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The contribution of neuroscience in evaluating human-robot collaboration: a multidimensional approach

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ABSTRACT

Collaborative robots (cobots) are a recent introduction in the industrial sector and are designed to work on shared tasks with humans with the aim to provide physical and cognitive support. This has led to a growing interest in the study of factors affecting human-robot collaboration (HRC) with the idea of making cobots more responsive to the human psychophysiological state. Several studies have begun to investigate dimensions such as mental workload and stress of the individual interacting with a cobot using behavioural and neurophysiological metrics, leading to a fruitful convergence between the worlds of neuroscience and robotics. It is therefore discussed the utility of a multidisciplinary and multidimensional approach in the study of HRC. Relevant physiological, neurophysiological, behavioural, and subjective measures are presented, as well as the necessity of their integration in HRC research. It is also introduced the importance of considering in HRC individual differences in terms of cognitive and emotional functioning, and factors related to individual representations and interpersonal environment.

Keywords: cobots; human-robot collaboration; mental workload; stress; neuroscience

1. Collaborative robotics and human-robot interaction

In the last decades industrial production has seen the introduction of new technologies including cobots, or collaborative robots. Cobots are specifically designed to work alongside with human operators on shared tasks and in a shared workspace, and in this they differ from traditional robots which are usually kept physically separated from human workers within protective barriers (Gervasi et al., 2020). For this reason, cobots are typically equipped with additional sensors, sometimes combined with artificial intelligence algorithms, that improve their awareness of the surrounding space and enable them to adapt power and speed based on the operator's position and other obstacles (Faccio et al., 2023). This allows a safe collaboration between human and robot with the main advantage of combining the unique abilities of the human being, such as flexibility, creativity, and problem-solving abilities, with the precision, power, and repeatability of the robot (ISO, 2016). This combination could increase productivity and quality of the industrial system while at the same time providing physical and cognitive support to the operator (Gervasi et al., 2024), for example relieving him from the most repetitive and physically demanding actions or suggesting the correct procedure in a task difficult to memorize.

For this reason, literature has recently given increasing attention to the study of Human-Robot Interaction (HRI) or Human-Robot Collaboration (HRC). HRI is a broad field of study "dedicated to understanding, designing, and evaluating robotic systems for use by or with humans" (Goodrich & Schultz, 2007). HRI addresses more in general the different ways in which humans interact with robots and their application, while HRC is more specifically related to the implementation of collaborative robots (Gervasi et al., 2020). Both are applied to different domains with a large literature, but in this context the focus will be narrowed to collaborative robotics in industrial settings. Specifically, one of the main challenges in this area is to identify the numerous factors that have a relevant impact on the quality of the relationship between human and robot during collaborative manufacturing tasks and to equip the cobot with the ability to adjust his behavior in response to the worker's psychophysiological state (Carissoli et al., 2023).

Indeed, in recent years several researches in the field of industrial engineering and ergonomics have approached the study of variables related to the human mental state that impact the interaction with cobots (Carissoli et al., 2023; Hopko et al., 2022; Liu et al., 2024). In ergonomics, these variables are referred to as "human factors", and a major focus in the literature is the study of how different features of the robot ("robot factors", such as speed, degree of automation, reliability) impact human factors (Hopko et al., 2022). Human factors frequently investigated are mental workload, trust and safety perception, anxiety, and fatigue, using a variety of subjective questionnaires, performance measures or objective metrics (Faccio et al., 2023; Hopko et al., 2022).

Mental workload in particular has received increasing attention in the scientific literature as an indicator of work-related stress and well-being in various contexts, including industrial ones (Carissoli et al., 2023). Mental workload is thought to be a multidimensional and multifaceted construct, influenced by various factor. A universally accepted definition is still missing but it can be summarily described as the demands imposed on the operator by the task and the subjective impact on the operator. It reflects the mental fatigue resulting from performing the task while taking into account the operator's capacity of facing such demands (Cain, 2007).

One of the main study objectives within industrial production is to measure and monitor the mental workload (or mental stress) of the operators to avoid a suboptimal workload. Mental workload impacts decision-making (Liu et al., 2024) and both a mental underload and overload have negative effects on the operator performance and health (Young et al., 2015).

Some authors (Carissoli et al., 2023; Cassioli et al., 2021; Rückert et al., 2023; Villani et al., 2020) therefore suggest designing cobots with the ability to detect and process physiological, cerebral, and behavioral signals of the workers' mental state in real time, using non-invasive sensors. This would allow cobots to automatically adapt in response to changes in the mental and physical state of the operator, that necessarily evolve during the time of the shift, and to operators with different individual characteristics, providing optimal workload and collaboration patterns.

