Mental Workload Monitoring: New Perspectives from Neuroscience

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Abstract. Mental Workload is nowadays a keyword used and sometimes abused in life sciences. The present chapter aims at introducing the concept of mental workload, its relevance for Human Factor research and the current needs of applied disciplines in a clear and effective way. This paper will present a state-of-art overview of recent outcomes produced by neuroscientific research to highlight current trends in this field. The present paper will offer an overview of and some examples of what neuroscience has to offer to mental workload-related research.

Keywords: Mental workload · Operational environments · Neuroscience · EEG · Neurometrics · BCI

1 Introduction to the Mental Workload Concept

Mental Workload is a complex construct that is assumed to be reflective of an individual's level of cognitive engagement and effort while performing one or more tasks [1]. Therefore, the assessment of mental workload can essentially be a quantification of mental activity resulting from such tasks. It is difficult to give a unique definition of *Mental Workload*. Various definitions have been given during the last decades:

- "Mental workload refers to the portion of operator information processing capacity or resources that is actually required to meet system demands" [2];
- "Workload is not an inherent property, but rather it emerges from the interaction between the requirements of a task, the circumstances under which it is performed, and the skills, behaviours, and perceptions of the operator" [3];
- "Mental workload is a hypothetical construct that describes the extent to which the cognitive resources required to perform a task have been actively engaged by the operator" [4];
- "The reasons to specify and evaluate the mental workload is to quantify the mental cost involved during task performance in order to predict operator and system performance" [5].

Apart from the definitions presented above, many other attempts to uniquely define Mental Workload concept have been made, demonstrating how mental it may not be a unitary concept because it is the result of different aspects interacting with each other.

L. Longo and M. C. Leva (Eds.): H-WORKLOAD 2019, CCIS 1107, pp. 3–19, 2019.
https://doi.org/10.1007/978-3-030-32423-0_1

In fact, several mental processes such as alertness, vigilance, mental effort, attention, stress, mental fatigue, drowsiness and so on, can be involved in task execution and they could be affected by specific tasks demand in each moment. In general, mental workload theory assumes that: (i) people have a limited cognitive and attentional capacity, (ii) different tasks will require different amounts (and perhaps different types) of processing resources, and (iii) two individuals might be able to perform a given task equally well, but differently in terms of brain activations [6, 7].

1.1 A Topic in the Human Factors Research

In some safety-critical operational environments, one or few operators could be responsible of the safety, and even more the life, of numerous people. For example, let us think to the transportation domain (e.g. Aviation, Rail, Maritime), where the safety of the passengers depends on the performance of the Pilot/Driver/Sailor, the Traffic-Controller or the Maintenance crew. In such contexts, a human error could have serious and dramatic consequences. In general, human error has consistently been identified as one of the main factors in a high proportion of all workplaces accidents. In particular, it has been estimated that up to 90% of accidents exhibits human errors as principal cause [8]. This is true also for other domains such as health care, the US Institute of Medicine estimates that there is a high people mortality per year (between 44.000 and 88.000) as a result of medical errors [9], with an impressive amount of accidents resulting from breast cancer treatments that doubles fatalities resulting from road accidents [10, 11]. Scientific publications regarding problem of medical surgeries, injuries and complications of treatment can be fairly dated to the 1991 as results of the Harvard Medical Practice Study [10, 11]. The reviews of 30,000 medical records of patients hospitalized in the New York state showed that the 4% of patients had complications of their treatment, which have been called *Adverse Events* (AE). Even more shocking was the finding that two-thirds of these injuries were due to medical operators' mistakes, highlighting the fact that they were preventable. The US study was replicated in other Countries [12, 13] with the same results trend (Australia: 13% of patients with *AE*; UK: 10%). The report "*To Err is Human*" of the *Institute of Medicine* (IOM), published in the 2000, had a dramatic effect in bringing patient safety to the medical and public attention. The IOM proclaimed that nationwide as many as 98,000 Americans died yearly because of medical mistakes [14]. It has also been estimated that inappropriate human actions and consequently the errors implicated are the main causes of 57% of road accidents and a contributing factor in over 90% of them [15]. The Aviation Safety Network reported 19 accidents with 960 casualties during the last years; in many cases factors related to workload, situation awareness and monitoring were a caused or contributing factors [16, 17]. Additionally, over the past four decades, human error has been involved in a high number of casualty catastrophes, including the Three Mile Island, Chernobyl and Bhopal nuclear power disasters, the Tenerife, Mont St Odile, Papa India and Kegworth air disasters, the Herald of Free Enterprise ferry disaster, the Kings Cross fire disaster, the Lad-broke Grove rail disaster, and many others [18]. Consequently, the human factor concern, with its possible causes and ways to mitigate its impact, received more and more attention, and it has been investigated across a wide range of domains, including military and civil aviation [19, 20], aviation maintenance

