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Design, Human Factors and Neuroergonomics for Safety in Manufacturing

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ABSTRACT

Occupational safety research has been directed toward defining the areas of most significant concern in identifying specific areas of psychosocial risk. Modern workplaces need to address the complex relationship between work, technology, health, and well-being. The Operator 4.0 must retain a high level of attention, reactivity, and accuracy while interacting physically with machines and robots that do intellectual activities. Proper design of work activities and workstations must consider the cognitive load and anthropometry of the worker by involving the worker in the risk assessment to improve occupational safety through neuro-ergonomics approaches and measuring neural signatures of performance with various neuroimaging techniques, including functional near-infrared spectroscopy (fNIRS) and electroencephalogram (EEG). Based on international standards and literature research on the main databases, the analysis and characterization of interaction performance parameters is carried out by bringing together the principles of neuroergonomics, User Centred Design and New Human Factors including performance shaping factors (PSF). Specifically, the research work compares a collection of studies focusing on technologies for sensing brain parameters through neuroimaging in a laboratory setting to provide the tools to structure a reliable, adaptable, and easily replicable testing protocol through a multidisciplinary approach. It's necessary to develop guidelines for the neuro-ergonomic design of human-machine-robot interaction in Industry 4.0 environments to improve operator safety and health by defining good practices.

Keywords: Neuroergonomy, Human machine interaction, Human factors, Safety manufacturing

INTRODUCTION

Modern workplaces can be considered as socio-technical systems (Lombardi et al., 2022), where the social, organizational, and technical levels are closely and dynamically interrelated, (Körner et al., 2019) to solve the complex relationship between work, technology, health, and well-being. In recent years, the development of occupational safety research has been oriented towards defining the areas of most significant concern to identify specific psychosocial risk areas and align existing tools with contextualised measures, operational resources and advanced technologies in line with worker-user needs. Industry 4.0, thanks to the integration of cyber-physical systems, has increased interest in the proper design of human-machine/robot interaction,which optimizes user contact and communication with technology (Song & Awolusi, 2020). Indeed, the 4.0 operator must handle complex information processing while maintaining high levels of focus, responsiveness, and accuracy. Continuous cognitive work results in mental fatigue, which can impair performance since it requires high levels of attention, multitasking abilities, cognitive flexibility, and situational awareness (Lombardi et al., 2022; Lai et al., 2014). Measurements of mental workload can be categorized according to performance, in relation to the process of subjective self-evaluation, or in response to psychophysiology or neurophysiology (Dehais et al., 2020).

OSHA accident reports, such as OSHA Accident Report, 202475737 from 2009, have showed that several fatal and non-fatal injuries connected to industrial robots and machines are partially caused by workers' inadequate safety awareness and excessive cognitive load (Lombardi et al., 2022). Therefore, it is useful to understand the mental stress or safety awareness of workers in order to improve safety conditions during interaction with machines and robots. Until today, numerous approaches for assessing people's mental stress or safety awareness have been proposed and applied in the literature, as direct and indirect physiological measurements (Lu et al., 2022).

The evolution of technical standards and national and international standards has made compliance with ergonomic criteria a requirement for the acceptance of workstations and workspaces, industrial equipment, and equipment for production processes. A proper design of work activities and workstations must take consideration of the cognitive load and anthropometry of the operator. Also, to address the issues exposed, it is important to estimate workers' awareness of their own safety (Körner et al., 2019) and relate it to the state of mental stress and fatigue in order to improve and make safe interaction with machines and robots. Over the past three decades (Parasuraman & Wilson, 2008), there has been a revolution in how we understand the brain processes that regulate human performance and attention. The creation of sophisticated, portable neuroimaging tools that enable non-invasive examination of the "brain at work" has fuelled advancements in the discipline (Dehais et al., 2020).

Here we present a literature review that aims to define a framework for analysing theories and tools of experiments for evaluating the perceptual and cognitive processes of users-operator in the interaction with industrial machines/robots in order to understand and mitigate human error, through neuroergonomics' approaches.

Neuroergonomics Approach for Human Factors Evaluation

In recent years, researchers have shown that the principles of neuroergonomic design in human-machine/robot interaction within Industrial Environments 4.0 need to be further developed in order to enable the improvement of operator safety and health. This is because, according to the state of the art, the aspects related to human reliability, fatigue, and physical/cognitive stress during the use of machines are not currently adequately investigated. Human Factors methodologies analyse mental workload by performing two main functions: (a) measuring the exchange of information between operators and a set of operational rules, technological systems, or task requirements and (b) estimating the probability of performance degradation in operational scenarios that might be safety-critical (Lu et al., 2022).

