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Review article

Mental stress and safety awareness during human-robot collaboration - Review

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ABSTRACT

Human-robot collaboration (HRC) is an emerging research area that has gained tremendous attention in both academia and industry. Yet, the feature that humans and robots sharing the workplace has led to safety concerns. In particular, the mental stress or safety awareness of human teammates during HRC remains unclear but is also of great importance to workplace safety. In this manuscript, we reviewed twenty-five studies for understanding the relationships between HRC and workers' mental stress or safety awareness. Specifically, we aimed to understand: (1) robot-related factors that may affect human workers' mental stress or safety awareness, (2) a number of measurements that could be used to evaluate workers' mental stress in HRC, and (3) various methods for measuring safety awareness that had been adopted or could be applied in HRC. According to our literature review, robot-related factors including robot characteristics, social touching and trajectory have relationships with workers' mental stress or safety awareness. For the measurement of mental stress and safety awareness, each method mentioned has its validity and rationality. Additionally, a discussion related to the potential co-robot actions to lower mental stress or improve safety awareness as well as future implications were provided.

1. Introduction

In recent years, the concept of human-robot collaboration (HRC), defined as collaborative processes in which robots and humans work together to achieve common goals, has gained acceptance in a variety of industries such as warehousing, healthcare, manufacturing, etc. In HRC, a human worker and a robot share a workplace and work together in a collaborative way. HRC takes advantage of the flexibility of humans and the endurance of robots to substantially improve productivity (Villani et al., 2018). A robot adopted in HRC is typically referred to as a collaborative robot or a co-robot. Traditional industrial robots are designed to perform a task at a distance from workers. Common types of robots include manipulator arms, autonomous mobile robots, gantry models and so on. They are often used to process an item in a single way: drilling, welding, picking and placing, loading and unloading and so on. These industrial robots are heavy, large, and fast, which makes the robots dangerous for workers and requires them to be isolated from workers. Since traditional robots work independently of the workers, they work in parallel rather than in a collaborative manner. Compared to traditional robots, a co-robot is defined as "a method and apparatus and for direct physical interaction between a general-purpose manipulator controlled by a computer and a person" (Colgate and Peshkin, 1999). Co-robots and human workers can work on the same task in the same physical area at the same time, such as a work cell or station. Compared to traditional industrial robots, co-robots are mainly mobile robots or robot arms, some with humanoid screens, and are designed to give the highest priority to human safety. Multiple engineering features (Michalos et al., 2015), such as limited end effector speed (International Organization for Standardization (ISO), 2016), torque sensors (Heinzmann and Zelinsky, 2003), and flexible exterior material (Pang et al., 2018) have been implemented in co-robot design in order to physically ensure human workers' safety.

Co-robots also affect the psychological states of workers in addition to the physical collision, as workers tend to view their co-robot teammate as a social entity (Sauppé and Mutlu, 2015). A psychological state is a person's state of mind which comprises a diverse class, including pain experience, perception, desire, belief, intention, emotion, and memory (Martin, 1990). A co-robot can evoke fears, surprise, and anxiety if it looks robust enough to harm humans or it moves at a rapid speed with a sharp end-effector or in an unpredictable trajectory. An important component of the co-robots design is to take human personality and human engagement into account when adapting a co-robot's

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behavior (Celiktutan et al., 2019). Therefore, it is important to ensure that co-robots are human-friendly and psychologically acceptable (Kokabe et al., 2008). Human-friendly means that the co-robots are both safe and in a good performance, and psychologically acceptable means co-robots should meet the functional expectations of human workers. To achieve these goals, the movements of the co-robots must be perceptible, comprehensible, and predictable without imposing mental stress. For example, in common industrial practice, the movement trajectory criterion is set to minimize the integral of the end effector jerk (a derivative of acceleration) or to minimize the total execution time (Gasparetto and Zanotto, 2008). Such trajectories could appear unpredictable to workers and may confuse them in the early stages of the movement (Dragan et al., 2015), and potentially cause mental stress to workers. Previous studies have revealed that humans and robots can communicate emotionally during collaboration with robots or machines (Andreasson et al., 2018; Li et al., 2021). With regard to the relationship between negative emotions and stress, some studies have shown that they are closely related to each other. Some negative emotions such as anger, fear, and anxiety are usually triggered by stress, which shows a relationship between stress and emotions (Epel et al., 2018). Here, mental stress is defined as a feeling of emotional pressure and strain in psychology, which is a kind of psychological pain (Rastogi, 2018). For example, a previous study (Fiedler et al., 2005) found that stress can significantly affect anxiety symptoms. In most articles on mental stress, participants are required to self-assess levels of anxiety, surprise and fear to represent their stress levels.

Another important psychological aspect of workers during HRC is safety awareness. Safety awareness is a concept derived from situation awareness that emphasizes workers' perception, comprehension, and projection of the safety-related elements and events at work (Stanton and Piggott, 2017). Situation awareness is the perception of elements in the environment and events in relation to time or space, the understanding of their meaning, as well as the projection of their status in the near future (Endsley and Kiris, 1995). To date, a large number of studies have been conducted in various fields such as aviation and ground transportation and proved situation awareness is of great importance to system safety (Kaber and Endsley, 1998). In HRC, safety awareness refers to workers' understanding of potential hazards related to the location, activities, and status of co-robots (Murashov et al., 2016). From a hazard control perspective, safety awareness is as important as engineering approaches, which refer to the engineering intervention to remove hazardous conditions at the workplace (Tweedy, 2005). For example, if a worker walks quickly toward a co-robot, depending on the walking speed, the co-robot's automatic obstacle avoidance function may not have enough time to retract its end effector and avoid the approaching worker. Serious injuries can still occur when workers are not aware of the existence of a co-robot in the shared workspace. Accident records of Occupational Safety and Health Administration (OSHA) have shown that multiple fatal and nonfatal injuries associated with robots are due in part to workers' low safety awareness (e.g., *OSHA Accident Report, 202475737*, 2009). In addition, some studies have shown that higher stress levels were significantly associated with lower safety awareness (Hancock and Szalma, 2008; Sneddon et al., 2013).

Since workers may be stressed or have low safety awareness during HRC, it is important to understand workers' mental stress or safety awareness to improve the safety conditions during HRC. To date, a number of approaches to assessing the mental stress or safety awareness of people have been proposed and applied in the literature. The main approaches include direct measurements and indirect physiological measurements. Direct measurements are those that can quantitively or qualitatively measure workers' mental stress or safety awareness directly through self-reports, questionnaires, or observations. For example, Or et al. (2009) examined the effects of moving speed and size of an industrial robot on workers' mental workload with subjective questionnaires. Indirect measurements are those that estimate workers' mental stress or safety awareness based on their performance or physiological data obtained through specialized sensors or devices. Performance is usually evaluated by response time or error in completing a task. Physiological data could be heart-beat rate (from electrocardiogram signal), skin conductance (from electrodermal activity signal), muscle current (from electromyography signal), and brain activity (from electroencephalography signal).

Previous review studies (Epel et al., 2018; Zhang et al., 2020) mainly focused on direct and indirect measurements of mental stress or safety awareness in applications that were not in the context of human-robot collaboration. For those limited review articles that are related to the use of physiological measures in human-robot collaboration (Bethel et al., 2007; Rani et al., 2007), the robot-related factors that may affect mental stress or safety awareness were not well examined. In the current study, we seek to cover 1) the measurements for both mental stress and safety awareness that have been or can be used in human-robot collaboration, and 2) the robot-related factors that may affect mental stress or safety awareness.

Three research questions were addressed in this review:

Research Question 1 – What robot-related factors affect workers' mental stress or safety awareness? Co-robots have been studied across a number of domains, but workers' mental safety has not been explicitly and fully considered. Identifying the potential relationship between co-robots and workers' mental stress or safety awareness could be of value to workers' mental health in the future of work.