[21], air traffic management [22, 23], rail [24], road transportation [25, 26], nuclear power and petrochemical reprocessing [27], military, medicine [9, 28], and even the space travel domain [29]. At this point, what are the causes of human errors? Human error is an extremely common phenomenon: people, regardless of abilities, skill level and expertise, makes errors every day. The typical consequence of error-occurrence is the failure to achieve the desired outcome or, even worst, the production of an undesirable outcome. When it happens in particular working environments, such error can potentially lead to accidents involving injuries and fatalities. Human error can be defined as the execution of an incorrect or inappropriate action, or a failure to perform a particular action. According to the scientific literature, there have been numerous attempts at de-fining and classifying the human error. However, a universally accepted definition does not yet exist. Rasmussen [30] pointed out the difficulty in providing a satisfactory definition of human error. In 1987, he suggested that "human error represents a mismatch between the demands of an operational system and what the operator does" [31]. The main causes of human errors can be searched within the internal or psychological factors of the operator [32]. In fact, errors could also arise from aberrant mental processes such as inattention, poor motivation, loss of vigilance, mental overload and fatigue that negatively affect the performance.

Among the various cognitive components of mental activity, mental workload is anyway considered to be the one indicating a comprehensive representation of an operator's mental state considering the amount of involved cognitive resources, therefore cognitive psychology aimed to establish the relationship between mental workload and human performance. Modelling such a relationship would help to predict human performance evolution along time thus preventing potentially risky situations. In this sense, the widest accepted hypothesis describes the relationship between mental workload and performance through an"inverted U-shape" (Fig. 1) function. This hypothesis relies on the Yerkes-Dodson theory, that more than one century ago (Robert M. Yerkes and John D. Dodson, 1908) described the effects on human performance referred to as physiological activation [33]. Reasonably, this theory has not to be intended as an exact one, but as a representative model, perhaps revised in different ways recently [34, 35], however the pillar is that such a relationship is not linear, and performance tends to degrades at both the boundaries of workload span. In other words, some levels of mental workload may help the user to reach high performance levels [36] since it stimulates positively the user and it keeps him/her awake with high attention level. Nevertheless, a period of mental inactivity and "under-stimulation" can cause a monotonous and boring state (underload), a low level of vigilance and attention, with low cognitive resources demand. For example, Warm and colleagues [37] showed how vigilance requires an important amount of cognitive resources, by using behavioural, neurophysiological and subjective measures. At the same time, an operative condition characterized by highly demanding multiple tasks can lead the user to an overload condition, equally impairing from a performance perspective [38, 39]. Both the cases bring to a variation in neurophysiological factors and often to a decrement of performance. Such performance reduction is highly undesired, especially in safety-critical domains, as discussed above.

In 1981 Wickens pointed out that the development of increasingly complex technologies was radically changing the role and load to which an operator was subjected,

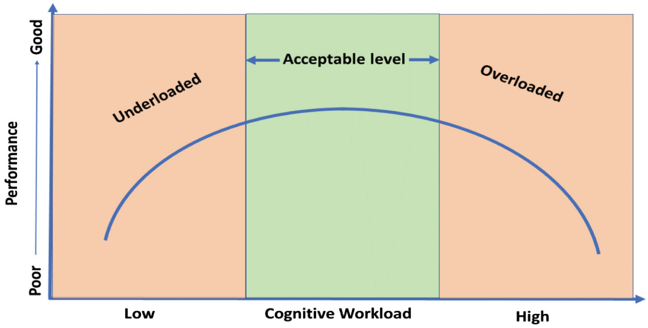

Fig. 1. Inverted U-shape relationship between mental workload and performance.

leading to the dual need to exploit the model of multiple resources to optimize the processing of human operator information in the definition of tasks ("Should one use keyboard or voice? Spoken words, tones, or text? Graphs or digits? Can one ask people to control while engaged in visual search or memory rehearsal?" [40]) and measure the operator's workload [41].

