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Review Article

Mental Workload: Definition and Measurement Review

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Abstract: The assessment of 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 an agreement on its definition, whether in technical or philosophical terms, is highly challenging. This study aims to critically examine the theories of MWL and offer a conceptual and operational definition for future researchers in the field. This paper also provides a review of MWL measurement by exploring the progress made in measuring MWL, including the development of novel techniques. We searched scientific databases 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 the TIR approach. Based on our review, the definition of MWL 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: Definition; Limited resource theory; Measurement; Mental workload; Multiple resource theory

1. Introduction

Mental workload (MWL) is generally defined as the amount of cognitive effort required to complete a task (Babaei et al., 2025). Young et al. (2015) describe MWL as the balance between cognitive capacity and the cognitive demands imposed by a task. In this sense, MWL can be understood as the degree to which cognitive resources are utilized during task performance. However, it is important to note that there is no universally accepted definition of MWL (Cain, 2007), and differences in interpretation persist among researchers in ergonomics and human performance.

The concept of MWL is often discussed in situations where an operator is heavily burdened by complex tasks that require divided attention, or when critical tasks demand sustained concentration, where even minor performance lapses may lead to serious consequences. Interestingly, MWL is also relevant in the context of monotonous tasks requiring minimal attention. In such cases, insufficient stimulation may lead to reduced vigilance and diminished performance. Thus, lower MWL does not necessarily equate to better outcomes; rather, an optimal level of MWL is generally sought to achieve peak human performance.

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The importance of MWL has grown in recent years for a couple of reasons. First, modern work environments and increasingly complex technologies often require operators to maintain continuous attention. This is particularly evident in sectors such as oil and gas, mining, and transportation/logistics. Similarly, industries such as the military, healthcare, emergency response, information technology, and maritime operations are also characterized by high demands that contribute to substantial MWL. In addition, the automation of many manufacturing processes has shifted the burden from physical to mental demands (Young et al., 2015).

Second, although MWL can often be judged intuitively after task completion, its operational definition and measurement remain challenging. Unlike physical workload, which can be readily assessed using objective measures such as muscle strength or endurance, MWL is less tangible. Physical workload can be measured through standardized instruments, but evaluating cognitive capacity and the proportion of that capacity engaged during task performance is far more complex (see discussion below).

A significant issue being discussed in the literature pertains to the relationships between MWL dan mental fatigue. MWL significantly contributes to mental fatigue by increasing workload (Nealley and Gawron, 2015) or prolonging time-on-task (Zhang et al., 2017). Furthermore, the relationship 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 MWL (Fallahi et al., 2016b), whereas increased fatigue can affect MWL (Fan and Smith, 2020). The most notable consequence of suboptimal workload and fatigue is deterioration in performance and safety (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. Therefore, the primary objective of measuring MWL is to quantify the mental cost associated with task completion to anticipate the responses of operators and systems (Longo et al., 2022).

However, the idea of MWL is often criticized because of its inherent complexity and subjective nature. Critics argue that establishing a universal definition of MWL is difficult because of 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 (Safari et al., 2024; Mohammadian et al., 2022; Piranveyseh et al., 2022), with additional variables of interest such as emotional/psychological aspect (Piranveyseh et al., 2022; López-López et al., 2018) 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 measurement of concepts. Owing to the subjective nature of cognitive demands, most MWL studies use subjective measurements, such as NASA-TLX (Safari et al., 2024; Mohammadian et al., 2022; Galy et al., 2018). In addition, behavioral measurement is also employed in most studies due to the presumed connection between cognitive demands and performance (Zakeri et al., 2023; Lobjois et al., 2021; Fallahi et al., 2016b), and to minimize 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 (Cabañero et al., 2019; Aghajani et al., 2017; Ahn et al., 2016), functional near-infrared spectroscopy/fNIRS (Verdière et al., 2018; Foy et al., 2016), electrocardiogram/ECG (Ahn et al., 2019; Tjolleng et al., 2017; Mansikka et al., 2016), or eye-tracker (Rodemer et al., 2023; Appel et al., 2018; 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 findings show that both the conceptual and operational definitions of MWL vary among researchers.

The authors propose that the diverse MWL measurement techniques fundamentally seek to quantify cognitive demands by including multiple dimensions for its measurement. Nonetheless, the existing framework in the literature inadequately encompasses 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 unclear concepts. Previous studies have attempted to clarify the definition of the concept, but they are either limited to a certain field (Pearson et al., 2006) or concentrate on a singular facet of MWL measurement (Charles and Nixon, 2019). Therefore, this paper aims to comprehensively review the concept of MWL and provide a theoretical framework for future researchers in the field. By articulating a comprehensive definition of mental workload, one can facilitate the development of more efficient workload management methodologies, in addition to the establishment of standardized measurement and conceptual frameworks.

2. Methods

A systematic literature review (SLR) is often employed in a paper review, which relies on a systematic approach to identify, evaluate, and integrate evidence from prior investigations to address a precisely articulated and focused inquiry. An SLR is usually employed with a specific topic to be discussed. The technique tends to be rigorous, and replicable in nature. This approach has been utilized when examining MWL within the context of human-computer interaction (Babaei et al., 2025). Such an approach has also been employed, for instance, when investigating different physiological methods in evaluating MWL (Tao et al., 2019). The review followed PRISMA guidelines, and obtained reports from several databases, including ABI/INFORM, MEDLINE, and PsycINFO. In this study, the use of specific search terms allows for results that are comparable to other similar reviews.

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). Theoretical integrative reviews (TIR) (Sukhera, 2022), a technique within the narrative review approach, were employed in this investigation. Theoretical integrative reviews (TIRs) function as an essential approach for synthesizing and advancing 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).

