front Psychol 14, 1122793. https://doi.org/10.3389/fpsyg.2023.1122793

Maior, H.A., Wilson, M.L., Sharples, S., 2018. Workload Alerts—Using Physiological Measures of Mental Workload to Provide Feedback During Tasks. ACM Trans. Comput.-Hum. Interact. 25, 9:1-9:30. https://doi.org/10.1145/3173380

Makishita, H., Matsunaga, K., 2008. Differences of drivers' reaction times according to age and mental workload. Accident Analysis & Prevention 40, 567–575. https://doi.org/10.1016/j.aap.2007.08.012

Mansikka, H., Virtanen, K., Harris, D., Simola, P., 2016. Fighter pilots' heart rate, heart rate variation and performance during an instrument flight rules proficiency test. Applied Ergonomics 56, 213–219. https://doi.org/10.1016/j.apergo.2016.04.006

Marinescu, A.C., Sharples, S., Ritchie, A.C., Sánchez López, T., McDowell, M., Morvan, H.P., 2018. Physiological Parameter Response to Variation of Mental Workload. Hum Factors 60, 31–56. https://doi.org/10.1177/0018720817733101

Midha, S., Maior, H.A., Wilson, M.L., Sharples, S., 2021. Measuring Mental Workload Variations in Office Work Tasks using fNIRS. International Journal of Human-Computer Studies 147, 102580. https://doi.org/10.1016/j.ijhcs.2020.102580

Miller, G.A., 1956. The magical number seven, plus or minus two: Some limits on our capacity for processing information. Psychological Review 63, 81–97. https://doi.org/10.1037/h0043158

Mohammadian, M., Parsaei, H., Mokarami, H., Kazemi, R., 2022. Cognitive demands and mental workload: A filed study of the mining control room operators. Heliyon 8, e08860. https://doi.org/10.1016/j.heliyon.2022.e08860

Nealley, M.A., Gawron, V.J., 2015. The Effect of Fatigue on Air Traffic Controllers. The International Journal of Aviation Psychology 25, 14–47. https://doi.org/10.1080/10508414.2015.981488

Nino, V., Monfort, S.M., Claudio, D., 2023. Exploring the influence of individual factors on the perception of mental workload and body postures. Ergonomics 1–16. https://doi.org/10.1080/00140139.2023.2243406

Oberauer, K., 2019. Working Memory and Attention - A Conceptual Analysis and Review. J Cogn 2, 36. https://doi.org/10.5334/joc.58

Pearson, A., Pallas, L.O., Thomson, D., Doucette, E., Tucker, D., Wiechula, R., Long, L., Porritt, K., Jordan, Z., 2006. Systematic review of evidence on the impact of nursing workload and staffing on establishing healthy work environments. Int J Evid Based Healthc 4, 337–384. https://doi.org/10.1111/j.1479-6988.2006.00055.x

Pei, H., Ma, Y., Li, W., Liu, X., Zhang, C., 2023. Mental workload evaluation model of receiver aircraft pilots based on multiple resource theory. Hum Ftrs & Erg Mfg Svc hfm.21018. https://doi.org/10.1002/hfm.21018

Pickup, L., Wilson, J.R., Sharpies, S., Norris, B., Clarke, T., Young, M.S., 2005. Fundamental examination of mental workload in the rail industry. Theoretical Issues in Ergonomics Science 6, 463–482. https://doi.org/10.1080/14639220500078021

Piranveyseh, P., Kazemi, R., Soltanzadeh, A., Smith, A., 2022. A field study of mental workload: conventional bus drivers versus bus rapid transit drivers. Ergonomics 65, 804–814. https://doi.org/10.1080/00140139.2021.1992021

Puspita, M.A., Muslim, E., Moch, B.N., Aristides, A., 2015. Fatigue Measurement in Car Driving Activity using Physiological, Cognitive, and Subjective Approaches Fatigue. International Journal of Technology 6, 971–975.