Research Question 2 – What measurements can be used to measure mental stress during HRC? A number of methods have been used to determine the correlation between mental stress and possible indicators such as performance, physiological signals, and self-reports. Measurements that can be used to test the mental stress during HRC have not been thoroughly examined.

Research Question 3 – What measurements can be used to measure safety awareness during HRC? Researchers currently test workers' safety awareness mainly through direct measures. Only a small number of studies have adopted indirect measures to understand participants' safety awareness. Measurements that can be used to measure workers' safety awareness during HRC have not been fully explored.

The rest of this manuscript was organized as follows: In Section 2, the review methodology was explained. Section 3 presented the results of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) procedures. In Section 4, robot-related factors that affect workers' mental stress or safety awareness were summarized. Section 5 and 6 presented various methods for measuring the mental stress and safety awareness that had been adopted or could be applied in HRC, respectively. Section 7 discussed potential co-robot actions that might lower mental stress and/or improve safety awareness. Section 7 also discussed the limitations of this review. Section 8 presented the conclusions and future work.

2. Methods

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method were used in this review to select literature. Four databases were searched, including Compendex, Web of Science, PubMed and Ergonomics Abstract. These databases provided diverse and comprehensive studies involving a number of subjects and domains.

2.1. Literature selection

The search syntax used in each database followed the expression: "((psychological states OR mental stress OR psychological stress OR situation awareness OR anxiety) AND (social touch OR trajectory OR speed OR robot size) AND robot) OR (stress AND physiological AND robot) OR (situation awareness AND (EEG OR human-robot collaboration OR eye-tracking))". During the title and abstract screening stage and full-text review stage, the following criteria were used:

- At least one direct measurement was used.
- The studies selected must measure short-term psychological change induced by robot movement or appearance rather than long-term change.
- The participants should be healthy adults.
- If a study used indirect measurements, this study needed to perform an analysis that can provide insight into the relationship between the direct and indirect measurements.

The database Compendex, Web of Science and PubMed was searched on October 6, 2021, and Ergonomic Abstract was searched on March 1, 2022. Two of our team members were assigned for doing a literature search and study screening independently. Disagreements that arose in this process were discussed and resolved by consensus after referring to the protocol. If they cannot reach a consensus, a third team member should be consulted. A team member created a database using Excel and then removed the duplicate entries automatically.

2.2. Data extraction

The following information was extracted from each article.

- *Research objectives.* Clear research objectives from each literature were extracted for each research question.
- *Study designs.* Study design and methodology were extracted from the experimental design described in each literature. Particularly the following information was examined: what the independent variables and dependent variables were, how different comparative conditions were obtained, what measurements were used for mental stress or safety awareness, how the data were obtained and analyzed and possible results.
- *Outcomes*: Comparative results were extracted from each literature. Results from each literature can confirm or reject the research problem underpinning the study. In this review, when the relationships between robot-related factors or other comparative conditions and workers' mental stress or safety awareness were examined, a p-value of 0.05 is used to verify if an experimental condition has a significant effect on workers' psychological states. Furthermore, the correlation between different measurements for a psychological state was also examined.

3. Results from PRISMA procedures

The PRISMA procedures and the number of obtained articles were shown in Fig. 1. This figure also presents the number of articles retrieved from each database. It resulted in 2347 articles after duplicates were removed. Following the screening criteria, 153 articles were kept for the full-text review. 25 articles were included in this final review.

4. Robot-related factors that affect worker's mental stress or safety awareness

Workers' mental stress and safety awareness can be affected by a variety of factors. A co-robot can be a stressor to evoke feelings of fear, anxiety or surprise when it appears as if it can hurt humans. For example, if a co-robot with a sharp end-effector moves towards a worker swiftly, or a co-robot moves unpredictably, the worker may feel fear because the robot appears to harm him or her. In this section, we provided a review of robot-related factors that may affect workers' mental stress or safety awareness including robot characteristics, social touching and trajectories. A total of 11 articles were included in the final analysis. Table 1 lists details about these articles.

4.1. Robot characteristics

Certain characteristics such as dimensions and speed of co-robots have been verified to have effects on human psychological states (Arai et al., 2010; Rahimi and Karwowski, 1990). Rahimi and Karwowski (1990) performed two experiments to assess participants' perception of safe robot speed and idle time, respectively. Participants were asked to verbally express the adjustment of the robot's speed of motion so that the preferred robot's safe speed was confirmed. In the second experiment, participants were required to enter a work envelope when they perceived a programmed idle was caused by a malfunction. These

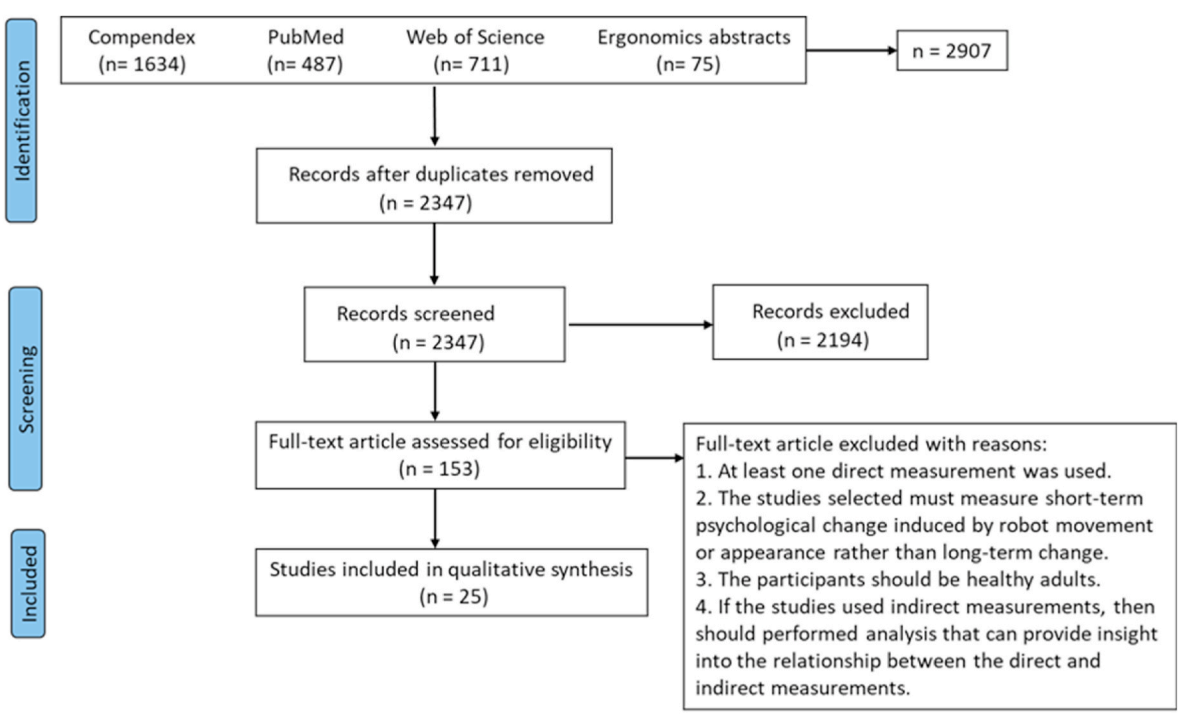

Fig. 1. PRISMA process used to identify and select studies.

Table 1
Studies selected for robot-related factors that may affect psychological states.