First, we identified two foundational theories that arguably form the basis of the mental workload construct: LRT and MRT. This is because both theoretical frameworks concentrate on comprehending the mechanisms by which cognitive resources are distributed and regulated throughout the execution of tasks (Pei et al., 2023; Chen et al., 2018). A systematic search of the literature was then conducted in the 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 met 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 concepts in relation to MWL’s limited or multiple resources, and (4) publications discussing MWL measurement. The final step of this search strategy was to review the abstracts and articles to ensure that they aligned with our objective. It is important to note that it is not necessary to encompass all publications pertaining to a subject in a narrative review (Demiris et al., 2019). The synthesis approach employed thematic analysis grounded in the following themes: LRT and MRT as the fundamental theories and relevant measurement methodologies. The summary of the search is presented in Table 1.

Table 1 Search strings and results

No.	Search string	Initial results	The inclusion criteria fulfilled	Abstract and screened articles
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 a single central attentional resource. Primarily focused on comprehending attention, the theory may also be expanded to encompass MWL knowledge. Bruya and Tang (2018) cited Kahneman's classical work demonstrating that the core attentional resource is required to handle the demands when presented with several stimuli, leading the operator to make strategic choices and allocate attentional capacity accordingly. The demand level generated by the task at hand or stimuli, including mental rehearsing, timed activities, mental arithmetic, or activities that require the use of working memory, is considered (Oberauer, 2019). These tasks can place a certain level of demands on the attentional resource, which has a limited capacity. Furthermore, human operators could regulate the distribution of the resources, i.e., strategies to allocate the limited capacity of attentional resources. Wickens et al. (2012) asserted that individuals tend to prefer heuristic-based methods that require little effort and provide satisfactory results. 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 perceived effort expenditure (Pickup et al., 2005).

According to this theory, the basic concept of MWL can be viewed as the interaction between the task's demands and the information processing resource allocated to the task's completion. The more resources allocated to complete the task, the higher the MWL. Figure 1 shows a visual representation 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 available resources. 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 task's demands. This region also contains spare capacity and attentional resources. The MWL is negatively correlated with the amount of available spare resource capacity in this area, indicating minimal task demands. The right portion of the image depicts a region where the available resources are insufficient to meet the task's requirements because the maximum resource capacity has been achieved. This is a domain characterized by high demands, where the performance of the primary task and MWL exhibit an inverse relationship. Therefore, a measure of primary task performance can determine the MWL level in this area.

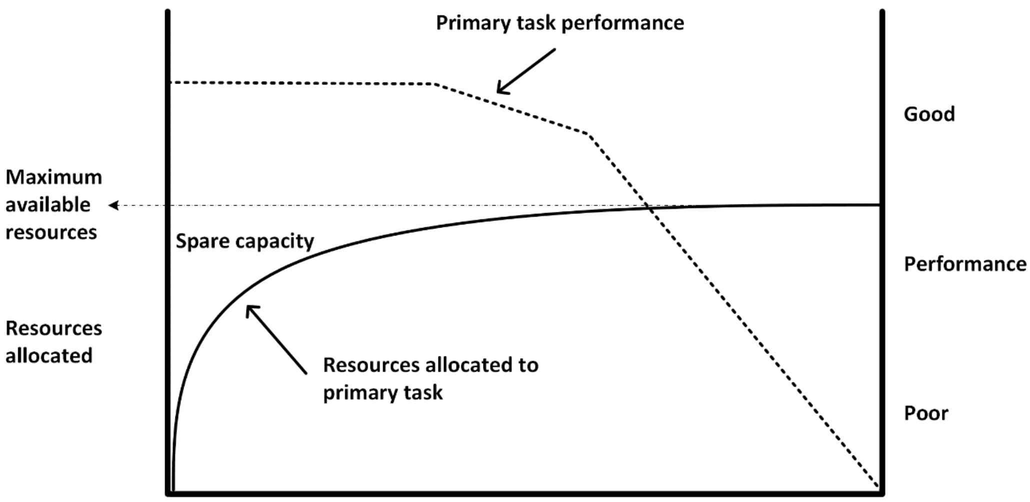

Figure 1 Graphical representation of the LRT

3.2. Multiple Resource Theory

In contrast to LRT, the primary proposition of MRT is that a person possesses various or distinct resources for processing information. The idea was not specifically developed to address MWL. However, it may be employed to comprehend MWL by examining how individuals perform many activities, especially in terms of their time allocation capacity (Wickens et al., 2012). At first, three distinct stages related to information processing were identified. These stages describe 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 visual channel as the fourth element. Figure 2 depicts the "cube" representing the model.

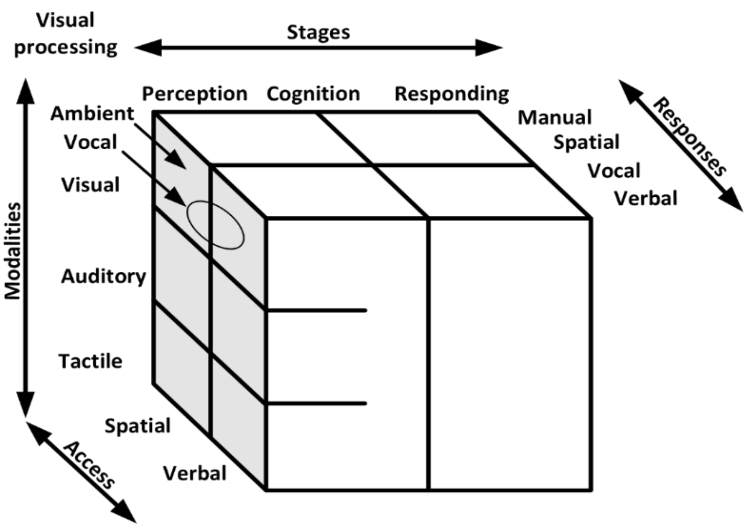

Figure 2 Graphical representation of the MRT

According to 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, such as decision-making. However, both types of activities require the use of working memory and rely on a shared resource to process information (Oberauer, 2019). The utilization of its resources for processing information in selection and response tasks, such as speech production, is another component (Serences et al., 2009). The separation of resources has an impact on performance (Grinschgl et al., 2023). Specifically, the performance of both tasks will not decline simultaneously if two activities differ in their processing phases (perceptual-cognitive versus response/selection). However, interference may negatively impact the performance of dual activities that involve separate phases but rely on the same perceptual and cognitive resources. Engaging in a phone call while driving can impair performance because both activities require the same mental and sensory resources (Horrey and Wickens, 2006).