Puusepp, I., Tammi, T., Linnavalli, T., Huotilainen, M., Laine, S., Kuusisto, E., Tirri, K., 2024. Changes in physiological arousal during an arithmetic task: profiles of elementary school students and their associations with mindset, task performance and math grade. Sci Rep 14, 1606. https://doi.org/10.1038/s41598-024-51683-7

Rann, J.C., Almor, A., 2022. Effects of verbal tasks on driving simulator performance. Cogn. Research 7, 12. https://doi.org/10.1186/s41235-022-00357-x

Reid, G.B., Nygren, T.E., 1988. The Subjective Workload Assessment Technique: A Scaling Procedure for Measuring Mental Workload, in: Advances in Psychology. Elsevier, pp. 185–218. https://doi.org/10.1016/S0166-4115(08)62387-0

Remington, R., Loft, S., 2015. Attention and multitasking, in: Boehm-Davis, D.A., Durso, F.T., Lee, J.D. (Eds.), APA Handbook of Human System Integration. American Psychological Association, pp. 261–276.

Rodemer, M., Karch, J., Bernholt, S., 2023. Pupil dilation as cognitive load measure in instructional videos on complex chemical representations. Front. Educ. 8. https://doi.org/10.3389/feduc.2023.1062053

Safari, M., Shalbaf, R., Bagherzadeh, S., Shalbaf, A., 2024. Classification of mental workload using brain connectivity and machine learning on electroencephalogram data. Sci Rep 14, 9153. https://doi.org/10.1038/s41598-024-59652-w

Sahaï, A., Barré, J., Bueno, M., 2021. Urgent and non-urgent takeovers during conditional automated driving on public roads: The impact of different training programmes. Transportation Research Part F: Traffic Psychology and Behaviour 81, 130–143. https://doi.org/10.1016/j.trf.2021.06.001

Salma, S.A., Widyanti, A., Muslim, K., Wijayanto, T., Trapsilawati, F., Arini, H.M., Wibawa, A.D., 2024. The Influence of Trust, Health Beliefs, and Technology Acceptance on The Intent to use an Mhealth in Indonesia: An Empirical Study of Users and Non-Users. IJTech 15, 1247. https://doi.org/10.14716/ijtech.v15i5.5291

Schoedel, R., Hilbert, S., Bühner, M., Stachl, C., 2018. One way to guide them all: Wayfinding strategies and the examination of gender-specific navigational instructions in a real-driving context. Transportation Research Part F: Traffic Psychology and Behaviour 58, 754–768. https://doi.org/10.1016/j.trf.2018.06.030

Scott, J.J., Gray, R., 2008. A Comparison of Tactile, Visual, and Auditory Warnings for Rear-End Collision Prevention in Simulated Driving. Hum Factors 50, 264–275. https://doi.org/10.1518/001872008X250674

Serences, J., Scolari, M., Awh, E., 2009. Online response-selection and the attentional blink: Multiple-processing channels. Vis cogn 17, 531–554. https://doi.org/10.1080/13506280802102541

Sharples, S., Megaw, T., 2015. Definition and measurement of mental workload, in: Wilson, J.R., Sharples, S. (Eds.), Evaluation of Human Work Fourth Edition. CRC Press, Boca Raton, FL, pp. 515–548.

Smith, B.T., Hess, T.M., 2015. The Impact of Motivation and Task Difficulty on Resource Engagement: Differential Influences on Cardiovascular Responses of Young and Older Adults. Motiv Sci 1, 22–36. https://doi.org/10.1037/mot0000012

Sudiarno, A., Dewi, R.S., Widyaningrum, R., Akbar, R.A., Sudianto, Y., Prastyabudi, W.A., Ahmadi, A., 2024. Analysis of Human Performance and Potential Application of Virtual Reality (VR) Shooting Games as a Shooting Training Simulator for Military Personnel. IJTech 15, 87. https://doi.org/10.14716/ijtech.v15i1.5303

Sukhera, J., 2022. Narrative Reviews: Flexible, Rigorous, and Practical. J Grad Med Educ 14, 414–417. https://doi.org/10.4300/JGME-D-22-00480.1

Sweller, J., 1994. Cognitive load theory, learning difficulty, and instructional design. Learning and Instruction 4, 295–312. https://doi.org/10.1016/0959-4752(94)90003-5