Authors	Sample Size	Examined Factors	Dependent Variables
Rahimi & Karwowski (1990)	30/24	Robot size, speed and accident exposure	Perceived maximum safe speeds
Karwowski et al. (1991)	12	Robot size, speed, and approach angle	Perception of maximum reach of robot's arm, selected distances from the robot
Or et al. (2009)	32	Robot size, speed, gende and simulated accident exposure	The length of time the participants waited before entering the robot work envelop
Hoffmann (2017)	84	Social touch	Self-reported questionnaire ratings
Willemse & van Erp (2019)	67	Social touch	Galvanic Skin Response (GSR), Heart Rate (HR), Heart Rate Variability (HRV), Respiration Rate (RR) and questionnaire ratings
Kokabe et al. (2008)	20	Trajectory	Subjective evaluations
Dehais et al. (2011)	12	Trajectory	Self-reports of legibility, safety and physical comfort, SCR and EMG
Dragan et al. (2013)	432	Trajectory	Subjective scaling and time were taken to predict
Dragan et al. (2015)	18	Trajectory	Questionnaire, coordination time, total task time, and concurrent motion time
Koppenborg et al. (2017)	28	Trajectory	Performance (response times and percentage of correct answers), subjective scaling, and physiological signal
Arai et al. (2010)	5	Distance, speed and notice	EDA

Note. GSR = galvanic skin response; HR = heart rate; HRV = heart rate variability; RR = respiration rate; SCR = skin conductance response; EMG = electromyogram.

experiments certified that robot speed and idle time affected workers' psychological states and safety behaviors. They further verified that robot size, moving speed and angle of approach had significant effects on workers' safety awareness (Karwowski et al., 1991). In this experiment, participants were asked to approach a robot along with one of the six angles to a point at which they felt it was the maximum reach of the arm of the robot. The perceived maximum reach of the arm of the robot was used as the dependent variable to measure the effects of robot size, moving speed and angle of approach. Arai et al. (2010) selected three design parameters to evaluate the effects of co-robot motions on human mental stress, which were the distance from the end-effector to a worker, moving speed and advance notice of co-robot motion, respectively. Both physiological and questionnaire results have shown high mental stress was caused when co-robots moved close to the workers or moved towards workers at high speed.

Or et al. (2009) replicated similar settings and experimental procedures as Rahimi and Karwowski (1990) in a virtual reality environment. The results confirmed that robot size and speed were significantly associated with workers' safety awareness in virtual reality as well. This study also validated the feasibility of measuring human psychological states in a virtual reality environment.

4.2. *Social touching*

As a teammate of a worker at the workplace, a co-robot should be able to cooperate and communicate with a worker like a human. Social touching is commonly seen in human-human communication and interaction and plays an important role in changing human psychological states and behavior (Calinon et al., 2010). Social touching is most commonly used to comfort people who are experiencing mental stress or suffering (Dolin and Booth-Butterfield, 1993). Derived from heuristics of human-human interaction, social touching motion can be designed to increase the social attribute of a co-robot, making it collaborate with workers more effectively.

Studies in the field of HRC have revealed that touching a soft robotic seal reduces one's depression, pain and stress (Hoffmann, 2017). Researchers also developed therapy robots based on tactile interaction such as touching, for psychological therapy (Schaefer, 2004; Shibata and Wada, 2011). These therapy robots validated the beneficial effects of touch on human's well-being. Based on the studies in the realm of robot therapy, Hoffmann examined the effects of touching on participants' psychological states (Hoffmann, 2017). Consequently, participants touched by the robot felt better during the human-robot conversation, then their negative effect lowered. This indicated that touch was able to improve one's psychological state compared to the participants who had the same interaction without touch.

Willemse and van Erp (2019) also investigated whether the robot's social touching could elicit positive responses in the participants from the viewpoint of psychological states. In their experiment, a thriller movie was used as a stressor. Participants watched the movie and were occasionally touched by a robot. Their findings implied robotic touches could reduce mental stress no matter with or without prior bonding, which is mainly reflected by the reduced heart rate during the interaction moments.

4.3. *Co-robot movement trajectory*

Trajectory planning is of great importance in HRC as unpredictable trajectories of a co-robot's end-effector can make a worker feel as if he or she may be hurt (A. D. Dragan et al., 2015; Gurgul, 2018) or confuse workers in the early phase of the movement (Dragan and Srinivasa, 2014). In industry practice, the objective functions of end-effector trajectory optimization include minimizing the total execution time, minimizing energy or minimizing the integral of end effector jerk (a derivative of acceleration) (Gasparetto and Zanotto, 2008). The minimum-time algorithm was proposed due to the need for productivity as well as the limited capability of actuators (Bobrow et al., 1985). Minimum-energy techniques produce natural-looking and smooth trajectories that are easy to track and reduce the force exerted on the actuators and manipulator structure. Minimum jerk techniques (Martin and Bobrow, 1999) generate trajectories that do not need sudden torque change, which can also result in a natural motion. Furthermore, minimum-jerk approaches can reduce the errors during tracking, the force exerted on the actuators and mechanical structure as well as excitation of resonance frequencies of robots (Kyriakopoulos and Saridis, 1988). Minimum-energy and minimum-jerk techniques can yield smooth interaction in HRC, which is able to improve workers' physical comfort to some extent. However, solely focusing on the adaptation and functionality of trajectories may decrease the predictability of the movements of robots. Trajectories generated from these criteria are less predictable and may confuse workers in the early phase of the movement, and possibly impose mental stress on workers (Dehais et al., 2011).

In HRC, workers need to clearly understand the intentions of co-robots. A co-robot should be able to plan the trajectories that are psychologically acceptable, predictable and legible to the workers. To make robot trajectories psychologically accepted by humans, Kokabe et al. (2008) examined human-to-human handing motions under different psychological feelings of the deliverer. In other words, the deliverer did hand-over motions with different feelings they need to express, and receivers did natural motions without knowing the adjective feelings. The authors then proposed an algorithm to generate co-robot handing motions simulating the motions of the human deliverer. By changing the parameters, psychologically acceptable co-robot handing movement can be realized.

Dehais et al. (2011) designed three co-robot motions with different levels of safety, legibility and physical comfort values. Participants were asked to rate different motions and three physiological signals were measured simultaneously. It has appeared that unpredictable motion led to higher galvanic skin response and negative subjective ratings. On the contrary, no such effects were found when the co-robot motion appeared safe, legible and comfortable. However, no data on task performance was measured in this experiment.

In previous studies, predictability and legibility were usually bound as a couple of desirable attributes of robot movements. Dragan et al. (2013) distinguished the predictability and legibility for the first time. In their study, predictable trajectories matched the expectation of a human when a target object was given, while legible trajectories enabled a worker to predict a target object confidently and quickly. They further investigated how different types of trajectories affected physical collaborations between co-robots and humans, which included functional motion, predictable motion and legible motion (Dragan et al., 2015). A functional motion was introduced as an unpredictable and erratic motion to be compared with a predictable and legible motion. In their experiments, the co-robot started to reach one of the objects along with different types of trajectories. The participants then predicted the co-robot's intention and gathered corresponding objects, and both co-robot and participants put their items on the same tray. Task performance data were measured as well as self-ratings. The results indicated functional motion was not suitable for human-robot collaborative tasks as it increased the amount of time to complete the task and decreased coordination fluency. Legible motion is preferable to predictable motion in HRC because it can express robot's intent more clearly and is in line with worker's expectations.

Koppenborg et al. (2017) experimentally investigated the effects of path predictability of an industrial collaborating co-robot on the worker. Participants completed tasks together with a co-robot in an industrial workplace simulated in virtual reality. The results have shown that a lower level of predictability and a higher level of speed increased the demands on workers, resulting in higher mental workload, anxiety, risk perception and a loss of task performance.

5. Methods to measure mental stress in human-robot collaboration

A total of 11 articles were included in the final analysis. Table 2 lists details about the 11 articles for methods to measure mental stress in human-robot collaboration.

