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Evaluating mental workload: A taxonomic approach to evaluation tools based on ISO 10075

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ABSTRACT

Recent technological transitions present in the manufacturing sector are transforming the way operators work, greatly impacting their mental workload and presenting new challenges for the cognitive ergonomics field. In an effort to design and implement human-centered management strategies, it is increasingly necessary to effectively explore and evaluate the various aspects related to mental workload. Despite the maturity of the field, in the existing literature a consensus on defining mental workload remains elusive. To bridge this gap, this paper introduces a comprehensive and holistic definition, drawing inspiration from the ISO 10075 standard. This novel taxonomic framework distinguishes various constructs related to mental workload, clarifying their causes and the consequences they induce. Additionally, an extensive literature analysis was conducted to develop a taxonomy of mental workload assessment tools, outlining their operational principles along with their strengths and weaknesses. This taxonomy can be used as a pragmatic guide for selecting appropriate tools based on specific contexts. Moreover, the existing literature was extensively investigated to ascertain the nature of the correlation—whether positive or negative—between the metrics of these tools and the range of the effects of mental workload fluctuations. This methodological approach addresses the common issue of misinterpreting results from mental workload measurements.

In essence, the research seeks to enrich the understanding of mental workload concepts and offers a critical evaluation of its measurement tools. The findings are intended to assist practitioners in the informed selection of measurement tools and to refine data interpretation, thereby facilitating better management of mental workload in manufacturing environments.

1. Introduction

The current shift from Industry 4.0 to Industry 5.0 is pushing towards a new industrial outlook, rooted in human-centered production processes (Gervasi et al., 2023a,b). This new perspective is becoming increasingly essential considering the escalating complexity of production systems (Bartolomei et al., 2025; Verna et al., 2023). As manufacturing moves from mass production to mass customization, operators face challenges such as managing complex information flows, adapting to changing work cycles, and making swift decisions. Poor management of these challenges can negatively impact mental workload, compromising operator's ergonomics, well-being, and production efficiency (Capponi et al., 2023, 2024a). Consequently, effective strategies to manage mental workload are required to promote cognitive ergonomics. Recent research emphasizes designing adaptive processes and assistive technologies that adjust to the physical and mental state of the operator, such as collaborative robotics (Barravecchia et al., 2023; Borghi et al., 2025; Stasch and Mack, 2025) and augmented reality (Bottani and Vignali, 2019). However, exploiting the potential of these technologies requires accurate tools to measure mental workload.

Measuring mental workload has been a topic of great interest to cognitive scientists, ergonomists, and engineers over the last decade. The primary challenge in this area stems from the complex nature of

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List of acronyms

ANS	Autonomic Nervous System
CNS	Central Nervous System
EC	Exclusion Criteria
ECG	Electrocardiography
EDA	Electrodermal Activity
EEG	Electroencephalography
EMG	Electromyography
ERP	Event-Related Potentials
FFT	Fast Fourier Transformation
HF	High-Frequency HRV band
HR	Heart Rate
HRV	Heart Rate Variability
IP/PCT	Information Processing/Perceptual Control Theory
LF	Low-Frequency HRV band
MF	Muscle Fatigue
NASA-TLX	NASA - Task Load Index
POP	Prediction of Operator Performance
PPG	Photoplethysmography
PSNS	Parasympathetic Nervous System
RMSSD	Root Mean Square of Successive Differences of R-R intervals
RTs	Reaction Times
SAM	Self-Assessment Manikin
SCL	Skin Conductance Level
SCR	Skin Conductance Response
SDNN	Standard Deviation of NN intervals
SNS	Sympathetic Nervous System
SWAT	Subjective Workload Assessment Tool
SWORD	Subjective Workload Dominance
TLAP	Timeline Analysis and Prediction
VACP	Visual, Auditory, Cognitive, and Psychomotor
VAS-F	Visual Analogue Scale – Fatigue
W/INDEX	Workload INDEX

mental workload, which hindered the definition of a single conceptualization (Young et al., 2015). In addition, the lack of a common reference for correlating metrics from assessment tools with the measurable effects of mental workload creates the risk of conflicting interpretations of assessment results, potentially affecting mental workload mitigation strategies.

With the aim of standardising relevant concepts and terms related to mental workload and cognitive ergonomics, this paper adopts a conceptualization of mental workload that is firmly anchored in the ISO 10075 standard (2017). This standard recognizes that mental workload consists of the interaction between *mental stress*, i.e., the demands placed on an individual by task and work environment characteristics, and *mental strain*, i.e., an individual's response to mental stress, modulated by their personal and emotional characteristics. Effective mental workload management requires the synergetic consideration of these two constructs. Managing mental stress involves reducing the mental demand that the operators have to face (e.g., simplifying tasks, improving work organization, or integrating assistive technologies), while managing mental strain focuses on mitigating its effects (e.g., adaptive work-rest cycles or implementing biofeedback-based interventions). The balance between these two approaches is crucial to promoting cognitive ergonomics and sustaining performance and well-being in the workplace.

In the literature, mental workload has often been treated as a singular construct with a uniform and predominantly negative measurable effect. However, ISO 10075 treats it as an umbrella term for mental stress and mental strain, emphasizing that mental strain effects can be both positive and negative. Despite extensive research on the mental strain effects cited in the ISO 10075, so far these effects have been studied in isolation and have never been explicitly linked to the broader concept of mental workload. This lack of integration has resulted in the absence of a unified model connecting these effects to mental workload, leading to inconsistencies in assessment and interpretation. At the same time, various tools have been developed to assess mental strain, each with distinct properties and specific applications. However, no structured comparison of these instruments exists, leaving practitioners without clear guidance on which tool is most appropriate for studying certain effects in a given manufacturing context. The absence of a comparative framework complicates the selection process and contributes to inconsistencies in mental strain assessment, ultimately limiting the reliability and applicability of measurement results.

Therefore, the objective of this paper is to address these gaps, specifically providing:

(i) A short overview of the ISO 10075 standard and a taxonomy of assessment tools related to mental stress and mental strain.
(ii) A set of criteria to guide the evaluator when selecting the tools to assess mental strain.
(iii) Some general interpretation matrices correlating the short-term effects of mental strain with the expected responses from assessment tools metrics.

Overall, this work provides structured guidelines for selecting measurement tools based on real-world scenarios and supports users in interpreting results. By aligning assessment methods with a unified framework, it facilitates consistent evaluation of mental strain effects, enhancing the reliability and diagnostic accuracy of mental workload analyses.

The paper is structured as follows: Section 2 redefines mental workload according to ISO 10075, introducing mental stress and strain. Section 3 updates the classification of assessment tools, aligning them with ISO 10075. Section 4 analyses the tools used to assess mental strain, outlines the criteria for their selection, presents matrices for interpreting the resulting metrics with respect to the short-term effects of mental strain, and provides suggestions for implementing the assessment tools in different manufacturing contexts. Section 5, dedicated to discussion and conclusions, analyses the contributions of the work, discusses its limitations, and highlights possible future developments.

2. Mental workload according to ISO 10075

Mental workload has been a much-debated topic in the literature in recent decades. Initially centered on measurement strategies in the 1980s, the focus gradually shifted towards its modelling in the 1990s and culminated in the development of practical applications for its management in the last decade (Young et al., 2015). Despite sustained interest, a universally accepted definition remains elusive. Fred Paas Juhani et al. (2003) state that mental workload depends on the relationship between the individual and the task. Haapalainen et al. (2010) clarify the nature of this relationship as the amount of information an operator processes to complete a task. Parasuraman et al. (2008) conceptualizes mental workload as the relationship between task-required and available mental resources. The characteristics of tasks that increase demand on mental resources are, among the others, time pressure and the frequency of decision-making (Bommer and Fendley, 2018). Young et al. (2015) offer a holistic definition, considering mental workload as the sum of resources needed to meet performance standards, influenced by task demands, external support, and prior experience. Neill (2011) highlights the significant role of the work environment in modulating mental workload.

This lack of uniformity in the definition of mental workload is due to the intangibility of this construct, but also to the lack of a framework that provides a clear and complete profile of all its causes and effects. In order to provide a univocal definition of mental workload and to pinpoint its causes and consequences, ISO 10075 (2017) was created.

ISO 10075 provides an overview of general concepts, terms and definitions related to mental workload, focusing particularly on the link between mental stress and mental strain and their consequent effects. It is worth mentioning that in the ISO 10075, the term "mental workload" is used as a generic umbrella term for referring to the domain of mental workload, which include concepts and constructs such as *mental stress* and *mental strain*.

According to ISO 10075, mental stress refers to total of all assessable factors impinging upon a human being from external sources and affecting that individual mentally. Mental stress encompasses various external factors that affect an individual as combined, not isolated, stressors that lead to cognitive and emotional processes. Examples of environmental constituents of mental stress are task requirements (e.g., information processing, task content), physical conditions (e.g., lighting, noise), social and organizational factors (e.g., organizational climate, conflicts), and societal factors external to the organization (e.g., social demands, cultural standards).

According to ISO 10075, mental strain refers to the immediate effect of the load imposed by mental stress within the individual depending on their characteristics and current condition. Mental stress can have both positive and negative effects, inducing also processes of increasing or decreasing mental strain, which are modulated by the characteristics of an individual (e.g., age, gender, skills, coping strategies, and attitude).

Fig. 1 provides a schema of the structural relationship between mental stress and mental strain. ISO 10075 also provides an overview of consequential effects of mental strain which can be either positive (facilitating effects) or negative (impairing effects), as well as with short-term or long-term potential. Table 1 provides a summary of the effects and their definition presented in the ISO 10075.

In the next sections, the ISO 10075 conceptualization of mental workload will be used to create the interpretation matrices for mental workload assessment tools.

3. Mental workload evaluation tools

The multifaceted nature of mental workload requires different tools for its measurement, each suited to various contexts. This section introduces a structured taxonomy to classify these tools and align them with the revised conceptualization of mental workload, which distinguishes between mental stress and mental strain (See Fig. 2). The proposed taxonomy is developed through the synthesis of established frameworks in the literature. The category names in this taxonomy serve as 'umbrella' terms designed to unify the varied terminologies used in the literature for conceptually similar constructs.

In this study, the term *tool* encompasses a broad range of techniques and methodologies employed to assess mental workload. These tools provide mental workload measures, which represent the quantitative or qualitative *metrics* derived from each assessment method (see last column of Table 2).

Xie and Salvendy (2000) introduce a fundamental classification of mental workload assessment tools, dividing them into analytical and empirical categories. Analytical tools, which focus on task characteristics, are referred to in this taxonomy as *task-centered analytical tools*. By

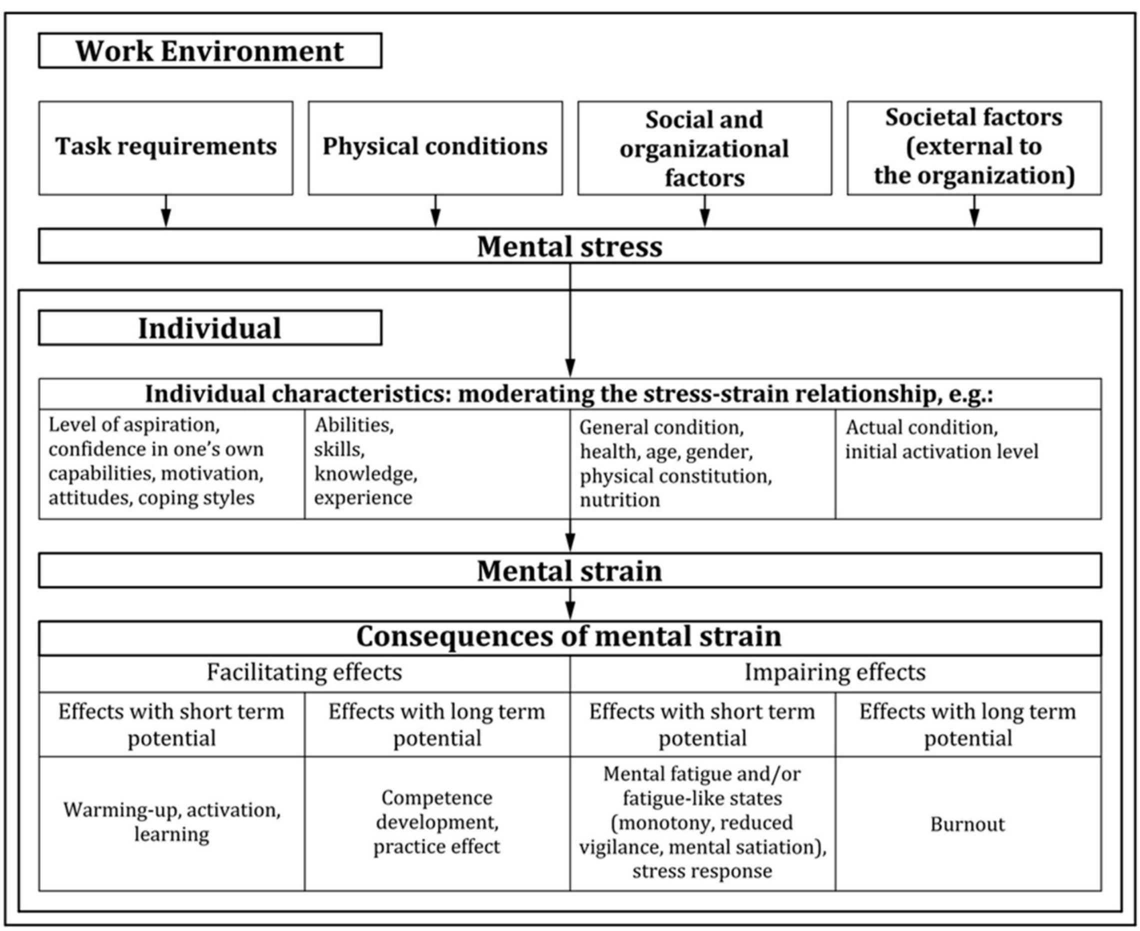


Fig. 1. Summary of the structural relations between mental stress, mental strain, and their consequences according to ISO 10075 (2017).