As defined in ISO 10075-3:2005 - Ergonomic Principles Related to Mental Workload - assessment and measurement must refer to different process steps:

1. the assessment of working conditions that produce mental stress;
2. the assessment and measurement of mental strain, produced by mental stress (e.g., to ascertain tolerability);
3. the measurement of the effects of strain on the worker (e.g., fatigue, monotony, saturation, or reduced vigilance).

Thus, the introduction of neuroergonomics refers to a multidisciplinary approach widely defined as the study of the human brain in relation to performance at work and in everyday contexts (Parasuraman & Rizzo, 2007).

The neuroergonomic approach emphasizes a switch from the characterization of poor human performance and associated states in relation to neurobiological mechanisms, instead of inadequate cognitive resources. Ergo, the term neuroergonomics is used to describe a multidisciplinary approach that basically refers to the investigation of how the human brain is related to task/work performance (Parasuraman & Rizzo, 2007). The neuroergonomic method focuses a change from the characterization of impaired human performance and associated states in relation to neurobiological mechanisms, rather than inadequate cognitive resources.

Neuroimaging, or brain imaging, which employs several techniques to map the structure, function, or physiology of the nervous system directly or indirectly, emphasizes technologies for identifying neuroergonomic events. By recognizing the mental stress and safety awareness of employees (Körner et al., 2019), these technologies make it possible to involve the crucial operator in risk assessment and interaction, improving safety conditions when engaging with machines and/or robots. Neuroimaging methods are divided into two categories: those that reflect metabolic brain processes associated with neural activity, like functional magnetic resonance imaging (fMRI) and transcranial Doppler sonography (TCD), and the ones that directly measure neural activity, like electroencephalography (EEG) and event-related potentials (ERPs) (Parasuraman & Wilson, 2008). The advantages and disadvantages of those techniques can be considered in terms of three criteria: (a) spatial resolution in localising neural activity within the brain; (b) temporal resolution in identifying the timing of neural processing; (c) ease of use.

In the literature, EEG, a method that detects electrical activities produced by the brain and produces an effective signal to represent changes in the autonomic nervous system, is the neuroimaging technology that is most frequently used for analysing and evaluating cognitive load during task performance. The level of mental stress is frequently reflected by an increase or reduction in brain activity in the frequency band. Some experimentations use math problems as a stimulo to cause various levels of mental stress, which could then be categorised based on EEG data (Al-Shargie et al., 2016). Instead, the non-invasive functional neuroimaging technique known as functional near-infrared spectroscopy (fNIRS), which is frequently employed to identify physiological elements connected to brain activity. It has a better temporal resolution than functional magnetic resonance imaging and a higher spatial resolution than EEG. The light intensity is measured by NIRS technology after it has passed through a tissue (Song et al., 2020; Perrey et al., 2010; Varandas et al., 2022; Suzuki et al., 2010).

Each neuroimaging technologies mentioned before has specific strengths and weaknesses and the sensitivity of each type of measurement may change depending on the level of workload experienced by the operator (Dehais et al., 2020). Compared to current neuroimaging methods, NIRS measurement is thought to place far less physical and psychological strain on the user (Doi et al., 2013).

METHODS AND RESULTS

By setting the database's parameters to English and research type, references were screened (original articles published in the peer-reviewed journal). PubMed, Scopus, Web of Science, and Embase were searched for studies published between January 2000 and March 2023. The paper is based on a literature review focused on workplace safety in the manufacturing sector. The following keywords (MESH and non-MESH terms) were used: 'Human-machine' OR 'Human-robot' OR 'Human-computer' AND 'Interaction*' OR 'Interface*' OR 'Cooperation' AND 'Occupational' OR 'Work*' AND 'Cognitive' OR 'Mental Stress' OR 'Fatigue' AND 'Neuroergonomics' AND 'EEG' OR 'fNIRS'. The citations (title and abstract) found in all sources were checked by a reviewer. The final collection of acceptable research was then selected through a full-text article review. Discussions with the other authors helped to settle disagreements. It was decided which variables to extract using a data extraction form. The following items were included: article identifiers (authors, year of publication); study identifiers (setting, technologies, design); the parameters included for the analysis. This is a qualitative summary of the studies that were included. The key conclusions are summarized in the Figure 1, where is possible to identify all the papers considered and to visually quantify the amount of studies for each keyword. The state of the art on accidents in the workplace is integrated with the one on measurements of the cognitive and physical strain of operators in the manufacturing sector, using neuroimaging technologies. Free software was used in the selection process (Zotero, Rayyan). We adhered to the PRISMA-ScR principles for conducting systematic scoping reviews (Tricco, 2018). Twenty-seven papers were examined and analysed.