5.1. Direct measurements

Self-report is the most commonly used direct method of psychological estimate. One can design a questionnaire based on psychological knowledge and then compute the stress index by the results. Or et al. (2009) examined the effects of moving speed and size of an industrial robot on workers' mental workload. The effects on workers were then estimated by subjective questionnaires. It was noted that when workers encountered a larger robot or a robot with a higher end effector speed, they perceived a significantly higher mental workload. One limitation of the direct measures is that participants may answer the questions in a way that they think the researchers want them to answer. Another issue is that to some extent the participant's responses depend on his or her mood on the day of the experiment (Bethel et al., 2007). The self-reports were commonly used as a reference to build the connection between participants' subjective stress levels and the objective physiological data.

5.2. Indirect measurements

Indirect measurements to estimate mental stress are mainly divided into psychological signals and facial expression recognition.

The major systems in the human body that respond to mental stress are the autonomic nervous system (ANS) and hypothalamic-pituitary-adrenal (HPA) axis. HPA is a neuroendocrine system that adjusts stress response, but the response is slow and not intuitionistic. Therefore, ANS response is more suitable for examining workers' mental stress (Park and Kim, 2018). Common physiological signals for ANS include blood pressure, cardiac response, electrodermal activity (EDA), Electroencephalogram (EEG) and electromyographic (EMG).

5.2.1. Cardiac response

Heart Rate Variability (HRV) affects determining the role of the human autonomic nervous system fluctuations. Increased sympathetic nervous system activity results in an acceleration of heart rate while an increased parasympathetic nervous system activity causes a decrease in the heart rate. Under mental stress, it is commonly observed that the parasympathetic activity of the heart decreases and the sympathetic activity increases. Rani et al. (2002) exploited this feature of heart rate variability to detect stress. They used video games to induce stress and acquire the electrocardiogram (ECG) waveforms, and then both Fourier Transform and Wavelet Transform were used to process the signals. These signals were then adopted to infer the stress condition based on the level of activation of the sympathetic and parasympathetic nervous systems using fuzzy logic.

5.2.2. Electrodermal Activity (EDA)

The change of skin electrical properties is referred to as electrodermal activity (EDA). EDA is affected by the sweat secreted by eccrine sweat glands (Safta and Grigore, 2011). Eccrine sweating is known as emotional sweating, which is a kind of sympathetic nervous activity involved with mental stress. EDA is divided into exosomatic measurement and endosomatic measurement (Bari et al., 2018). Exosomatic methodology mainly includes Skin Conductance Response (SCR), Galvanic Skin Response (GSR) and Skin Resistance Response (SRR). Endosomatic methodology mainly includes Skin Potential Response (SPR), Galvanic Skin Potential (GSP) and Skin Potential Level (SPL) (A.

Table 2
Studies selected for the method to measure mental stress.

Authors	Sample Size	Application Domain/Environment	Measurements	Independent Variables
Or et al. (2009)	32	Virtual reality industrial environment	Only subjective questionnaire	Robot size, speed, exposure to a simulated accident
Rani et al. (2002)	/	Visual field	ECG	/
Dehais et al. (2011)	12	Human-robot collaboration	EDA	Three robot motions
Arai et al. (2010)	5	Human-robot collaboration	EDA	Distance, speed and notice
Al-Shargie et al. (2016)	12	Montreal imaging stress task	EEG	Arithmetic problems at three levels
Wijsman et al. (2013)	30	Visual field	EMG	Three different stress conditions
Orguc et al. (2018b)	10	Classification of facial gestures	EMG	/
Lerner et al. (2007)	92	/	Facial expression	Three stress-challenge tasks
(Bueno and González-Fierro, 2013)	/	Human-robot collaboration	Facial expression	/
Rani et al. (2007)	6	Human-machine collaboration	Multimodal	Anagrams of varying difficulty
Pourmohammadi & Maleki (2020)	34	Medical diagnosis and analysis	Multimodal	Increasing difficulty of tasks

Note. ECG = electrocardiogram; EDA = electrodermal Activity; EEG = electroencephalogram; EMG = electromyogram.

Affanni and Chiorboli, 2014). Most research use GSR or SCR to analyze mental stress based on EDA. Dehais et al. (2011) examined the effects of the different types of co-robot trajectories on galvanic skin conductance response. The results suggested that a strong GSR was observed when a participant was surprised by a quickly approaching co-robot.

SPR signal is more difficult to obtain because it needs complicated and high-cost instrumentations (Antonio Affanni et al., 2018). However, endosomatic methodology exhibits a faster response to stress stimuli than exosomatic methodology, which makes exosomatic methodology more suitable to measure mental stress in time. Arai et al. (2010) investigated mental stress of workers when they are working together with a moving co-robot by measuring the SPR. The results showed that when a worker felt high mental stress at a condition the co-robot moved too near to them or the moving speed was too fast, the rate of occurrence of spike of SPR was greater.

5.2.3. Electroencephalogram (EEG)

EEG is an imaging technique that detects the electrical activities generated by the brain (Teplan, 2002). EEG signal is an effective signal to represent the changes in autonomic nervous system. To gain useful information, the decomposition of EEG signals in some frequency bands is extracted using a band filter (alpha (8–13 Hz), beta (14–30 Hz), theta (4–8 Hz) and delta (0.5–4 Hz)) (Saidatul et al., 2011). The increased or decreased level of brain activities in frequency band often reflects the level of mental stress (Yang et al., 2010). Al-Shargie et al. (2016) utilized arithmetic tasks as stress stimuli to induce different levels of mental stress and classified the stress based on the EEG signals. The results demonstrated that participants appeared less attentive and could not relax under a high level of stress based on the analysis of alpha and beta rhythm power values. In general, the studies revealed EEG was an effective method to detect mental stress and the right prefrontal cortex played a leading role in mental stress.

5.2.4. Electromyogram (EMG)

The electromyogram (EMG) measures the electrical activity related to muscle contraction level. In stressful situations, the EMG activity in some muscles increases compared to non-stressful situations. Wijsman et al. (2013) measured EMG signals generated by the upper trapezius muscle in three different stressful conditions. The results have shown that the amplitude of the EMG signal during stress situations was much higher than in rest situations. The relative time with gaps decreased during stressful conditions because fewer gaps would occur during stressful situations than during rest. The results suggested that EMG was a useful method to detect stress. Orguc et al. (2018) adopted an EMG-based facial gesture recognition system that could classify different jaw movements. They used discrete wavelet transforms to extract features and a support vector machine to classify jaw movements at different stress levels.

5.2.5. Facial expressions

From the psychological perspective, facial expression is a highly reliable measure to infer mental stress (Mauss and Robinson, 2009). There are two main techniques to measure emotional facial expressions (Höfling et al., 2020). One is recording the activities of specific muscles with EMG, as mentioned in the previous section. The other technique is by applying computer vision algorithms to face images to infer human stress levels in real-time (Mollahosseini et al., 2017).

For example, an intelligent tutoring system uses facial expressions of a student to decide whether a student is confused and needs more practice or is ready to proceed to more difficult concepts. Lerner et al. (2007) experimentally revealed the facial expressions corresponded with the biological stress response. The participants were required to perform stress-challenge tasks, during which the facial expressions, as well as several other physiological signals and subjective emotional experiences, were evaluated. As the results have shown, the facial expression of fear was positively associated with stress whereas the facial expression of anger and disgust was negatively associated with stress.

Bueno and González-Fierro (2013) proposed a method of emotional interaction between a robot and a human. The robot could recognize the human emotion changes based on Neural Evolution Algorithm and Active Appearance Models and then perform adaptive actions to mitigate workers' negative emotions.

5.3. Multimodal measurements

Although each physiological indicator to measure mental stress has its validity and rationality, two main concerns need to be considered when these methods are applied. One is the large individual difference in physiological response, and the other is that the same physiological signal may be triggered by a range of psychological states (Kulić and Croft, 2003). For these reasons, some studies sought to compare the stress level derived from different methods and infer mental stress in a multimodal way.