Regarding encoding processing, the MRT model delineates a distinction between analog-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 used in the stages of perceiving, thinking, or responding during information processing. Simultaneous driving (spatial) and listening to unfamiliar voices (verbal) 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 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 resources to both visual and auditory modalities leads to superior performance compared with allocating attention to either auditory or visual modalities (Atkin et al., 2023). This might be attributed to the fact that tasks that use identical modalities would deplete the resource more rapidly than activities that use distinct modalities. Using a navigation device (visual) while driving (visual) would have a greater negative impact on driving performance than 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 an additional pathway for gathering sensory information (Scott and Gray, 2008). This aspect of the theory is exemplified by stick-shakers in contemporary aircraft cockpits, which alert pilots to stall situations.

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 a text. On the other hand, ambient vision mostly includes peripheral vision and is used for sensing direction. An example of this aspect is a driver maintaining the vehicle's position in the correct lane (ambient) while simultaneously comprehending a traffic sign (focal). The use of distinct resources within the visual modality channel increases the probability of successful completion of these tasks (Lenneman and Backs, 2018).

Table 2 provides an overview of the studies that form the empirical basis for both the LRT and MRT, along with how these findings have contributed to shaping the concept of MWL.

Table 2 Empirical studies supporting LRT and MRT, and their contributions to MWL conceptualization

No	Sources	Context	MWL conceptualization
1	(Bruya and Tang, 2018)	LRT	Kahneman's argument was the basis for MWL as it suggests that effort is a cognitive, objective, and metabolic expenditure closely tied to attention. However, this notion has been debated, with some evidence indicating that attention may not always involve the utilization of metabolic resources but rather the readiness of these resources, which can be experienced as effortful or effortless depending on the context
2	(Oberauer, 2019)	LRT	This paper provides a foundation for the concept of mental workload, which refers to how much of a person's limited attentional resources are demanded by a task. When a task requires more attention than the available capacity, the working memory becomes overloaded, leading to high mental workload and decreased performance. Thus, mental workload reflects the proportion of attentional resources (that support working memory) being consumed by current cognitive demands.
3	(Wickens et al., 2012)	LRT	Wickens uses this limited-resource view of attention and working memory as the backbone of its mental workload theory. He argues that tasks impose demands on perceptual, cognitive (working memory/attention), and motor resources, and that mental workload reflects how much of these limited resources a task consumes. Performance suffers, and workload becomes excessive, when task demands exceed the available attentional/working-memory capacity.

Table 2 Empirical studies supporting LRT and MRT, and their contributions to MWL conceptualization (Cont.)

No	Sources	Context	MWL conceptualization
4	(Pickup et al., 2005)	LRT	Mental workload depends not only on task characteristics but also on their current state (e.g., arousal, motivation), strategies, and priorities, which influence how limited attentional and working-memory resources are allocated. Tasks that are automated or require little controlled processing typically place lower demands on these resources, while multitasking, high task difficulty, or interference between tasks increase the load. Organizational context and individual differences (such as perceived priority, acceptable effort, and performance standards) further shape how resources are distributed. Overall, perceived task difficulty and subjective effort play a key role in determining the operator's mental workload at any moment.
5	(Serences et al., 2009)	MRT	The attentional blink effect is strongest when two targets rely on the same processing channel (e.g., both visual), overwhelming a shared, limited pool of attentional resources. However, when the two targets come from different modalities or use different types of processing (such as visual vs auditory), they interfere less, and the blink is reduced. This supports Multiple Resource Theory by indicating that mental workload depends not just on how much information is processed, but on whether tasks draw from separate or shared resource pools.
6	(Grinschgl et al., 2023)	MRT	The interplay between cognitive offloading and secondary task performance is influenced by the ability to manage cognitive load through offloading, the trust in offloading tools, and the modality of tasks. Offloading can significantly enhance performance on secondary tasks by freeing up cognitive resources, especially in high-demand situations.
7	(Horrey and Wickens, 2006)	MRT	Lane keeping relies on a distinct set of attentional resources, typically spatial–motor resources dedicated to continuous control of the vehicle, whereas hazard response tasks draw more on discrete perceptual–decision resources. Because these two tasks tap into different resource pools, they are affected differently when another task is added. As concurrent task demands increase, lane keeping performance may remain relatively stable until its specific spatial–motor resources are taxed, while hazard detection and response can deteriorate more quickly due to competition within the perceptual–decision channel.
8	(Rann and Almor, 2022)	MRT	The model builds on Salvucci and Taatgen's threaded cognition framework by treating driving and conversation as separate task goals that repeatedly request attentional resources. A central procedural resource manages these requests in 50 ms cycles, rapidly switching between tasks based on availability, and allowing parallel processing only when resource conflicts do not occur. This coordination mechanism explains how driving and conversation run concurrently, while Wickens' Multiple Resource Theory is used to describe how the two tasks draw on shared or distinct attentional resources.
9	(Atkin et al., 2023)	MRT	The model indicates that performance improves when attentional resources are spread across both visual and auditory modalities, rather than being restricted to a single channel. By drawing on two different resource pools, the system reduces competition within any one channel, allowing information to be processed more efficiently and supporting better overall task performance.
10	(Scott and Gray, 2008)	MRT	Tactile warnings are typically most effective for rear-end collision avoidance, with visual alerts being less reliable due to visual overload and auditory alerts being more prone to distraction. Multimodal cues (e.g., tactile + auditory) yield the quickest reaction times and highest urgency with minimal annoyance. These findings support Multiple Resource Theory, suggesting that tapping multiple processing channels enhances performance by reducing competition within a single resource pool.
11	(Lenneman and Backs, 2018)	MRT	Focal and ambient attention rely on separate, limited-capacity resources, and during divided attention, performance depends on how these resources are shared. When the available resources are insufficient to support both tasks, or when one task is prioritized, performance is expected to drop on one or both tasks compared to doing them individually.