Since then, the measure of the workload has spread from the aeronautical field [16, 42] to the educational [43] and to the clinical [44] domains. Mental Workload assessment techniques should be able to solve these questions, being sensitive to fluctuations in task cognitive demands while operating or interacting with systems by without intruding external interferences on primary task performance [45, 46]. To this regard, three are the main categories of techniques investigated and employed in Ergonomic field for mental workload monitoring [47, 48]:

- Behavioural measures, generally derived from measures of operator's performance with respect to the main and/or an additional task;
- Subjective measures, generally collected through self-confrontation reports and questionnaires, such as the Instantaneous Self-Assessment (ISA, [49]) and NASA-Task Load indeX (NASA-TLX, [3]);
- Neurophysiological measures, i.e. those techniques that infer human mental states from specific variations of human biosignals, such as brain activity, hearth activity, skin sweating, and so on.

The targeted level of sensitivity is unobtainable with behavioural and subjective measures alone. In this regard, neurophysiological techniques have been demonstrated to be able to assess mental workload of humans with a high reliability, even in operational environments [50–54]. Moreover, neurophysiological techniques afford another important advantage: unlike alternative subjective assessment techniques, neurophysiological measures do not require the imposition of an additional task either concurrently (as in secondary task techniques) or subsequently (as in subjective workload assessment techniques) the primary one. Neurophysiological measures can be obtained continuously, even online, with little intrusion, i.e. without interrupting the operator's work with additional tasks or questions [50]. In addition, it will become more and more difficult to measure cognitive capacities with performance indices in future workstations, since they will be characterized by higher levels of automation, therefore reducing the manual interaction between the humans and the machine. Also, any eventual performance degradation would become “measurable” by the system when the operator already suffered a mental impairment, i.e. “after the fact” [55]. Finally, neurophysiological measures have been demonstrated to be reliably diagnostic of multiple levels of arousal, attention, learning phenomena, and mental workload in particular [56–65]. Such applications will be discussed in the following paragraphs. Thus, the online neurophysiological measurements of mental workload could become very important, not only as monitoring techniques, but mainly as support tools to the user during his/her operative activities. In fact, as the changes in cognitive activity can be measured in real-time, it should also be possible to manipulate the task demand (adaptive automations) in order to help the user to keep optimal levels of mental workload under which he or she could be operating [66]. In other words, the neurophysiological workload assessment could be used to realize a *passive Brain Computer Interface* (passive-BCI, please see Par. 3) application in real environments.

2 Neuroscientific Contribute to the Mental Workload Assessment

Neuroimaging methods and cognitive neuroscience have steadily improved their scientific and technological maturity over the past decade, consequently producing a growing interest in their use to examine the neural circuits and physiological phenomena behind human complex tasks representative of perception, cognition, and action as they occur in operative settings. At the same time, many fields in the biological sciences, including neuroscience, are being challenged to demonstrate their relevance to practical real-world problems [48]. Although the different conjugations of the discipline name, for example Bioengineering or Cognitive Neuroscience or Neuroergonomy (in general due to a different point of view of the same problem), scientific research in these fields is aiming at inferring and assessing humans’ workload, and more generally their *Internal States (IS)*, through neurophysiological measures. In fact, such a concept of measuring humans’ IS, where IS has to be intended as the generalization of all the possible mental, or purely cognitive (e.g. workload, attention, situation awareness), and affective, or purely emotional (e.g. stress, pleasantness, frustration) psychophysical states, is based on the assumption that each biological activity is regulated by the human Central Nervous System (CNS). The brain is of course the main actor of CNS, but it is also important to take into account the activity of the Autonomic Nervous System, that acts largely unconsciously and regulates bodily functions such as the heart rate, respiratory rate, pupillary response, skin sweating and so on [67]. Variations of these biological activities correspond to internal reactions because of modification of external (environment) and internal (cognition, emotions, etc.) factors, therefore neurophysiological signals become the interface to access what is happening within the human mind. Just to make few examples, the electrical activity of the brain’s prefrontal cortex in EEG Theta frequency band increases while cognitive demand is increasing [68], increased skin sweating is related to higher levels of arousal and attention [69], while heart rate tends to accelerate under stress conditions [70]. The last decades have been fruitfully spent by the scientific community in investigating the correlation between such variations and specific human ISs, enabling the possibility of obtaining measures (i.e. *Neurometrics*), of several concepts such as attention, stress, workload, emotion, etc., and to use them (i) to provide a feedback to the user [56]; (ii) to modify the behaviour of the interface the user is interacting with [71]; or (iii) to obtain insights related to user's feelings while experiencing specific situations (e.g. eating, or watching tv, or any other everyday activity) without any verbal communication [72, 73]. These potentialities have been usually demonstrated in controlled settings (i.e. Laboratory), but recent technological progresses are allowing more and more low invasive and low cost wearable devices that can open the door to applications in everyday natural settings. From a technological point of view, many companies are moving forward to develop biosignal acquisition devices more and more wearable and minimally invasive and at the same time sensors (e.g. gel-free electrodes for EEG systems, or bracelets/watches already integrating sensors for PPG and GSR) able to ensure high signal quality and comfort at the same time [74, 75]. Just to have an idea of the effort recently produced in this field, many works have been performed in operational environments, e.g. aviation [50, 76–78], surgery [79], city traffic monitoring [80–82], power plant control centres [83], and many others [59, 73, 84–86] to demonstrate the usefulness of Neurometrics.