Results and Discussion

The twenty-seven selected studies were systematised to construct a framework of the trials. This framework synthesises and compares all the trials

Figure 1: Freely re-interpreted and integrated scheme. (Lombardi et al., 2022).

by characterising them according to the compatibility examined (physical-dimensional [F1]; functional [F2] and perceptual-sensorial [F3]), the neuroimaging and physiological technologies used to monitor the user-operator, the experimental setting and the performance shaping factors (PSF) analysed.

From the analysis of the studies, we can affirm that conventional approaches like questionnaires don't capture real-time activity in the cognitive state, determining the relative influence of mental workload and psychological stress when performing complicated tasks. The creation of intelligent adaptive systems, which in turn can help reduce the harmful effects of human error when doing complicated tasks, depends on a sensitive and accurate collection of metrics to identify between various levels of mental exertion and psychological stress in real time (Parent et al., 2019).

The combination of measurements of brain and physiological parameters is particularly helpful for emotional studies, providing a method for examining the theoretical process of fatigue, being uncontaminated by technical interference as both detection methods are based on different working principles, as shown in the summary table (see Figure 2) of the case studies identified and analysed (Perrey et al., 2008; Lai et al., 2013; Farguson et al., 2013; Manthoo et al., 2018; Matsumoto et al., 2020; Eyam et al., 2021; Brunzini et al., 2021; Teng et al., 2022; Savkovic et al., 2022).

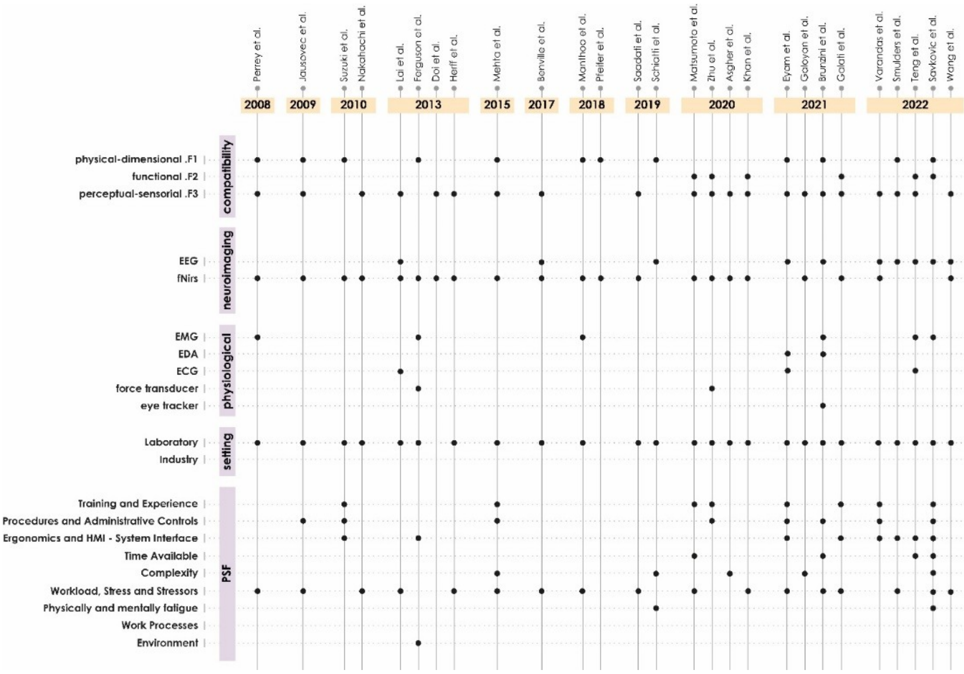

Figure 2: Framework's table of the reviewed studies.

In fact, as shown in studies using the measurement of physiological parameters as feedback of cognitive activity, heart and breathing rate variability are influenced by both acute stress and mental workload. Therefore, physiological measurements are objective and not subject to desirability and other biases that influence questionnaires and self-assessments. The analysis shows that the common approach is to study peripheral manifestations of high mental stress such as cardiovascular responses, while more direct measures of brain activity such as electroencephalography (EEG) or functional near-infrared spectroscopy (fNIRS) are recorded.