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 a task, demand will be placed in the cognitive processing system of the operator. There are two distinct techniques under this category: primary and secondary task evaluations. Primary task measurements are derived from the direct evaluation of variables associated with the main task (Silva, 2014). For example, one way to measure an aircraft pilot's MWL is by evaluating their proficiency in controlling the airplane during flight, using 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 (e.g., flying in adverse weather conditions), the performance indicators diverge further from their desired objective. Therefore, MWL may be deduced from these objective indices, implying that a greater divergence from the ideal aim may indicate a larger MWL. A potential drawback of primary task approaches is that if the demands remain within the operator's total resource capacity, performance may not decline even as demands grow (Young et al., 2015).

The secondary task strategy is employed to address the problem. The primary principle of the secondary task strategy is to provide a task that can compete with the primary task for the same attentional resources (Grant et al., 2013). The measurements obtained from the secondary task can be used to ascertain the MWL level generated by the primary task. In this scenario, the secondary task might serve as a proxy for the primary task's remaining spare resource capacity. Hence, if the primary task demand increases, the spare capacity will diminish, leading to a decline in the secondary task performance (Warvel and Scerbo, 2015). For instance, drivers must prioritize the main driving objective, 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 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 their allocation of attentional capacity, resulting in their interference with the primary task that is being used to evaluate workload (Kuchinsky et al., 2024).

3.3.2. Subjective techniques

As previously stated, the experience of the MWL operator is highly subjective. Consequently, the assessment of MWL frequently involves inquiring about operators' subjective experience during or after task completion. The NASA Task Load Index (NASA-TLX) (Hart, 2006) is a widely used measure for measuring MWL. NASA-TLX has been used in many studies to assess the amount of operator workload associated with specific tasks. This instrument is commonly used to identify the MWL level in a preliminary investigation (Hsu et al., 2015; Fairclough et al., 2005) or to serve as a main measure for a dependent variable (Takae et al., 2010). Other popular subjective MWL scales include the subjective workload assessment technique (SWAT) (Huggins and Claudio, 2018) or workload profile (Moustafa and Longo, 2019; Moustafa et al., 2017).

These subjective scales are typically administered after the task is completed. 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 answered, which might disrupt the task's continuity. The instantaneous self-assessment of workload (ISA) instrument (Leggatt, 2005) provides a practical alternative for this issue, which appears to be suitable for monitoring subjective MWL changes while completing tasks. The ISA is a method used to evaluate the MWL experienced *during* a task. It was initially designed to measure the ATC workload. The instantaneity of the scale makes it less obtrusive and more suitable for real-time evaluation. The scale employs a five-point rating system to assess the operator's perceived workload, 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).

3.3.3. Psychophysiological techniques

The rationale for the psychophysiological measurement of MWL is clear: an increase in MWL is accompanied by heightened arousal, which is reflected in changes in autonomic nervous system (ANS) activity. The primary purpose of developing these techniques is to enable continuous and unobtrusive MWL assessment in real-world operational settings, thereby overcoming the temporal and practical limitations of traditional methods. Prior to the emergence of psychophysiological measures, subjective approaches, most notably the NASA Task Load Index (NASA-TLX), had gained widespread acceptance as the principal instruments for MWL assessment. However, as previously noted, NASA-TLX and comparable tools are inherently retrospective, as they require administration after task completion. Attempting to administer them during ongoing task execution not only introduces potential distractions but may also alter task performance and compromise ecological validity.

These limitations become particularly salient in high-stakes operational environments, such as aviation, driving, or complex medical procedures, where interrupting an operator to collect subjective data could jeopardize both safety and task performance. Furthermore, subjective measures are vulnerable to biases stemming from individual differences in self-perception, memory, and reporting tendencies, which may undermine their reliability and comparability across contexts. In contrast, psychophysiological approaches provide real-time, objective indicators that can capture subtle fluctuations in workload without interfering with task execution. Nevertheless, challenges remain regarding the specificity of these measures to MWL, the potential influence of extraneous factors (e.g., emotional states or environmental stressors), and the practical feasibility of implementing them outside laboratory conditions. Addressing these challenges is critical to advancing the reliability, validity, and applicability of psychophysiological measurement in both experimental and applied research on MWL. Ultimately, the integration of psychophysiological indices with behavioral and subjective measures represents a promising direction for developing a multidimensional and ecologically valid framework for workload assessment.

Psychophysiological measurements appear to be gaining prominence in MWL research. Advancements in sophisticated and practical measuring instruments have 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 (Wanyan et al., 2018; Dahlstrom et al., 2011; Wilson, 2002), or fNIRS (Verdière et al., 2018; Causse et al., 2017; Foy et al., 2016; Ayaz et al., 2012), eye-gaze behavior using an eye-tracker (Rodemer et al., 2023; He et al., 2022; Widyanti et al., 2017; Di Nocera et al., 2007), and facial thermography (Marinescu et al., 2018). Nevertheless, the performance of fNIRS is insufficiently sensitive for tasks with small demand variations, such as office work or tasks with a large 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 an indicator of increased MWL (Li et al., 2021), although Tao et al. (2019) demonstrated that a decrease in both LF and HF reflects an increase in MWL.