Table 1
Effects of mental strain presented (ISO 10075, 2017).

Type of effect	Temporal domain	Consequence of mental strain	Description
Facilitating effect	Short-term	Warming-up effect	A phenomenon that consists, immediately after the start of an activity, of a reduction in the effort required to perform that activity compared to the effort initially required.
		Activation	An internal state resulting in increased mental and physical activity. Distinct levels of activation can manifest, depending on the duration and intensity of mental strain, and there is an optimal range in which the level of activation provides the best functional efficiency.
		Learning	A process based on experiences that lead to lasting changes in an individual behavior or behavioral potential, such as plans and attitudes.
	Long-term	Practice effect	Enduring improvement in individual performance as a result of repeated experiences of the same kind of mental strain. It is associated with learning processes.
		Competence development	Complex form of learning concerned with acquisition, consolidation, or enhancement of individual abilities as a result of active engagement in an activity.
Impairing effect	Short-term	Mental fatigue	Internal state consisting of temporary impairment of mental and physical functional efficiency (e.g., feelings of tiredness and/or occurrence of errors), from which one can recover by resting.
		Fatigue-like states	Internal states resulting from situations offering little variety, the recovery from which can be achieved after changes in the task and/or the environment (i.e., not necessarily through rest). These states tend to be highly influenced by interindividual differences.
		Monotony	Slow-developing state of reduced activation that is mainly associated with drowsiness, fatigue, and decreased performance, responsiveness, and adaptability. Monotony usually occurs in repetitive, long, uniform tasks (e.g., assembly processes).
		Reduced vigilance	State associated with reduced activation and detection performance during monitoring or inspection tasks (e.g., surveillance) with little variety.
		Mental satiation	State of nervousness and strong emotional rejection (e.g., anger, tendency to withdraw) of a repetitive activity, in which the experience is of “marking time” or “not getting anywhere”. It is often associated with increased activation.
		Stress response	State within the individual characterized by increased mental and/or physical activation resulting from the negative interpretation of mental stress (e.g., perceived threat or hindrance to one’s goals or values)
	Long-term	Burnout	State characterized by perceived mental, emotional, and/or physical exhaustion, a distant attitude towards one’s job, and perceived reduced performance capacities, resulting from prolonged exposure to specific kinds of mental stress

contrast, empirical tools, which aim to quantify the individual’s responses to a mental stimulus, are termed as *individual-centered empirical tools*. In line with Cain (2007), individual-centered empirical tools can be further subdivided based on the specific type of response they measure:

- *Self-perception methodologies:* quantify the mental workload perceived by operators using rating scales or questionnaires. Prominent examples include the *NASA-Task Load Index* (*NASA-TLX*; Hart and Staveland, 1988) and the *Subjective Workload Assessment Technique* (*SWAT*; Reid and Nygren, 1988).
- *Performance-based approaches*: infer mental strain by analyzing trends in error-proneness and reactivity. Cain (2007) further classifies these approaches into *primary task performance measures*, which evaluate mental workload based on an operator’s execution of the primary task, and *secondary task performance measures*, which introduce an auxiliary task alongside the primary task to provide an indirect assessment of mental workload.
- *Psychophysiological signals*: these approaches are based on the premise that fluctuations in mental workload are concomitant with physiological responses. As outlined by Charles and Nixon (2019) and Tao et al. (2019), physiological signals can be categorized into several domains, including neural activity (e.g., EEG), ocular metrics (e.g., fixations, pupil dilation), cardiovascular responses (e.g., heart rate variability), electrodermal activity (e.g., skin conductance), and muscular responses (e.g., EMG). These measures provide an objective assessment of workload by capturing involuntary physiological fluctuations.

Task-centered analytical tools estimate mental workload based on task requirements and attributes. Unlike empirical tools, these work prior to task performance without operator on the loop, using a predictive approach. According to Xie and Salvendy (2000) prominent categories of task-centered analytical tools include:

- *Task-analysis methodologies*: use computational models with task-related information, such as scheduling and physical requirements, to estimate mental workload. An example is the *Visual Auditory Cognitive Psychophysical* (*VACP*; Bierbaum et al., 1987; McCracken and Aldrich, 1984), developed within Wickens’ multi-resource theory (Wickens, 2002).
- *Projective methodologies*: determine mental workload through expert opinions. Experts use projective variations of rating scales like SWAT

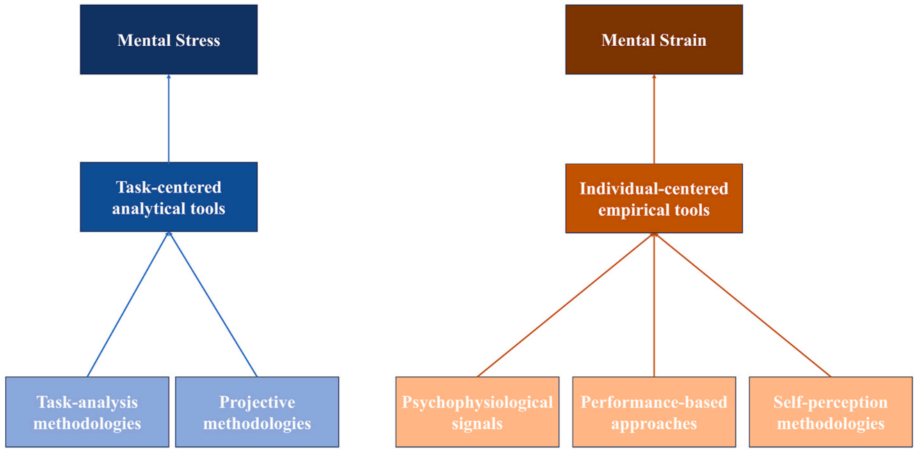


Fig. 2. Framework illustrating the relationship between the categories of tools for measuring mental workload and the mental strain and mental stress constructs introduced by ISO 10075 (2017).

to predict workload without complex computational analysis (Reid et al., 1984).

Fig. 2 presents the classification of mental workload measurement tools within the ISO 10075 framework. Individual-centered empirical tools assess an individual's response to mentally demanding stimuli, capturing variations due to personal characteristics, expectations, and emotional states, making them appropriate for quantifying mental strain. In contrast, task-centered analytical tools evaluate task and environmental characteristics independently of the operator, making them suitable for measuring mental stress but insufficient for assessing mental strain due to the absence of individual-level data. This distinction provides a systematic basis for tool selection. When the objective is prognostic, focusing on identifying and quantifying sources of mental stress, task-centered analytical tools offer the most relevant approach. Conversely, when the goal is diagnostic, monitoring an individual's response to mental stress, individual-centered empirical tools are necessary. In the subsequent sections, the novel conceptualization of mental workload introduced by ISO 10075 will be applied on the analysis of the tools. Furthermore, since the primary aim of this study is the development of a supportive framework for the diagnostic assessment of the mental strain construct, emphasis will predominantly be placed on individual-centered empirical tools.

4. Mental strain assessment – individual-centered empirical tools

Individual-centered empirical tools are standard for assessing mental strain in manufacturing (Bommer and Fendley, 2018; Filho et al., 2024). These tools are based on the principle that increased mental strain leads to measurable operator responses, indicating the intensity and nature of the strain. Assessing mental strain with individual-centered empirical tools involves two main challenges: (i) selecting the most suitable tools for specific use cases; and (ii), accurately interpreting evaluation results. This section provides a structured framework to address these issues, focusing on methodologies for tool selection and efficient data analysis. A comprehensive set of selection criteria, distinguishing the strengths and weaknesses of various assessment tools, is provided in Table 3. Criteria include *sensitivity*, *diagnosticity*, *implementation ease*, *physical intrusiveness*, *task intrusiveness*, and *data processing ease*. Due to the time-sensitive, dynamic nature of manufacturing tasks and the concurrent presence of both cognitive and physical demands, the selection of mental strain assessment tools should ensure a balance between effectiveness and practical feasibility, task and physical intrusiveness.

Building on these criteria, Table 4 presents a preliminary comparative classification of widely adopted individual-centered empirical tools in manufacturing. The classification should be interpreted as a support tool rather than a definitive taxonomy. Its purpose is to assist in early-stage selection decisions by synthesizing recurring insights from the literature and known technological characteristics of each tool.

The attribution of levels (i.e., low, medium, and high) to each criterion is the result of a structured comparative analysis. For example, subjective self-assessment tools generally exhibit moderate sensitivity, as they are effective in distinguishing coarse variations in mental strain rather than subtle changes (Cain, 2007; R. K. Mehta and Agnew, 2015). Conversely, psychophysiological signals—such as EEG and HRV—have demonstrated the ability to detect even minimal fluctuations in mental activity (Lei and Roetting, 2011).

In terms of *diagnosticity*, subjective ratings offer only general mental workload profiles without isolating specific sources of strain this limitation is partially overcome by multidimensional tools (Rubio et al., 2004). Performance-based measures share this limitation, as changes in primary or secondary task performance do not easily map onto discrete cognitive processes. Conversely, psychophysiological signals, when correctly interpreted, offer superior diagnostic resolution (Lei and Roetting, 2011).

Regarding *implementation ease*, subjective methods are advantageous due to their low technical requirements and minimal training needs (Cain, 2007). Performance-based approaches require moderate implementation efforts, including task adaptation and software development. In contrast, psychophysiological techniques often demand specialized equipment and operator expertise, making them less feasible for routine application (Diarra et al., 2025).

Physical intrusiveness is minimal for subjective and performance-based methods, which do not rely on additional hardware. However, psychophysiological tools may introduce discomfort or encumbrance due to the need for wearable devices—such as EEG caps—resulting in higher physical intrusiveness (Longo et al., 2022).

Task intrusiveness depends on the modality and timing of the assessment. When self-report instruments are administered post-task, their intrusiveness is negligible (Longo et al., 2022). However, if used concurrently (e.g., repeated VAS ratings), they can momentarily distract the user and thus increase task interference. Secondary task paradigms are particularly intrusive, as they actively divert attention from the main activity (Cain, 2007). In contrast, most psychophysiological tools collect data passively, allowing for continuous measurement with minimal interference.

Finally, with regard to *data processing ease*, subjective and performance-based tools offer relatively straightforward analysis procedures. Psychophysiological signals, on the other hand, require complex preprocessing pipelines, artifact correction, and often domain-specific expertise to ensure valid interpretation (Diarra et al., 2025).

Table 2
Taxonomy of Mental Workload evaluation tools, based on established taxonomies (Cain, 2007; Charles and Nixon, 2019; Tao et al., 2019; Xie and Salvendy, 2000).

Categories	Subcategories	Examples of evaluation tools	Examples evaluation tools metrics
Individual-centered empirical tools	**Self-perception methodologies**	NASA-TLX (Hart and Staveland, 1988)	*NASA-TLX overall score*
		SWAT (Reid and Nygren, 1988)	*SWAT overall score*
		VAS-F (Lee et al., 1991)	*VAS-F subscales scores*
		SAM (Bradley and Lang, 1994)	*SAM dimensions scores*
	Performance-based approaches	Primary task	*Number of Errors* *RTs*
		Secondary Task	*Number of Errors* *RTs*
	Psychophysiological signals	Brain activity	*Delta (δ) power* *Theta (θ) power* *Alpha (α) power* *Beta (β) power* *Gamma (γ) power* *N1 Amplitude* *P3 Amplitude*
		Ocular activity	*Number of fixations* *Mean duration of fixation* *Saccade amplitude* *Saccade peak velocity* *Pupil diameter*
		Heart activity	*HR* *RMSSD* *SDNN* *LF* *HF*
		Electrodermal activity	*SCR* *SCL*
		Muscular Activity	*Peripheral muscles* *Facial muscles*
Task-centered analytical tools	**Task-analysis methodologies**	VACP (McCracken and Aldrich, 1984)	*VACP Score*
		W/INDEX (North and Riley, 1989)	*W/INDEX Score*
		TLAP (McMillan et al., 1989)	*TLAP Score*
		POP (Fowles-Winkler et al., 2004)	*POP Score*
		IP/PCT (Fowles-Winkler et al., 2004)	*IP/PCT Score*
		POP/IP (Fowles-Winkler et al., 2004)	*POP/IP Score*
	Projective methodologies	Pro-SWORD (M. A. Vidulich et al., 1991)	*Pro-SWORD Score*
		Pro-SWAT (Kuperman, 1985)	*Pro-SWAT Score*

Table 3
Description of selection criteria for mental strain assessment tools.

