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Impatto dell'interazione tra persona e cobot sui parametri legati al benessere dei lavoratori

Impact of Human-Cobot Interaction related to Workers' Well-being Benchmarks

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SUMMARY

1. INTRODUCTION

The advent of Industry 4.0 has generally been considered as a net positive for the manufacturing industry and the economy at large, not only boosting environmentally friendly features (Oláh et al., 2020; Romero et al., 2021), but improving performances of enterprises that implement its main attributes (Ślusarczyk et al., 2020). It is necessary to address the possible criticalities of Industry 4.0 implementation in the workplace, which prioritizes automation instead of psychological and psychopathological difficulties and needs that can arise in the workers working with advanced production technologies. It is likewise important to acknowledge that changes in the work set-up can often be determined by leadership and supervisors and enforced on the general workforce (Kokkinidis, 2012), potentially exacerbating the aforementioned issues.

Of all the technologies encompassed by the concept of Industry 4.0 (Shahin et al., 2020; Frank et al., 2019), one most interesting and useful to scrutinize are collaborative robots (Faccio et al., 2023), due to their ability to work directly and collaboratively with workers.

Industry 4.0's focus on technological advancements and post hoc assessment and resolution of difficulties in the workforce has since been taken on by the newest paradigm shift, labeled Industry 5.0. Industry 5.0 is centered on human and societal wellbeing, not only aiming at economic growth and sustainability, but also at merging the concepts of human-centricity and human-robot interaction (Leng et al., 2022).

To aid in this effort, the aim this systematic literature review is to gauge the effects of human-robot collaboration, as conceived in the context of Industry 4.0, on six of the most famous and renowned benchmarks of workers' psychological health: mental workload, distress, stress, anxiety, depression and, more generally, affective wellbeing. In the following chapters there will be a trough description of these constructs, a report on the methodology of research employed and a recollection and analysis of the results.

2. THEORETICAL BACKGROUND

Before proceeding with the main structure of the research, it is important to address and define the main constructs that will be discussed and analyzed in the systematic review. Although these definitions will be used to guide the interpretation of the research included, it needs to be noted that most are not universally applied, hence a degree of interpretation and adaptation is needed for the aims of the systematic literature review.

2.1 Understanding Collaborative Robots (Cobots): Definitions and Collaboration Levels

The term cobot, shorthand for Collaborative Robot, identifies a vast array of lightweight machines and industrial robots employed in the workplace, capable of handling a shared payload in collaboration with the human worker (Peshkin et al., 1999). The most modern definition is even broader, is considered a cobot «any robot operating alongside humans without the presence of a fence» (Adiraensen et al., 2021, p. 2). Based on the level of collaboration and modality of task allocation, the human-cobot interaction is divided in four categories (Cesto et al., 2016; El Zaatari et al., 2019) [Fig. 1]:

- *Independent*: human worker and cobot work simultaneously and independently on different workpieces; the only collaborative aspect is the coexistence of both in the workplace without a separation in-between.
- *Simultaneous*: human and cobot operate simultaneously but on distinct aspects and processes, on the same workpiece. The cobot needs a level of spatial awareness, to avoid colliding with, and possibly hurting, the worker.
- *Sequential*: operator and cobot work synchronously on the same workpiece. One can start his or its task only after the other completes his or its own. The nature of the collaboration is time dependent.
- *Supportive*: the highest level of collaboration between human and cobot, both work on the same workpiece interactively. The main objective of the cobot is assisting the human operator in the process.

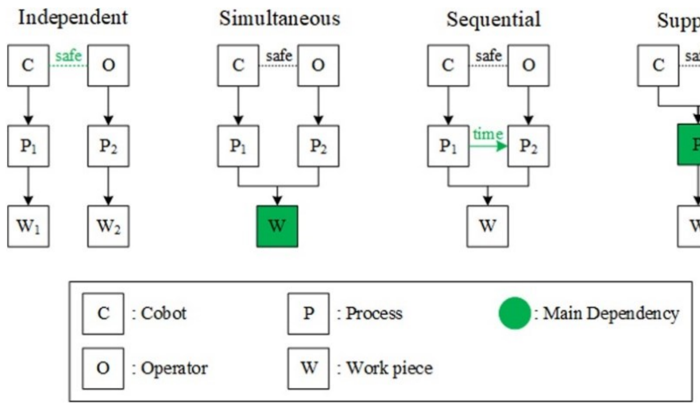


Figure 1. Degrees of collaboration in industrial scenarios (El Zaatari et al., 2019).

The only category that does not imply a possible intrinsic risk for the psychological and physical wellbeing of the worker is the independent one, since there is no contact with the cobot, there is no reason to feel threatened by its movements; however, the constraints it poses significantly limit the quality of the collaboration, reducing the definition of cobot to a mere theoretical characterization (Adiraensen et al., 2021). Since human-robot interaction (HRI) and collaboration (HRC) are a staple of Industry 4.0, it is essential to explore and implement alternative methods to reduce psychological distress, rather that universally applying the initial level of to all industrial processes.

Adopting the Industry 5.0 framework, the implementation of cobot in the workplace offers an increased flexibility if compared to "classical" automated tasks and at the same time a higher level of productivity than manual tasks involving human labor. Considering human physical well-being, collaboration with a cobot allows for less demand for physical strain, that can be delegated to the collaborative robot (Faccio et al., 2022), and synchronization between the two parties can offer a fluid interaction and production process (Taesi et al., 2023). The reduction in physical workload offered by HRC is clear, whilst its effects on mental workload are not.

2.2 Definition of Mental Workload in HRC

Mental workload (MWL) is mostly used as a synonym of cognitive load, which is defined as «the relative demand imposed by a particular task, in terms of mental resources required.» (APA Dictionary of Psychology).

An independent, universally accepted definition of mental workload does not exist yet in the literature. According to the aim of this study the aforementioned American

Psychological Association Dictionary of Psychology's definition will be utilized in tandem with the specific operational definition of MWL offered by Longo et al. (2022):

> « Mental workload (MWL) represents the degree of activation of a finite pool of resources, limited in capacity, while cognitively processing a primary task over time, mediated by external stochastic environmental and situational factors, as well as affected by definite internal characteristics of a human operator, for coping with static task demands […] » (p. 18)

From both these definitions it is clear that mental workload is not necessarily detrimental to the psychological well-being of the individual, and if maintained under a specific threshold can be stimulating, leading to an increase of productivity in the workplace (Bowling et al., 2012).

While collaboration with a cobot should theoretically lower the mental demand on one hand, by sharing parts of the production process, on the other hand it could introduce new, detrimental features, such as increased work pace and need to oversee the cobot's actions (Carissoli et al., 2023).