Table 3 presents a consolidated overview of the empirical studies employed to operationalize and MWL. These studies span a range of methodologies and task environments, each contributing specific physiological, behavioral, or subjective used to quantify MWL. Together, they provide a foundation for understanding how MWL is indexed across different experimental contexts and support the selection of appropriate measurement modalities in the present research.

Table 3 Overview of empirical studies used to operationalize and measure mental workload across diverse tasks and methodologies

No.	Sources	Techniques	Operationalization of MWL
1.	(Silva, 2014)	Primary task	MWL is measured as variations in lateral position and the time elapsed before lane departure, reflecting the driver's ability to maintain primary task performance, i.e. lateral control of the vehicle within road boundaries, a psychomotor activity dependent on eye–hand coordination, and can be assessed using objective performance metrics.
2.	(Young et al., 2015)	Primary task	MWL is defined as variations in a driver's ability to maintain acceptable performance on the primary task, that is, the capability to control the vehicle with a low likelihood of error and a high level of efficiency. The most widely used category of measures relies on directly recording this performance capacity. In traffic psychology research, such task-performance indicators are closely linked to vehicle handling, including both lateral and longitudinal control (e.g., steering and car-following behavior).
3.	(Grant et al., 2013)	Secondary task	MWL is the variation in intervals generated by participants as primary task demands increase. Participants are asked to respond whenever they believe a target interval has passed and continue doing so until instructed to stop or the trial ends. As workload rises, the intervals they produce typically become less precise and more variable.
4.	(Warvel and Scerbo, 2015)	Secondary task	MWL is defined as variations of spare processing capacity, assessed through changes in secondary task performance and subjective workload ratings as primary task demands are manipulated. In this study, participants completed a peg transfer task under different camera angles while simultaneously performing a ball-and-tunnel secondary task. A decline in secondary task performance at a 90° camera angle compared with 0° was expected to indicate reduced spare capacity, while higher subjective scores under dual-task and more demanding camera-angle conditions were anticipated to reflect increased workload.
5.	(Hart, 2006)	Subjective	MWL based on NASA-TLX is measured by variations in subjective workload scores provided by participants. These scores represent the perceived mental, physical, and temporal demands of the task, as well as effort, performance, and frustration levels. As the conditions of the primary task become more demanding, the NASA-TLX ratings typically increase, indicating a higher MWL.
6.	(Huggins and Claudio, 2018)	Subjective	MWL is defined as changes in SWAT scores, a subjective workload assessment technique that evaluates perceived demands across three key dimensions: time load, reflecting how rushed or time-pressured a task feels; mental effort load, indicating the level of cognitive processing and concentration required; and psychological stress load, representing the emotional strain or tension experienced while performing the task. As task demands increase, SWAT scores typically rise across these dimensions, signaling a higher level of mental workload.
7.	(Moustafa and Longo, 2019; Moustafa et al., 2017)	Subjective	MWL is defined as variations in the WP index, a subjective workload measure based on eight dimensions of information processing and response demands: perceptual/central processing, response processing, spatial processing, verbal processing, visual processing, auditory processing, manual responses, and speech responses. During assessment, operators are asked to estimate the proportion of their attentional resources allocated to each dimension on a scale from 0 to 1. Increases in the WP index across these dimensions indicate that greater mental resources are being consumed by the task and therefore reflect higher levels of mental workload.
8.	(Leggatt, 2005; Marinescu et al., 2018)	Subjective	MWL is defined as variations in mean ISA scores, whether expressed in raw or normalized form, which reflect the operator's self-rated intensity of mental demand during task performance. Higher ISA scores indicate that individuals perceive themselves to be operating closer to the upper limits of their available attentional resources, whereas lower scores suggest that sufficient spare capacity remains available. Thus, increases in mean ISA scores are interpreted as evidence of elevated mental workload under more demanding task conditions.

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Table 3 Overview of empirical studies used to operationalize and measure mental workload across diverse tasks and methodologies (Cont.)