Selection Criteria	Description	Levels	Example
Sensitivity	Degree to which a tool is able to differentiate between subtle variations in the intensity of mental strain.	• **Low:** detects only large shifts in mental strain; unsuitable for capturing marginal variations. • **Medium:** capable of identifying moderate fluctuations in mental strain. • **High:** exhibits high signal resolution and responsiveness, enabling the detection of subtle, rapid, or context-specific variations in mental strain.	Eye-tracking can detect minute changes in ocular metrics that can indicate varying levels of focus and strain.
Diagnosticity	Degree to which an instrument can distinguish different sources of mental strain (e.g., perceptual, cognitive, emotional load etc.) and different effects (e.g., mental fatigue, monotony etc.).	• **Low:** provides undifferentiated global indices; lacks the granularity to trace the origin or type of mental strain. • **Medium:** offers partial decomposition of mental strain sources or effects, typically distinguishing broad domains. • **High:** allows precise attribution of mental strain to specific functional components or neurocognitive processes based on multivariate or localized measurement.	Brain activity can differentiate between various mental strain effects by monitoring the different areas of brain activation as well as the specific wave band involved.
Implementation ease	Level of expertise required to manage and implement the tool and duration of set-up time.	• **Low:** requires advanced technical skills, calibration procedures, and specialized hardware/software; unsuitable for unsupervised use. • **Medium:** involves some setup complexity or training but can be feasibly integrated into experimental workflows by trained personnel. • **High:** minimal setup and operator training; useable with standard tools or self-administered protocols in both laboratory and applied settings.	Rating scales like the NASA-TLX require minimal training for practitioners and can be deployed rapidly in both field and laboratory settings.
Task intrusiveness	The extent to which the tool	• **Low:** fully passive or post hoc; does	Performance-based approaches that

(continued on next page)

Table 3 (*continued*)

Selection Criteria	Description	Levels	Example
	disrupts the natural flow and completion of tasks by an individual being evaluated.	not divert attention or introduce concurrent cognitive demands during task execution. • **Medium:** involves minor concurrent actions (e.g., button presses, occasional prompts) that marginally affect task continuity. • **High:** requires concurrent performance of a secondary task or frequent user input, significantly affecting cognitive resource allocation and task performance.	measure the execution of a secondary task significantly disrupt the primary task by adding an additional task to be managed simultaneously.
Physical intrusiveness	The extent to which an assessment tool physically disrupts or interferes with an individual's natural condition, potentially causing discomfort or other negative effects.	• **Low:** no physical contact or negligible interference (e.g., non-contact sensing, post-task questionnaires). • **Medium:** requires wearing light, tolerable equipment (e.g., eye-tracker glasses, wrist sensors) that may constrain movement or cause mild discomfort. • **High:** involves cumbersome or obtrusive hardware (e.g., full EEG cap, chest straps, conductive gels) that can affect user comfort, mobility, or task compliance.	EEG involves wearing a cap with electrodes and sometimes applying a conductive gel, which can be intrusive, especially during longer sessions.
Data processing ease	The degree of simplicity associated with the extraction and analytical processing of data generated by an evaluation.	• **Low:** demands advanced signal processing, artifact correction, synchronization with task logs, and often manual annotation. • **Medium:** requires pre-processing and parameter tuning but supported by standard toolkits or semi-automated workflows. • **High:** generates structured, immediately interpretable output (e.g., raw scores or timing metrics) with minimal pre-processing or analytical effort.	Performance-based approaches generate straightforward, quantitative data that facilitate rapid analysis and interpretation, significantly reducing the complexity of data processing.

This classification is intended to provide initial guidance for tool selection across different scenarios, highlighting both benefits and limitations based on established literature. It does not claim universal validity but serves as a synthesis of current evidence. The following subsections provides an in-depth analysis of the different categories of individual-centered empirical tools, enriching the description of the strengths and weaknesses presented in Table 4. In addition, to foster consistent data analysis, an interpretation matrix is proposed for each category based on a detailed literature analysis. This framework is designed to clarify the nature of the correlations—whether positive or negative—between the metrics associated with each tool and the intensification of short-term effects of mental strain as outlined in ISO 10075.

4.1. *Methodology for literature analysis*

A literature analysis was conducted to examine existing studies on the short-term effects of mental strain and their association with the metrics outlined in the proposed taxonomy. The objective was to identify consistent patterns and strong associations between these two elements across different research domains. A structured but adaptable approach was used, ensuring a rigorous selection process while accommodating the interdisciplinary nature of the topic based on the main scientific databases (i.e., Scopus, Web of Science and Google Scholar). The methodology consisted of four phases: (1) literature search, (2) inclusion and exclusion criteria application, (3) selection and expansion of relevant studies, and (4) analysis of findings to evaluate the reliability of associations. A general scheme of the literature analysis is presented in Fig. 3.

4.1.1. *Phase 1: literature search*

Given the interdisciplinary nature of the matter, studies were sourced from *manufacturing, computer science, human-machine interaction, neuroscience, ergonomics*, and *psychology*. The search process began with identifying key terms related to short-term effects of mental strain, prioritizing terminology from ISO 10075 alongside commonly used synonyms in academic contexts, and common methodologies for detecting the mental strain effects. The literature search was conducted using Scopus and Web of Science databases with keyword combinations tailored to capture relevant journal articles. Details on the query used can be found in Appendix A. After combining the two search results by screening overlapping papers, papers with a citation count below a variable reference threshold based on publication year were removed. This first phase yielded papers with relevant scientific impact without excluding potentially useful studies to explore the relationship between short-term effects of mental strain and evaluation tools.

4.1.2. *Phase 2: Inclusion and exclusion criteria application*

Following the initial selection, studies were further filtered using a two-step process. First, applying exclusion criteria to remove non-relevant or low-quality studies, and then applying inclusion criteria to refine the selection of studies deemed relevant.

The exclusion criteria (EC) were established to ensure methodological rigor and focus on operational, non-clinical settings:

- *EC1:* studies focusing on pathological conditions or clinical populations, as the review is concerned with workload in operational, non-medical settings.
- *EC2:* studies that did not involve human participants, such as those based solely on simulations, animal models, or computational approaches.
- *EC3:* studies lacking methodological rigor, including those with small sample sizes (i.e., less than 10) without justification of statistical power, inadequate experimental control (i.e., absence of control conditions or randomization), or insufficient methodological description that hinder replicability.

Table 4
Framework reviewing the most popular mental strain assessment tools with regard to selection criteria. Legend: "EEG" Electroencephalography; "PPG" Photoplethysmography; "EMG" Electromyography; "Low" the tool has a low level in the corresponding selection criterion; "Medium" the tool has a moderate level in the corresponding selection criterion; "High" the tool has a high level in the corresponding selection criterion.

Selection Criteria	Individual-centered empirical tools										
	Self-perception methodologies				Performance-based approaches		Psychophysiological signals				
	NASA-TLX	*SWAT*	*SAM*	*VAS-F*	*Primary Task*	*Secondary Task*	*Brain Activity (with EEG)*	*Ocular activity (with Infrared-Eye Tracking)*	*Heart activity (with PPG)*	*Electrodermal Activity (with Skin Conductance)*	*Muscular Activity (with EMG)*
Sensitivity	Medium	Low	Medium	Medium	Low	High	High	High	High	High	Medium
Diagnosticity	Medium/ High	Medium	Medium	Medium	Medium	Medium	High	High	High	High	Medium
Implementation ease	Medium	Low	Medium	Medium	High	Medium	Low	Low	Medium	Medium	Low
Task intrusivity	Medium	Medium	Low	Medium/ High	Low	High	Low	Low	Low	Low	Low
Physical intrusivity	Low	Low	Low	Low	Low	Low	Medium/ High	Medium	Medium	Medium	High
Data processing ease	Medium	Medium	Medium	Medium	High	High	Low	Low	Low	Low	Low

Notably, reviews explicitly discussing mental strain effects and reporting empirical studies for reference were not excluded, as they provide valuable synthesized insights that may complement empirical findings. After applying these EC, inclusion criteria (IC) based on ISO 10075 effect descriptions were introduced to ensure the selected studies contributed to understanding the relationship between mental strain short-term effects and measurement tools metrics (see Table 5).

4.1.3. Phase 3: selection and expansion of relevant studies

The goal of this phase was to include additional relevant and useful studies to delineate associations between mental strain effects and assessment instruments, which were not included in the initial selection process. First, a forward-backward snowball approach was employed starting from the selected articles of the previous phase, during which both the reference lists of the sampled articles and the papers that cited the sampled articles were checked for relevance. Priority was given to studies with a high number of citations and studies published in high-impact journals or reputable conferences. Finally, some other relevant articles were found through manual search conducted on Google Scholar.

4.1.4. Phase 4: analysis

The selected studies were analysed to derive the relationships between metrics for evaluating mental strain and short-term effects. The rationale used for determining these relationships is as follows:

- *Positive relationship:* studies consistently indicate a clear relationship between the insurgence of a mental strain effect and the metric, demonstrating a stable pattern of association.
- *Negative relationship:* studies consistently show a negative correlation between the insurgence of a mental strain effect and the metric.
- *Contrasting results:* cases where studies report opposing findings, indicating no clear consensus in the literature.
- *Inconsistent results*: instances where no substantial differences are detected in the analysed metrics, or when no studies were found assessing a specific effect with a given metric.

This synthesis allowed for a structured interpretation of the findings, ensuring a critical evaluation of the strength of evidence available in the literature.

4.2. Self-perception methodologies

Self-perception methodologies aim to evaluate an individual's perceived mental exertion during specific tasks. These methodologies are widely used across sectors such as Human-Computer Interaction (HCI) (Drouot et al., 2022), industrial manufacturing (DiDomenico and Nussbaum, 2008), and defence operations (Colle and Reid, 2005).

Upon further exploration of this domain, attention is drawn to two primary self-perception methodologies: *NASA-Task Load Index* (NASA-TLX; Hart and Staveland, 1988), *Subjective Workload Assessment Tool* (SWAT; Reid and Nygren, 1988).

The *NASA-TLX* is known for its comprehensive and multidimensional approach. It consists of six dimensions: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration (see Fig. 4). Each dimension is scored on a scale from 0 to 100. The final result is obtained from the weighted sum of the scores on each dimension, with the weights of each dimension obtained through pairwise comparisons by the participant prior to the experience of the task under evaluation.

The *SWAT* breaks down mental strain into three dimensions: Mental Effort Load, Psychological Stress Load, and Time Load. Participants rate each dimension on a 3-point scale (low, medium, high). These ratings are combined using conjoint scaling to produce a single workload score ranging from 0 to 100. The restricted number of rating levels have been shown to impede the capacity of SWAT to discern subtle fluctuations in mental strain, particularly at lower intensities (Luximon and Goonetilleke, 2001).

The NASA-TLX and SWAT are widely used mental workload assessment tools with strong psychometric properties. NASA-TLX has shown good reliability with a Cronbach's alpha of 0.80 and strong construct validity, correlating with performance measures (Rubio et al., 2004). SWAT also demonstrates high internal consistency, with Cronbach's alpha above 0.80 and test-retest reliability ranging from 0.516 to 0.753, supporting its reliability and validity (Rubio et al., 2004).

These tools primarily examine task difficulty variations that require increased effort and activation. Nevertheless, NASA-TLX and SWAT have also been used in studies investigating learning, showing a downward trend in scores (Hancock et al., 1995; Jaquess et al., 2018; Shuggi et al., 2017a). In addition, NASA-TLX scores correlate positively with reduced vigilance, monotony, and mental fatigue (Grier et al., 2003; Finomore et al., 2013). While SWAT's sensitivity to these effects has not yet been demonstrated, it is plausible to assume a similar response due to the similarity in evaluation dimensions. Finally, negative emotional responses like mental satiation and stress can be measured by the Frustration and Psychological Stress Load dimensions in NASA-TLX and SWAT.

