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Mental Workload and Human-Robot Interaction in Collaborative Tasks: A Scoping Review

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ABSTRACT
In human-robot collaboration (HRC), operators work side by side with collaborative robots (cobots), a new type of machines able to function safely on tasks shared with humans. Despite the increasing presence of cobots in factories, the quality of experience associated by workers with HRC is an underexplored topic. This review is focused on the mental workload (MWL) reported by operators interacting with cobots, its major sources, and the potential solutions to optimize it during HRC. Out of 165 papers identified, 23 were selected as specifically devoted to the exploration of workers' MWL in a HRC activity. Cobot motion, predictability, task organization and communication patterns emerged as the major factors contributing to operators' MWL during HRC. Endowing cobots with the capacity to meet both task demands and human needs through modulation of motion rhythm, flexible physical interaction, and more efficient communication patterns may contribute to mitigating workers' MWL.

KEYWORDS
Mental workload; stress; collaborative robots; cobots; human-robot interaction; human-robot collaboration; industrial settings

1. Introduction

The European Foundation for the Improvement of Living and Working Conditions warned on the association of work-related stress with a variety of mental disorders (Parent-Thirion et al., 2007). Workplace stress is reported as a common phenomenon by around 51% of European workers (EU-OSHA, 2013); it also represents a serious concern for nearly 80% of the companies within the EU, as it contributes to about 50% of all lost working days. Occupational stressors can negatively affect employees' job performance and satisfaction, commitment, subjective well-being, prosocial behaviour, and intention to stay (Darvishmotevali & Ali, 2020). A survey conducted by the European Agency for Safety and Health at Work (EU-OSHA, 2015; Rial-González et al., 2010) showed that work-related stress and psychosocial risks can cause mental and physical disorders, resulting in high costs for the individual, the economy, and the whole society.

One of the major dimensions of work-related stress investigated in the scientific literature is Mental Workload (MWL), a multidimensional construct that reflects the mental fatigue resulting from performing a task under demanding conditions, taking into account the operator's capability to face those demands (Cain, 2007). Derived from the Cognitive Load Theory in the field of education (CLT: Sweller, 1988, 1994; Sweller et al., 1998), MWL has been investigated in different domains; as a consequence, a clear and universally accepted definition is still missing (Cain, 2007; Longo et al., 2022). In cognitive psychology, for example, it refers to the amount of working memory resources used during a task (Chen et al., 2016); in the ergonomics and human factors literature, it is labelled as mental effort or mental demand, and it represents the amount of mental activity required to perform a task (e.g. Van Acker et al., 2018; Young et al., 2015). The term workload can also refer to the demands imposed on the operator, the subjectively experienced effort, and the impact of those demands on the operator (Cain, 2007), or "the relationship between primary task performance and the resources demanded by the primary task" (Wilson & Sharples, 2015, p. 521). Suboptimal workload (overload or underload) may lead to errors, mistakes, and performance degradation (Young et al., 2015), and it may have detrimental health consequences in the long run (Holm, 2010; Holm et al., 2009; Young et al., 2015). More specifically, mental overload may lead to mental fatigue, lower selective attention, decreased performance, and lower efficiency at the workplace (González-Muñoz & Gutiérrez-Martínez, 2007; Lagomarsino et al., 2022); mental underload - for example, too limited stimulation in repetitive tasks - may also negatively affect attention levels, increasing the risk of errors and attentional lapses (Wickens et al., 1998; Wixted & O'Sullivan, 2014). An optimal level of

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mental workload can instead prevent errors, safety risks, and performance inefficiency (Brolin et al., 2017; Longo, 2015; Morton et al., 2019; Parmentier et al., 2020). Moreover, an optimal MWL level may sustain workers' engagement, well-being and long-term mental and physical health (Brolin et al., 2017; Demerouti et al., 2020; S. Hopko et al., 2022; Kolbeinsson et al., 2017; Segura Parra et al., 2020).

1.1. MWL and stress: An intricate relationship

The relationship between MWL and stress is widely acknowledged (Gaillard, 1993; 2001; Macdonald, 2003; Niculescu et al., 2009). Several studies showed a significant strong positive correlation between these constructs (Alsuraykh et al., 2019; Gjoreski et al., 2017; Hou et al., 2015; Matthews et al., 2002). Such a strong relationship however becomes problematic when exploring MWL literature: In some studies, the term "mental stress" is used to refer to both dimensions (Hjortskov et al., 2004); in other studies, MWL is considered as a source of both stress (Macdonald, 2003; Pande, 1992), and stress responses (Sato et al., 2009); other works define stress as a core component of MWL (Alsuraykh et al., 2019; Castillo et al., 2021; Hart & Staveland, 1988; Kantowitz, 1987; Macdonald, 2003; Wierwille et al., 1985).