Such neuroscientific researches are based on the use of neuroimaging technologies and neurophysiological measures, including *Electroencephalography* (EEG), *functional Near-InfraRed* (fNIR) imaging, *functional Magnetic Resonance Imaging* (fMRI), *Magnetoencephalography* (MEG), and other types of biosignals such as *Electrocardiography* (ECG), *Electrooculography* (EOG) and *Galvanic Skin Response* (GSR) [68, 87, 88]. Neuroimaging methods such as *Positron Emission Tomography* (PET) and fMRI are excellent tools in this endeavour, enabling the examination of how the brain adapts itself in response to practice or repeated exposure to particular tasks. However, their limitations in terms of cost, space and invasiveness make them not suitable for real working environment settings, where a less invasive approach would be preferable and the costs for its implementation and usage has to be limited. In fact, PET and fMRI techniques require expensive instruments and high maintenance costs, In addition, fMRI [89] and MEG techniques require room-size equipment that are not portable. On the other hand, EOG, ECG and GSR activity measurements highlighted a correlation with some mental states (stress, mental fatigue, drowsiness), but they were demonstrated to be useful only in combination with other neuroimaging techniques directly linked to the *Central Nervous System* (CNS), i.e. the brain [68, 90, 91]. Consequently, the EEG and fNIRs are the most likely candidates that can be straightforwardly employed to investigate human brain behaviours in operational environments. The propensity for using EEG or fNIRs techniques has not been clarified yet. There are several factors to take into account about real operative scenarios. For example, both EEG and *Fast Optical Signal* (FOS)-based fNIR have similar bandwidth and sample rate requirements, as the FOS appears to directly reflect aggregated neural spike activity in real-time and can be used as a high-bandwidth signal akin to EEG [92]. However, EEG and fNIRs systems have different physical interfaces, sizes, weights and power budgets, thus different wearability and usability in real operative contexts. In this regard, the presence of hair may impact negatively on both photon absorption [93] and the coupling of the probes with the underlying scalp, thus the fNIRs technique is very reliable only on those un-hairy brain areas, like the *Pre Frontal Cortex* (PFC). For the mental states investigation, also other cortical regions, such as the parietal brain sites play an important role. Derosière et al. [94] pointed out how some fNIRs-measured hemodynamic variables were relatively insensitive to certain changes during the brain activity. In conclusion, due to its higher temporal resolution and usability, in comparison with the fNIRs technique, the EEG technique overcomes such issues related to the fNIRs and appears to be the better candidate for such kind of applications in operational environments. With particular regard to the mental workload literature, neurophysiological measurements have been and are often used to evaluate the level of cognitive demand induced by a task [16, 95, 96]. Most part of the EEG research showed that the brain electrical activities mainly considered for the mental workload analysis are the Theta and Alpha rhythms typically gathered from the *Pre-Frontal Cortex* (PFC) and the *Posterior Parietal Cortex* (PPC) regions. In this regard, previous studies demonstrated as that EEG Theta rhythm over the PFC present a positive correlation with mental workload [97, 98]. Moreover, published literature stressed the inverse correlation between the EEG power in the alpha frequency band over the PPC and mental workload [68, 99–103]. Only few studies have reported significant results about the modulation of the EEG power in other frequency bands, i.e. the delta, beta and gamma. Therefore, the most accepted evidences about EEG correlates of mental workload could be resumed in an increase of the theta band spectral power, especially on the frontal cortex, and a decrease in alpha band over the parietal cortex, with increasing mental workload [17, 68] (Fig. 2).