To target mental fatigue and emotional responses two other

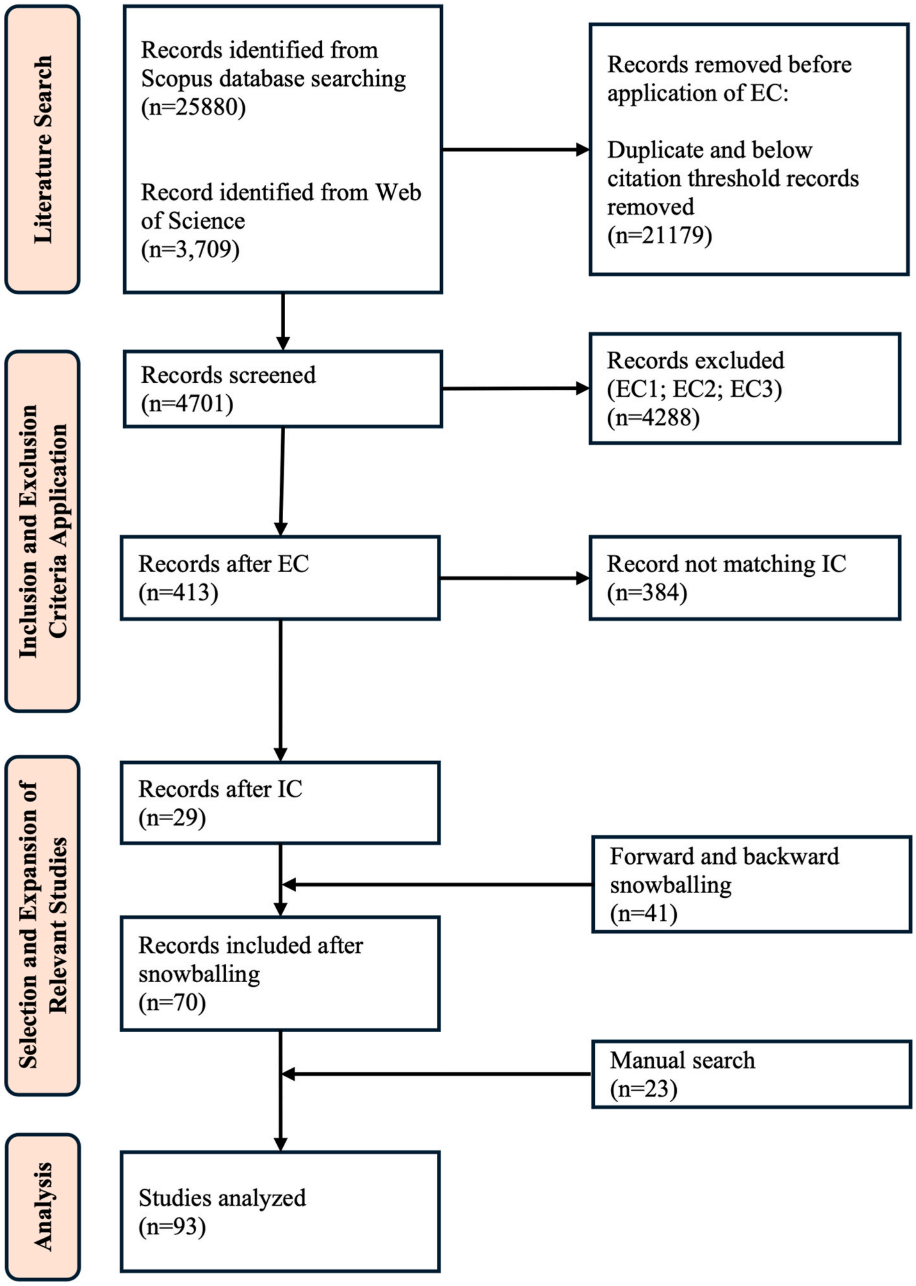


Fig. 3. Schematic overview of the methodology applied for the literature analysis. Legend: "EC" exclusion criterion; "IC" inclusion criterion.

Table 5
Inclusion Criteria for short-term effects of mental strain based on ISO 10075 (2017) effect descriptions.

Short-term effect	Inclusion Criteria
Activation	Studies with short-duration tasks characterized by variations in difficulty or comparisons between resting states and task execution.
Learning, Warming-up	Studies analysing metrics evolution over time, focusing on adaptive improvements due to practice.
Mental fatigue	Studies involving complex and cognitively demanding tasks that require sustained effort for an extended period.
Monotony, Reduced vigilance	Studies with prolonged but low-complexity tasks that demand continuous attentional engagement.
Mental satiation	Studies examining negative emotions characterized by high arousal and low valence.
Stress response	Studies assessing states of rejection resulting in high arousal and low valence.

instruments that directly investigate these effects can be considered in the evaluation toolkit.

The *Visual Analogue Scale-Fatigue (VAS-F)*, proposed by Lee et al. (1991), is a standard tool for measuring mental fatigue. It comprises a 13-item Fatigue subscale and a 5-item Energy subscale, with respondents indicating their perception on a 10 cm line. The VAS-F is a reliable and sensitive tool for mental fatigue (Gharagozlou et al., 2015). Although its use for other effects of mental strain is less common, the subscales of the VAS-F show their potential for capturing effects such as decreased vigilance and monotony or increased activation.

The *Self-Assessment Manikin (SAM)* is another essential tool for assessing short-term effects like mental satiation and stress response. SAM is a non-verbal, pictorial tool that measures emotional responses along three dimensions: Valence, Arousal, and Dominance (see Fig. 5). Participants select images matching their emotional state on a scale from 1 to 9. Despite its simplicity, SAM shows high correlation and sensitivity in assessing emotional responses to mental strain (Ahsan and

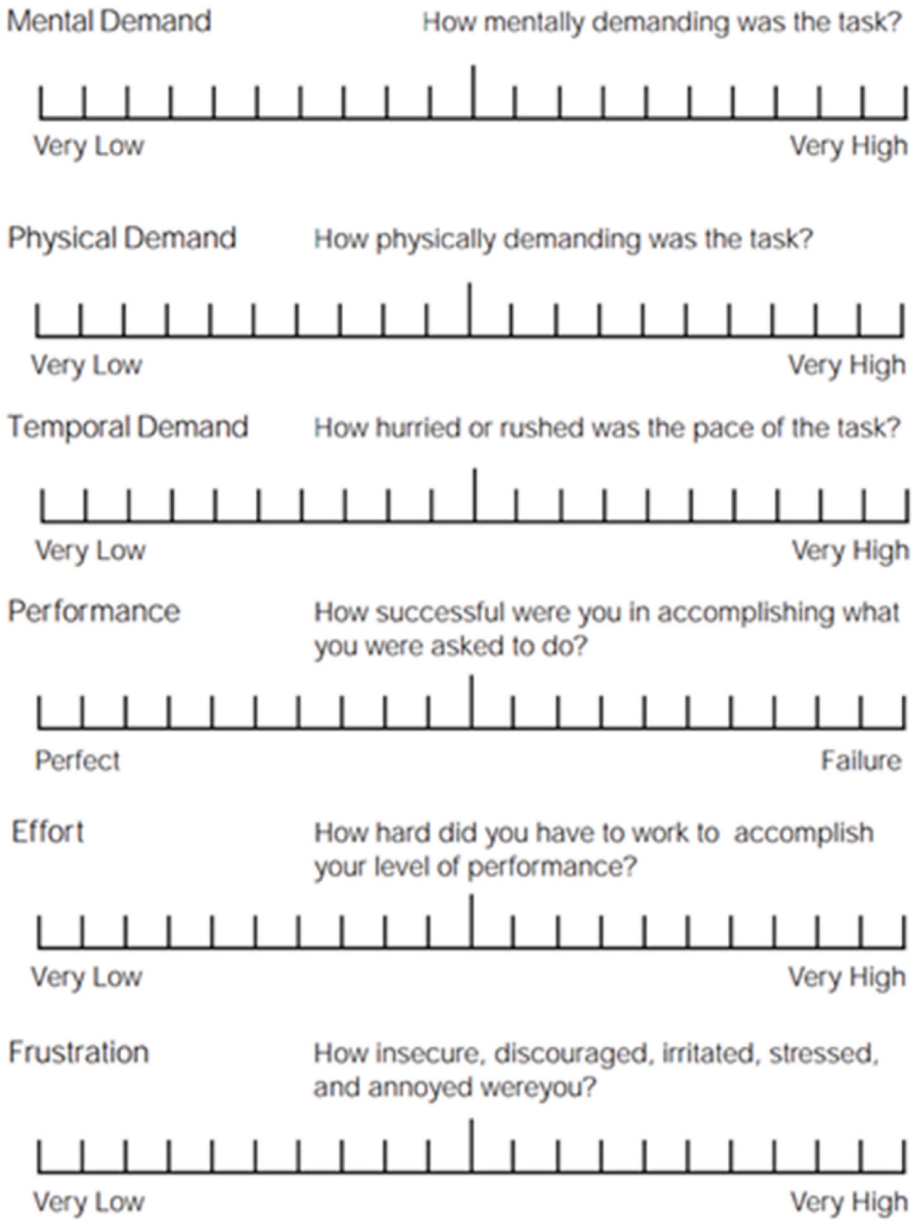


Fig. 4. NASA-TLX rating sheet.

Obaidellah, 2023; Bradley and Lang, 1994; Gervasi et al., 2022). However, its sensitivity to other effects of mental strain is limited.

In general, the above-mentioned tools offer a comprehensive perspective on all the short-term effects of mental strain. However, several other instruments of a similar nature that can be used and demonstrate discrete performances. The *Workload Profile* (WP; Rusnock and Borghetti, 2018), is the result of aggregating the participant's assessment of the resources consumed in various cognitive functions, with scores ranging from 0 to 1. The *Subjective WORkload Dominance* (SWORD; Vidulich, 1989), which estimates the mental strain of a task by computing scores on comparative judgements with other tasks. Finally, Instantaneous self-assessment workload technique (ISA; Brennan, 1992), which represents a simple one-dimensional scaling alternative to get an immediate snapshot of mental strain.

The matrix in Table 6 summarizes the responses of different self-perception methodologies to short-term mental strain effects. For the purposes of this paper's analysis, monotony and reduced vigilance, as well as learning effect and warming up, have been grouped together due to their identical correlations with the metrics.

Despite their unique characteristics, self-perception methodologies collectively provide a direct and non-invasive method for immediate data gathering and analysis. However, they also present notable shortcomings. Firstly, self-perception methodologies often fall short compared to psychophysiological signals in terms of sensitivity, capturing only consciously recognized mental strain (Cain, 2007). Additionally, data manipulations in some methods often violate scaling properties, requiring cautious statistical evaluations to prevent misleading or unsubstantiated conclusions (Cain, 2007). Lastly, self-perception methodologies provide an average mental strain snapshot rather than a dynamic view, necessitating increased evaluation frequency for online monitoring, which leads to more task interruptions and higher intrusiveness, particularly for time-consuming tools like VAS-F (Wierwille, 1988), even if the implementation of such methods can also take place via wearable devices such as smartwatches (Mach et al., 2022).

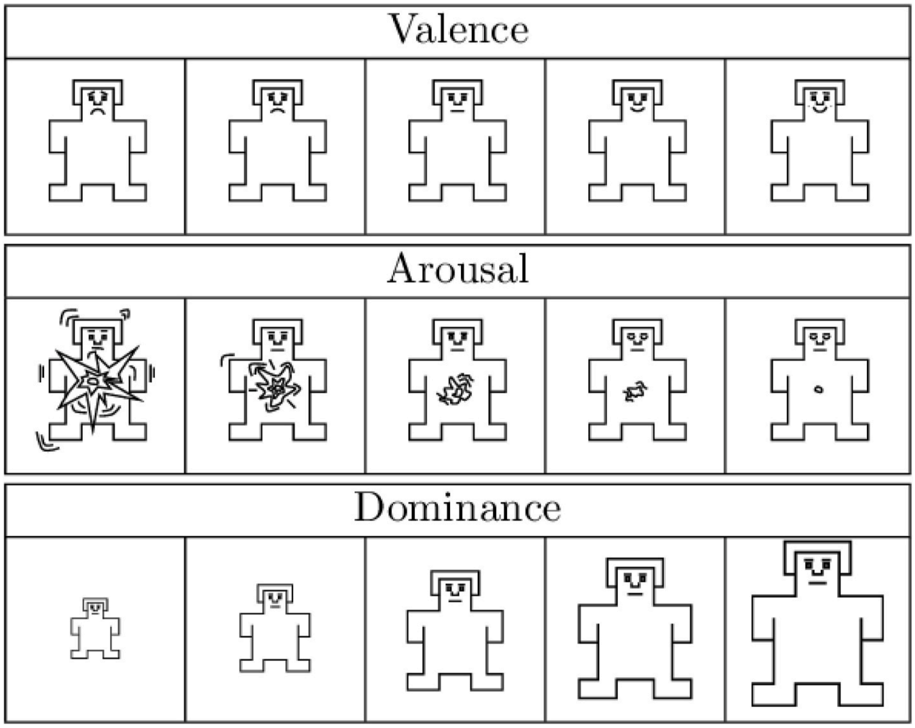


Fig. 5. Self-Assessment Manikin (SAM) and its dimensions: Valence, Arousal and Dominance.