Some crucial differences were however detected between MWL and stress (Chen et al., 2016; Hidalgo-Muñoz et al., 2018). More specifically, it is possible to experience high mental workload in demanding conditions, without cognitive strain or adverse physiological effects; to the opposite, it is possible to experience high levels of stress in a low mental workload condition (Gaillard, 1993; Gaillard & Wientjes, 1994). This can be partially explained through the Appraisal Theory (Lazarus & Folkman, 1984) of stress: As the cognitive load increases, individuals tend to unconsciously evaluate their ability to cope with the demand. Stress would only arise when the situation is subjectively deemed as exceeding available personal resources; therefore, a highly demanding situation may be perceived as stressful or not, based on the individual perception of personal resources in facing it.

1.2. Cobots and MWL

Over the last decades the increase in automation, and specifically the massive introduction of robots, has brought about substantial changes in human operators' role (Körner et al., 2019), job tasks' structure, workers' experience and MWL (Peeters & Plomp, 2022). Although robots convey benefits to humans, such as relieving them from tedious, repetitive, and dangerous tasks, they also require continuous monitoring; supervision tasks can be positively perceived as mentally stimulating, because they require knowledge and decision-making capabilities (Smids et al., 2020), but they can also make workers feel simple "machine controllers," rather than active agents in production. Moreover, automatization of workflow may result in new demands and stressors for human operators (Mital & Pennathur, 2004; Warm et al., 2008; Woods, 1996), such as increased workload, reduced control over tasks, lower skill mobilization and development, increased work pace, higher psychological pressure due to electronic performance monitoring (EPM, i.e. the use of technological instruments to observe, record, and analyse information directly or indirectly related to the workers job performance), reduced social interaction, higher psychological/cognitive demands, increased supervisory control, and job insecurity (Carayon et al., 1999).

In this context, a recent advancement in robotics technology is represented by *cobots*, collaborative robots that are increasingly used in laboratory and industrial environments. Compared to industrial robots, large machines positioned in an enclosed workspace with no or very limited interaction with workers, cobots are designed to physically interact with human operators in a shared workspace (International Organization for Standardization, 2016; Litzenberger, 2019). They are flexible and cost-effective machines with limited power and force, equipped with sensors and safety functions to minimize workers' exposure to injury in case of contact; in addition, they can be easily modified to perform different tasks.

Cobots currently account for about 5% of all robot sales[1], but this percentage is expected to jump to 34% in 2025, as reported by the International Federation of Robots[2]. Their increasing presence in factories has promoted research about related human workers' experience.

Thanks to their flexibility and limited dimensions, cobots can jointly work with humans through different interaction patterns: coexistence, cooperation, and collaboration. Coexistence is the weakest form of collaboration, as it simply implies the presence of humans and robots in the same working space, without direct contact (Wang et al., 2018). In cooperative tasks, the operator and the cobot share the same workspace and work at the same product, with direct contact if necessary. Each of them is responsible for a portion of the production task, but they do not depend on each other to reach the common goal (Gervasi et al., 2020; Roschelle & Teasley, 1995). Collaboration instead implies to share the same task on the same product or part of it, in the same workspace (Schmidtler et al., 2015): humans and robots work together to reach a common goal, continuously interacting, negotiating, understanding and accommodating to one another's behaviour (Gervasi et al., 2020).

Working shoulder-to-shoulder with a collaborative robot modifies usual practices and poses several challenges to humans (Körner et al., 2019; Sauppé et al., 2015), as it implies changes in subjective job perception, intrinsic job structure (Fletcher & Webb, 2017; Wallace, 2021), and social relations at workplace (Maurtua et al., 2016; Michaelis et al., 2020; Wallace, 2021). The efficiency and tirelessness of robots may result in workers' concerns about their job security and employment status (Abeliansky & Beulmann, 2019). The human-machine proximity elicits fear of potential harm (De Simone et al., 2022; Lu et al., 2022; Szalma & Taylor, 2011). In addition, the complexity of the interaction with cobots may increase workers' mental workload, with negative consequences for their mental health (De Simone et al., 2022; Lu et al., 2022; Robelski & Wischniewski, 2016, 2018).

Besides challenges, collaborative robots can also lead to positive changes in the working place, as humans and machines can assist each other with complementary skills. Some studies have highlighted that cobots can relieve human operators from performing repetitive or heavy and dangerous tasks, thus supporting optimal levels of mental workload and increasing productivity (Welfare et al., 2019; Zanchettin et al., 2018).