Pourmohammadi at el. (2020) classified stress levels by detecting the EMG signal of right and left erector spinal muscles and the right and left trapezius muscles and ECG signal. ECG signal was applied as a reference to evaluate the efficiency of EMG signals for stress detection. The results indicated EMG and ECG signals together could successfully classify stress into multiple levels with satisfactory accuracy. It has also been shown that the EMG signal of the right trapezius muscle recognized stress better than other muscles. Rani et al. (2007) focused on jointly detecting and recognizing stress through ECG, blood volume pulse (BVP), pulse transit time (PTT), SCR, skin temperature and EMG signal from both corrugators supercilii muscle (eyebrow) and masseter muscle (jaw). The results were compared with the participant's self-reported psychological state. The physiological data were classified using fuzzy logic along with decision tree learning. It was concluded that this approach was able to detect affective states reliably.

To summarize this section, it is concluded that each measure reviewed in this paper has its validity and rationality, and a combination of different methods may provide a more comprehensive and accurate assessment.

6. Methods to measure safety awareness in human-robot collaboration

A total of 6 articles were included in the final analysis. Table 3 lists details about the 6 articles for methods to measure safety awareness in human-robot collaboration.

6.1. Direct measurements

Safety awareness can be evaluated through questionnaires or reports, which are direct approaches to determine a person's situation awareness regarding safety. The most commonly applied measures are Situational Awareness Rating Technique (SART) (Taylor, 2017), Situation Awareness Global Assessment Technique (SAGAT) (Endsley and Kiris, 1995) and Situational Present Assessment Method (SPAM) (Durso et al., 2004). As a subjective method, SART outcomes are easy to obtain as the queries are genetic. SART measures one's situation awareness from ten dimensions, each of these dimensions has a seven points rating scale. Both SAGAT and SPAM are objective measures, which provide an unbiased estimation of a worker's situation awareness (Endsley, 2019). The queries for SAGAT and SPAM are specially designed according to the situation, and the questions can be scored correct or false objectively and are asked during live missions.

SART questionnaire is provided after the trial, and it is based on subjective estimation of situation awareness of the worker. de Merwe et al. (2019) developed a VR mediated HRC framework for non-professional workers. They compared workers' situation awareness and attentional demand under the full information and preprocessed

Table 3
Studies selected for the methods to measure safety awareness.

Authors	Sample Size	Application Domain	SA Measurements	Physiological Measurements	Independent Variables
de Merwe et al. (2019)	20	Human-robot collaboration	SART	/	full information or preprocessed context
Unhelkar et al. (2014)	24	Human-robot collaboration	SAGAT	/	Human assistant or robotic assistant
Yeo et al. (2017)	36	Flight	SPAM	EEG	Conditions of conflict resolution
Dini et al. (2017)	20	Human-robot collaboration	SAGAT/SART	Eye-tracking	/
Catherwood et al. (2014)	10/15	Visual field	QASA	EEG	/
Kästle et al. (2021)	32	Visual field	PEBL based on SAGAT	EEG	/

Note. SART = situational awareness rating technique; SAGAT = situation awareness global assessment technique; SPAM = situational present assessment method; EEG = electroencephalogram; PEBL = Psychology Experiment Building Language; QASA = quantitative analysis of situation awareness.

information context based on the answers to SART questionnaire. The results suggested that there was no significant difference in workers' situation awareness between the two information contexts. However, attentional demand scores were significantly greater for the full information context.

SAGAT is a popular freeze probe technique. A task is interrupted when the SAGAT is applied, and participants are required to answer the questions regarding the current situation. Unhelkar et al. (2014) evaluated workers' awareness of a mobile robotic assistant in a task environment through SAGAT. The designed questions were about the features of robotic assistants and human assistants. The results showed that participants were significantly more aware of the tray's color after delivery was performed by a robotic assistant. In contrast, the background environment was noticed better by participants after delivery was performed by a human assistant. This suggests that the co-robot may have a transitory distracting effect that degrades situation awareness, even after the robot left the participant.

SPAM questionnaire is performed in real-time but with no freeze while the participants carry out their operational tasks. Yeo et al. (2017) used four parameters obtained from SPAM to measure situation awareness and workload in an air traffic control context. The percentage of correct responses and the latency of the response were two parameters to measure the situation awareness while the time taken to be ready and the number of ready responses were used as workload measures. It is suggested to conduct nine situation awareness probes at a 6-min interval.

Although the self-report methods are easy to apply, they also have some limitations (Zhang et al., 2020). SART is subject to memory decay since participants must complete the questionnaire at the end of the task (Gatsoulis et al., 2010). SAGAT requires interrupting tasks, which limits its application in case the task cannot be stopped (Sneddon et al., 2013). SPAM requires participants to answer questions while performing tasks, which could have a negative effect on the participant's performance. Furthermore, the obtained data from SPAM may suffer from bias because participants' attention may be oriented to the relevant situation awareness elements due to the questionnaire (Salmon et al., 2006).

6.2. Indirect measurements

There are only a limited number of studies examining using indirect measures to infer situation awareness. Eye-tracking is the most commonly used physiological measure and accounts for the majority of the relevant literature. Another commonly used physiological method is EEG.

6.2.1. Eye-tracking

Eye-tracking is an approach to measuring situation awareness unobtrusively in an environment where multiple tasks exist. The situation awareness can be estimated by locating human gaze. Dini et al. (2017) developed a methodology to measure situation awareness from gaze interaction with objects of interest in the context of human-robot handover events. Their research question was whether SAGAT or SART questionnaire could be replaced by 3D-gaze tracking. The results showed that fixation distribution analysis significantly served the purpose to measure situation awareness. Besides, the look rate, average dwell time and turn rate were all features considered in the frame. Although not all the metrics had significant correlations with situation awareness, discriminative features were selected to predict situation awareness and made successful estimations.

6.2.2. Electroencephalogram (EEG)

Brain wave activities in the beta band are related to active thoughts and problem-solving (Yeo et al., 2017). It has been demonstrated by some studies that there is a negative correlation between workload and situation awareness while a positive correlation exists between situation awareness and performance (Dini et al., 2017; Schuster et al., 2012). EEG is widely deployed to examine the pilot or driver's brain activities during their driving tasks and what correlations are built between the brain activities and situation awareness (Borghini et al., 2014). Catherwood et al. (2014) recorded participants' brain activities with EEG during the loss of situation awareness. They required participants to identify target patterns or "threats" in urban scenes and then changed the target to enforce a loss of situation awareness. By analyzing the EEG data obtained from different brain areas, it is concluded that there was a co-activity in visual and high-order perception regions during a loss of situation awareness. Kästle et al. (2021) proposed a novel analytical methodology to correlate EEG signals to situation awareness. Participants completed the situation awareness test in Psychology Experiment Building Language (PEBL). PEBL is a psychological assessment framework containing a situation awareness test based on SAGAT technique. EEG data were collected throughout the whole test process. After processing the EEG data, the features were extracted and classified into high and low situation awareness categories. A correlation was found between the beta and gamma frequency bands and situation awareness.

7. Discussion

7.1. Potential co-robot actions to lower mental stress or improve safety awareness

The factors affecting workers' mental stress or safety awareness and methods to measure mental stress and safety awareness have been presented in the previous sections. In general, the robot types in the selected papers were mainly manipulator arms, mobile robots and personal robots. Manipulator arms are usually used to conduct tasks such as pick and place or handover and can be found in a wide range of tasks such as assembly and sorting. Mobile robots are usually served as delivery robots for transporting items from one location to another. For the measurements of mental stress, skin response is the most commonly used objective method because it responds rapidly and can be measured in a non-intrusive way. Some other measurements, such as EMG, have also been used for quantifying mental stress levels, but the number of literature is limited. The measurements of safety awareness mainly rely on direct measurements such as SAGAT, SPAM or SART. The most used physiological measurements are eye-tracking and EEG.