No.	Sources	Techniques	Operationalization of MWL
9.	(Chowdhury et al., 2018)	ECG	MWL is reflected by changes in heart rate variability (HRV), with decreases in HRV commonly interpreted as signs of elevated MWL. HRV represents the fluctuation in time intervals between successive heartbeats and serves as an indicator of autonomic nervous system balance, particularly the interplay between sympathetic and parasympathetic activity. When cognitive demands rise, sympathetic dominance increases and parasympathetic influence diminishes, resulting in a reduction of HRV. Accordingly, sustained decreases in HRV are taken as physiological evidence that an operator is experiencing higher levels of MWL.
10.	(Mansikka et al., 2016)	ECG	MWL is reflected by variations in heart rate (HR) and heart rate variability (HRV) components. An increase in HR signals higher sympathetic activation and is therefore associated with greater MWL, whereas an increase in HRV, reflecting stronger parasympathetic influence and more flexible cardiovascular control, is generally associated with a lower level of MWL. Thus, increased MWL conditions typically result in increased HR alongside reduced HRV, while lower MWL conditions show the opposite pattern.
11.	(Causse et al., 2022)	fMRI	MWL refers to changes in brain activity across the fronto-parietal network, particularly in regions such as the dorsolateral prefrontal cortex (DLPFC), dorsal anterior cingulate cortex (dACC), and the parietal cortex. Increases in BOLD (blood-oxygen-level-dependent) signal within these areas are typically interpreted as reflecting higher levels of MWL.
12.	(Wanyan et al., 2018)	EEG	Mental workload has been linked to distinct changes in mismatch negativity (MMN) responses across different brain regions. Specifically, it is associated with an increase in the MMN amplitude over frontal areas, while simultaneously showing a decrease in MMN amplitude over temporal regions. This suggests that higher demands may shift neural processing resources toward frontal executive networks at the expense of sensory processing areas in the temporal cortex.
13.	(Dahlstrom et al., 2011)	EEG	MWL is reflected in changes in neural oscillatory activity. Specifically, as MWL increases, there is typically a reduction in alpha-band power (8–12 Hz), which is thought to index decreased cortical idling or inhibition, and a concurrent increase in delta-band power (1–4 Hz), often associated with heightened cognitive effort and attentional demand. These frequency-specific changes serve as reliable electrophysiological markers of escalating MWL.
14.	(Wilson, 2002)	EEG	MWL during demanding flight phases, such as takeoff and landing, is reflected in characteristic EEG patterns, notably a decrease in alpha-band power and a rise in delta-band power. These oscillatory shifts align with prior findings indicating that reduced alpha activity reflects heightened cortical engagement, while elevated delta activity signals increased cognitive effort. Together, these changes provide converging electrophysiological evidence of greater cognitive demand in challenging operational contexts like aircraft takeoffs and landings.
15.	(Verdière et al., 2018)	fNIRS	MWL is closely tied to neural activity within the prefrontal cortex, a key region involved in higher-order cognitive control and executive processing. Increases in activation within this area are typically interpreted as signaling increased MWL, reflecting the recruitment of additional cognitive resources to meet task demands.
16.	(Causse et al., 2017)	fNIRS	MWL can be inferred from hemodynamic changes in the prefrontal cortex: as task difficulty rises, there is a systematic increase in oxygenated hemoglobin (HbO_2) and a corresponding decrease in deoxygenated hemoglobin (HHb) in this region. These fNIRS-based responses reflect enhanced cerebral oxygen delivery and utilization, indicating that more metabolic resources are being recruited in the prefrontal cortex to support the heightened cognitive demands of the task being performed.
17.	(Foy et al., 2016)	fNIRS	MW was operationalized using prefrontal cortical activity measured via hemodynamic responses. Specifically, increases in deoxygenated hemoglobin (HHb) levels in the prefrontal cortex have been shown to rise during periods of increased demand. For example, during the overtake phase, which represents a high MWL condition, and remain elevated into the subsequent overtake departure period. This sustained increase in HHb suggests prolonged recruitment of prefrontal resources to meet ongoing cognitive demands.

Table 3 Overview of empirical studies used to operationalize and measure mental workload across diverse tasks and methodologies (Cont.)

No.	Sources	Techniques	Operationalization of MWL
18.	(Ayaz et al., 2012)	fNIRS	MWL during a simulated air traffic control task was indicated by increases in activation in the anterior medial prefrontal cortex when the number of aircraft to be monitored were higher. This increase in prefrontal activation signals the recruitment of greater executive and attentional resources to manage the increased complexity and cognitive demands of the task.
19.	(Rodemer et al., 2023)	Eye-tracker	MWL Is indexed through pupillometry. Specifically, pupil diameter was found to be significantly larger in a dynamic signaling condition relative to a control condition without such signals. This pattern Is interpreted as reflecting increased cognitive effort and higher MWL under more demanding task circumstances.
20.	(He et al., 2022)	Eye-tracker	MWL is quantified using ocular indices, with two well-established markers being blink rate and pupil diameter. Increased blink frequency is thought to indicate increased cognitive strain and processing demands, potentially reflecting greater depletion of attentional resources. Concurrently, dilation of the pupil is widely interpreted as an autonomic response linked to increased mental effort and sustained attentional engagement. Collectively, these oculometric measures offer sensitive, non-invasive indicators of escalating MWL in task-intensive environments.
21.	(Widyanti et al., 2017)	Eye-tracker	MWL is reflected in patterns of spontaneous eye blinks. Specifically, a decrease in blink rate has been consistently observed under conditions of increased cognitive demand, suggesting increased concentration and allocation of attentional resources. Lower blink frequency is therefore interpreted as a physiological marker of higher MWL, as individuals suppress blinking to maintain visual focus and cognitive processing during more demanding tasks.
22.	(Di Nocera et al., 2007)	Eye-tracker	MWL is measured through spatial dispersion metrics of crew gaze behavior. In this study, these indices were highly sensitive to fluctuations in task demands, showing greater values during cognitively intensive flight phases such as departure and landing, moderate levels during climb and descent, and the lowest dispersion during the relatively less demanding cruise phase. This pattern suggests that spatial dispersion measures can serve as effective indicators of MWL, rising as operational complexity and cognitive requirements increase.
23.	(Marinescu et al., 2018)	Facial thermography	MWL can additionally be inferred from peripheral physiological markers such as facial skin temperature. Specifically, a decrease in nose temperature has been observed to accompany periods of increased cognitive demand, likely reflecting sympathetic vasoconstriction associated with stress and mental effort. Thus, a drop in nasal temperature is interpreted as a thermoregulatory indicator of increased MWL, signaling greater activation of the autonomic nervous system during demanding tasks.