2. The contribution of neuroscience in measuring human-robot collaboration and mental workload

The increasing attention in measuring and modeling human factors such as stress and mental workload of workers during the interaction with cobots inevitably calls neuroscience into question. As proposed by Cassioli et al. (2021), a holistic, multimodal neuroscientific approach to the study of human-robot dynamics would prove extremely useful in investigating the complexity of HRC and in developing fully collaborative cobots applications. In fact, progresses in neuroscientific technology have led to a variety of instruments for the measurement of behavioral and neurophysiological parameters that can be used in synchrony and are suitable for interactive and dynamic tasks. Neuroscience could therefore supply an important contribute to the study of HRC by providing appropriate metrics and a framework in which to interpret them.

2.1 Measuring mental workload

Mental workload or mental stress during collaborative tasks with cobot has been measured using a variety of physiological, neurophysiological, subjective, and performance measures.

Specifically, some common peripherical parameters in the study of mental workload are Electro Dermal Activity (EDA) or cardiovascular measures such as Heart Rate (HR) or Heart Rate Variability (HRV). Several studies (Arai et al., 2010; Carissoli et al., 2023; Gervasi et al., 2022, 2024; Lu et al., 2024; Pollak et al., 2020; Su et al., 2024; Villani et al., 2020) have investigated changes in such parameters within different modalities of human-cobot interaction while performing tasks that simulate industrial production processes. According to Gervasi et al. (2024) the diffusion and the high potential for naturalistic applications in industrial settings of these parameters derives from today's wide availability of noninvasive and relatively affordable wearable biosensors, such as wristbands, and from the non-excessive difficulty in implementing, analyzing, and interpreting their signals.

Cardiovascular activity has been extensively investigated in studies that assess mental workload in different domains, beside collaborative robotics. It proves to be a sensitive measure in discriminating tasks with different mental workload levels, with a general increase in HR, an increase in HF/LF ratio (the ratio between low frequency band and high frequency band), and a decrease in IBI (Interbeat Interval) when mental workload increases (Tao et al., 2019). Measurements of electrodermal activity are less diffuse and more controversial (Longo et al., 2022) but some studies show positive correlations between skin conductance and mental workload (Foy & Chapman, 2018; Mehler et al., 2009).

A few studies with collaborative robots have also measured central neurophysiological parameters of brain activity. For example, a recent study (Zakeri et al., 2023) used EEG (electroencephalography) and fNIRS (functional near-infrared spectroscopy), combined with subjective and behavioral measures, to investigate changes related to task complexity, cobot speed and cobot payload capacity. Differences has been found in theta, alpha and initial beta bands and in levels of oxygenation in left prefrontal cortex. Another study (Memar & Esfahani, 2020) used EEG to identify neurophysiological characteristics that can predict perceived workload in operators in a predominantly sensory-motor task with cobot. In the broader mental workload literature, it has been suggested that beta and theta waves increase and alpha waves decrease when mental workload is higher, while increased theta and delta bands reflect transition into mental fatigue (Borghini et al., 2014; Kutafina et al., 2021; Tao et al., 2019).

In addition, EEG and fNIRS signal can be used to gain insight into emotion recognition trough the analysis of frontal asymmetry, with an increased right frontal activity for negative and aversive emotions and an increased left activity for positive emotions (Balconi et al., 2014; Balconi & Mazza, 2010) and to investigate attentional processes, in particular selective attention, trough ERP approach (Cassioli et al., 2021).

Other frequent measurements used to assess mental workload and attention during HRC are behavioral measurements. They can be collected through performance measurements such as number of errors, reaction time, accuracy; or using ocular metrics with eye-tracking devices, where eye movements, blink activity, pupil diameter and fixation duration can be collected as indicators of mental workload, fatigue, drowsiness and attention (Borghini et al., 2014; Cassioli et al., 2021; Foy & Chapman, 2018; Tao et al., 2019).

Finally, self-report measurements are often used to assess mental workload. One of the most frequently used tools is the NASA Task Load Index (NASA-TLX; Hart & Staveland, 1988), which assesses associations between perceived mental workload and six factors: mental, physical, and temporal demands, performance level, effort, and frustration. Other scales have been used to assess factors associated with mental workload, including among others the Perceived Stress Scale (PSS; Cohen et al., 1983), the State-Trait Anxiety Inventory (STAI; Spielberger et al., 1983), the Self-Assessment Manikin (SAM; Bradley & Lang, 1994) for emotions valence and arousal evaluation, or the Negative Attitude toward Robots Scale (NARS; Nomura et al., 2004).

2.2 A multidimensional and multidisciplinary approach to human-robot collaboration

According to some authors one limitation in the current mental workload literature is the tendency to use the above-mentioned categories of measurements (physiological, neurophysiological, behavioral and subjective) in isolation or in pairs but rarely all together (Longo et al., 2022). Instead, a comprehensive and multidimensional approach would be advisable since every category taken alone has its limitations and does not provide complete information (Carissoli et al., 2023; Cassioli et al., 2021; Longo et al., 2022).

Self-reports are the only ones that can offer an insight of what is happening in the mind of the person from his point of view, but they are usually completed after task execution and are subjected to bias or errors in recalling the experience.