The debate around the contribution of cobots to operators' MWL is still ongoing. What is certain is that an appropriate level of cognitive workload needs to be granted in order to manage the machine's impact on the operator, especially in terms of performance and safety (Panchetti et al., 2023). Therefore, understanding which factors influence MWL level and which solutions can be implemented to optimize it has become a crucial issue (Baltrusch et al., 2022; Van Acker et al., 2018; Young et al., 2015). Despite the growing interest in the investigation of mental workload (Faccio et al., 2023), most studies in the domain of HRC are aimed at understanding how to improve performance of the human-cobot team (Storm et al., 2022; Lorenzini et al. 2023), whereas little is known about strategies and practical solutions to promote an optimal level of workers' mental workload (Van Acker et al., 2018). For this reason, a scoping review of research studies investigating mental workload during HRC was undertaken, paying specific attention to the approaches adopted to measure it, and to the main sources of MWL that were identified, with the aim of providing practical solutions for the implementation of healthy work settings. The following research questions were formulated:

RQ1: Which measures are currently used to assess MWL during HRC in industrial contexts?

RQ2: Which are the prominent sources of MWL during collaboration with cobots in industrial tasks?

RQ3: Which solutions can be implemented to attain optimal levels of workers' MWL in HRC?

2. Methods

A scoping review was deemed as the most adequate approach to pursue the study aims, as it allows for broadly mapping what is known about this topic, without excluding sources based on their publication venue, study design and quality, thus offering a broader scope for research questions (Levac et al., 2010). We followed the five stages for scoping reviews outlined by Arksey and O'Malley (2005): (1) identifying the research question, (2) identifying relevant studies, (3) study selection, (4) charting the data, and (5) collating, summarizing, and reporting the results. In addition, the PRISMA-ScR checklist (included as electronic supplementary material) was used to guide reporting (Tricco et al., 2018). Ethical approval for this study was not required, as results were extracted from published papers and no primary data collection was performed.

2.1. Identifying relevant studies and eligibility criteria

Due to the multidisciplinary nature of the topic, the search was conducted on four different digital libraries, covering psychological and technological areas: Web of Science, Scopus, Psycinfo and IIEE Explore. Three sets of keywords were chosen, coherently with the three research questions (Table 1): The first set concerned keywords related to Human-Robot Collaboration (HRC); specifically, we decided to include studies involving tasks designed and described as collaborative, in which human operators and cobots are in the same workspace, working together to reach a common goal. This type of interaction requires a coordinated and synchronized activity from all parties involved, which also entails direct physical contact (haptic or auditory).

The second set of keywords referred to mental workload. As described in the introductory section, there is a lack of clarity in how stress and MWL are related, because they are often used to describe similar phenomena. Moreover, the international standards on mental workload terminology (ISO, 2017) specifically endorse the connection of MWL with mental stress (intended as "total of all assessable factors impinging upon an individual mentally"; see ISO, 2017, Section 3.1.1) and mental strain (intended as "immediate effect of mental stress"; see ISO, 2017, Section 3.1.2) (Young et al., 2015). Therefore, following Alsuraykh and colleagues' suggestion (2019), we decided to include both "mental workload" and "stress" in the search strategy.

Finally, in line with the aims of the study, the third keyword set circumscribed the search to industrial contexts. All possible combinations of keywords from the three sets were considered, using the Boolean "AND" operator between each set, and the "OR" operator within each set. The asterisk was used as a truncation function, which allows for searching a word through all its possible variants.

Searches covered titles, keywords, and abstracts of papers in the databases.

The search led to the identification of 155 publications; a manual search in Google Scholar based on the reference lists of the selected papers (snowballing method) or suggestions by experts allowed to identify 10 additional papers, leading to a corpus of 165 salient studies.

Publications referring to HRC with physical or virtual robots, and studies conducted in laboratory or work settings were deemed as relevant to the review purposes, regardless of their publication year.

Regarding restriction criteria, the review was limited to articles written in English, with full text available, and focused on MWL during HRC in real or simulated industrial settings. Additional exclusion criteria were text unavailability; study not related to all three sets of keywords; study not related to the industrial context; studies that focused solely on the physical dimension of workload assessment. Reviews and theoretical

Table 1. Set of keywords used in the search.