Table 6
Matrix short-term effects of mental strain/Self-Perception Methodologies. Legend: "$\uparrow$" the metric increases as the short-term effect intensifies; "$\downarrow$" the metric decreases as the short-term effect intensifies; "$\uparrow_F$" the score on the fatigue subscale of VAS-F increases as the intensity of the short-term effect increases; "$\downarrow_F$" the score on the fatigue subscale of VAS-F decreases as the intensity of the short-term effect increases; "$\uparrow_E$" the score on the energy subscale of VAS-F increases as the intensity of the short-term effect increases; "$\downarrow_E$" the score on the energy subscale of VAS-F decreases as the intensity of the short-term effect increases; "$\downarrow_V$" the score on the valence dimension of SAM decreases as the intensity of the short-term effect increases; "$\uparrow_A$" the score on the valence dimension of SAM increase as the intensity of the short-term effect increases; "-" inconclusive data or contradictory findings reported in the literature.

Self -Perception Methodologies					
		NASA-TLX overall score (Grier et al., 2003; Jaquess et al., 2018; Li et al., 2019; Shuggi et al., 2017; Finomore et al., 2013; Yurko et al., 2010)	*SWAT overall score* (Hancock et al., 1995; Hankey and Dingus, 1990; R. Mehta and Agnew, 2011)	*VAS-F subscales scores* (Lee et al., 1991)	*SAM dimensions scores* (Ahsan and Obaidellah, 2023; Balconi et al., 2015; Bradley and Lang, 1994; Gervasi et al., 2022)
Short-term effects of mental strain	*Activation*	$\uparrow$	$\uparrow$	$\uparrow_E$ Items interested: • Energy subscale	-
	Learning, Warming up	$\downarrow$	$\downarrow$	$\downarrow_F$ Items interested: • Fatigue subscale	-
	Mental fatigue	$\uparrow$	$\uparrow$	$\uparrow_F$ $\downarrow_E$ Items interested: • Fatigue subscale • Energy subscale	-
	Monotony, Reduced vigilance	$\uparrow$	$\uparrow$	$\uparrow_F$ $\downarrow_E$ Items interested: • Fatigue subscale • Energy subscale	-
	Mental satiation	$\uparrow$	$\uparrow$	-	$\downarrow_V$ and $\uparrow_A$ Dimensions interested: • Valence • Arousal
	Stress response	$\uparrow$	$\uparrow$	-	$\downarrow_V$ and $\uparrow_A$ Dimensions interested: • Valence • Arousal

4.3. Performance-based approaches

Assessing mental strain via performance measures is based on the concept of mental resource allocation (Shuggi et al., 2017). Operators have finite mental resources for tasks. When task demands exceed these resources, performance degrades, reflecting the load on the operator's mental capacity. Two different approaches can be used to assess mental strain and its effects through task performances:

- *Primary task*: in primary task approaches, the focus is on the performance of operator's main task. Common performance metrics, used in the manufacturing field, derived from primary task, are the number of errors and reaction times (RTs). This approach is non-invasive, minimally disruptive to the operator's workflow and yields metrics that are straightforward to process. Despite notable advantages, the primary task approach presents shortcomings regarding sensitivity and diagnosticity of the derived metrics. Such limitations stem from the surplus of cognitive resources individuals possesses, which may not be fully engaged by the primary task alone.
- *Secondary task*: this approach involves introducing an additional task designed to utilize the operator's full reserve of mental resources. Typical secondary tasks may require responses to various stimuli, ranging from memorization and arithmetic tasks to sound recognition. By allocating the operator's complete reserve of mental resources to both primary and secondary tasks, any incremental mental strain from the primary task exhausts the available resources, precipitating a decline in task performance (Cain, 2007). This decline is measured using the same metrics as the primary task approach. While offering enhanced sensitivity and diagnostic accuracy in detecting changes in mental workload, the secondary task approach has significant drawbacks. It disrupts the operator's workflow and adds mental strain from multitasking (Meshkati et al., 1995), complicating implementation compared to the primary task approach.

Considering the short-term effects of mental strain, the metrics of performance-based approaches exhibit mixed behaviour. Positive effects such as increased activation, warming up or learning lead to decreased errors and RTs (Gervasi et al., 2023a,b, 2024; Jamieson and Mewhort, 2009). Conversely, negative effects of mental strain, such as mental fatigue, reduced vigilance or monotony, lead to increased errors and prolonged RTs (Al-Shargie et al., 2019; Capponi et al., 2024b; Corsi-Cabrera et al., 1996; Gervasi et al., 2023a,b; Langner et al., 2010; Yung et al., 2020). The matrix summarising the relationships between short-term effects and performance-based approach metrics is illustrated in Table 7.

Table 7

Matrix short-term effects of mental strain/Performance-Based approaches. Legend: "↑" the metric increases as the short-term effect intensifies; "↓" the metric decreases as the short-term effect intensifies; "-" inconclusive data or contradictory findings reported in the literature.

Performance-Based Approaches			
		Primary Task and Secondary Task	
		Number of errors (Al-Shargie et al., 2019; Cain, 2007; Capponi et al., 2024b; Gervasi et al., 2024; Gervasi et al., 2023; Yung et al., 2020)	*RTs* (Al-Shargie et al., 2019; Corsi-Cabrera et al., 1996; Jamieson and Mewhort, 2009; Langner et al., 2010)
Short-term effects of mental strain	*Activation*	↓	↓
	Learning and Warming-up	↓	↓
	Mental fatigue	↑	↑
	Monotony, Reduced vigilance	↑	↑
	Mental satiation	–	–
	Stress response	–	–

4.4. Psychophysiological signals

Exposing an operator to mental stress elicits measurable psychophysiological responses. When faced with an external stimulus, the nervous system rapidly activates, coordinating multiple organ functions for an appropriate regriesponse (Kramer, 1990). By monitoring the organs' functions, it is possible to deduce the type and intensity of the external stimulus as well as the individual mental condition. The subsequent sections will delineate several approaches using psychophysiological signals to assess mental strain. Tao et al. (2019), identify psychophysiological measures as reliable indicators of mental strain, with varying sensitivity degrees. Their review reports that heart activity measures, such as heart rate variability (HRV) and heart rate (HR), were found to be effective in 76 % and 69 % of the studies analysed, respectively. Similarly, brain activity (EEG, 73 %), ocular activity (eye-tracking, 67 %), and electrodermal activity (EDA, 86 %) showed strong associations with mental strain, emphasizing the role of physiological signals in its assessment.

These findings confirm that physiological signals offer a comprehensive view of mental workload, with each method bringing unique strengths depending on the context of use.

4.4.1. Brain activity

The brain, a vital component of the Central Nervous System (CNS), exhibits significant fluctuations in electrical activity in response to mental demanding stimulus (Kramer, 1990). These fluctuations are trackable in real-time using methodologies like electroencephalography (EEG), which records bioelectric potentials from about 100 billion cortical neurons (Siuly et al., 2016). EEG monitors the brain's electrical dynamics by placing electrodes across the scalp, typically covering the four lobes of the cerebral cortex: frontal, temporal, parietal, and occipital (see Fig. 6)Breedlove and Watson (2013). Each lobe is responsible for distinct functions, such as emotion regulation, sound perception, and memory. EEG enables the quantification of the intensity of electrical activity in the brain, as well as the precise localisation of the origins of this activity across different cerebral regions.

In mental strain assessment, EEG data are classified into *frequency domain* (frequency bands analysis) and *time domain* (Event-Related Potentials, ERPs) (Mulert and Lemieux, 2023). Frequency domain analysis involves measuring the power of EEG signals in specific frequency ranges (see Fig. 7a and Fig. 7b), each correlating with different cognitive states and brain activities (Siuly et al., 2016).

The frequencies band discussed in this work, as well as their relationship with mental strain short-term effects, are described as follows:

- *Delta power (δ, frequency band* $<$ 4 Hz*):* is predominantly linked to unconscious or deep sleep phases (Uygun and Basheer, 2022). It increases in the frontal and parietal areas during mental fatigue, reduced alertness from monotonous tasks, or lowered vigilance (Borghini et al., 2014; Lal and Craig, 2001). Emotional responses give rise to asymmetrical delta-wave activity, whereby stimuli with low valence and high arousal, such as mental satiety or the stress response, give rise to heightened delta activity to a greater extent in the right than in the left hemisphere (Balconi et al., 2015).
- *Theta power (θ, frequency band 4*–8 Hz): is typically associated with states of drowsiness and mind-wandering (Rodriguez-Larios and Alaerts, 2021; Snipes et al., 2022). In relation to mental strain effects, an increase in theta power in the frontal or parietal regions during a task may indicate either increased mental activation or decreased

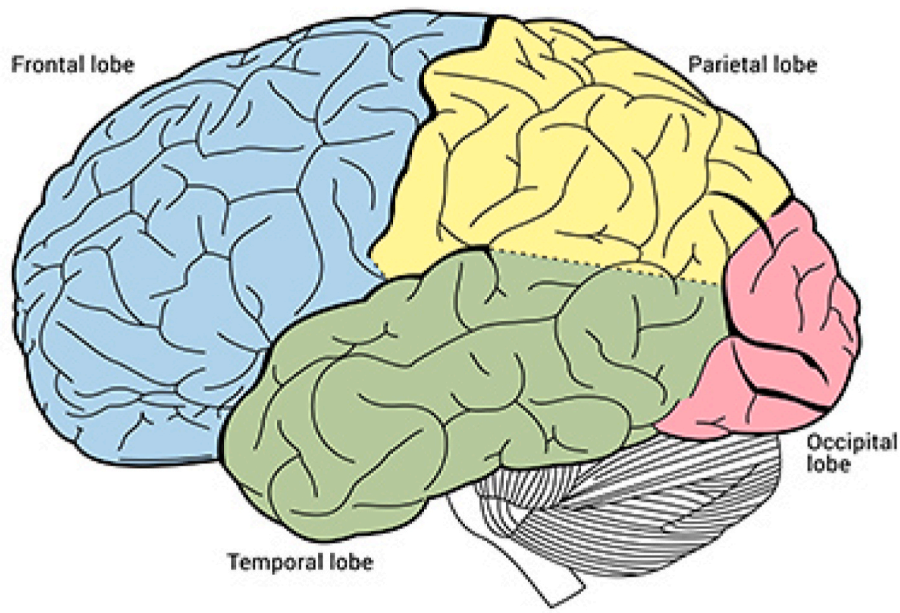


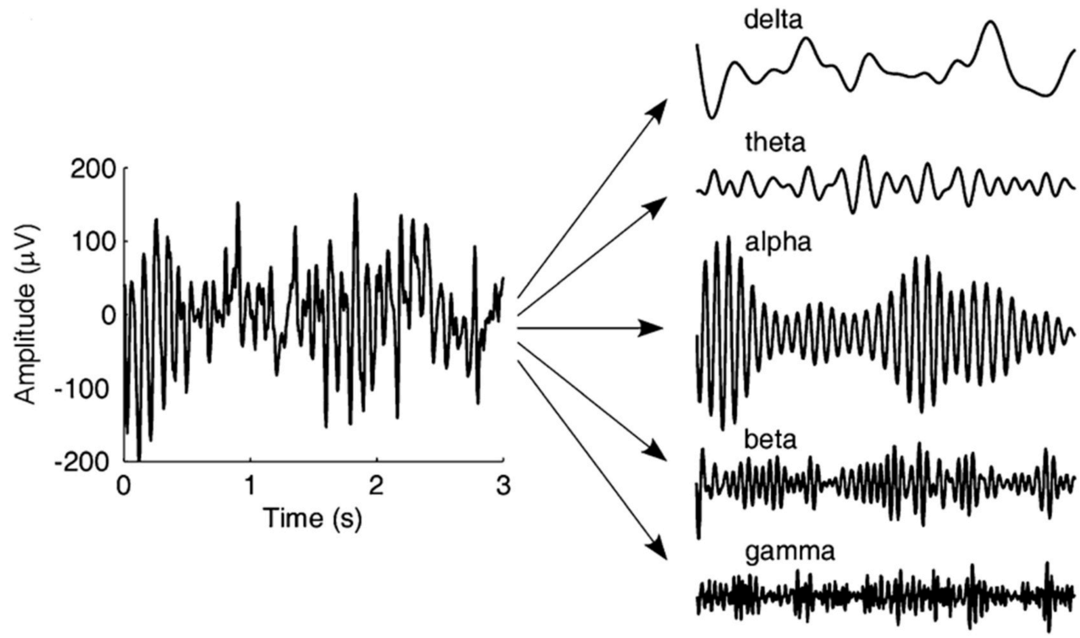
Fig. 6. The four lobes forming the cerebral cortex (Queensland Brain Institute).

effort due to task familiarity (Gevins et al., 1997; Jaquess et al., 2018; Onton et al., 2005). Furthermore, theta power in the frontal and occipital areas of the brain shows a positive correlation with mental fatigue (Wascher et al., 2014). Finally, in instances of negative emotional responses, such as mental satiation or stress, asymmetric increases in theta activity are observed, with a surge in the right frontal area (Balconi et al., 2015).