Below we provided a review of potential co-robot actions to reduce mental stress or improve safety awareness. One strategy to reduce mental stress and improve safety awareness is to notify workers before performing high-risk activities. This could be a simple strategy because notification of high-risk motion is open-loop control, which from the design perspective, is less complicated than a closed-loop control where robots detect workers' mental stress or safety awareness through sensors. Advance notice of robot motion is able to reduce mental stress and improve safety awareness effectively. The most commonly used signals are visual and audible signals. Arai et al. (2010) evaluate the effects of advance notice of co-robot motions on human mental stress. Comparative experiment outcomes showed that advance notice of the maximum speed of co-robot motion can reduce workers' mental stress.

An alternative way to reduce mental stress or increase safety awareness is to enable a co-robot to take mitigation actions in response to the worker's psychological states. During HRC, information exchange between humans and co-robots is bidirectional and equally important in terms of workflow for both humans and robots (Murashov et al., 2016). Not only do humans respond to co-robot actions, but also co-robots also need to respond to human behaviors to form a communication channel between workers and co-robots. As mentioned in Section 3 and Section 4, mental stress and safety awareness can be recognized and classified by various measures. Assume that workers' mental stress or safety awareness information along with other environmental inputs can be observed and processed by co-robots, co-robots may be able to infer workers' internal mental stress or safety awareness and adjust their actions to improve mental safety during HRC. For example, when high mental stress or distraction is detected, a co-robot can reduce the speed, touch the worker or alternate end-effector trajectory. Yet, very few studies have applied customized co-robot actions in response to workers' mental stress or safety awareness during collaborative tasks.

7.2. Limitations and future implications

This paper describes the robot-related factors that may affect mental stress or safety awareness and methods for measuring mental stress and safety awareness. Much effort has been made to reveal the relationships between robot-related factors and mental stress or situation awareness. However, there are still several research gaps that need to be filled. First, physiological data can be affected by environmental conditions. While one can keep the laboratory environment stable, the real-world industry-specific environment can change from time to time and affect the quality of physiological signals. In addition, most laboratory-based studies have focused on short time recording from seconds to minutes. If the mental stress or safety awareness of workers needs to be monitored for hours in a real-world environment, the data collection could be challenging. For example, the airtight sticker of GSR sensors can result in sweating, so that the skin conductance can be artificially altered without stress level changes. Special attention needs to be paid to how to obtain stable and high-quality physiological signals in real-world environments. Second, researchers have endeavored to find the stress-related or situation awareness-related features from physiological signals. Yet, the extracted features are mainly in the time domain. While time-domain analysis can provide information about how a signal changes over time, frequency-domain analysis can reveal how the signal's energy is distributed over a range of frequencies. Only a few papers have examined the features in frequency domain. Future works need to examine which feature combinations across time domain and frequency domain from physiological signals are the most correlated with mental stress or situation awareness. Third, the number of studies examining the relationship between mental stress and safety awareness was limited. Although the measurements for both mental stress and safety awareness overlap to some degree, the correlation between mental stress and safety awareness remains less studied.

8. Conclusions and future directions

This manuscript provided a brief review regarding the robot-related factors affecting mental stress or safety awareness and possible methods for assessing mental stress and safety awareness during HRC. According to our literature review, some robot-related factors, such as size and moving speed, are associated with a worker's mental stress or safety awareness. A number of measurements can be adopted to measure mental stress or safety awareness, including self-reports and physiological signals. In general, experiments that have been carried out in HRC scenarios employed both indirect physiological measurements and direct self-report measurements. These measurements together provide a full picture of mental stress or safety awareness. Future work is needed to explore solutions to measure the physiological signal in the real-world working environment and to investigate the most relevant features extracted from the signals in both the time and frequency domains.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Affanni, A., Chiorboli, G., 2014. Wearable instrument for skin potential response analysis in AAL applications. In: 20th IMEKO TC4 Symposium on Measurements of Electrical Quantities: Research on Electrical and Electronic Measurement for the Economic Upturn, Together with 18th TC4 International Workshop on ADC and DCA Modeling and Testing, IWADC 2014, pp. 807–811.

Affanni, Antonio, Bernardini, R., Piras, A., Rinaldo, R., Zontone, P., 2018. Driver's stress detection using Skin Potential Response signals. Measurement: J. Int. Meas. Confed. 122, 264–274. https://doi.org/10.1016/j.measurement.2018.03.040. March.

Al-Shargie, F.M., Tang, T.B., Badruddin, N., Kiguchi, M., 2016. Mental stress quantification using EEG signals. IFMBE Proceedings 56, 15–19. https://doi.org/10.1007/978-981-10-0266-3_4.

Andreasson, R., Alenljung, B., Billing, E., Lowe, R., 2018. Affective touch in human–robot interaction: conveying emotion to the nao robot. Int. J. Soc. Robot. 10 (4), 473–491. https://doi.org/10.1007/s12369-017-0446-3.

Arai, T., Kato, R., Fujita, M., 2010. Assessment of operator stress induced by robot collaboration in assembly. CIRP Ann. - Manuf. Technol. 59 (1), 5–8. https://doi.org/10.1016/j.cirp.2010.03.043.

Bari, D.S., Aldosky, H.Y.Y., Tronstad, C., Kalvøy, H., Martinsen, G., 2018. Electrodermal responses to discrete stimuli measured by skin conductance, skin potential, and skin susceptance. Skin Res. Technol. 24 (1), 108–116. https://doi.org/10.1111/srt.12397.

Bethel, C.L., Salomon, K., Murphy, R.R., Burke, J.L., 2007. Survey of psychophysiology measurements applied to human-robot interaction. In: Proceedings - IEEE International Workshop on Robot and Human Interactive Communication, pp. 732–737. https://doi.org/10.1109/ROMAN.2007.4415182.

Bobrow, J.E., Dubowsky, S., Gibson, J.S., 1985. Time-Optimal control of robotic manipulators along specified paths. Int. J. Robot Res. 4 (3), 3–17. https://doi.org/10.1177/027836498500400301.

Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., Babiloni, F., 2014. Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. Neurosci. Biobehav. Rev. 44, 58–75. https://doi.org/10.1016/j.neubiorev.2012.10.003.

Bueno, J.G., González-Fierro, M., 2013. Facial emotion recognition and adaptative postural reaction by a humanoid based on neural evolution. Int. J. 3 (10), 481–493. http://www.ijpg.org/index.php/IJACSci/article/view/488.

Calinon, S., Sardellitti, I., Caldwell, D.G., 2010. Learning-based control strategy for safe human-robot interaction exploiting task and robot redundancies. IEEE/RSJ 2010 Int. Conf. Intell. Robots Syst. IROS 2010 - Conf. Proc. 249–254. https://doi.org/10.1109/IROS.2010.5648931.

Catherwood, D., Edgar, G.K., Nikolla, D., Alford, C., Brookes, D., Baker, S., White, S., 2014. Mapping brain activity during loss of situation awareness: an EEG investigation of a basis for top-down influence on perception. Hum. Factors 56 (8), 1428–1452. https://doi.org/10.1177/0018720814537070.

Celiktutan, O., Skordos, E., Gunes, H., 2019. Multimodal human-human-robot interactions (MHHRI) dataset for studying personality and engagement. IEEE Trans. Affect. Comput. 10 (4), 484–497. https://doi.org/10.1109/TAFFC.2017.2737019.