HRC	Impact on workers	Context
Cobot OR co-robot OR collaborative robot OR human robot collaboration OR HRC	Mental workload OR fatigue OR stress	Work* OR industry* OR manufact*

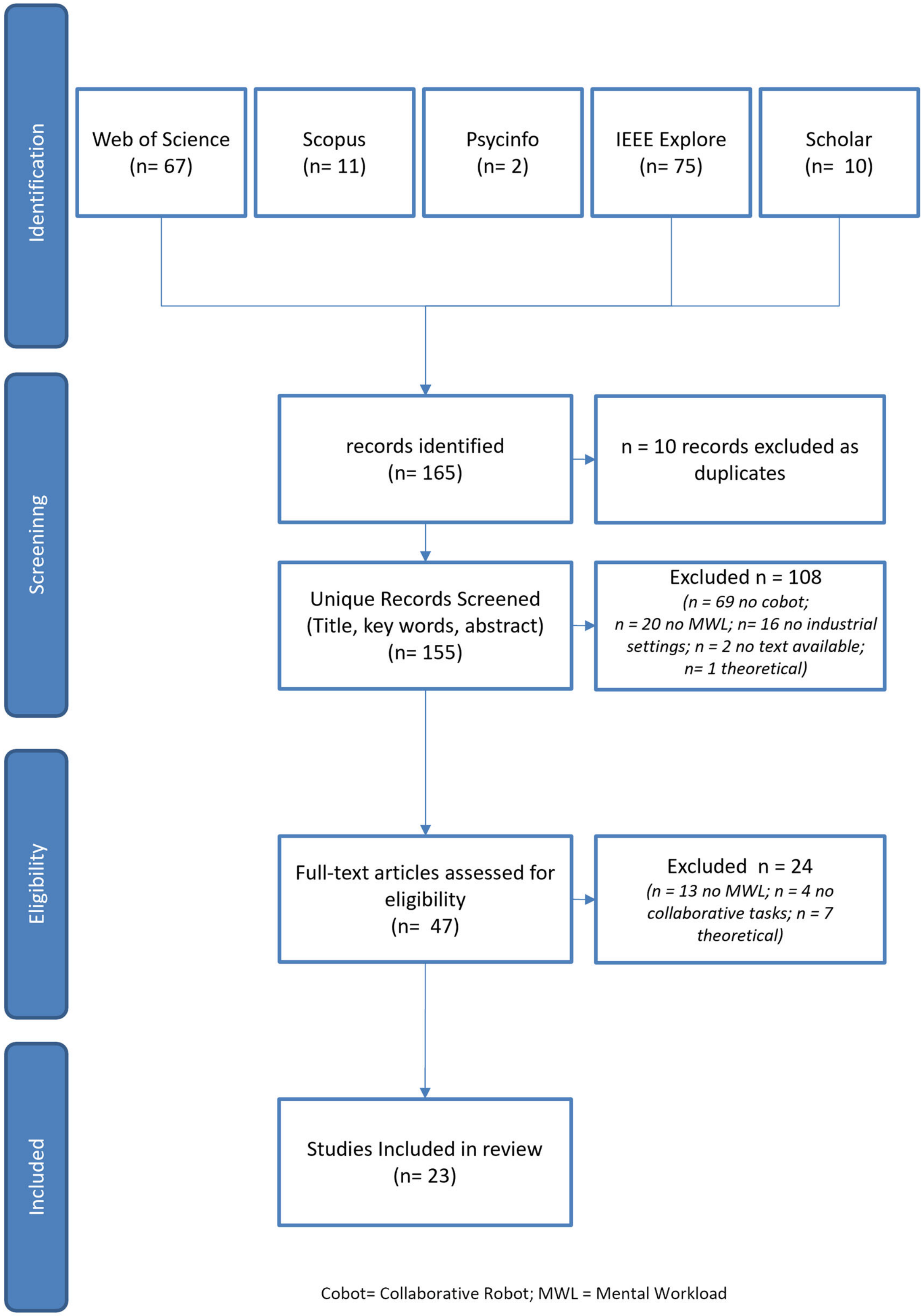

Figure 1. Flow chart of the screening process.

papers were excluded, but they were cited in the Introduction and Discussion sections of the present work, when appropriate.

2.2. Study selection

The selection process was articulated in two stages. After removal of duplicate records, two authors independently screened the publications according to their title, abstract and keywords. In the second stage, a careful reading of the full texts of the selected papers was undertaken, to identify the studies fully consistent with the research questions. Any discrepancy and disagreement were resolved by consensus or discussion among all authors. The Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) chart (Figure 1) was adopted to illustrate the phases of paper identification and selection.

2.3. Charting the data, collating, summarizing, and reporting the results

A standardized data extraction form was developed to guide data charting, and relevant information was extracted from the papers selected in the second stage of the screening. Specifically, the following fields were considered:

- *Main characteristics:* Title, author(s), year of publication, journal/proceedings, country, area of research, and study aims (summarized in Table 2). Figure 2 provides a visual description of the publication trend of the selected papers over time.
- *MWL measures:* The research instruments adopted in the selected studies to assess MWL were divided into three categories: self-report, physiological and performance measures (see Table 3).
- *Study design and findings*: Setting, type of cobot, task, sample size, dependent and independent variables, and findings are reported in Table 4. Table 4 also includes the factors representing potential sources of MWL associated with HRC identified in each paper, grouped into three categories: (1) Motions, predictability, and proximity of robot; (2) Robots' communication skills; (3) Task organization.
- *Possible solutions identified to manage workers' MWL:* Solutions reported by the selected studies were described in the last paragraph of the result section.