2.3 A Holistic and Multidimensional Perspective on Affective Well-Being

All the constructs henceforth listed and defined represent factors impacting, directly or indirectly, the general state of the person, reason why they have been selected as benchmarks. This general state can be operationalized using the construct of well-being. Although a consensus definition of well-being has not been proposed yet (37, 38), the term as been employed extensively in the field of psychology and physiology, and even in the World Health Organization's constitution (WHO; 1946) definition of health as «a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity» (p. 1).

This research will condense multiple interpretations to better encompass and analyze the term in the contexts it will be employed. The Cambridge dictionary defines well-being as «the state of feeling healthy and happy» (Cambridge Dictionary), which offers limited practical utility. The APA definition provides a more specific definition, describing well-being as «a state of happiness and contentment, with low levels of distress, overall good physical and mental health and outlook, or good quality of life» (APA Dictionary of Psychology). However, this definition risks becoming circular when considered alongside the WHO definition of health. The American Psychological Association (APA) provides a definition of subjective well-being, subdivided in affective well-being, meaning a presence of positive affect and absence of negative affect, and cognitive well-being, which considers a more general evaluation of one's life (APA Dictionary of Psychology).

The *hedonic perspective* of well-being focuses on the subjective rating of happiness and judgments on the aspects, positive and negative, of one's life, and it is the most widely used. In contrast, the *eudaimonic perspective* of well-being is centered on individual self-fulfillment and self-actualization (Bartels et al., 2019). Both define different aspects of well-being, and in conjunction with one another embody the construct in its various connotations (Ryff et al., 2021). Lastly, one of the most recent definitions is offered by Simons and Baldwin (2021), who describe it as «a state of positive feelings and meeting full potential in the world. […] measured subjectively and objectively using a salutogenic approach.» (p. 7). *Salutogenesis* is the specific, constructionist approach to wellness, which is focused not on pathology or pathologizing, but instead on health promotion (Harrop et al., 2006; Antonovsky, 1979), applicable in several circumstances.

Well-being is strongly affected by stress, anxiety and depression (Rahimnia et al., 2013), reason why these will be considered as important indicators of a lack of well-being, if present in workers engaging in HRC.

The state of the art on the subject of cobot introduction's effects on affective well-being are not conclusive: Paliga (2023) reports no negative nor positive correlation between advanced production technologies and well-being, whilst Tobias et al. (2023) simply propose an empathy-based framework.

2.3.1 Providing an Operational Interpretation of Distress

Commonly defined as a more specific type of stress, and often employed just as one of its synonyms (APA Dictionary of Psychology), distress will be considered here as a general negative affect, following the definition from the authors of the Depression Anxiety Stress Scale (DASS) validation study. This definition encompasses some of the core components of depression, anxiety and stress (Brown et al., 1997), providing a theoretical and simultaneously operational and quantifiable link between the three (Watson et al., 1984).

Another remarkable quality of the DASS is the distinction between the shared components of these three and the independent ones (hyperarousal of anxiety and absence of positive affect of depression), enabling a more targeted analysis of each (Brown et al., 1997; Parkitny et al., 2010; Samani et al., 2007).

The direct link between HRC and distress of workers has not been ascertained, what is clear is that an important factor of distress are stress and anxiety due to the increased feeling of job precarity, brought about by the introduction of cobots in the workplace (Tomidei et al., 2022).

Since distress is definable as a general negative affect, comprising stress, anxiety and depression, these more specific constructs will be further discussed in the following sub-chapters.

2.3.2 Untangling the Complexities of Stress: Definitions, Effect, and the Influence of Cobots

Stress is a multifaceted construct, not without what could be considered paradoxical expressions (Levine, 1985). Thus, a definition that encompasses this polymorphic aspect needs to be broad and at the same specify every different facet. APA Dictionary of Psychology (APA Dictionary of Psychology) defines it as:

> « The physiological or psychological response to internal or external stressors. Stress involves changes affecting nearly every system of the body, influencing how people feel and behave. […] stress contributes directly to psychological and physiological disorder and disease and affects mental and physical health, reducing quality of life. »

Stress is distinguished from the far less explored construct of eustress (Kupriyanov et al., 2014), because the former is considered a strictly negative psychological response to external or internal stressors, while the latter is the optimal level of stimulation in reaction to a challenging but achievable task (APA Dictionary of Psychology).

Chronic stress is defined as a «response to a prolonged internal or external stressful event.» (APA Dictionary of Psychology) and has been long considered as correlated with, if not a proper predictor of, depression (Van Praag, 2004; Tennant, 2001). Therefore, one can conclude that minimizing the prolonged exposure of the workforce to stressors could be employed as an efficient and effective prevention of depression symptoms, addressing two major problems with a single and specific legislation change.

Another significant, if not slightly self-evident, correlation has been found between stress and mental workload: a low to moderate level of mental workload corresponds to a moderate level of stress (Jaafar et al., 2020), whilst a high level of mental workload corresponds to a high level of stress, resulting in a decrease in performance (Alsuraykh et al., 2019).

Cobot introduction's effect on worker's stress as a phenomenon has not been investigated, with Carissoli et al. (2023) focusing on cobot speed, communication skills and proximity to operators and Jost et al. (2018) proposing an Augmented Reality interface to resolve such criticalities.

2.3.3 Defining Anxiety: Implications for Workplace Productivity and the Impact of Cobot Integration

Anxiety is defined by the APA Dictionary of Psychology (APA Dictionary of Psychology) as an:

> « Emotion characterized by apprehension and somatic symptoms of tension in which an individual anticipates impending danger, catastrophe, or misfortune. […] Anxiety is considered a future-oriented, long-acting response broadly focused on a diffuse threat, whereas fear is an appropriate, present-oriented, and short-lived response to a clearly identifiable and specific threat. »

Completing the APA definition, the construct will be also considered in its unconscious and subconscious connotations and with attention to its detrimental effects on productivity in the workplace (Coventry, 2022), since these aspects are overlooked and nonetheless valuable for the research.

As for the other constructs, anxiety has not been indagated as a dependent variable of cobot introduction to the workplace, focusing on more specific aspect of cobots. As an example, Kato et al. (2010) and Khalid et al. (2017) reported analyses of advanced production technologies effects on workers anxiety.