4. Discussions

4.1. Conceptual and Operational Definition of the MWL

Based on the two previously reviewed theories, four elements should be included in defining MWL conceptually. The first element concerns 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 Miller's classical hypothesis of "the magic number seven plus or minus two" to more contemporary hypothesis stating that the number of information pieces humans can retain is around three to four (Gilchrist et al., 2008) or five (Halford et al., 2007). Although the precise quantity of information that may be stored in a person's working memory is under discussion, these experiments demonstrate that our cognitive processing ability is limited. This restriction is intended to either save energy or facilitate future information retrieval (Cowan, 2010). Individuals must choose which information they need to be conscious of to execute certain behaviors effectively due to its restricted capacity. Attention plays a crucial role in information selection 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 have also connected cognitive activities with changes in physiological activities. An increase in MWL increases arousal, which is reflected in the ANS activity. 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). 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 task demand level. Tasks are a significant focus of human factors and ergonomics studies because they are closely linked to humans. A significant amount of endeavor in this field is focused on comprehending how individuals successfully accomplish their 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 to achieve a desired outcome. This definition encompasses the actions and functions necessary to accomplish the intended goal. Tasks and humans interact by imposing physical and mental demands on humans, and humans must fulfill these demands to complete the tasks. Given the increasing cognitive demands of contemporary work (Young et al., 2015), comprehending tasks is crucial in MWL. In an MWL study, tasks are often altered by adjusting the amount of demand (Devlin et al., 2020). This allows for the observation and measurement of MWL changes.

The third element focuses on task performance. The third attribute of the definition is task performance. Although a particular task consistently creates specific demands, the manner in which a human operator accomplishes the task may vary. 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 because operators prefer to actively check their performance and system 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, ultimately changing their workload. The performance results might modify subsequent expectations by altering the task. For instance, if a pilot fails to execute their landing process correctly, they must perform an additional task to retake the landing operations from the initial stage. This undoubtedly amplifies their workload. In conclusion, performance must be included in the definition of MWL.

The fourth attribute is subjective experience. MWL encompasses the subjective evaluation of a task’s demands. 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 assesses 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 because 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, which can be indicated by changes in physiological indices, performance, or subjective experience. More operationally, a higher MWL can be attributed to a tendency to have poorer performance or higher scores 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 (Galoyan et al., 2021; Causse et al., 2017; Ayaz et al., 2012), or increased pupil diameter (Appel et al., 2018).

4.2. Measurement Framework

Based on the review, a framework for measuring MWL can be utilized based on the components involved in MWL formation. Figure 3 shows the components and their interplay. Operator workload refers to the level of effort or strain that an operator experiences while performing a task. This aspect is mostly subjective but can also be deduced from physiological or behavioral 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 influence the operator's work experience (Astin and Nussbaum, 2002). Operators can 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 the number of mistakes/errors (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 (Ellinas et al., 2017). This factor is crucial in the construction of MWL to a certain degree. However, this framework lacks an explanation of physiological changes and mechanisms. We argue that this element could be placed alongside performance, as changes in this element occur immediately in response to demand, and thus MWL changes (Puusepp et al., 2024).

The interplay between these components is also distinctive. It is not as straightforward as deducing that 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 because they might define the magnitude of the demands. For instance, an identical task might result in varying demands for novice and expert operators (Byrne et al., 2013). However, performance and physiological changes are 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 effectively maintain their performance (Gathmann et al., 2015). Operators can frequently obtain feedback on their performance by utilizing self-assessment or by observing indicators or displays. Performance feedback might subsequently impact an operator's workload assessment and has the potential to not only impact how heavy the task is perceived but also alter the level of expectations (Maior et al., 2018). Inadequate performance may lead to the emergence of additional unforeseen tasks aimed at restoring performance to the intended standard. As mentioned earlier, internal and external factors, such as the selection of behavioral strategies, can influence the perceived MWL, which can in turn affect task demands.

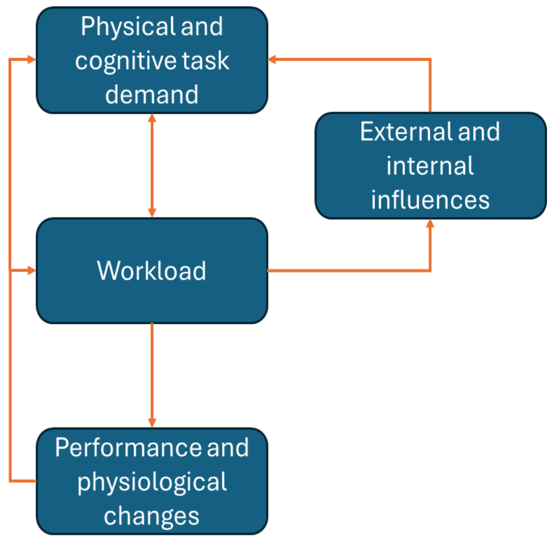

Figure 3 Dynamic framework for measuring the MWL

4.3. Limitations and Challenges

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). Transparent methodological selections, encompassing the criteria for literature inclusion and the approach to synthesis, have been established to alleviate these challenges. This review 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.

Several challenges and issues continue to surround MWL research. One of the reasons for this is that most research on MWL is conducted in controlled laboratory settings (often using simulators), which can limit external validity. Nevertheless, MWL assessment is undeniably beneficial in practical situations. Given the progress made in psychophysiological theory and the development of methodologies to assess MWL, conducting research that applies these measures in actual work environments is necessary (Midha et al., 2021). The primary goal of real-time MWL monitoring is to offer operators with 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, providing feedback and warnings can be 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 endeavored to quantify MWL by employing diverse psychophysiological methods in actual work environments, including traffic control centers (Fallahi et al., 2016a), driving (Sahaï et al., 2021; Schoedel et al., 2018; Lei et al., 2017), 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 the research conducted by Maior et al. (2018) within a controlled laboratory environment. These studies can eventually provide insights into the feasibility of implementing MWL measurement, particularly by utilizing psychophysiological approaches, in specific real-world work environments. Virtual reality (VR) can also be employed to provide a more realistic simulated environment for measuring the MWL and performance of operators (Sudiarno et al., 2024). Gaining insights into the perspective of operators or subject-matter experts/SMEs on MWL sensors and their implementation in actual workplaces is essential as it can predict the acceptance of the technologies (Salma et al., 2024). Incorporating MWL into brain-machine interfaces (Whulanza et al., 2024) has the potential to enhance the development and implementation of neurofeedback in workplace settings.