3. Results

3.1. Study characteristics

The literature search was conducted in June 2022; the two-stage screening resulted in the inclusion of 23 publications, listed in Table 2.

As shown in Figure 2, the selected papers were published between 2009 and 2022, with the majority being published in the last four years ($N = 14$, 60.9%). Most papers were included in conference proceedings ($N = 15$, 65.2%), while eight (34.8%) were published in peer-review journals.

Most studies ($N = 17$, 73.9%) were conducted in laboratory settings, three (13.0%) in virtual working scenarios, and one study (4.4%) in a simulation environment based on mathematical equations. Only two studies (8.7%) were conducted in factories with workers. Around half of the studies ($N = 12$, 52.2%) involved less than 20 participants, seven (30.4%) involved 20 to 50 participants, three (13.0%) more than 50, and one study (4.4%) was conducted through a mathematical simulation, without participants.

Concerning the methodology approach, eight (34.8%) of the selected papers proposed a solution to reduce MWL in the working context of HRC (Arntz et al., 2020; Bettoni et al., 2020; Lagomarsino et al., 2022; Messeri et al., 2023; Rahman & Wang, 2015; Rajavenkatanarayanan et al., 2020; Roncone et al., 2017; Tan et al., 2009). In one paper (4.4%), workers were directly invited to report perceived advantages and disadvantages of HRC collaboration (Brun & Wioland, 2021); in another paper (4.4%) a mathematical model was developed to analyse human cognitive performance during HRC (Rabby et al., 2019). The remaining studies (N = 13, 56.5%) investigated MWL and associated factors during HRC in laboratory settings.

3.2. Measures of mental workload

Table 3 summarizes the MWL measures used in the selected papers, comprising physiological and self-report measures, as well as measures of performance. Six studies (26.1%) included all three types of assessment (Bettoni et al., 2020; Etzi et al., 2020; S. K. Hopko et al., 2021; Kato et al., 2010; Koppenborg et al., 2017; Zhao et al., 2020). Two types were adopted in nine studies (39,1%; Chacón et al., 2021; Fournier et al., 2022; Lagomarsino et al., 2022; Messeri et al., 2023, 2021; Pollak et al., 2020; Rahman & Wang, 2015; Roncone et al., 2017; Tan et al., 2009); more specifically, three studies combined physiological measures with performance data (Messeri et al., 2023, 2021; Tan et al., 2009), two included physiological and self-report measures (Lagomarsino et al., 2022; Pollak et al., 2020), three studies combined performance assessment and quantitative or qualitative self-report measures (Chacón et al., 2021; Fournier et al., 2022; Rahman & Wang, 2015; Roncone et al., 2017). Among the remaining eight studies (34.8%), three adopted only physiological measures (Arai et al., 2010; Fujita et al., 2010; Rajavenkatanarayanan et al., 2020), four only self-report instruments (Arntz et al., 2020; Brun & Wioland, 2021; Müller et al., 2017; Ustunel & Gunduz, 2017), and one paper relied on a mathematical procedure (Rabby et al., 2019).

3.2.1. Self-report measures

Self-reports are based on the assumption that individuals can evaluate and rate their own cognitive processes, including - for example - the level of mental workload during completion of a task (Anmarkrud et al., 2019, p. 5). Their advantages are low cost, high sensitivity, low intrusiveness, and high easiness. Their disadvantages include difficulties to compare results between participants, and the impossibility to administer them during the execution of the task, but only after interrupting or completing it (Butmee et al., 2019; Cain, 2007; Longo et al., 2022).

In over half of the selected studies ($N = 14$, 60.8%) MWL was assessed through self-report measures, primarily quantitative scales (N = 13, 56.5%, of which two were adapted versions of standardized questionnaires). Qualitative methods, such as interviews or open-ended questions, were adopted in three studies (13.0%).

The most frequently used instrument was the National Aeronautics and Space Administration-task load index (NASA-TLX; Hart, 2006), employed in 11 studies (47.8%). This multidimensional measure allows for assessing the

Table 2. Studies main characteristics.