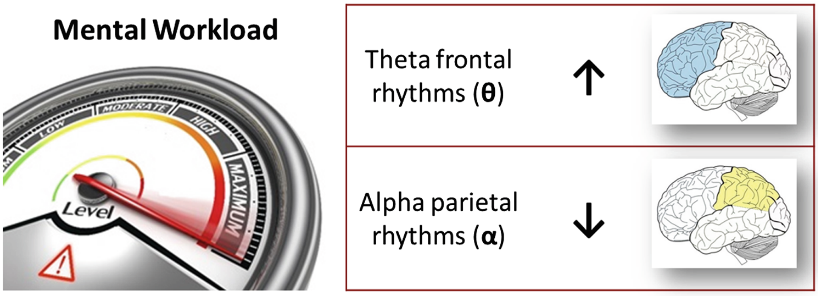

Fig. 2. Schematic summary of the main EEG features variations when the mental workload increasing.

Several studies, in particular in the aviation domain, have highlighted the high reliability of EEG-based mental workload indexes [99]. The results showed that the effects of task demand were evident on the EEG rhythms variations. EEG power spectra increased in the theta band, while significantly decreased in the alpha band as the task difficulty increased, over central, parietal, frontal and temporal brain sites. More recently, Shou and colleagues [104] evaluated mental workload during an ATC experiment using a new *time-frequency Independent Component Analysis* (tfICA) method for the analysis of the EEG signal. They found that "the frontal theta EEG activity was a sensitive and reliable metric to assess workload and time-on-task effect during an ATC task at the resolution of minute(s)". In other recent studies involving professional and trainees ATCOs [52, 105], it was demonstrated how it was possible to compute an EEG-based Workload Index able to significantly discriminate the workload demands of the ATM task by using machine-learning techniques and frontal-parietal brain features. In those studies, the ATM tasks were developed with a continuously varying difficulty levels in order to ensure realistic ATC conditions, i.e. starting form an easy level, then increasing up to a hard one and finishing with an easy one again. The EEG-based mental workload indices showed to be directly and significantly correlated with the actual mental demand experienced by the ATCOs during the entire task. However, the algorithms proposed were affected by some weaknesses, such as parameters manual settings and performance decreasing over time, that limited their employment in real operational environments. Moreover, other studies about mental workload estimation by using neurophysiological measurements, have been performed in other types of transport domain, in particular considering road transport (e.g. car drivers) [59, 68, 106, 107], and in the military domain [108].

3 Passive Brain-Computer Interfaces and Automation

Neuroergonomics research field aims at developing systems that take such limitations of a human's mental capacity to process information into account and avoid performance degradation, by adapting the user's interface to reduce the task demand/complexity or by intervening directly on the system [109]. Over the past two decades, researchers in the field of augmented cognition worked to develop novel technologies that can both monitor and enhance human cognition and performance. Most of this augmented cognition research was based on research findings coming from cognitive science and cognitive neuroscience. On the basis of such findings and the technological improvements, that have allowed to measure human biosignals in a more reliable and no-invasive way, it has been possible to evaluate the actual operator mental states by using neurophysiological indexes, and to use them as input toward the interface the operator is interacting. Such kind of application is called *passive Brain-Computer Interface* (passive-BCI). In its classical assumption, a Brain-Computer Interface (BCI) is a communication system in which messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and muscles [110]. More recently, Wolpaw and Wolpaw [111] defined a Brain-Computer Interface as "a system that measures Central Nervous System (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment". In the BCI community, the possibility of using the BCI systems in different contexts for communication and system control [112, 113], developing also applications in ecological and operational environments, is not just a theory but something very closed to real applications [114–116]. In fact, in the classic BCI applications the user can modulate voluntarily its brain activity to interact with the system. In the new BCI concept, i.e. the passive BCI, the system recognizes the spontaneous brain activity of the user related to the considered mental state (e.g. emotional state, workload, attention levels), and uses such information to improve and modulate the interaction between the operator and the system itself [117]. Thus, in the context of Adaptive Automation (AA) in operational environments, the passive-BCI perfectly match the needs of the system in terms of *Human-Machine Interaction* (HMI) (Fig. 3).