2.3.4 A Psychologically Functional Description of Depression

Defined by the APA Dictionary of Psychology (APA Dictionary of Psychology) as:

> « A negative affective state, ranging from unhappiness and discontent to an extreme feeling of sadness, pessimism, and despondency, that interferes with daily life. Various physical, cognitive, and social changes also tend to co-occur, including altered eating or sleeping habits, lack of energy or motivation, difficulty concentrating or making decisions, and withdrawal from social activities. »

The newfound popularity of the term carries with it the risk of misuse, often adopting 'depression' as a synonym for 'melancholy', 'sadness' or other, non-psychopathological constructs. To avoid this occurrence in this thesis, we adopted the definition offered by José Eduardo Rondón Bernard (2018, p. 2), which offers a high level of specificity in regard to the symptomatology:

> « Depression constitutes a multi factorial disorder that involves a set of specific behavioral or motor symptoms […], cognitive symptoms (negative assessment of the self, of the environment and of the future), social symptoms (increase of dependence on others and avoidance of recreational-social interaction) and biological symptoms […], that causes the subject to lose reinforcement of their environment consequently generating difficulties in their daily functioning. »

Depression symptoms, as already ascertained, are linked to stress symptoms to the extent that the latter is considered as a risk factor, if not a direct precursor of the former (Van Praag, 2004; Tennant, 2001; Anisman et al., 1982; Shields, 2006).

Its comorbidity with anxiety has also been investigated, suggesting a significant positive correlation between the two, as well as a temporal proximity between the onset of one before the other (Kalin, 2020; Merikangas et al., 2010).

Experiencing depression symptoms in the workplace can be significantly challenging, with different expressions that range from absenteeism, when an employee habitually avoids coming to the workplace (Darr et al., 2008; Thomas et al., 2002), to presenteeism, when an employee is present in the workplace when they would need to recover from an illness or are in general somewhat impaired, both leading to a decrease in productivity for the organization and a worsened quality of life for the worker

(Haslam et al., 2005; Bender et al., 2008; Callen et al., 2013). The direct and indirect consequences of experiencing depression disorder entail the highest medical plan costs of all other diagnoses (Conti et al., 1994), with a total cost, only in Europe, of 117 billion euros, corresponding to 1% of the total European GDP (Sobocki et al., 2006). Depression has not been, as of today, fount to be correlated to the introduction of cobots to the workplace.

3. METHODS

3.1 Article Selection

For the aim of gauging the effects of human-robot collaboration (HRC) on cognitive workload and affective well-being (a construct that encompasses depression, anxiety, stress and distress), a systematic literature review methodology has been selected. The decision was based on the replicability and transparency that this type of review affords (Lamé et al., 2019), but especially to be able to comprehensibly and thoroughly scan all articles consistent with the aim of the research.

The systematic review has been conducted using the Preferred Reported Items for Systematic Reviews and Meta–analyses (PRISMA; Page et al., 2021) workflow model, through Scopus, ACM Digital Library, Web of Science and IEEE Xplore digital databases. The PRISMA guidelines support the research to avoid possible biases due to researchers' personal opinions and ensure a high level of clarity (Selçuk et al., 2019), since every major step of the research must be included in the PRISMA flow chart. Following the PRISMA model, the screening phase of the research has been subdivided into two, and the screening itself was based on inclusion and exclusion criteria mentioned below. The first screening was based on title and abstract of the articles, the second screening on the analysis of the full-text of each article.

3.1.1 Screenings and Inclusion Criteria

The keywords used in the research where always couped whit the keyword "cobot": anxiety, stress, workload, depression, distress, well-being, wellbeing, as well as the synonyms automatically searched by the databases. To be included in the review, the studies needed to: (i) be conducted in, or with a direct implication for, manufacturing companies, (ii) assess the effects only of cobots, (iii) be composed of a sample of healthy adults without a previous DSM-5-TR diagnosis, (iv) avoid the use of digital twin, if not strictly for assessing experimentally the implications of a collaborative environment for the participants.

During the first screening all the articles included in systematic, scoping and metanalytic reviews were analyzed in the screening following the snowballing method. All articles resulting from the first screening were read fully.

3.1.2 Exclusion Criteria

All articles that met the listed criteria were excluded from the review: articles including in their analysis (i) traditional industrial robots or machines different from the definition of cobot that guided the research, articles (ii) without the full-text availability or not fully written in English, articles that (iii) did not include the aforementioned constructs nor a synonym that could, with a degree of interpretation and using the context of the article, be directly correlated to the constructs (e.g., using robot instead of cobot, while in the study addressing a collaborative robot) and (iv) purely theoretical articles.