N.	Title	Authors	Year	Journal/Proceedings	Country	Area of research	Study aims
1	Human-robot collaboration in cellular manufacturing: Design and development	Tan J. T. C., Duan F., Zhang Y., Watanabe K., Kato R., Arai T.	2009	the 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems	Japan	Robotics	Developing solution to reduce MWL
2	Development of advanced cellular manufacturing system with human-robot collaboration	Kato R., Fujita M., Arai T.	2010	19th International Symposium in Robot and Human Interactive Communication	Japan	Robotics	Investigating MWL factor in HRC
3	Assessment of operators' mental strain induced by hand-over motion of industrial robot manipulator	Fujita M., Kato R., Tamio A.	2010	19th International Symposium in Robot and Human Interactive Communication	Japan	Robotics	Investigating MWL factor in HRC
4	Assessment of operator stress induced by robot collaboration in assembly	Arai, T., Kato R., Fujita M.	2010	CIRP ANNALS - Manufacturing Technology	Japan	Robotics	Investigating MWL factor in HRC
5	Dynamic affection-based motion control of a humanoid robot to collaborate with human in flexible assembly in manufacturing	Rahman, S.M.M., Wang, Y.	2015	ASME 2015 Dynamic Systems and Control Conference	USA	Engineering	Developing solution to reduce MWL
6	Human-robot collaboration on an assembly work with extended cognition approach	Ustunel, Z., Gunduz, T.	2017	Journal of Advanced Mechanical Design, Systems and Manufacturing	Turkey	Engineering	Investigating MWL factor in HRC
7	Subjective Stress in Hybrid Collaboration	Müller, S.L., Stiehm S., Jeschke S., Richert A.	2017	Social Robotics, ICSR 2017	Germany	Social robotics	Investigating MWL factor in HRC
8	Effects of movement speed and predictability in human–robot collaboration	Koppenborg M., Nickel P., Birgit N., Lungfiel A., Huelke M.	2017	Human Factors and Ergonomics in Manufacturing	Germany	Occupational health	Investigating MWL factor in HRC
9	Transparent role assignment and task allocation in human robot collaboration	Roncone A., Mangin O., Scassellati B.	2017	2017 IEEE International Conference on Robotics and Automation (ICRA)	United States	Robotics	Developing solution to reduce MWL
10	An Effective Model for Human Cognitive Performance within a Human-Robot Collaboration Framework	Rabby K. M., Khan M. Karimoddini A., Jiang S. X.	2019	2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)	USA	Human-robot interaction	Investigating MWL factor in HRC
11	Stress in manual and autonomous modes of collaboration with a cobot.	Pollak, A., Paliga M., Pupopulos M.M., Kozusznik B., Kozusznik M. W.	2020	Computers in Human Behavior	Poland	Human-robot interaction	Investigating MWL factor in HRC
12	Using Virtual Reality to test Human-Robot Interaction during a collaborative task	Etzi R., Huang S.Y., Scurati G.W., Lyu S., Ferrise F., Gallace A., Gaggioli A., Chirico A., Carulli M. Bordegoni M.	2020	IDETC-CIE International Design Engineering Technical Conferences & Computers and Information in Engineering Conference	Italy	Engineering	Investigating MWL factor in HRC
13	Task Interdependence in Human-Robot Teaming	Zhao F.Y., Henrichs C., Mutlu B.	2020	19 IEEE International Workshop on Robot and Human Communication (ROMAN)	USA	Social robotics	Investigating MWL factor in HRC

(*continued*)

Table 2. Continued.