Colgate, J. E., & Peshkin, M. A. (1999). Cobots U.S. Patent No. 5,952,796. 19, 35. https://patents.google.com/patent/US5952796A/en.

de Merwe, D.B., Van Maanen, L., Ter Haar, F.B., Van Dijk, R.J.E., Hoeba, N., der Stap, N., 2019. Human-robot interaction during virtual reality mediated teleoperation: how environment information affects spatial task performance and operator situation awareness. In: Chen, J.Y.C., Fragomeni, G. (Eds.), Virtual, Augmented and Mixed

Reality. Applications and Case Studies. Springer International Publishing, pp. 163–177.
Dehais, F., Sisbot, E.A., Alami, R., Causse, M., 2011. Physiological and subjective evaluation of a human-robot object hand-over task. Appl. Ergon. 42 (6), 785–791. https://doi.org/10.1016/j.apergo.2010.12.005.
Dini, A., Murko, C., Yahyanejad, S., Augsdorfer, U., Hofbaur, M., Paletta, L., 2017. Measurement and prediction of situation awareness in human-robot interaction based on a framework of probabilistic attention. IEEE Int. Conf. Intell. Robots Syst. 4354–4361. https://doi.org/10.1109/IROS.2017.8206301. -*Septe*(c), 2017.
Dolin, D.J., Booth-Butterfield, M., 1993. Reach out and touch someone: analysis of nonverbal comforting responses. Commun. Q. 41 (4), 383–393. https://doi.org/10.1080/01463379309369899.
Dragan, A.D., Bauman, S., Forlizzi, J., Srinivasa, S.S., 2015. Effects of robot motion on human-robot collaboration. In: Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction, 2015-March, pp. 51–58. https://doi.org/10.1145/2696454.2696473.
Dragan, A.D., Lee, K.C.T.T., Srinivasa, S.S., 2013. Legibility and predictability of robot motion. ACM/IEEE Int. Conf. Human-Robot Interact. 301–308. https://doi.org/10.1109/HRI.2013.6483603.
Dragan, A., Srinivasa, S., 2014. Integrating human observer inferences into robot motion planning. Aut. Robots 37 (4), 351–368.
Durso, F.T., Dattel, A.R., Banbury, S., Tremblay, S., 2004. SPAM: the real-time assessment of SA. Cognit. Approach Situat. Awareness: Theory Appl. 1, 137–154.
Endsley, M.R., 2019. A systematic review and meta-analysis of direct objective measures of situation awareness: a comparison of SAGAT and SPAM. Hum. Factors 63 (1), 124–150. https://doi.org/10.1177/0018720819875376.
Endsley, M.R., Kiris, E.O., 1995. Situation Awareness Global Assessment Technique (SAGAT) TRACON Air Traffic Control Version User Guide. Texas Tech University, Lubbock, TX.
Epel, E.S., Crosswell, A.D., Mayer, S.E., Prather, A.A., Slavich, G.M., Puterman, E., Mendes, W.B., 2018. More than a feeling: a unified view of stress measurement for population science. Front. Neuroendocrinol. 49 (March), 146–169. https://doi.org/10.1016/j.yfrne.2018.03.001.
Fiedler, N., Laumbach, R., Kelly-McNeil, K., Lioy, P., Fan, Z.H., Zhang, J., Ottenweller, J., Ohman-Strickland, P., Kipen, H., 2005. Health effects of a mixture of indoor air volatile organics, their ozone oxidation products, and stress. Environ. Health Perspect. 113 (11), 1542–1548. https://doi.org/10.1289/ehp.8132.
Gasparetto, A., Zanotto, V., 2008. A technique for time-jerk optimal planning of robot trajectories. Robot. Comput. Integrated Manuf. 24 (3), 415–426. https://doi.org/10.1016/j.rcim.2007.04.001.
Gatsoulis, Y., Virk, G.S., Dehghani-Sanij, A.A., 2010. On the measurement of situation awareness for effective human-robot interaction in teleoperated systems. J. Cognit. Eng. Decis. Making 4 (1), 69–98. https://doi.org/10.1518/155534310X495591.
Gurgul, M., 2018. Industrial robots and cobots: everything you need to know about your future co-worker. Michał Gurgul.
Hancock, P.A., Szalma, J.L., 2008. Performance under Stress. Ashgate Publishing, Ltd.
Heinzmann, J., Zelinsky, A., 2003. Quantitative safety guarantees for physical human-robot interaction. Int. J. Robot Res. 22 (7–8), 479–504.
Hoffmann, L., 2017. That Robot Touch that Means So Much: on the Psychological Effects of Human-Robot Touch. February 2017. http://duepublico.uni-duisburg-essen.de/servlets/DerivateServlet/Derivate-43096/Hoffmann_Laura_Diss.pdf.
Höfling, T.T.A., Gerdes, A.B.M.M., Föhl, U., Alpers, G.W., 2020. Read my face: automatic facial coding versus psychophysiological indicators of emotional valence and arousal. Front. Psychol. 11 https://doi.org/10.3389/fpsyg.2020.01388.
International Organization for Standardization (ISO), 2016. Robots and Robotic Devices – Collaborative Robots. *ISO/TS 15066:2016)*.
Kaber, D.B., Endsley, M.R., 1998. Team situation awareness for process control safety and performance. Process Saf. Prog. 17 (1), 43–48. https://doi.org/10.1002/prs.680170110.
Karwowski, W., Rahimi, M., Parsaei, H., Amarnath, B.R., Pongpatanasuegsa, N., 1991. The effect of simulated accident on worker safety behavior around industrial robots. Int. J. Ind. Ergon. 7 (3), 229–239. https://doi.org/10.1016/0169-8141(91)90006-8.
Kästle, J.L., Anvari, B., Krol, J., Wurdemann, H.A., 2021. Correlation between situational awareness and EEG signals. Neurocomputing 432, 70–79. https://doi.org/10.1016/j.neucom.2020.12.026.
Kokabe, M., Shibata, S., Yamamoto, T., 2008. Modeling of handing motion reflecting emotional state and its application to robots. Proc. SICE Annu. Conf. 495–501. https://doi.org/10.1109/SICE.2008.4654706.
Koppenborg, M., Nickel, P., Naber, B., Lungfiel, A., Huelke, M., 2017. Effects of movement speed and predictability in human–robot collaboration. Hum. Factors Ergon. Manuf. 27 (4), 197–209. https://doi.org/10.1002/hfm.20703.
Kulić, D., Croft, E.A., 2003. Estimating intent for human-robot interaction. IEEE Int. Conf. Adv. Robotics 810–815.
Kyriakopoulos, K.J., Saridis, G.N., 1988. Minimum Jerk Path Generation, pp. 364–369.
Lerner, J.S., Dahl, R.E., Hariri, A.R., Taylor, S.E., 2007. Facial expressions of emotion reveal neuroendocrine and cardiovascular stress responses. Biol. Psychiatr. 61 (2), 253–260. https://doi.org/10.1016/j.biopsych.2006.08.016.
Li, W., Cui, Y., Ma, Y., Chen, X., Li, G., Zeng, G., Guo, G., Cao, D., 2021. A spontaneous driver emotion facial expression (DEFE) dataset for intelligent vehicles: emotions triggered by video-audio clips in driving scenarios. IEEE Trans. Affect. Comput. 3045 (c), 1–14. https://doi.org/10.1109/TAFFC.2021.3063387.
Martin, B.J., Bobrow, J.E., 1999. Minimum-effort motions for open-chain manipulators with task-dependent end-effector constraints. Int. J. Robot Res. 18 (2), 213–224. https://doi.org/10.1177/027836499901800206.
Martin, D.C., 1990. Physical 207, vols. 924–926. http://www.ncbi.nlm.nih.gov/books/NBK320/.
Mauss, I.B., Robinson, M.D., 2009. Measures of emotion: a review. Cognit. Emot. 23 (2), 209–237.
Michalos, G., Makris, S., Tsarouchi, P., Guasch, T., Kontovrakis, D., Chryssolouris, G., 2015. Design considerations for safe human-robot collaborative workplaces. Procedia CIrP 37, 248–253.
Mollahosseini, A., Hasani, B., Mahoor, M.H., 2017. Affectnet: A Database for Facial Expression, Valence, and Arousal Computing in the Wild. *ArXiv Preprint ArXiv: 1708.03985*.
Murashov, V., Hearl, F., Howard, J., 2016. Working safely with robot workers: recommendations for the new workplace. J. Occup. Environ. Hyg. 13 (3), D61–D71. https://doi.org/10.1080/15459624.2015.1116700.
Or, C.K.L.L., Duffy, V.G., Cheung, C.C., 2009. Perception of safe robot idle time in virtual reality and real industrial environments. Int. J. Ind. Ergon. 39 (5), 807–812. https://doi.org/10.1016/j.ergon.2009.01.003.
Orguc, S., Khurana, H.S., Stankovic, K.M., Leel, H.S., Chandrakasan, A.P., 2018a. EMG-based real time facial gesture recognition for stress monitoring. In: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2018-July, pp. 2651–2654. https://doi.org/10.1109/EMBC.2018.8512781.
Orguc, S., Khurana, H.S., Stankovic, K.M., Leel, H.S., Chandrakasan, A.P., 2018b. EMG-based real time facial gesture recognition for stress monitoring. In: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2018-July, pp. 2651–2654. https://doi.org/10.1109/EMBC.2018.8512781.
Pang, G., Deng, J., Wang, F., Zhang, J., Pang, Z., Yang, G., 2018. Development of flexible robot skin for safe and natural human-robot collaboration. Micromachines 9 (11), 1–15. https://doi.org/10.3390/mi9110576.
Park, J., Kim, S., 2018. Wearable Photoplethysmography Sensor. *TENCON 2018 - 2018 IEEE Region 10 Conference*. October, pp. 1899–1902.
Pourmohammadi, S., Maleki, A., 2020. Stress detection using ECG and EMG signals: a comprehensive study. Comput. Methods Progr. Biomed. 193 https://doi.org/10.1016/j.cmpb.2020.105482.
Rahimi, M., Karwowski, W., 1990. Human perception of robot safe speed and idle time. Behav. Inf. Technol. 9 (5), 381–389. https://doi.org/10.1080/01449299008924252.
Rani, P., Sarkar, N., Adams, J., 2007. Anxiety-based affective communication for implicit human-machine interaction. Adv. Eng. Inf. 21 (3), 323–334. https://doi.org/10.1016/j.aei.2006.11.009.
Rani, P., Sims, J., Brackin, R., Sarkar, N., 2002. Online stress detection using psychophysiological signals for implicit human-robot cooperation. Robotica 20 (6), 673–685. https://doi.org/10.1017/S0263574702004484.
Rastogi, R., 2018. Statistical Analysis for Effect of Positive Thinking on Stress Management and Creative Problem Solving for Adolescents A Novel Approach for Residential Society Maintenance Problem for Better Human Life View Project Human Emotions View Project. July. https://www.researchgate.net/publication/326710205.
Safta, I., Grigore, O., 2011. Emotion Detection Using Psycho-Physiological Signal Processing, vols. 2–5.
Saidatul, A., Paulraj, M.P., Yaacob, S., Yusnita, M.A., 2011. Analysis of EEG signals during relaxation and mental stress condition using AR modeling techniques. In: Proceedings - 2011 IEEE International Conference on Control System, Computing and Engineering, ICCSCE 2011, pp. 477–481. https://doi.org/10.1109/ICCSCE.2011.6190573.
Salmon, P., Stanton, P.N., Walker, G., Green, D., 2006. Situation Awareness Measurement- A review of applicability.pdf. Appl. Ergon. 37 (2), 225–238.
Sauppé, A., Mutlu, B., 2015. The social impact of a robot co-worker in industrial settings. In: Conference on Human Factors in Computing Systems - Proceedings, 2015-April, pp. 3613–3622. https://doi.org/10.1145/2702123.2702181.
Schaefer, K., 2004. The Perception and Measurement of Human-Robot Trust. http://library.ucf.edu.
Schuster, D., Keebler, J.R., Zuniga, J., Jentsch, F., 2012. Individual differences in SA measurement and performance in human-robot teaming. 2012 IEEE Int. Multi-Discipl. Conf. Cognit. Methods Situat. Awareness Decis. Support, CogSIMA 187–190. https://doi.org/10.1109/CogSIMA.2012.6188378, 2012.
Shibata, T., Wada, K., 2011. Robot therapy: a new approach for mental healthcare of the elderly - a mini-review. Gerontology 57 (4), 378–386. https://doi.org/10.1159/000319015.
Sneddon, A., Mearns, K., Flin, R., 2013. Stress, fatigue, situation awareness and safety in offshore drilling crews. Saf. Sci. 56, 80–88. https://doi.org/10.1016/j.ssci.2012.05.027.
Stanton, N.A., Piggott, J., 2017. Situational awareness and safety situational awareness and safety, 7535, pp. 189–204. https://doi.org/10.1016/S0925-7535(01)00010-8. December 2001.
Taylor, R.M., 2017. Situational awareness rating technique (SART): the development of a tool for aircrew systems design. In: In Situational Awareness. Routledge, pp. 111–128.
Teplan, M., 2002. Fundamental of EEG measurement. Meas. Sci. Rev. 2.
Tweedy, J.T., 2005. Healthcare Hazard Control and Safety Management. Taylor \& Francis. https://books.google.com/books?id=cWzLBQAAQBAJ.
Unhelkar, V.V., Siu, H.C., Shah, J.A., 2014. Comparative performance of human and mobile robotic assistants in collaborative fetch-and-deliver tasks. ACM/IEEE Int. Conf. Human-Robot Interact. 82–89. https://doi.org/10.1145/2559636.2559655.
Villani, V., Pini, F., Leali, F., Secchi, C., 2018. Survey on human–robot collaboration in industrial settings: safety, intuitive interfaces and applications. Mechatronics 55 (February), 248–266. https://doi.org/10.1016/j.mechatronics.2018.02.009.