Performance measures could be inadequate in capturing cognitive workload or fatigue of the workers because some kinds of tasks could induce very few changes in the behavioral responses of the worker (Longo et al., 2022), especially considering that in industrial manufacturing operators are experienced and can perform repetitive tasks with very limited decision making involved.

Physiological and neurophysiological signals are more reliable but they can be influenced by many internal or external factors (Longo et al., 2022). Cardiovascular activity for example is highly influenced by physical effort, while workload classification based on EEG activity is effective but is generally task-specific and therefore difficult to generalize (Ke et al., 2014). This is because different tasks activate different cognitive functions and different neural activity patterns (Memar & Esfahani, 2020). Even a slightly different task can lead to the implementation of different strategies and to a different weight of the various functions involved. Investigating neurophysiological activity of the brain without considering the cognitive functions involved in that specific task and the general cognitive functioning of the individual performing the activity is not completely informative. Research on mental workload would therefore benefit from the investigation and assessment of neuropsychological functions involved in task completion, such as selective attention, working memory, stimuli inhibition, cognitive flexibility (Cassioli et al., 2021).

Besides, HRC is a complex interplay involving robot and humans functioning and their interaction, therefore its study should integrate the perspective of experts in robotics and industrial engineering with experts of the human psychological functioning (Carissoli et al., 2023). An interdisciplinary and comprehensive approach to the study of HRC should consider a variety of factors that have an impact on the person mental and psychophysiological state. These are not limited to the impact of robot features on the individual (Hopko et al., 2022) or to the effects of task complexity on mental workload, but comprehend emotional, cognitive, representational, interactional, and environmental aspects. How people experience a given situation in fact varies from person to person and within the same person in different times and circumstances. In cognitive psychology theories of appraisal (Lazarus & Folkman, 1984) emphasize that the evaluation of the situation is essential in determining the nature of the emotional reaction and experience. A specific event is defined as stressful not only because of the effect of the external stimulus on the person but depending on how the person perceives and evaluates the external stressor. This cognitive appraisal comprehends different levels from the interpretation and relevance of the stimulus, the evaluation of one's abilities and resources to cope with the situation, the immediate and long-term consequences to the individual's goals and values (Lazarus & Folkman, 1984; Scherer, 2001).

It is therefore important to consider the individual differences, both in terms of trait and state, that impact the perception of the situation on a representational, cognitive, and affective level. Some examples could be familiarity with robots, trust and acceptance of technology, executive functions, coping strategies, physiological vulnerability, individual characteristics such as cognitive flexibility and openness to experiences, the mood and mental state of the operator in that specific moment, and others. Some of these have been already considered in cobot literature, but not extensively.

Another factor of great importance is the environment in which the person operates. In addition to the effects of the physical environment on human performance, the social aspects of the environment are also of relevance. One limitation of studies that investigate HRC is that they are often conducted in laboratory settings (Liu et al., 2024) with usually only one person interacting with one robot. In real life industrial settings could be very different from that of the laboratory. In the latter, moreover, relationships and interactions with coworkers and different roles within the organization are inevitably not considered. Besides, working alone with a cobot or within a team of people and cobots could be very different. Hyperscanning (Montague et al., 2002) is a recent neuroscientific paradigm that is increasingly being used in the study of simultaneous and reciprocal interactions between human agents. In fact, it can be used to obtain information about neuro and psychophysiological synchronization and social adaptation both in dual and group interactions (Balconi & Fronda, 2020; Balconi & Vanutelli, 2017). Hyperscanning paradigm could therefore provide a novel insight into the study of HRC in realistic and complex work environments with multiple humans and cobot agents (Cassioli et al., 2021).

3. Conclusions

In this work it is discussed the contribution that neuroscience can give to the study of human-robot collaboration in industrial contexts. The diffusion of cobots in industries has led to the introduction of new models of interaction between humans and technology. Within this context the interest in studying the effects of such collaboration on the human mental state has increased, with a particular focus on mental stress and mental workload assessment during collaborative activities (Carissoli et al., 2023; Hopko et al., 2022). Some authors suggest that making cobots responsive to the psychophysiological state of the operator could improve collaboration patterns and reduce operator's workload (Carissoli et al., 2023; Cassioli et al., 2021; Rückert et al., 2023).

It is therefore discussed the utility of a multidimensional and multidisciplinary approach to the assessment of human-robot interaction. Such an approach should integrate expertise from different disciplines regarding robot science and human science, and should consider different cognitive, affective, representational, and social variables that have an impact on the behaviour and mental state of the individual. It is highlighted the importance of combining different methodologies, such as autonomic physiological measurements, central brain activity measurements, behavioural/performance measurements, and subjective measurements, to achieve a comprehensive and fully informative understanding of human-cobot dynamics. Besides, it is introduced the importance of considering individual differences in terms of cognitive functioning, mental representation of cobots and technology, coping strategies, personality traits and emotional states.

Limitations and future challenges in the study of this complex topic are also mentioned, particularly with respect to the ecological validity of the studies and the possibility of investigating dynamics related to the environment and the social interaction with multiple agents trough hyperscanning paradigm.

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