N.	Title	Authors	Year	Journal/Proceedings	Country	Area of research	Study aims
14	Towards a Real-Time Cognitive Load Assessment System for Industrial Human-Robot Cooperation	Rajavenkatanarayanan A., Nambiappan H.R., Kyrarini M., Makedon F.	2020	2020 29th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)	USA	Human-robot interaction	Developing solution to reduce MWL
15	Mutualistic and adaptive human-machine collaboration based on machine learning in an injection moulding manufacturing line	Bettoni A., Montini E, Righi M., Villani V., Tsvetanov R., Borgia S., Secchi C., Carpanzano E.	2020	53rd CIRP Conference on Manufacturing Systems	Switzerland	Engineering	Developing solution to reduce MWL
16	Augmenting the human-robot communication channel in shared task environments	Arntz A., Eimler S C., Hoppe H. U.	2020	26th International Conference, CollabTech 2020 Tartu	Germany	Human-robot interaction	Developing solution to reduce MWL
17	Effect of Cognitive Fatigue, Operator Sex, and Robot Assistance on Task Performance Metrics, Workload, and Situation Awareness in Human-Robot Collaboration	Hopko S. K., Khurana R., Mehta R. K., Pagilla P. R.	2021	IEEE Robotics and Automation Letters	USA	Robotics	Investigating MWL factor in HRC
18	Human-Robot Collaboration: Optimizing Stress and Productivity Based on Game Theory	Messeri C., Masotti G., Zanchettin A.M., Rocco P.	2021	IEEE Robotics and Automation Letters	Italy	Robotics	Developing solution to reduce MWL
19	Cognitive interaction analysis in Human-Robot Collaboration using an asssembly task	Chacón, A., Ponsa P., Angulo C.	2021	Electronics	Spain	Engineering	Investigating MWL factor in HRC
20	Prevention of occupational risks related to the Human-Robot Collaboration	Brun L., Wiol, L.	2021	IHIET 2020: Human Interaction, Emerging Technologies and Future Applications III	France	Human-robot interaction	Investigating MWL factor in HRC
21	Robot Trajectory Adaptation to Optimise the Trade-off between Human Cognitive Ergonomics and Workplace Productivity in Collaborative Tasks	Lagomarsino, M., Lorenzini, M., De Momi, E., Ajoudani, A.	2022	IEEE/RSJ International Conference on Intelligent Robots and Systems	Italy	Robotics	Developing solution to reduce MWL
22	The Impacts of Human-Cobot Collaboration on Perceived Cognitive Load and Usability during an Industrial Task: An Exploratory Experiment	Fournier E., Kilgus D., Landry A., Hmedan B., Pellier D., Fiorino H, Jeoffrion C.	2022	IISE Transactions on Occupational Ergonomics and Human Factors	France	Occupational health	Investigating MWL factor in HRC
23	On the effects of leader-follower roles in dyadic human-robot synchronisation	Messeri C., Zanchettin A.M., Rocco P., Gianotti E., Chirico A., Magoni S., Gaggioli A.	2023	EEE Transactions on Cognitive and Developmental Systems	Italy	Human-robot interaction	Investigating MWL factor in HRC

Legenda: MWL = Mental Workload; Cobot = Collaborative Robot; HRC = Human Robot Collaboration

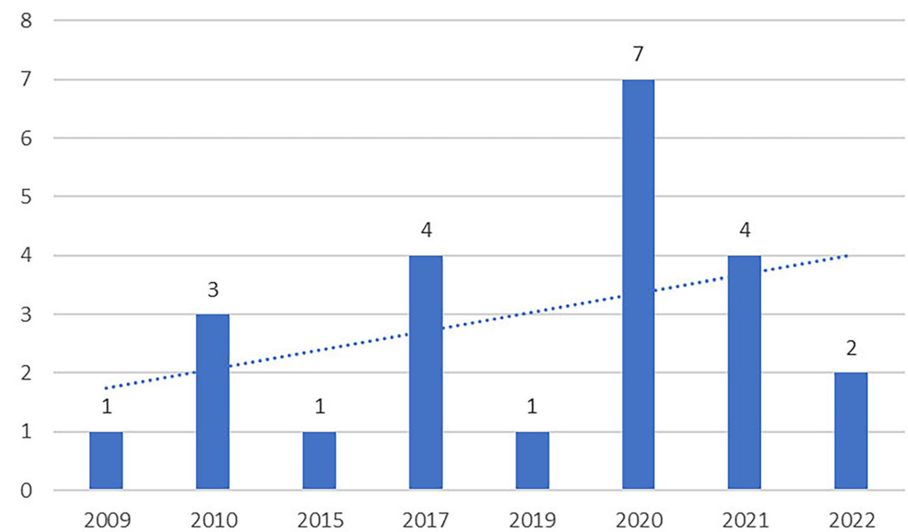

Figure 2. Number of papers per year (up to June 2022).

Table 3. MWL measures used in the selected studies.

N.	Study	Self-report	Physiological	Performance
1	Tan et al., 2009	==	EDA	Completion time and quality
2	Kato et al., 2010	NASA RTLX (Hart, 2006)	EDA	Completion time
3	Fujita et al., 2010	==	EDA	==
4	Arai et al., 2010	==	EDA	==
5	Rahman and Wang, 2015	NASA RTLX (Hart, 2006)	==	Accuracy and efficiency
6	Ustunel and Gunduz, 2017	NASA RTLX (Hart, 2006)	==	==
7	Müller et al., 2017	Short Stress State-Questionnaire (Helton, 2004)	==	==
8	Koppenborg et al., 2017	NASA RTLX (Hart, 2006)	IBI	Completion time and accuracy
9	Roncone et al., 2017	Open questions	==	Completion time
10	Rabby et al., 2019	==	==	==
11	Pollak et al., 2020	Four items from Primary and secondary appraisal scale (PASA - Gaab at al., 2009)	HR	==
12	Etzi et al., 2020	Questions on feelings and user experience	EDA, HR	Completion time and accuracy
13	Zhao et al., 2020	NASA RTLX (Hart, 2006)	HRV	Completion time
14	Rajavenkatanarayanan et al., 2020	==	HRV, and EDA	==
15	Bettoni et al., 2020	Questionnaire adapted from NASA RTLX (Hart, 2006)	HRV	Productivity
16	Arntz et al., 2020	Cohen's perceived stress scale (Cohen, 1994); Frustration from NASA TLX Load index (Hart, 2006)	==	==
17	Hopko et al., 2021	Questions about fatigue; NASA TLX (Hart, 2006)	HRV	Efficiency and accuracy
18	Messeri et al., 2021	==	HRV	Productivity
19	Chacón et al., 2021	NASA RTLX (Hart, 2006)	==	Completion time
20	Brun and Wioland, 2021	Interviews	==	==
21	Lagomarsino et al., 2022	NASA RTLX (Hart, 2006)	HRV	==
22	Fournier et al., 2022	NASA RTLX (Hart, 2006)	==	Completion time and accuracy
23	Messeri et al., 2023	==	HRV	Completion time