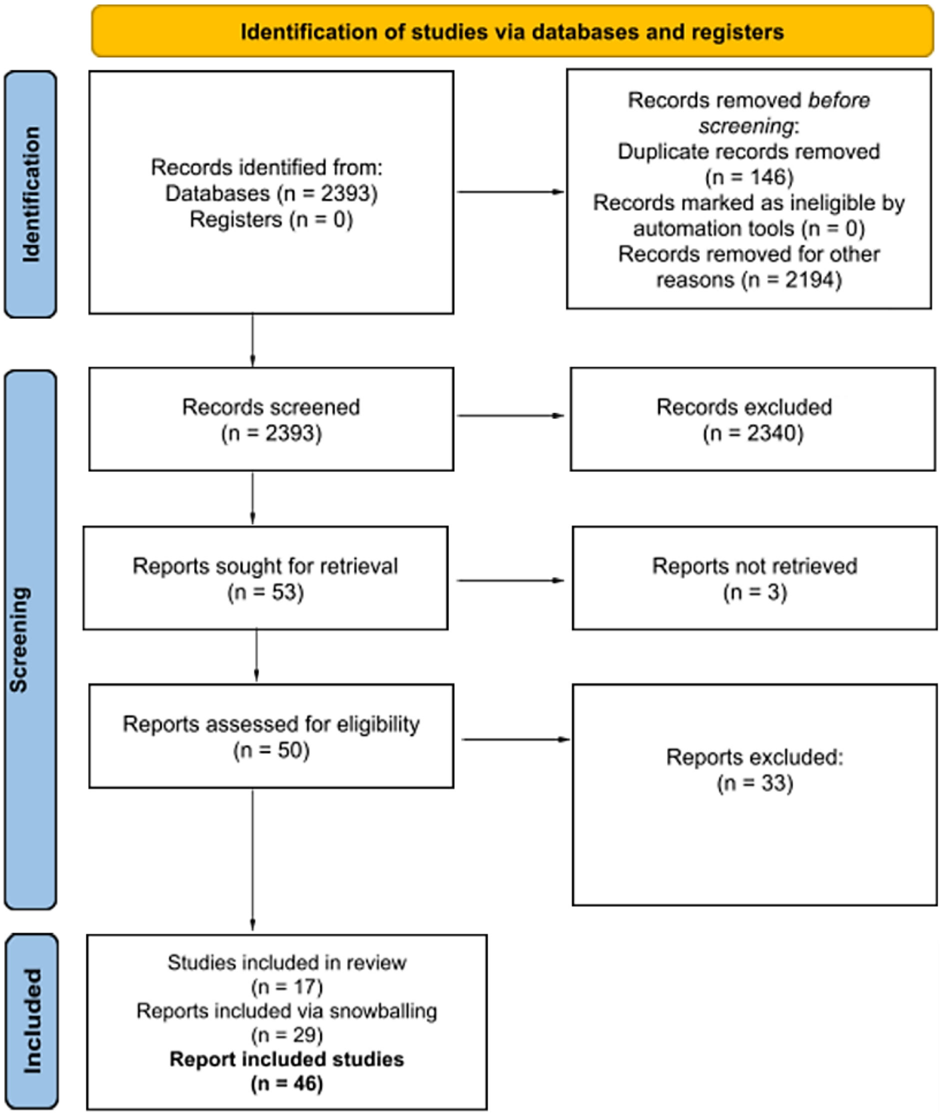
3.2 Data Collection and Classification

A data extraction and classification have been conducted by two independent reviewers following a double-blind process. The data in question included the sample characteristics (sample size and demographic variables such as age and gender), the theoretical framework, the type of study (laboratory based or field study) and the type of measurement of affective well-being or cognitive workload.

4. RESULTS

Figure 2 shows the PRISMA workflow. In particular, from a total of 2393 articles screened, 46 were included in the review. 17 articles were retrieved following the first and second screening, and 29 more articles were selected following the snowballing sampling method.

Figure 2. PRISMA workflow detailing the selection process (Page et al., 2021).



4.1 Demographic Variables of the Included Studies

Across all articles, a total of 1031 volunteers participated, with an average sample size of 22 participants per study. Of these, n = 436 participants were researchers or students (university and graduate) and n = 61 were workers; n = 534 volunteers had no specified profession or scholar engagement.

Due to ambiguity regarding the definitions of gender and sex employed, it has been assumed that all participants referred as "male" and "female" were "men" and "women", respectively. A total of n = 13 studies did not specify participants' gender; thus, a total of n = 146 participants have been excluded from the following description. Considering the studies that included gender distribution (Table 1), a slight majority of the total sample is composed by men (n = 535; 60.45%), followed by women (n = 350; 39.55%).

Moreover, n = 28 studies reported an overall mean age of 28.97 years (± 6.49), with an age range between 18 to 70 years. A total of n = 18 studies did not specify the age of participants.

Table 1. Sample size and its gender composition reported by each study (N = 46 articles).

Study	Sample Size	Men (N; %)	Women (N; %)
Amanhoud et al. (2021)	12	12 (100%)	/
Arai et al. (2010)	5	/	/
Arntz et al. (2020)	80	40 (50%)	40 (50%)
Aromaa et al. (2018)	19	7 (37%)	12 (63%)
Baxter et al. (2018)	11	9 (82%)	2 (18%)
Bettoni et al. (2020)	4	3 (75%)	1 (25%)
Brun et al. (2020)	8	/	/
Brunzini et al. (2021)	8	7 (88%)	1 (12%)
Chacón et al. (2021)	18	/	/
Dehais et al. (2011)	12	10 (83%)	2 (17%)
Eimontaite et al. (2019)	90	51 (57%)	39 (43%)
Eyam et al. (2021)	1	/	/
Fournier et al. (2022)	54	12 (22%)	42 (78%)
Fraboni et al. (2022)	14	/	/
Fujita et al. (2010)	5	/	/
Gervasi et al. (2022)	42	30 (71%)	12 (29%)
Gervasi et al. (2023)	12	6 (50%)	6 (50%)
Gualtieri et al. (2021)	14	/	/
Hopko et al. (2021)	16	8 (50%)	8 (50%)
Hopko et al (2024)	30	/	/
Kalatzis et al (2023)	15	7	8
Koppenborg et al. (2017)	28	13	15
Lagomarsino et al (2022) a	14	7 (50%)	7 (50%)
Lagomarsino et al (2022) b	12	7 (58%)	5 (42%)
Lemasurier et al. (2021)	84	58 (69%)	26 (31%)
Luo et al. (2023)	8	5 (63%)	3 (37%)
Mariscal et al. (2023)	32	22 (69%)	10 (31%)
Memar et al. (2019)	18	11 (61%)	7 (39%)
Messeri et al (2021)	15	11 (73%)	4 (27%)
Messeri et al (2023)	33	28 (85%)	5 (15%)
Nenna et al. (2023)	21	16 (76%)	5 (24%)
Panchetti et al. (2023)	14	11 (79%)	3 (21%)
Pantano et al. (2020)	19	15 (79%)	4 (21)
Pluchino et al. (2023)	11	7 (64%)	4 (36%)
Pollak et al. (2020)	45	19 (42%)	26 (58%)
Rahman et al. (2024)	20	/	/
Rajavenkatanarayanan et al. (2020)	25	15 (60%)	10 (40%)

Study	Sample Size	Men (N; %)	Women (N; %)
Rossato et al. (2021)	20	12 (60%)	8 (40)
Sadrfaridpour et al. (2016)	5	/	/
Sadrfaridpour et al. (2018)	20	14 (70%)	6 (30%)
Storm et al. (2023)	7	/	/
Tan et al. (2009)	10	/	/
Ustunel et al (2017)	40	22 (55%)	18 (45%)
Van Dijk et al. (2023)	20	15 (75%)	5 (25%)
Zakeri et al. (2023)	9	/	/
Zhao et al. (2020)	31	25 (81%)	6 (19%)

4.2 Measures Employed by the Reviewed Articles

Table 2 shows specific measurements used by each study. In the next sub-titles these will be grouped and discussed based on the construct they propone to assess and the type of measure. As a general overview, most of the studies used both self-assessment and physiological measures (n = 23 out of N = 46); n = 15 studies only relied on self-assessment tools and n = 7 studies only on physiological tools. Only 2 studies (Brun et al., 2020; Gualtieri et al., 2021) conducted semi-structured interviews, the only qualitative assessment conducted in the included studies.

Table 2. Studies measure instruments for each construct assessed.