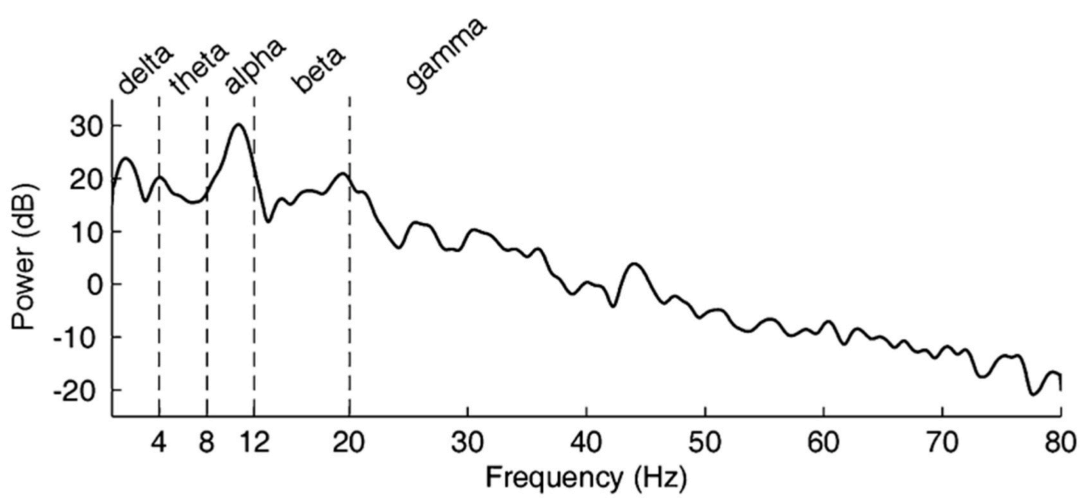
- *Alpha power (α, frequency band 8*–13 Hz*):* alpha rhythms, predominantly observed in a relaxed yet awake state (Hughes and Crunelli, 2005), are sensitive to concentration, learning, and attention. A decrease in alpha power, especially in frontal and parietal areas, can indicate heightened cognitive activation due to increased task demand (Keil et al., 2006; Puma et al., 2018). On the contrary, an increase in parietocentral alpha power suggests positive cognitive processes like learning and warming up (Bays et al., 2015; van der Cruijsen et al., 2021). Conversely, a widespread increase across parietal, occipital, and temporal regions correlates with reduced vigilance (Larue et al., 2011; Pershin et al., 2023) and mental fatigue (Boksem et al., 2005; Käthner et al., 2014). Alpha power can also reflect emotional and behavioural responses, with right hemisphere reductions and left hemisphere increases linked to negative emotions such as stress response and mental satiation (Davidson et al., 1990).
- *Beta power (β, frequency band 13*–20 Hz*):* brain oscillations in the beta rhythm range have been traditionally linked to sensory and motor processing (Spitzer and Haegens, 2017). Beta oscillations also support cognitive functions like working memory and decision-making (Engel and Fries, 2010). Increased frontal beta power indicates heightened mental activation (Brookings et al., 1996), while mental fatigue or reduced arousal due to task monotony suppresses beta in frontal and parietal areas (Lal and Craig, 2001; Zhao et al., 2012). Finally, the role of beta oscillations in emotional processing remains debated, as some studies report beta power increases in response to negative stimuli (Güntekin and Başar, 2010), while others suggest that high-arousal emotional stimuli, including negative ones, are associated with decreased lower beta-band power (Schubring and Schupp, 2021)
- *Gamma power (γ, frequency band* > 20 Hz*):* is linked to higher-level cognitive functioning and consciousness (Herrmann et al., 2010; Herrmann et al., 2004). Predominant during tasks requiring enhanced attention and information processing, a diffuse increase in gamma power indicates elevated cognitive activation (Fitzgibbon et al., 2004). On the contrary, reduced gamma activity, especially in the right parietal area, reflects lower mental effort due to warming-up effect or increased familiarity with the task at hand (Perfetti et al., 2011). Similarly, decreased frontal gamma activity is observed with diminished task engagement, either due to diminished vigilance or the repetitive nature of the task (Borghetti et al., 2021). Detecting gamma waves is challenging due to their small amplitude and overlap with muscle artifacts, requiring meticulous signal processing (Sauseng and Klimesch, 2008). The role of gamma power in emotional processing are contradictory, as both positive and negative stimuli have been shown to increase gamma activity (Headley and Paré, 2013).

On the other hand, within the time domain, ERPs represent a standard analysis for evaluating the temporal-spatial dynamics of cognitive processes and are defined as a series of positive and negative deflections - named according to polarity and latency-of brain activity (Luck, 2005) that influences the spontaneous EEG activity due to the occurrence of a specific sensory, cognitive, or motor event. This paper, in particular, focuses on two significant ERP components, P3 and N1, which reflect attention and perceptual information processing and for which results were found in association with mental strain:

- *N1*: this negative ERP component appears about 100 ms after stimulus onset. Increased N1 indicates greater attention to external stimuli, suggesting increased activation (Lange and Schnuerch, 2014; Luck et al., 1990). Suppression of N1 can indicate decreased attention due to reduced vigilance or mental fatigue (Boksem et al., 2005).
- *P3*: the P3 is a positive ERP component observed approximately 300 ms after stimulus presentation, and its amplitude reflects the effort engaged in stimulus categorization. Like the N1, the P3 amplitude increases in response to heightened mental demand during task performance, reflecting a state of activation (Ullsperg et al., 1988). In contrast, in states of mental fatigue, the amplitude of P3 shows a decreasing trend (Monteiro et al., 2019). Likewise, the P3a, a variant of the P3, exhibits a decrease in amplitude in conditions where cognitive engagement is reduced, typically due to decreased vigilance or increased task monotony (Haubert et al., 2018). The relationship between P3 and stress response or mental satiation, both linked to high arousal and low valence, remains debated. P3



(a)



(b)

Fig. 7. (a): Example of EEG signal in the time domain (Hu and Zhang, 2019). (b) Example of EEG signal in the frequency domain showing wavelength intervals and power distribution (Hu and Zhang, 2019).

primarily reflects arousal, increasing with stimulus intensity regardless of valence, making it unclear whether amplitude changes indicate positive excitement or negative emotions (Leite et al., 2012).

The matrix mapping mental strain with brain activity metrics is shown in Table 8, while Table 4 illustrates the ratings assigned to the EEG technique based on the defined criteria. EEG is rated with high sensitivity and high diagnosticity since it can accurately detect variations in brain activity related to mental strain, enabling a detailed analysis of cognitive responses. Data processing ease is rated low, as EEG analysis relies on specialized complex processes for signal processing, artifact reduction, and feature extraction. While some tools offer automated processing, EEG is rated more complex than self-report questionnaires or performance-based measures, which require less technical expertise. Task intrusiveness is rated low, as EEG recording does not directly interfere with task execution. However, physical intrusiveness is rated medium/high because, despite advancements in wireless and dry-electrode devices, electrode placement on the head makes EEG more cumbersome than other wearable biosensors.

4.4.2. *Ocular activity*

Sight is the primary means of perceiving and processing external information, especially in tasks requiring sustained attention or extensive visual processing (Kramer, 1990). Research across disciplines has consistently affirmed the effectiveness of ocular metrics in assessing mental strain (Marquart et al., 2015). The use of eye-trackers allows real-time observation of eye behaviour in real-world scenarios. Using

Table 8
Matrix short-term effects of mental strain/Brain Activity. Legend: "ERP" Event-Related Potentials; "↑" the metric increases as the short-term effect intensifies; "↓" the metric decreases as the short-term effect intensifies; "$\uparrow_{RH}$" the power of the correspondent wave intensifies on the right hemisphere as the intensity of the short-term effect increases; "$\downarrow_{RH}$" the power of the correspondent wave decreases on the right hemisphere as the intensity of the short-term effect increases; "$\uparrow_{LH}$" the power of the correspondent wave intensifies on the left hemisphere as the intensity of the short-term effect increases; "$\downarrow_{H}$" the power of the correspondent wave decreases on the left hemisphere as the intensity of the short-term effect increases; "-" inconclusive findings reported in the literature. "↑↓" contradictory findings reported in the literature.

Brain Activity								
		Frequency Bands Metrics					*ERP Metrics*	
		Delta (δ) power (Balconi et al., 2015; Borghini et al., 2014; Lal and Craig, 2001)	*Theta (θ) power* (Balconi et al., 2015; Gevins et al., 1997; Jaquess et al., 2018; Onton et al., 2005; Pershin et al., 2023; Wascher et al., 2014)	*Alpha (α) power* (Bays et al., 2015; Davidson et al., 1990; Käthner et al., 2014; Keil et al., 2006; Pershin et al., 2023; Puma et al., 2018; Reuderink et al., 2013; van der Cruijsen et al., 2021)	*Beta (β) power* (Brookings et al., 1996; Lal and Craig, 2001; Schubring and Schupp, 2021; Zhao et al., 2012)	*Gamma (γ) power* (Borghetti et al., 2021; Fitzgibbon et al., 2004; Headley and Paré, 2013; Perfetti et al., 2011; Sauseng and Klimesch, 2008)	*N1 Amplitude* (Boksem et al., 2005; Lange and Schnuerch, 2014; Luck et al., 1990)	*P3 Amplitude* (Haubert et al., 2018; Leite et al., 2012; Monteiro et al., 2019; Ullsperger et al., 1988)
Short-term effects of mental strain	*Activation*	–	↑ Brain lobes interested: • Frontal • Parietal	↓ Brain lobes interested: • Frontal • Parietal	↑ Brain lobes interested: • Frontal	↑ Brain lobes interested: • Frontal • Parietal • Temporal • Occipital	↑	↑
	Learning, Warming-up	–	↑ Brain lobes interested: • Frontal	↑ Brain lobes interested: • Parietal	–	↓ Brain lobes interested: • Parietal	–	–
	Mental fatigue	↑ Brain lobes interested: • Frontal • Parietal	↑ Brain lobes interested: • Frontal	↑ Brain lobes interested: • Parietal • Temporal • Occipital	↓ Brain lobes interested: • Frontal • Parietal	–	↓	↓
	Monotony, Reduced vigilance	↑ Brain lobes interested: • Frontal • Parietal	–	↑ Brain lobes interested: • Frontal • Parietal • Temporal • Occipital	↓ Brain lobes interested: • Frontal • Parietal	↓ Brain lobes interested: • Frontal	↓	↓
	Mental satiation	$\uparrow_{RH}$ and $\downarrow_{LH}$ Wave power differs between the right hemisphere (RH) and left hemisphere (SH).	$\uparrow_{RH}$ and $\downarrow_{LH}$ Wave power differs between the right hemisphere (RH) and left hemisphere (SH).	$\downarrow_{RH}$ and $\uparrow_{LH}$ Wave power differs between the right hemisphere (RH) and left hemisphere (SH).	↑↓	↑↓	-	–
	Stress response	$\uparrow_{RH}$ and $\downarrow_{LH}$ Wave power differs between right hemisphere (RH) and left hemisphere (SH).	$\uparrow_{RH}$ and $\downarrow_{LH}$ Wave power differs between the right hemisphere (RH) and left hemisphere (SH).	$\downarrow_{RH}$ and $\uparrow_{LH}$ Wave power differs between the right hemisphere (RH) and left hemisphere (SH).	↑↓	↑↓	↑↓	↑↓

infrared illumination and high-resolution cameras, these devices track various ocular parameters, including fixations, saccades, pupil size, and blinking (see Fig. 8). Analysing these parameters provides comprehensive metrics reflecting cognitive processes and mental strain levels:

- *Ocular fixation:* the sustained focus of eyesight on a specific point, is often reflective of the recording of spatial or verbal information and the performance of decision-making processes. Concerning the relation between ocular fixation and mental strain, key metrics are the number of fixations and their mean duration. Regarding activation, these two metrics presented contrasting results. Cognitive tasks (high information processing) increase fixation duration and decrease fixation number, while perceptual tasks (high information diversity) show the opposite trend (Liu et al., 2022). Decreased vigilance or task monotony also increases fixation duration and decreases fixation number (Mehrabi and Kim, 2022).
- *Saccade:* is defined as a rapid movement of the eyes, which shifts the focus of attention between different elements. In relation to mental strain effects, the principal parameters are peak velocity, average velocity and amplitude. As task demand increases, there is a corresponding decrease in both peak velocity and amplitude of saccades (Di Stasi et al., 2010, 2011) which is indicative of increased activation. An analogous trend is observed for all metrics in the onset of mental fatigue (Di Stasi et al., 2012, 2016). Ultimately, only saccade amplitude demonstrated alterations in response to reduced vigilance

Fig. 8. Example of the raw output of an eye-tracking session with the size of the circles being proportional to the intensity of fixations. Legend: "circle" represents the fixation points; "line" depicts a saccade.

and task monotony, exhibiting a negative correlation (Bafna and Hansen, 2021).