Wijsman, J., Grundlehner, B., Penders, J., Hermens, H., 2013. Trapezius muscle EMG as predictor of mental stress. Trans. Embed. Comput. Syst. 12 (4), 1–20. https://doi.org/10.1145/2485984.2485987.

Willemse, C.J., van Erp, J.B., 2019. Social touch in human–robot interaction: robot-initiated touches can induce positive responses without extensive prior bonding. Int. J. Soc. Robot. 11 (2), 285–304. https://doi.org/10.1007/s12369-018-0500-9.

Yang, Q., Jiang, D., Sun, J., Tong, S., 2010. Cortical synchrony change under mental stress due to time pressure. In: Proceedings - 2010 3rd International Conference on Biomedical Engineering and Informatics, BMEI 2010, 5(Bmei), pp. 2004–2007. https://doi.org/10.1109/BMEI.2010.5639664.

Yeo, L.G., Sun, H., Liu, Y., Trapsilawati, F., Sourina, O., Chen, C.H., Mueller-Wittig, W., Ang, W.T., 2017. Mobile EEG-based situation awareness recognition for air traffic controllers. In: 2017 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2017, 2017-Janua, pp. 3030–3035. https://doi.org/10.1109/SMC.2017.8123090.

Zhang, T., Yang, J., Liang, N., Pitts, B.J., Prakah-Asante, K.O., Curry, R., Duerstock, B.S., Wachs, J.P., Yu, D., 2020. Physiological measurements of situation awareness: a systematic review. Hum. Factors 3, 1–22. https://doi.org/10.1177/0018720820969071.