Study	Construct	Physiological Measure	Self-assessment Measure
Amanhoud et al. (2021)	Workload	/	NASA Task Load Index (NASA-TLX)
Arai et al. (2010)	Stress	Skin Potential Response (SPR)	Semantic Differential questionnaire
Arntz et al. (2020)	Stress Workload	/ /	Perceived Stress Scale (PSS) NASA-TLX frustration subscale
Aromaa et al. (2018)	Workload	/	NASA-TLX
Baxter et al. (2018)	Workload	/	NASA-TLX
Bettoni et al. (2020)	Stress Workload	Heart Rate Variability (HRV) Electrodermal Activity (EDA) Skin temperature /	/ Questionnaire adapted from NASA-TLX
Brun et al. (2020)	Stress	/	Interviews
Brunzini et al. (2021)	Workload Stress	/ /	NASA-TLX Numerical Analogue Scale (NAS)
Chacón et al. (2021)	Workload	/	NASA-TLX
Dehais et al. (2011)	Stress	Galvanic Skin Response (GSR)	Visual Analog Scale (VAS)
Eimontaite et al. (2019)	Anxiety	Facial Expressions Analysis	Robot Anxiety Scale (RAS)
Eyam et al. (2021)	Stress	EEG	/
Fournier et al. (2022)	Workload	/	NASA-TLX
Fraboni et al. (2022)	Workload	/	Single Item from NASA-TLX
Fujita et al. (2010)	Stress	SPR	Ad Hoc Semantic Differential questionnaire
Gervasi et al. (2022)	Stress	Skin Conductance Response (SCR)	Self-Assessment Manikin (SAM)
Gervasi et al. (2023)	Stress	Skin Conductance Level (SCL) HRV	/
Gualtieri et al. (2021)	Stress Workload	/ /	Ad hoc questionnaires, interviews and observations Ad hoc questionnaires, interviews and observations

Study	Construct	Physiological Measure	Self-assessment Measure
Hopko et al. (2021)	Stress Workload	HRV /	/ NASA-TLX Situation Awareness Rating Technique (SART)
Hopko et al (2024)	Workload	Functional Near-Infrared Spectroscopy (fNIRS)	NASA-TLX
Kalatzis et al (2023)	Workload	HRV	NASA-TLX SART
Koppenborg et al. (2017)	Stress Anxiety Workload	/ / /	SAM Short State-Trait Anxiety Inventory (STAI-S) NASA-TLX
Lagomarsino et al (2022)a	Stress Workload	GSR SCL SCR HRV	/ NASA-TLX
Lagomarsino et al (2022)b	Workload	HRV	/
Lemasurier et al. (2021)	Workload	/	NASA-TLX
Luo et al. (2023)	Workload	Eye/Pupil Tracking	/
Mariscal et al. (2023)	Stress Workload	Eye-tracking /	/ NASA-TLX
Memar et al. (2019)	Anxiety	Electroencephalography (EEG)	/
Messeri et al (2021)	Stress	HRV	/
Messeri et al (2023)	Stress Anxiety	/ /	Positive and Negative Affect Schedule (PANAS) State-Trait Anxiety Inventory (STAI)
Nenna et al. (2023)	Workload	Eye-tracking	NASA-TLX

Study	Construct	Physiological Measure	Self-assessment Measure
Panchetti et al. (2023)	Stress Workload	/ Eye-tracking	Short Stress Questionnaire Reduced version of NASA-TLX
Pantano et al. (2020)	Workload	/	NASA-TLX
Pluchino et al. (2023)	Workload Wellbeing	Eye-tracking HRV /	/ Wellbeing questionnaire
Pollak et al. (2010)	Stress	HR	Primary and Secondary Appraisal (PASA)
Rahman et al. (2024)	Workload	/	NASA-TLX
Rajavenkatanarayanan et al. (2020)	Stress Anxiety	SCL EEG	/ /
Rossato et al. (2021)	Workload	/	NASA-TLX frustration subscale
Sadrfaridpour et al. (2016)	Workload	/	NASA-TLX
Sadrfaridpour et al. (2018)	Workload	/	NASA-TLX
Storm et al. (2023)	Workload	HRV	Short questionnaires (ESM forms)
Tan et al. (2009)	Workload	Skin potential reflex (SPR)	/
Ustunel et al (2017)	Workload	/	NASA-TLX
Van Dijk et al. (2023)	Workload	/	NASA-TLX
Zakeri et al. (2023)	Anxiety Workload	EEG EEG fNIRS	/ NASA-TLX
Zhao et al. (2020)	Stress Anxiety	HRV HRV	/ /

4.2.1 Tools Used to Measure Mental Workload

Out of the 46 articles reviewed, 32 (Amanhoud et al., 2021; Arntz et al., 2020; Aromaa et al., 2018; Baxter et al., 2018; Bettoni et al., 2020; Brunzini et al., 2021; Chacón et al., 2021; Fournier et al., 2022; Fraboni et al., 2022; Gualtieri et al., 2021; Hopko et al., 2021; Hopko et al., 2024; Kalatzis et al., 2023; Koppenborg et al., 2017; Lagomarsino et al., 2022a; Lagomarsino et al., 2022b; Lemasurier et al., 2021; Luo et al., 2023; Mariscal et al., 2023; Nenna et al., 2023; Panchetti et al., 2023; Pantano et al., 2020; Pluchino et al., 2023; Rahman et al., 2024; Rossato et al., 2021; Sadrfaridpour et al., 2016; Sadrfaridpour et al., 2018; Storm et al., 2023; Tan et al., 2009; Ustunel et al., 2017; van Dijk et al., 2023; Zakeri et al., 2023) assessed workload in conjunction with other constructs and 21 assessed it as the single relevant construct.

Self-report tools – Of these 32 studies, 26 used the NASA Task Load Index (NASA-TLX; Hart et al., 1988), one of its subscales or an adaptation, to measure perceived mental workload. The NASA-TLX is subdivided in six dimensions: mental demands, physical demands, temporal demands, own performance, effort, and frustration. Each dimension corresponds to an item, rated from 1 to 20. A total of n = 2 studies used only the frustration subscale, whilst n = 2 others adapted and shortened it. One study used only one item, referring to mental demand.
A total of n= 2 other studies employed the Situation Awareness Rating Technique (SART; Taylor et al., 1990), to measure perceived cognitive workload. This scale is subdivided in three dimensions: amount of demand on attentional resources, availability of attentional resources, and understanding of the situation.

Psychophysiological measures – A total of n = 12 out of the N = 32 studies assessing mental workload employed physiological measures: eye-tracking tools were used in n = 4 articles to measure pupil diameter, number and duration of gaze fixations, and in general gaze behaviors to assess the construct; n = 5 studies employed measures of heart rate variability (HRV); n = 3 other articles employed Functional Near-Infrared Spectroscopy (fNIRS) to measure hemoglobin flux, neural activation at cortical lever, and generally brain activity; lastly, only one study, (Tan et al., 2007) used skin potential reflex as a measure of general activation, and therefore mental workload.