- *Pupil size:* changes in pupil diameter can be an informative psycho-physiological marker in the context of mental strain. Changes in pupil diameter can indicate different short-term effects: (i) an increase in pupil diameter suggests increased activation, often due to heightened task demand (Marinescu et al., 2018; Pfleging et al., 2016); (ii) a decrease in pupil diameter is associated with increased mental fatigue, which can result from prolonged exposure to high levels of strain (Bafna and Hansen, 2021); (iii) a decrease in pupil diameter may indicate a drop of task engagement, typically due to reduced vigilance or the monotony of the task (McIntire et al., 2014a, b).
- *Eye Blinking*: is an involuntary reflex whose main function is lubrication and protection of the eye. However, the role of blinking also extends to cognitive processes such as attention and stimulus

Table 9
Matrix short term-effects of mental strain/Ocular Activity. Legend: "↑" the metric increases as the short-term effect intensifies; "↓" the metric decreases as the short-term effect intensifies; "-" inconclusive findings reported in the literature.

Ocular Activity								
		Ocular fixation		*Saccade*		*Pupil Size*	*Eye blinking*	
		Number of fixations (Liu et al., 2022; Mehrabi and Kim, 2022)	*Mean duration of fixation* (Liu et al., 2022; Mehrabi and Kim, 2022)	*Saccade amplitude* (Bafna and Hansen, 2021; Bodala et al., 2016; Di Stasi et al., 2011)	*Saccade peak velocity* (Bafna and Hansen, 2021; Bodala et al., 2016; Di Stasi et al., 2010, 2011, 2016)	*Pupil diameter* (Bafna and Hansen, 2021; Marinescu et al., 2018; McIntire et al., 2014; Pfleging et al., 2016)	*Blink rate* (Bafna and Hansen, 2021; McIntire et al., 2014a, b; Mosaly et al., 2018; Recarte et al., 2008; Stern et al., 1994; Bachurina and Arsalidou, 2022)	*Blink duration* (Bafna and Hansen, 2021; Herlambang et al., 2019; Li et al., 2019b; Marquart et al., 2015; McIntire et al., 2014)
Short-term effects of mental strain	*Activation*	↑: Perceptual demand ↓: Cognitive demand	↑: Cognitive demand ↓: Perceptual demand	↓	↓	↑	↑: Cognitive demand ↓: Perceptual demand	↓
	Learning, Warming up	–	–	–	–	–	–	–
	Mental fatigue	–	–	↓	↓	↓	↑	↑
	Monotony, Reduced vigilance	↓	↑	↓	↓	↓	↑	↑
	Mental satiation	–	–	–	–	–	–	–
	Stress response	–	–	–	–	–	–	–

processing. The key metrics for assessing blinking in relation to mental strain are blink rate and blink duration. Blink rate measures how often blinks occur, while blink duration measures how long the eyelids stay closed. Cognitively demanding tasks increase blink rate, reflecting higher activation (Recarte et al., 2008). Conversely, visually demanding tasks decrease blink rate due to the need for greater visual processing (Bachurina and Arsalidou, 2022; Mosaly et al., 2018). Blink duration generally decreases with increased activation (Marquart et al., 2015), while mental fatigue, monotony and reduced vigilance increases both blink rate and duration (Herlambang et al, 2019; Li et al., 2019; McIntire et al., 2014a,b).

The relationships between the short-term effects of mental strain and the ocular activity metrics are summarised in the short-term effects of mental strain/Ocular Activity matrix shown in Table 9.

Table 4, presents the ratings assigned to eye-tracking devices based on the defined criteria. Eye-tracking devices are rated with high sensitivity and high diagnosticity, as they effectively capture subtle variations in ocular behavior related to cognitive load. Task intrusiveness is rated low, since eye-trackers do not interfere with task execution. However, physical intrusiveness is rated medium, as although many modern eye-trackers are lightweight, they often require head-mounted devices or close-range infrared cameras, which may introduce some level of discomfort or constraint. Implementation ease is rated low, as environmental factors such as ambient light and focal distances must be carefully controlled to ensure data reliability, increasing setup complexity and limiting applicability in dynamic settings. Additionally, data processing ease is rated low, as analyzing ocular activity requires specialized software for data processing and expertise. While automated tools assist in processing, eye-tracking data interpretation remains more complex than self-report questionnaires or performance-based measures.

4.4.3. Heart activity

Cardiac function reflects the activity the *Autonomic Nervous System (ANS)*, composed by the *Sympathetic Nervous System (SNS)* and the *Parasympathetic Nervous System (PSNS)*. As mental demands fluctuate, corresponding changes in heart function occur, reflecting the body's psychophysiological adaptation. Heart activity can be monitored through electrocardiography (ECG). However, a popular and non-invasive technique for measuring heart rate activity in manufacturing is photoplethysmography (PPG). This technique utilizes light-based technology to measure blood volume changes in the microvascular bed of tissue. Heart activity is composed of two distinct components:

- *Heart Rate (HR):* HR reflects the number of heart beats per minute. Regarding HR, its relationship with mental strain is multifaceted. An increase in mental effort or confrontation with negative emotional responses related to task demands typically results in a corresponding rise in HR (Kreibig, 2010; Veltman and Gaillard, 1996). On the other hand, mental fatigue, arising from prolonged cognitive exertion, usually results in a decreased HR (Gergelyfi et al., 2015; Mascord and Heath, 1992), signalling reduced arousal and the body's transition to a restful state for recovery from intense mental activities.
- *Heart Rate Variability (HRV):* HRV measures the variation in time intervals between heartbeats, called R-R intervals (Fig. 9). The analysis of HRV can be limited to the time domain or extended to the frequency domain, employing Fast Fourier Transformation (FFT) or an analogous method to partition HRV into its main frequency bands. The main measures of HRV are described in the following:
- *HRV in the time domain*: HRV in the time domain is assessed using two key metrics: Root Mean Square of Successive Differences (RMSSD) and Standard Deviation of NN intervals (SDNN). RMSSD measures short-term HRV variations, while SDNN provides a broader view of overall HRV. Both metrics decrease with heightened mental activation or negative emotional states (Delliaux et al., 2019; Hjortskov et al., 2004; Kreibig, 2010). In contrast, HRV increases during mental fatigue, reduced vigilance, or monotony (Gergelyfi et al., 2015; McGarry et al., 2023). Similar trends are observed after learning or during a warming-up phase due to reduced mental resource consumption.
- *HRV in the frequency domain*: HRV in the frequency domain assesses mental strain using three components: Low Frequency (LF), High Frequency (HF), and their ratio (LF/HF). LF (0.04–0.15 Hz) reflects sympathetic activity, while HF (0.15–0.40 Hz) is linked to respiratory rhythms and parasympathetic activity. Sympathetic activity typically indicates a stress response or increased mental effort, while parasympathetic activity is associated with relaxation and recovery. Intense mental activation, fatigue, monotony, or reduced vigilance shifts dominance towards the sympathetic system, shown by increased LF power and LF/HF ratio, and decreased HF (Chua et al., 2012; Qin et al., 2021).

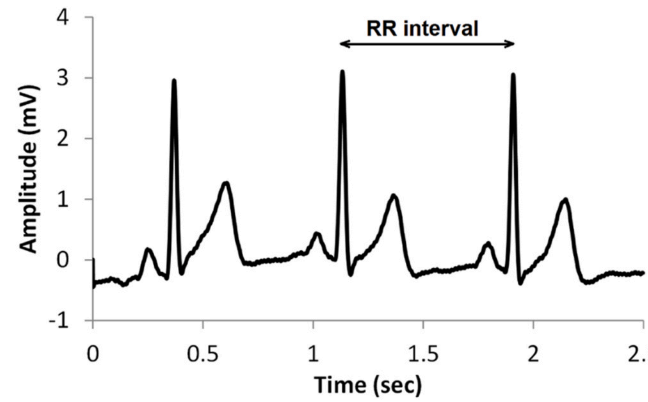


Fig. 9. Illustration of Photoplethysmography (PPG) Signals featuring R-R Intervals (Cornforth et al., 2014).

The relationships between cardiac activity metrics in the time and frequency domains and the short-term effects of mental strain are summarised in the matrix short-term effects of mental strain/Heart activity in Table 10.

As shown in Table 4, PPG is rated with high sensitivity, as it effectively detects mental strain through variations in cardiac activity, offering valuable physiological insights. Its physical and task intrusiveness are both rated low, since it typically involves small, non-invasive sensors such as wristbands, which do not interfere with task execution or user comfort, making it highly portable and practical for various applications. However, implementation ease is rated medium, as PPG's accuracy is influenced by external factors such as motion artifacts and ambient light variations. These elements can introduce noise into the signal, requiring carefully controlled conditions or advanced filtering techniques to ensure data reliability. In dynamic environments, maintaining stable measurements becomes more challenging, limiting its applicability outside of controlled settings. Furthermore, data processing ease is rated low, as PPG signal analysis requires specialized expertise to distinguish relevant physiological changes from noise and artifacts. While modern software can assist in processing, effective interpretation still demands a deep understanding of cardiovascular dynamics and signal processing techniques.

4.4.4. Electrodermal activity

Electrodermal Activity (EDA) reflects sweat gland activity regulated by the SNS (Fig. 10). When an individual is exposed to emotional and cognitive stimuli the SNS is triggered, resulting in heightened activation of the sweat glands. The presence of sweat, rich in electrolytes, reduces skin resistance and increases conductance. EDA is measured non-

Table 10
Matrix short-term effects of mental strain/Heart Activity. Legend: "↑" the metric increases as the short-term effect intensifies; "↓" the metric decreases as the short-term effect intensifies; "-" inconclusive findings reported in the literature.

Heart Activity							
		Heart Rate (HR)	*Heart Rate Variability (HRV)*				
			Time Domain		*Frequency Domain*		
		HR (Gergelyfi et al., 2015; Kreibig, 2010; Mascord and Heath, 1992; Pattyn et al., 2008; Veltman and Gaillard, 1996)	*RMSSD* (Delliaux et al., 2019; Gergelyfi et al., 2015; Hjortskov et al., 2004; Kreibig, 2010; McGarry et al., 2023)	*SDNN* (Hjortskov et al., 2004; Kreibig, 2010; Qin et al., 2021; Zhang et al., 2021)	*LF* (Chua et al., 2012; Delaney and Brodie, 2000; Qin et al., 2021; Tran et al., 2009)	*HF* (Chua et al., 2012; Delaney and Brodie, 2000; Qin et al., 2021; Tran et al., 2009)	*LF/HF* (Chua et al., 2012; Delaney and Brodie, 2000; Qin et al., 2021)
Short-term effects of mental strain	*Activation*	↑	↓	↓	↑	↓	↑
	Learning, Warming up	↓	↑	↑	–	–	–
	Mental fatigue	↓	↑	↑	↑	↓	↑
	Monotony, Reduced vigilance	↓	↑	↑	↑	↓	↑
	Mental satiation	↑	↓	↓	–	–	–
	Stress response	↑	↓	↓	–	–	–

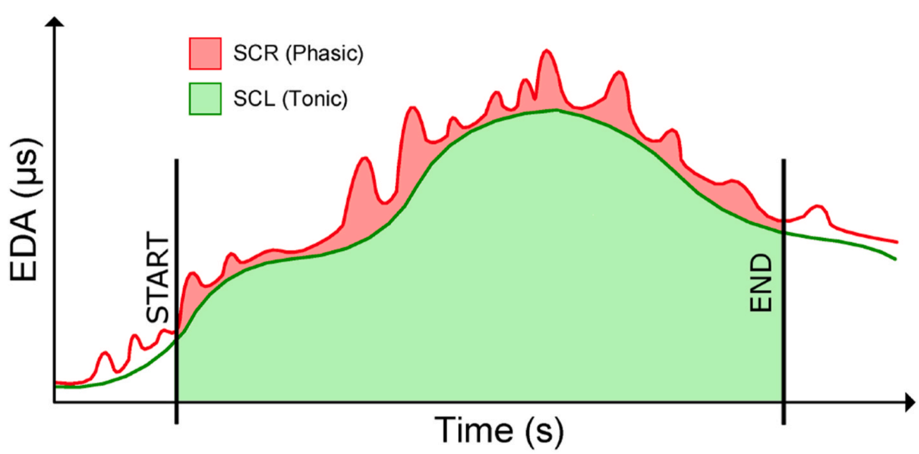


Fig. 10. Example of an EDA signal showing SCR and SCL components (Loizaga et al., 2023).

invasively using surface electrodes that detect conductance fluctuations and has two main components: the phasic and the tonic. The phasic component, measured by *Skin Conductance Response (SCR)* metric, captures rapid, transient conductance changes in response to sudden stimuli, making it valuable for assessing immediate body responses. The tonic component, measured by means of *Skin Conductance Level (SCL)* metric, reflects the subject's baseline levels of conductance and is therefore useful for gauging the effect of a given stimulus on the subject's mental state over a longer timeframe.