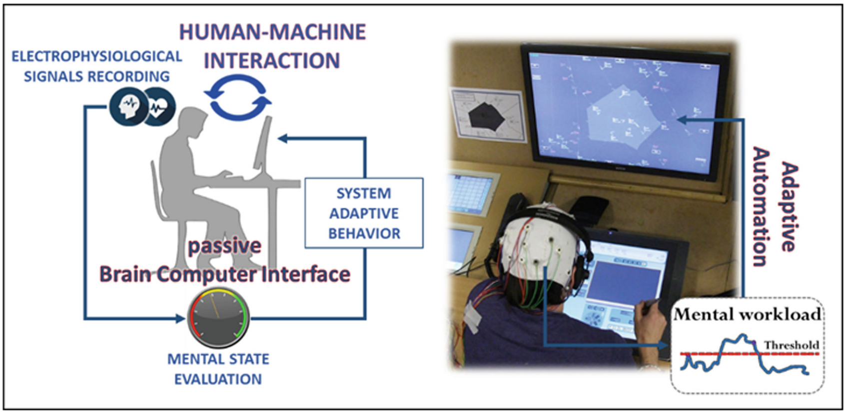

Fig. 3. Representation of the passive-BCI concept applied to enhance the Human-Machine Interaction by adapting the automation of an Air Traffic Management workstation. Source: https://doi.org/10.1109/TBME.2017.2694856 [117].

One of the main limitations of the use of EEG is its wearability. However technology improvements [75, 118–121] have being developed and tested in terms of dry electrodes (no gel and impedances adaptation issues), comfort, ergonomic and wireless communications (no cables between EEG sensors and the recording system). EEG-based passive-BCI systems appear the best candidate to be integrated in the development of AA-based systems and dynamically trigger the tasks allocation, on the basis of the user's actual mental state, i.e. his Mental Workload, in order to support him/her during his/her work activities consequently improving his/her performance, thus the safety of the whole environment. An issue that is still very much open is the development of a systematic method, in other words an algorithm, able to assess the user's Mental Workload online, despite all the problems related to operational environments (i.e. no controlled settings, artefacts, time cost in terms of calibration and computation, invasiveness on the subject, etc.), and in a way that is transferrable to various diverse environmental conditions.

4 Conclusions

Researchers in human factors and ergonomics sectors studied human capabilities and limitations, both cognitive and physical, and used such knowledge to design technologies and work environments to be safer and more usable, efficient, and enjoyable for people to interact with [7, 63, 122–124]. In today's technology-driven environment, where human capabilities are struggling to keep up with technology offerings, techniques for augmenting human performance are becoming the critical gap to preclude realizing the full benefits that these technology advances offer [125–134]. The concept of human performance augmentation is not so recent. The idea was developed during the past decade [64, 65], and, at the same time, the concept of Augmented Cognition (AugCog) was borne out of the Defense Advanced Research Projects Agency's (DARPA) pushing for technologies that enhanced the Warfighter's communication skills and those technologies that involved biosensors for medical applications [66]. More in general, because of the technological progresses, Human Factor research also evolved, and it now includes also the forefront techniques provided by Neuroscientific disciplines, that are looked upon with increasing interest by the scientific community and society in general. Alongside the latest technological development also the aims of workload assessment methods have evolved: the ultimate goal in particular is now geared towards Workload Adaptation, the process of workload management to aid learning, healing or limiting human errors. Moreover, workload measurement affects both the design and management of interfaces. On the one hand, by testing the workload of subjects during the use of web interfaces [122], for example, it is possible to direct the design. On the other hand, in the field of adaptive automation, it is the continuous monitoring of the workload level of the subject that allows the system to vary the feedback in response to the mental state of the operator [50, 71].

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