Takae, Y., Yamamura, T., Kuge, N., Miyake, S., Yamada, S., Hagiwara, C., 2010. Effects of Alcohol Intoxication on a Multi-task Simulator Operation Performance. Review of Automotive Engineering 31, 150–155.
Tao, D., Tan, H., Wang, H., Zhang, X., Qu, X., Zhang, T., 2019. A Systematic Review of Physiological Measures of Mental Workload. Int J Environ Res Public Health 16, 2716. https://doi.org/10.3390/ijerph16152716
Tjolleng, A., Jung, K., Hong, W., Lee, W., Lee, B., You, H., Son, J., Park, S., 2017. Classification of a Driver's cognitive workload levels using artificial neural network on ECG signals. Applied Ergonomics 59, 326–332. https://doi.org/10.1016/j.apergo.2016.09.013
Tsang, P.S., Velazquez, V.L., 1996. Diagnosticity and multidimensional subjective workload ratings. Ergonomics 39, 358–381. https://doi.org/10.1080/00140139608964470
Van Acker, B.B., Parmentier, D.D., Vlerick, P., Saldien, J., 2018. Understanding mental workload: from a clarifying concept analysis toward an implementable framework. Cogn Tech Work 20, 351–365. https://doi.org/10.1007/s10111-018-0481-3
Verdière, K.J., Roy, R.N., Dehais, F., 2018. Detecting Pilot's Engagement Using fNIRS Connectivity Features in an Automated vs. Manual Landing Scenario. Front. Hum. Neurosci. 12, 1–14. https://doi.org/10.3389/fnhum.2018.00006
Vitense, H.S., Jacko, J.A., Emery, V.K., 2003. Multimodal feedback: an assessment of performance and mental workload. Ergonomics 46, 68–87. https://doi.org/10.1080/00140130303534
Wanyan, X., Zhuang, D., Lin, Y., Xiao, X., Song, J.-W., 2018. Influence of mental workload on detecting information varieties revealed by mismatch negativity during flight simulation. International Journal of Industrial Ergonomics 64, 1–7. https://doi.org/10.1016/j.ergon.2017.08.004
Waxenbaum, J.A., Reddy, V., Varacallo, M., 2021. Anatomy, Autonomic Nervous System, in: StatPearls. StatPearls Publishing, Treasure Island, FL.
Whulanza, Y., Kusrini, E., Sangaiah, A.K., Hermansyah, H., Sahlan, M., Asvial, M., Harwahyu, R., Fitri, I.R., 2024. Bridging Human and Machine Cognition: Advances in Brain-Machine Interface and Reverse Engineering the Brain. IJTech 15, 1194. https://doi.org/10.14716/ijtech.v15i5.7297
Wickens, C.D., Hollands, J.G., Banbury, S., Parasuraman, R., 2012. Engineering Psychology and Human Performance. Taylor & Francis Group, London.
Widyanti, A., Sofiani, N.F., Soetisna, H.R., Muslim, K., 2017. Eye Blink Rate as a Measure of Mental Workload in a Driving Task: Convergent or Divergent with Other Measures? International Journal of Technology 8, 283–291. https://doi.org/10.14716/ijtech.v8i2.6145
Wilson, G.F., 2002. An Analysis of Mental Workload in Pilots During Flight Using Multiple Psychophysiological Measures. The International Journal of Aviation Psychology 12, 3–18. https://doi.org/10.1207/S15327108IJAP1201_2
Young, M.S., Brookhuis, K.A., Wickens, C.D., Hancock, P.A., 2015. State of science: mental workload in ergonomics. Ergonomics 58, 1–17. https://doi.org/10.1080/00140139.2014.956151
Zakeri, Z., Arif, A., Omurtag, A., Breedon, P., Khalid, A., 2023. Multimodal Assessment of Cognitive Workload Using Neural, Subjective and Behavioural Measures in Smart Factory Settings. Sensors 23, 8926. https://doi.org/10.3390/s23218926
Zhang, J.-Y., Liu, S.-L., Feng, Q.-M., Gao, J.-Q., Zhang, Q., 2017. Correlative Evaluation of Mental and Physical Workload of Laparoscopic Surgeons Based on Surface Electromyography and Eye-tracking Signals. Sci Rep 7, 11095. https://doi.org/10.1038/s41598-017-11584-4