Both SCL and SCR increase in response to heightened mental demands, reflecting escalated activation (Mehler et al., 2012). This pattern is also observed with high-arousal low-valence emotions, such as mental satiation and stress (Balconi et al., 2015; Kreibig, 2010). Conversely, reduced vigilance or experienced monotony leads to a decrease in EDA (Stuldreher et al., 2023).

The relationships between EDA metrics and the short-term effects of mental strain are illustrated in the matrix short-term effects of mental strain/Electrodermal Activity in Table 11.

EDA is rated with high sensitivity, as it effectively detects mental strain through variations in skin conductance, providing valuable physiological insights. Its physical and task intrusiveness are both rated low, since it typically involves small, non-invasive sensors that do not

Table 11
Matrix short-term effects of mental strain/Electrodermal Activity. Legend: "↑" the metric increases as the short-term effect intensifies; "↓" the metric decreases as the short-term effect intensifies; "-" inconclusive findings reported in the literature.

Electrodermal Activity			
		SCR (Balconi et al., 2015; Kreibig, 2010; Mehler et al., 2012; Stuldreher et al., 2023)	*SCL* (Kreibig, 2010; Mehler et al., 2012; Stuldreher et al., 2023)
Short-term effects of mental strain	*Activation*	↑	↑
	Learning, Warming up	↓	↓
	Mental fatigue	-	-
	Monotony, Reduced vigilance	↓	↓
	Mental satiation	↑	↑
	Stress response	↑	↑

interfere with task execution or user comfort, making it a practical and portable option. However, implementation ease is rated medium, as EDA measurements – specifically SCL – are influenced by extrinsic factors like physical activity (Ji et al., 2019), ambient temperature (Qasim et al., 2022), humidity (Bari et al., 2018), and prior emotional states (Naveteur and Freixa I Baque, 1987). Furthermore, data processing ease is rated low, as interpreting EDA signals requires specialized expertise to distinguish meaningful physiological responses from noise and artifacts. While modern software can aid in analysis, accurate interpretation still depends on a deep understanding of autonomic nervous system activity and signal processing techniques.

4.4.5. Muscular activity

Electromyographic (EMG) metrics are key indicators of mental strain (Tao et al., 2019). EMG measures the electrical activity of motor units using electrodes on the skin above body or facial muscles. Body muscle EMG indicates muscle activation and fatigue (Raimona zadry et al., 2011), while facial EMG is used to assess mental fatigue, effort (Veldhuizen et al., 2003), and empathic emotional responses (Balconi et al., 2011; Balconi and Canavesio, 2016).

Research shows that trapezius EMG activity significantly increases with mental (Krantz et al., 2004). Facial muscles like the corrugator supercilii, frontalis, and orbitalis also show correlated EMG activity with mental strain (Van Boxtel and Jessurun, 1993). The corrugator supercilii specifically responds to negative stimuli (Larsen et al., 2003), while both the corrugator and frontalis indicate mental fatigue (Veldhuizen et al., 2003). Table 12 represents the correlations between EMG-derived metrics and short-term effects of mental strain.

As shown in Table 4, EMG effectively captures mental strain and its effects, with medium sensitivity and minimal task intrusiveness. However, physical intrusiveness is rated high, as attaching electrodes to the skin can cause discomfort. Additionally, movement artifacts introduce noise, complicating data interpretation. These factors contribute to its low ratings for implementation and data processing ease, as proper electrode placement and advanced signal filtering are required for reliable measurements.

Table 12
Matrix short-term effects of mental strain/Muscular Activity. Legend: "↑" the metric increases as the short-term effect intensifies; "↓" the metric decreases as the short-term effect intensifies; "-" inconclusive findings reported in the literature.

Muscular Activity			
		Bodily peripheral muscular activity (Krantz et al., 2004; Raimona zadry et al., 2011)	Facial muscular activity (Balconi et al., 2011; Balconi and Canavesio, 2016; Larsen et al., 2003; Van Boxtel and Jessurun, 1993; Veldhuizen et al., 2003)
Short-term effects of mental strain	*Activation*	↑ Muscle interested: • Trapezius	↑ Muscles interested: • Corrugator supercilii • Frontalis • Orbitalis
	Learning, Warming up	-	-
	Mental fatigue	-	↓ Muscles interested: • Corrugator supercilii • Frontalis
	Monotony, Reduced vigilanc	-	-
	Mental satiation	-	↑ Muscles interested: • Corrugator supercilii
	Stress response	-	↑ Muscles interested: • Corrugator supercilii

4.5. Suggested evaluation tools for different manufacturing processes

The assessment of short-term effects of mental strain in manufacturing environments requires a combination of self-perception methodologies, performance-based approaches and psychophysiological signals, each of which offers distinct advantages. In this section we provide some preliminary suggestions regarding which assessment tools could be best suited to the characteristics of the main types of production processes (i.e., *assembly*, *machining*, *finishing*, *quality control & testing*, *forming & molding*, and *logistics & material handling*; Wright, 2005), as well as the feasibility of implementing these tools both in controlled laboratory research and in real manufacturing environments.

Table 13 presents an overview of the tools suggested for each type of production process. In conjunction with other empirical measures centered on the individual, self-perception methodologies enable to collect valuable information about subjective perceptions in relation to a task. Furthermore, these methodologies are easy to implement and are physically non-intrusive. These characteristics make them easily adaptable to all production processes. However, given their task intrusiveness, in real manufacturing contexts it is advisable to use these methodologies outside the actual performance of the task (e.g., breaks or end of shift). Among performance-based approaches, task-based evaluations are the most advisable in a real manufacturing context, as the introduction of a secondary task could hinder the performance of the main activity.

For psychophysiological signals, the peculiarities of the types of production processes have a greater influence on implementation preferences. Monitoring brain activity with EEG is advisable in processes with medium/high decision-making involvement and low physical involvement (e.g., machining and quality control & testing) given its sensitivity to movement artifacts. Ocular activity monitoring with infrared eye-tracking is suitable where considerable decision-making is involved due to the variability of activities (e.g., assembly, machining, finishing, and quality control & testing). Heart activity monitoring with PPG could have some limitations for processes with also high physical involvement (e.g., finishing and logistics & material handling), as heart activity is also strongly influenced by physical effort. However, there may be exceptions based on the characteristics of the process: for example, monitoring the cardiac activity of an operator performing material handling with the support of an electric forklift (instead of a pallet truck) may provide information more related to mental strain. EDA monitoring is suitable for all production processes. Although this signal can also be influenced by physical activity, the phasic component of the signal (i.e. the SCR) still provides valuable information on the psychophysical state of an individual. Finally, monitoring muscle activity with EMG to evaluate the short-term effects of mental strain can be rather invasive as it often requires the positioning of sensors on the face to obtain a good level of diagnosticity and consequently it can be more suitable in research contexts.

5. Discussion and conclusion

The emergence of Industry 5.0 has reinvigorated interest in ergonomics, particularly emphasizing the creation of a human-centric work environment. While substantial research in manufacturing has been dedicated to physical ergonomics, cognitive ergonomics—equally crucial for overall well-being—has not received commensurate attention in this sector. Advances cognitive ergonomics in the workplace necessitate a comprehensive understanding of mental workload concept, its effects, and precise evaluations methodologies. This study systematically addressed these challenges. Adhering to the ISO 10075 standard,

Table 13
Suggestions for the implementation of individual-centered evaluation tools based on the type of context.

Application field	Suggested Individual-centered empirical tools to implement										
	Self-perception methodologies				Performance-based approaches		Psychophysiological signals				
	NASA-TLX	*SWAT*	*SAM*	*VAS-F*	*Primary Task*	*Secondary Task*	*Brain Activity (with EEG)*	*Ocular activity (with Infrared-Eye Tracking)*	*Heart activity (with PPG)*	*Electrodermal Activity (with Skin Conductance)*	*Muscular Activity (with EMG)*
Laboratory controlled research	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Assembly	✓	✓	✓	✓	✓	–	–	✓	✓	✓	–
Machining	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	–
Finishing	✓	✓	✓	✓	✓	–	–	✓	–	✓	–
Quality Control & Testing	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	–
Forming & Molding	✓	✓	✓	✓	✓	–	–	–	✓	✓	–
Logistic & Material Handling	✓	✓	✓	✓	✓	-	–	–	–	✓	–

mental workload was conceptualized as the interaction between two constructs: (i) *mental stress*, defined as the objective load imposed resulting from task requirements, work environment, and societal demands; and (ii) *mental strain*, characterized as the subjective response to mental stress, influenced by individual factors and attitudes.

The effective management of mental stress requires the design of work environments that mitigate excessive mental demands inherent in tasks and the work setting. To address this, the paper provided an overview of potential sources contributing to increased mental stress and proposed a preliminary taxonomy of assessment tools, offering valuable insights for the design of optimized work environments.

In terms of mental strain, the capacity to diagnose and quantify its effects is essential for the informed implementation of real-time management strategies. To this end, an exhaustive analysis of the effects of mental strain was presented. Furthermore, a taxonomy of evaluation tools was proposed, together with a set of criteria for their selection. Finally, a set of interpretation matrices establishing the correlation between short-term effects of mental strain and evaluation tool metrics was provided. Overall, these contributions represent a first step towards the standardization of mental strain evaluation, aimed at eliminating inconsistencies in the diagnosis of its effects and informing policies to support human-centered processes implementation.

However, there are some limitations. The tools presented for the measurement of mental stress (e.g., W/INDEX, VACP, and Pro-SWAT) mainly consider task-related aspects and working conditions. Their sensitivity to social factors inside and outside the organisation described in ISO 10075 is less robust. Regarding the assessment of mental strain with an approach based on physiological signals, the focus of this paper was on the assessment techniques most frequently used in the manufacturing context. Other techniques exist in the literature and may have different characteristics and complementary potential. Finally, details regarding the cost of implementation of the different tools presented were not addressed, since, especially for psychophysiological signals, it is a rather variable factor and is also highly influenced by the degree of technological development of biosensors.

Future work will be focused on expanding the characterization of the components of mental stress, in order to provide more in-depth guidance. The presented scenarios will be also used to develop real-time models for dynamically assessing operators' mental conditions, guiding the adaptive behaviour of human-centered assistance technologies. Future work will also focus on exploring evaluation tools for long-term effects of mental strain and providing a framework to support ergonomists in response interpretation.

CRediT authorship contribution statement

Mirco Bartolomei: Writing – original draft, Methodology, Data curation. **Riccardo Gervasi:** Writing – original draft, Methodology, Formal analysis, Data curation. **Carlotta Acconito:** Writing – original draft, Investigation, Data curation. **Laura Angioletti:** Methodology, Data curation. **Davide Cannizzaro:** Project administration, Conceptualization. **Michela Balconi:** Supervision, Methodology, Conceptualization. **Luca Mastrogiacomo:** Supervision, Methodology, Conceptualization. **Fiorenzo Franceschini:** Supervision, Methodology, Conceptualization.

Ethical approval

The authors respect the Ethical Guidelines of the Journal.

Availability of data and materials

Not applicable.

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Competing interests

The authors do not have conflict of interest.

Appendix A

This section describes the query used to identify articles in *Phase 1* of the literature analysis presented in Section 4.1. All articles published up to the year in which the analysis was conducted (i.e., 2024) and belonging to the fields of manufacturing, computer science, human-machine interaction, neuroscience, ergonomics, and psychology were considered. The query is composed of the following three groups, that were combined using the Boolean operator "AND":

1. The first group is related to keywords concerning mental workload ("mental workload" OR "mental effort" OR "mental fatigue" OR "vigilance decrement" OR "mental stress" OR "emotional response" OR "emotional processing" OR "cognitive load" OR "mental demand" OR "phsychological stress").
2. The second group of keywords is related to mental workload evaluation tools ("eeg" OR "ppg" OR "eda" OR "emg" OR "eye tracking" OR "nasa-tlx" OR "swat" OR "self assessment manikin" OR "visual analogue scale").
3. The third group is used for an initial exclusion of articles with keywords related to diseases, pathologies, animal experiments, children, or adolescents (NOT ("Child" OR "Depression" OR "Mental Disease" OR "Schizophrenia" OR "Autism" OR "Epilepsy" OR "Animal Experiment" OR "Alzheimer Disease" OR "Animal Model" OR "Animal Tissue" OR "Animal" OR "Adolescent") OR "Middle Aged")).

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