4.2.2 Tools Used to Measure Well-being

As already mentioned, the construct of affective well-being is closely linked to distress, stress, anxiety and depression (Rahimnia et al., 2013). Therefore, a tool proposed to measure each of those constructs will also indirectly measure affective well-being, since a high score in distress, stress, anxiety or depression symptoms indicates a low level of affective wellbeing. All tools aimed at directly measuring these four constructs, but not well-being, will be discussed further in the present thesis.

Only one study (Pluchino et al., 2023) employed a measure of well-being, using an ad hoc 'wellbeing and work experience' questionnaire, comprised of 14 items with a 5-point Likert scale, from "not at all" to "extremely".

4.2.3 Tools Used to Measure Distress Levels

As ascertained, distress is a multifaceted construct that encompasses symptoms of stress, anxiety and distress, reason why a measurement of these could be considered as an indirect measurement of distress. Still, no study employed a direct measurement tool to assess distress.

4.2.4 Tools Used to Measure Stress Levels

A total of N = 21 articles (Arai et al., 2010; Arntz et al., 2020; Bettoni et al., 2010; Brun et al., 2020; Brunzini et al., 2021; Dehais et al., 2011; Eyam et al., 2021; Fujita et al., 2010; Gervasi et al., 2022; Gervasi et al., 2023; Gualtieri et al., 2021; Hopko et al., 2021; Koppenborg et al., 2017; Lagomarsino et al., 2022a; Mariscal et al., 2023; Messeri et al., 2021; Messeri et al., 2023; Panchetti et al., 2023; Pollak et al., 2010; Rajavenkatanarayanan et al., 2020; Zhao et al., 2020) out of 46 measured stress, of which n = 9 studies measured only stress symptoms, whilst other n = 9 measured stress symptoms in conjunction with mental workload symptoms, and 3 measured stress symptoms in conjunction with anxiety symptoms.

Self-report tools – The tools used to measure stress symptoms varied significantly, for a total of 9 different tools. A total of n = 2 studies employed a Semantic Differential Questionnaire, used to evaluate stress levels after each experimentation with cobots. The Self-Assessment Manikin (SAM; Bradley et al., 1994) was utilized by 2 studies, measuring three sub-dimensions: valence, arousal and dominance. The SAM is a non-verbal, pictural tool which proposes anthropomorphic figures for each of the subdimension, on a scale ranging from 1 (respectively Pleasant; Exited; Dependent) to 5 (respectively Unpleasant; Calm; Independent). Arntz et al. (2020) used the Perceived Stress Scale (PSS; Chan et al., 2013), a 14-item self-report measure of stress, ranging from 0-("never") to 4-("very often"), after each specific situation. Brunzini et al. (2021) employed a Numerical Analogue Scale, a self-report measure of one's perceived stress using a line segmented numerically from 1 to 10, whilst Dehais et al. (2011) utilized a Visual Analog Scale, ranging from 1-("very low") to 9-("very high"), to assess volunteers' legibility, safety and physical comfort, with safety indicating the level of stress experienced. The Positive and Negative Affect Schedule (PANAS; Watson et al., 1988), a 20-items scale ranging from 1-("very slightly or not at all") to 5-("extremely"), was employed by Messeri et al. (2023) to assess subjects' changes in affective states, measuring positive and negative affect. Panchetti et al. (2023) used the Short Stress State Questionnaire (SSSQ; Helton, 2004), a shorter version of the Dundee Stress State Questionnaire (DSSQ; Matthews et al., 1999). The SSSQ is a 24-item scale, ranging from 1-("not at all") to 5-("extremely"), which measures Task Engagement, Distress, and Worry. Pollak et al. (2010) employed the Primary and Secondary Appraisal (PASA; Gaab et al., 2005) tool to measure Primary Appraisal, describable as the potential threat a situation or event poses to one's well-being, and Secondary Appraisal, or the ability to cope with such a stressful situation or event, with 4-items on a 5-point, Likert scale ranging from 0-("not at all important") to 5-("very important").

Psychophysiological measures – there were several physiological measures employed to measure stress levels, which will be grouped based on similarities in the somatic expressions they gauge. Most studies (n = 8) focused on monitoring Electrodermal Activity (EDA) to measure Skin Conductance Levels (SCL), Skin Potential Response (SPR), Electrodermal Activity, Skin Temperature and Galvanic Skin Response (Bettoni et al., 2020; Gervasi at al., 2022; Gervasi et al., 2023; Lagomarsino et al., 2022a; Rajavenkatanarayanan et al., 2020; Arai et al., 2010; Fujita et al., 2010; Dehais et al., 2011). HRV was employed in n = 7 studies (Bettoni et al., 2020; Gervasi et al., 2023; Hopko et al., 2021; Hopko et al., 2024; Messeri et al., 2021; Pollak et al., 2010; Zhao et al., 2020), analyzing heart beats per minute (bpm) and its variation to assess stress symptoms. Eyam et al. (2021) adopted Electroencephalography (EEG) signals to evaluate the brain bioelectrical activity as an indicator of emotions, placed in the Pleasure-Arousal-Dominance axes (PAD; Mehrabian, 1996). Gervasi et al. (2022) employed the Photoplethysmogram to measure blood volume changes in the tissue's microvascular bed, and Mariscal et al. (2023) utilized eye-tracking to gather measurements of pupil diameter.

4.2.5 Tools Used to Measure Anxiety Symptoms

Only n = 7 articles (Eimontaite et al., 2019; Koppenborg et al., 2017; Memar et al., 2019; Messeri et al., 2023; Rajavenkatanarayanan et al., 2020; Zakeri et al., 2023; Zhao et al., 2020) assessed workers' anxiety symptoms when collaborating with cobots, and only n = 2 focused solely on this construct, with most of the others analyzing it in conjunction with stress symptoms.

Self-report tools – Only n = 2 articles employed self-report tools to assess anxiety symptoms. Messeri et al. (2023) used the State-Trait Anxiety Inventory (STAI; Spielberger et al., 1970), and Koppenborg et al. (2017) utilized the Short State-Trait Anxiety Inventory (STAI-S; Marteau et al., 1992), of 20 and 6 items respectively, estimating both *trait* and *state* anxiety. Trait anxiety is considered as the tendency of an individual to present state anxiety, and the latter is defined as the anxious reaction to an adverse event or situation.

Psychophysiological measures – A total of n = 3 articles investigated anxiety symptoms using EEG, as variations in brain activity are correlated both with stress and anxiety symptoms (Norman, 2000; Seo et al., 2010). Zhao et al. (2020) measured HRV. Eimontaite at al. (2019) recorded Facial Expressions, a behavioral measure, and systematically interpreted them with automated facial coding. The expressions were subdivided into 7 categories (neutral, happy, sad, angry, surprised, scared and disgusted), with "surprised" and "scared" being considered as related to anxiety symptoms.