4.4. Implications and Significance

The outcomes of this review could serve as a crucial reference point for the ongoing discourse surrounding the definition of MWL. By consolidating diverse perspectives, this review not only contributes to theoretical clarity but also supports the development of a more unified and operational understanding of the concept. A clearly articulated definition is indispensable because MWL remains a multifaceted construct that cuts across numerous fields of inquiry. Within psychology, for instance, it is frequently associated with cognitive load, attention, and information-processing limitations, whereas in engineering it is more often framed in terms of human-machine interaction, ergonomics, and system efficiency. Medicine, in contrast, may emphasize the implications of MWL for clinical decision-making, diagnostic accuracy, and fatigue-related errors. Without a shared conceptual ground, researchers and practitioners risk employing incompatible frameworks, which can lead to divergent, and sometimes even contradictory, findings. These inconsistencies not only hinder cumulative scientific progress but also obstruct the translation of research outcomes into practical applications in real-world settings.

Beyond theoretical concerns, the establishment of a more standardized conceptualization of MWL carries significant practical implications. In occupational domains where safety and performance are paramount, such as aviation nuclear power, healthcare, or military, misjudging MWL can result in catastrophic consequences. A clear and widely accepted definition can inform the development of training protocols, workload management systems, and ergonomic interventions that mitigate the risk of overload or underload. Similarly in educational context, understanding MWL allow instructors to design learning experiences that optimize cognitive engagement without overwhelming students, thereby promoting deeper learning and long-term knowledge retention. In the corporate sector, organizations can benefit by designing work environments and schedules that balance productivity with employee well-being, reducing burnout and turnover. Thus, the implications of definitional clarity extend far beyond academia, reaching into very structure of professional practice and human performance.

Equally important is the systematic evaluation of the instruments used to measure MWL. This review highlights the wide spectrum of available tools, ranging from subjective self-report questionnaires such as NASA-TLX and SWAT, to psychophysiological indices including fNIRS, EEG, ECG, or eye-tracker, as well as objective performance-based indicators like reaction times and error rates. Each of these approaches carries distinct advantages and limitations, and the lack of a universally accepted gold standard further complicates cross-study comparisons. By mapping these methods within a coherent framework, this review underscores the necessity for developing multi-modal assessment strategies that triangulate data from different sources. Such integration, could yield more robust and ecologically valid insights, thereby enhancing both research precision and practical decision-making in applied settings.

In the long term, this review directs forthcoming research toward the establishment of reliable, standardized methodologies that can bridge disciplinary boundaries. Future scholars may pursue efforts to create hybrid models that combine subjective, behavioral, and physiological data into composite indices of MWL, supported by advances in machine learning and wearable sensor technologies. The proliferation of ubiquitous computing devices offers unprecedented opportunities for real-time, unobtrusive monitoring of MWL in naturalistic environments, enabling dynamic workload management systems that adapt tasks to individual states in real time. Such innovations hold the potential to revolutionize task design by ensuring that human cognitive capacities are respected and optimized rather than overused.

Finally, the insights synthesized in this review are not academic in nature but also instrumental in shaping safer, more effective, and more humane work systems. By offering a consolidated perspective on both definitions and measurement approaches, this work lays the groundwork for future research that aspires to unify theoretical rigor with practical applicability. In doing so, it contributes to a broader agenda of promoting human well-being, enhancing organizational performance, and safeguarding against the risks that emerge when MWL is poorly understood or inadequately managed. The pursuit of definitional clarity and methodological standardization is therefore not a mere intellectual exercise. It is a necessary step toward advancing interdisciplinary collaboration, fostering innovation in MWL management, and ultimately ensuring human capabilities are aligned with the increasing demands of complex technological and social environments.

5. Conclusions

This study critically examined the conceptualization and measurement of MWL by grounding the discussion in two foundational theoretical frameworks, the Limited Resource Theory (LRT) and the Multiple Resource Theory (MRT). Based on this review, we contend that a robust conceptual definition of MWL should integrate four essential elements: the bounded nature of cognitive processing capacity, variability of task demands, observable changes in performance and physiological functioning, and the subjective experience of effort or strain. Operationally, increased MWL can be inferred as a function of increased task demands, typically reflected in decline in performance, elevated subjective ratings, and changes in physiological responses.

The measurement of MWL has drawn upon a range of methodological approaches, with psychophysiological techniques currently positioned as primary indicators owing to their capacity to provide objective, sensitive, and real-time assessments during task performance. These technique captures fluctuations in MWL that may not be readily detectable through behavioral or self-report measures alone. Nonetheless, both theoretical and methodological challenges persist. These include the need to account for individual variability in baseline physiological responses, the multidimensionality nature of MWL, and the practical constraints associated with Implementing such measures in applied settings.

Future research should therefore aim to refine the integration of psychophysiological, behavioral, and subjective approaches in order to develop a more comprehensive and ecologically valid framework for assessing MWL across diverse task environments. Such integration would allow for a multidimensional assessment that captures both the objective and subjective facets of workload, thereby increasing sensitivity to task- and context-specific variations. Moreover, advancing this line of inquiry would contribute to the development of standardized protocols that enhance cross-study comparability, facilitate the translation of laboratory findings into applied settings, and support evidence-based interventions in domains such as education, healthcare, and human–machine interaction.

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Author Contributions

Ridwan Aji Budi Prasetyo: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Writing – original draft; Hardianto Iridiastadi: Conceptualization, Supervision, Validation, Writing – review & editing.

Conflict of Interest

The authors have no conflicts of interest to declare.

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