The ability of EEG to measure spatial resolution is constrained, even though that it has several outstanding characteristics for assessing mental workload, including superior temporal resolution (Li et al., 2022). In addition, setup time and tolerance to motion artifacts must be considered as well for a less intrusive solution. Techniques for optical imaging provide a workable substitute for taking note of the operator's mental state. Functional near-infrared spectroscopy (fNIRS), on the other hand, provides a potential portable system for measuring mental workload under field conditions. The spatial resolution capability of fNIRS has important advantages for measuring mental workload in neuroergonomic studies while people perform or develop skills in task (Li et al., 2022). Both technologies have limitations (for example external disturbance factors, motion artefacts, etc.), so the combination of EEG-fNIRS revealed better results, indicating that additional data sources may be useful for the detection of cognitive fatigue. For example, it's demonstrated that a hybrid system (EEG + fNIRS) allows higher classification accuracy for mental workload than using the two technologies alone.

Using combined EEG and fNIRS, a recent study distinguished between stressful and non-stressful settings during a mental arithmetic test with over 90% accuracy (Al-Shargie et al., 2016; Parent et al., 2019).

The functional neuroanatomy of task performance may evolve, according to current concepts of automaticity associated to the growth of competence in particular activities, supporting continuing assessments of cognitive effort (Tanida et al., 2004). Operator skill and mental workload typically have an inverse relationship. The accuracy and interpretation of psychophysiological variables as markers of mental workload are impacted by this inverse relationship between skill and cognitive demand for a specific task. Stress (anxiety) is viewed as an inefficient expenditure of energy that does not sustain performance but instead results in unpleasant feelings like worry (Lu et al., 2022). Mental strain, interpreted as mental effort, is characterized as an efficient expenditure of energy, enhancing or sustaining performance.

Neuroimaging technologies are used to analyse human factors based on a pipeline that includes the signal acquisition phase, the signal-to-noise ratio-improving step, the feature extraction stage, the classification step to identify the current mental states, and the adaptation step (Pfeifer et al., 2018; Li et al., 2022). At this final step, explicit decision-making units are put into place in order to dynamically close the loop by invoking the most suitable cognitive countermeasures. The classification of mental workload and psychological stress, which is connected to inter-individual variability, is another issue raised in the numerous studies. When estimating mental states, physiological measures must consider the fact that different people may respond psychologically and physiologically in various ways to workload or stress. In addition to task complexity, prefrontal brain activations are also connected to each person's level of mental effort (Parent et al., 2019). Therefore, it is appropriate to define not only the psychophysiological indicators but also those that relate to the person's personality, a requirement for identifying factors that cause mental stress/strain while doing a task.

CONCLUSION

It is necessary to approach the study of Human Factors from a neuroscience perspective, looking forward at the new paradigms of Industry 5.0 and focusing on the operator and his capabilities because aspects related to human reliability, fatigue, and physical/cognitive stress (Perrey et al., 2010) during the use of machinery have not yet been adequately investigated. As a result, guidelines for the neuro-ergonomic design of human-machine/robot interaction in Industry 4.0 environments are needed. These recommendations will enable us to take action to improve operator safety and health by outlining the key requirements, safe operating procedures, and best practices for interactions between humans, machines, and robots that are physical (F1), functional (F2), and perceptual (F3) in nature. The almost all of neuroadaptive experimental studies have concentrated on human-machine/robot dyad situations, which may open up promising perspectives for improving teaming such as human-human, human-machine, and human-robot interactions thanks to hyperscanning, physiological synchrony, and collaborative BCI.

In conclusion, both mental and physical workload and psychological stress are common in work environments, and these concepts can have a mutual influence on each other (Parent et al., 2019). Due to environmental factors, task complexity or repetitiveness, and work organization, the 4.0 operator is exposed to significant cognitive load. Therefore, correct design of work activities and workstations must ensure total operator involvement, risk assessment, and interaction to improve safety. Through a proper analysis of Performance Shaping Factors (PSF) and the identification of weak points, it is possible to maximize desirable effects (e.g., performance, learning) by improving operator safety conditions and mitigating the risk of errors. The development of integrated and adaptive systems could substantially improve safety conditions in working environments by ensuring better quality of productivity, well-being, and proactive safety measures.

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