4.2.6 Tools Used to Measure Depression Symptoms

None of the articles included in the systematic review assessed depression symptoms, although their correlation with stress, anxiety and distress symptoms renders the construct fundamental to evaluate affective well-being in a holistic and comprehensive way (Rahimnia et al., 2013).

4.3 Results of the Reviewed Studies

Most studies reviewed do not simply assess effects of collaboration with cobots on the constructs with a comparison between HRC and standard human's work routine, hence the results are not generalizable to the presence/absence of cobots. Findings will thus regard various, different factors mediating HRC effects on workers' affective well-being and mental workload.

4.3.1 Findings Regarding Mental Workload in HRC

The overall results, comparing collaboration with a cobot and with other humans or in solitary, are as follows: Mariscal et al (2023) reported that collaboration with a cobot does not generate more mental workload than collaboration with humans, whilst Fournier et al. (2022) report a positive effect on time demand perceived by workers in collaboration with cobots. Bettoni et al. (2020) goes as far as sharing that HRC reduces perceived mental workload, when compared with a standard workspace. Storm et al. (2023) study noted that participants experienced a longer amount of time in the 'focus zone' when working with cobots. Finally, Gualtieri et al. (2021) assessed mental workload variations in three, by tweaking workstation layouts, robot system features, robot system performance and organizational measures, resulting in sequentially more collaborative scenarios, and noting a significant decrease in the third scenario.
Further results involve more specific variables, which have been grouped for legibility's sake.

Cobot-specific features **–** Multiple studies focused on cobots' features, such as speed, force assistance and feedback capabilities. Speed was the most indagated variable, with 4 studies reporting that mental workload levels increased with higher cobot speed and decreased with the workers capacity of setting it (Fraboni et al., 2022; Koppenborg et al., 2017; Tan et al., 2009; van Dijk et al., 2023). Tan et al. (2009) also noted that workers' physical distance from the cobot decreased mental strain. Amanhoud et al. (2021) reported that cobots' force assistance reduces physical and performance demands, impacting positively the level of frustration and mental workload of workers. Rahman et al. (2024) employed affective expressions from the cobot, inducing better communication perception and smoother workflow, leading to a reduction in workload levels. Lemasurier et al. (2021) reported that implementing motion-based signals as feedback from the cobot reduced cognitive workload significantly.

Interaction Modalities - Lagomarsino et al. (2022) noted that transparency in the cobot movements reduces mental workload, whilst Pantano et al. (2020) reported that interfaces based on touch-only input result in lower mental workload compared with communication trough a smartpad. In contrast with such result, Sadrfaridpour et al. (2018) noted that requiring manual control over the system results in higher workload compared to an automated assistance condition. Memar et al. (2019) reported that high-dumping setups lower perceived workload if involving fine co-manipulation. Aromaa et al. (2018) noted high levels of frustration and effort among participants using a computer vision-based system. Sadrfaridpour et al. (2016) proposed a novel, trust-based framework, and noted that its application resulted in the lowest perceived workload of all experimental conditions. Ustunel et al. (2017) employed an extended cognition approach to workplace design, finding that it leads to lower mental workload levels when compared to standard workplace designs. Extended cognition refers to the implementation of advanced technology and collaborative tools to aid and enhance cognitive abilities. Lastly, Panchetti et al. (2023) noted that usability guidelines, to render the cooperative interfaces accessible, help reduce mental workload in multiples scenarios, obtained by tweaking cobots' speed, autonomy and trajectories.

Human-related Variables – 2 studies assessed potential differences in mental workload based on demographic variables: Rossato et al. (2021) noted higher frustration among senior workers (upward of 55 years old) compared to young workers (35 to 54 years old) in HRC, and in particular in the manual control modality; Hopko et al. (2024) assessed differences in mental workload between males and females, finding a marginally, although still significant, higher perceived mental workload in females compared with males.

Dual-tasks Impact – 4 articles (Brunzini et al., 2021; Chacón et al., 2021; Nenna et al., 2023; Pluchino et al., 2021) assessed the effect of a dual-task during HRC on mental workload, all resulting in a significantly higher load on workers while performing both tasks. Chacón et al. (2021) specifically noted a high level of mental workload during tasks involving the Tower of Hanoi game, both in single and dual-task conditions.

4.3.2 Findings Regarding Affective Well-being in HRC

Considering the only study which aimed to measure directly well-being (Pluchino et al., 2023), no differences were reported comparing HRC with standard working arrangements. Results about general effects of cobot presence in the workplace on stress and anxiety symptoms, as well as effects of more specific variables will be grouped and reviewed in subsequent sections: “HRC Effects on Stress Symptoms” and “HRC Effects on Anxiety Symptoms”.

***HRC Effects on Stress Symptoms* –** Mariscal et al. (2023) did not find any significant difference in stress levels between HRC and standard collaboration with other humans, whilst Brun et al. (2020) noted a decrease in stress symptoms in workers when collaborating with cobots.

2 studies reported that a high cobot speed increased stress indicators (Fujita et al., 2010; Gervasi et al., 2022). Eyam et al. (2021) offered a solution by employing an adaptive system, lowering automatically cobot speed in response to workers stress symptoms. Furthermore, Gualtieri et al. (2021) found that providing workers with the capacity to control and modify cobot speed decreased experienced stress symptoms. Pollak et al. (2020) also noted lowers stress levels among workers when employing manual control modalities as opposed to autonomous modalities. Dehais et al. (2011) added two more variables: human-aware planning and grasp detection. In combination with cobot speed, the effects of three types of cobot motions were tested. The first type, employing medium velocity, human-aware planning and grasp detection, resulted in the lowest stress levels; the second type, with high velocity, no human-aware planning and no grasp detection, elicited the highest stress responses. As for workers’ positioning, Arai et al. (2010) noted a positive correlation between physical proximity to the cobot and stress levels.

As regards communication between workers and cobots, Arntz et al (2020) analyzed the effects of lights, gestures and visual written messages as augmented communication employed by the cobot, noting a reduction in stress levels compared to non-augmented communication. Amanhoud et al. (2021) reported that force-assistance in shared tasks decreases perceived stress.

Both Lagomarsino et al. (2022a) and Messeri et al. (2023) assessed the effect of different roles of operators and cobots on stress levels, reporting lower stress symptoms in conditions that gave workers a ‘leader role’ and the cobot an assistance/‘follower’ role, as opposed to conditions of human assistance. Zhao et al. (2020) reported, albeit non conclusively, higher stress levels among workers in conditions that necessitated higher coordination and interdependence.

HRC Effects on Anxiety Symptoms – 2 studies reported a correlation between high cobot speed and anxiety symptoms in workers (Koppenborg et al., 2017; Zakeri et al., 2023). Zakeri et al. (2023) also noted that task complexity is linked to an increase in anxiety levels.

Eimontaite et al. (2019) remarked that graphical signage (non-text based symbols) and cobot task accuracy decreases the prominence of anxiety symptoms.

Messeri et al. (2023) also assessed the effect of Leader-Follower roles on anxiety levels, showing results in line with those previously described: the ‘follower’ role leads to an increase in anxiety levels. Zhao et al. (2020) study’s analysis of interdependence includes anxiety along with stress symptoms, noting that anxiety symptoms are also positively correlated with the need of high coordination.

5. QUALITATIVE ANALYSIS AND DISCUSSION

In this section an analysis of the general outcomes of the studies will be conducted, as well as a critical discussion of the potential areas of improvement.

Limitations of Reviewed Studies **–** The first limitation concerns what could be considered the practice of theoretical integrationism (Romaioli et al., 2012; Arnkoff et al., 1995), noticeable in the articles: most of the studies employ a 'grafting' of multiple constructs, from different epistemological backgrounds, to a preferred theoretical framework, with no regard to potential incompatibilities. This thesis has tried to adopt what is called technical eclecticism (Lazarus et al., 1993), which consists in a synchresis of multiple theoretical paradigms not to create a new theory but expressly on an applicative/practical level, with the aim of offering base of interpretation for the systematic review as wide and flexible as possible. What seems like a mere rhetoric difference is indeed a strive for a more rigorous methodology.

From a practical standpoint, the sample sizes of a not irrelevant number of studies leads to question the generalizability of the results. 10 studies gather their results on a sample size of less than 10 volunteers (Arai et al., 2021; Bettoni et al., 2020; Brun et al., 2020; Brunzini et al., 2021; Eyam et al., 2021; Fujita et al., 2010; Luo et al., 2023; Sadrfaridpour et al., 2016; Storm et al., 2023; Zakeri et al., 2023), with Eyam et al. (2021) assessing the experience of only one participant. Although the numerosity seems lacking, the combination of self-report and psychophysiological measurement tools somewhat permit to reach objective results. It is not specified if the lack of female representation is due to an effort to portray the skewed nature of industrial workers' sex and gender composition. Moreover, 13 studies (Arai et al., 2010; Brun et al.,2020; Chacón et al., 2021; Eyam et al., 2021; Fraboni et al., 2022; Fujita et al., 2010; Gualtieri et al. 2021; Hopko et al., 2024; Rahman et al., 2024; Sadrfaridpour et al., 2016; Storm et al., 2023; Tan et al., 2009; Zakeri et al., 2023) do not provide the gender composition of their sample, rendering an analysis of potential gender differences in the results unfeasible.

Key Aspects of HRC Highlighted in the Review **–** The studies that assessed the effects of cobots introduction on mental workload (Mariscal et al., 2023; Fournier et al., 2022; Bettoni et al., 2020; Storm et al., 2023; Gualtieri et al., 2022) and affective well-being

(Pluchino et al., 2023) in general reported neutral or positive effects of collaborating with cobots. Moreover, studies assessing effects on stress levels (Mariscal et al., 2023; Brun et al., 2020) also reported positive or at least neutral effects. Still, the limited sample size of these studies leads to surmise a non-generalizability of the results.

More specifically, cobots' speed is a factor reported to be positively correlated with high levels of mental workload (Fraboni et al., 2022; Koppenborg et al., 2017; Tan et al., 2009; van Dijk et al., 2023), stress (Fujita et al., 2010; Gervasi et al., 2022) and anxiety symptoms (Koppenborg et al., 2017; Zakeri et al., 2023), and the adaptivity of the system or capacity of the workers to control it as factors that modulate such effects. Distance is also a factor that proportionately decreases mental workload and stress levels, with a distance of 1.0 to 1.5 meters being the optimal set-up. The capacity of force assistance of cobots seems to straightforwardly positively impact workload and stress symptoms. Lastly, cobot communication, carried out with expressions, motions, lights or visual written messages impacts positively mental workload and stress levels, with the cobot being perceived as more foreseeable.

Focusing on the construct of mental workload, the analysis of manual and touch-only inputs effects on mental workload (Pantano et al., 2020; Sadrfaridpour et al., 2018) reached mixed results, possibly because of differences in the context and execution of the studies. Different frameworks were implemented and tested, such as a high-dumping setup, a trust-based system and an extended cognition approach, all resulting in a lower mental workload level when compared to standard workplace designs, whilst the use of a computer vision-based system resulted in higher levels of frustration and effort. Old age has been shown to correlate with higher levels of mental workload when collaborating with cobots.

As an aside, all studies focusing on the effects of a dual-task on mental workload (Brunzini et al., 2021; Chacón et al., 2021; Nenna et al., 2023; Pluchino et al., 2021) reported a higher level of mental workload in the dual-task condition, primarily proving that performing one task elicit less mental workload than performing two, without necessarily involving cobots in this relation.

Lastly, enforcing a high degree of close interdependence can increase stress levels. However, when workers take on a leading role with cobots providing support, it appears to reduce stress and anxiety symptoms.

6. CONCLUSIONS

This thesis aimed to ascertain the effects of the introduction of cobots in the workplace on various aspects of human affective well-being and cognitive workload by conducting a systematic qualitative review of 46 articles on the topic. The resulting data suggests that the introduction of cobots in the workplace is more likely to yield positive results. Furthermore, high levels of stress, anxiety and cognitive workload can be triggered by specific aspects of the cobots implemented (speed, predictability and physical proximity), the dynamics of human-cobot collaboration, as well as some demographic factors of the operators. Ultimately, HRC is a multi-faceted phenomenon, which offers clearly positive outcomes, but needs to be implemented with caution and perspective, to avoid all the negative, specific after-effects and maximize workers health and productivity.

Future research could be carried out to confirm the results about the effects of cobot presence in the workplace, comparing a collaborative condition to a standard one. Moreover, it has been highlighted that a larger sample size is needed, along with more rigorous assessment of factors such as sex/gender, age, and occupation of operators. Lastly, it is necessary to carry out studies specifically aimed at evaluating the impact of HRC on depression symptoms. Current research only allows for conjecture about the effects of stress and anxiety symptoms of depression levels, without providing direct measurements of these impacts.

As for this thesis itself, even employing technical eclecticism a theoretical limitation arises when trying to interpret different constructs trough the paradigm chosen by the study, and "making ends meet" between different theories has proven an arduous task. The research methodology was carried out relying on the "find synonyms" function intrinsic in most of the databases, and being its workings not disclosed some articles eligible for the analysis may have not been included.

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