Notes. MWL = Mental Workload; Cobot = Collaborative Robot; EDA = Electrodermal Activity; IBI = Interbeat interval of heart rate; HR = Heart Rate.

association between perceived MWL and six factors: mental, physical, and temporal demands, performance level, effort, and frustration. Participants are invited to rate the level of MWL perceived in relation to each factor on scales ranging from 0 to 100. Single factor scores are then averaged to determine total MWL. The instrument has good reliability and validity; it is primarily used in the context of flight simulation, air traffic control, and vigilance tasks.

Considering the above-described interconnections between MWL and stress, three of the selected studies (13.0%) adopted stress scales. The Short Stress State Questionnaire (SSSQ; Helton, 2004), adopted in Müller et al. (2017) is a 24-item instrument on a 5-point Likert-type scale, aimed at assessing the multiple dimensions of task related stress - task engagement, distress, and worry - in pre-task and post-task conditions. The Primary Appraisal Secondary Appraisal scale

Table 4. Study design and findings.

N.	Study	Setting	Cobot	Task	Sample Size	Dependent Variable	Independent Variable	MWL Source 1	MWL Source 2	MWL Source 3	Findings
1	Tan et al., 2009	Lab	Twin-manipulator	Assembly	5	EDA and performance	Cobot speed and distance	x	==	==	Mental workload increases as robot motion increases and human-robot distance decreases
2	Kato et al., 2010	Lab	Twin-manipulator	Assembly	13	EDA and performance	Cobot speed, distance, and notice	x	==	==	Cognitive and emotional stress increases as robot speed increases, as human-robot distance decreases and in absence of adequate information about the robot's motion and speed
3	Fujita et al., 2010	Lab	Twin-manipulator	Assembly	5	EDA and performance	Cobot speed, distance, and notice	x	==	==	Cognitive and emotional stress increases as robot speed increases, as human-robot distance decreases and in absence of adequate pre-knowledge about robot motion
4	Arai et al., 2010	Lab	Twin-manipulator	Assembly	5	EDA and performance	Cobot speed, distance, and notice	x	==	==	Cognitive and emotional stress increases as robot speed increases, as human-robot distance decreases and in absence of adequate pre-knowledge about robot motion
5	Rahman and Wang, 2015	Lab	Dual arm	Assembly	20	Subjective MWL, and performance	Cobot's affective expression	==	x	==	Mental workload is lower when working with a robot able to use dynamic affective expression compared to a standard machine
6	Ustunel and Gunduz, 2017	Lab	Single arm	Assembly	40	Subjective MWL	Extended cognition	==	x	==	Cognitive load is lower when information about collaborative task is provided
7	Müller et al., 2017	Virtual Scenario	Virtual industrial and humanoid	Assembly	112	Subjective stress level	Cobot appearance and reliability	x	==	==	Stress levels are unrelated to robot appearance and behavior
8	Koppengborg et al., 2017	Virtual Scenario	Virtual robotic arm	Pick and place	28	Subjective MWL, IBI, and performance	Cobot's speed and predictability	x	==	==	High mental workload is associated with high robot speed
9	Roncone et al., 2017	Lab	Dual arm	Assembly	8	subjective MWL and performance	Cobot role	==	==	x	Cognitive load is lower when interacting with a robot able to reason about role assignment and task
10	Rabby et al., 2019	Simulated Scenario	Virtual robotic arm	Pick and place	==	Cognitive WL (mathematical model)	Cobot performance	==	x	==	Higher cognitive workload and lower cognitive performance are associated with decrease in robot performance
11	Pollak et al., 2020	Lab	Single arm	Pick and place	45	Subjective MWL and HR	Cobot modes (autonomous and manual)	==	==	x	Stress levels increase with the decrease of operators' control during HRC

(*continued*)

Table 4. Continued.

N.	Study	Setting	Cobot	Task	Sample Size	Dependent Variable	Independent Variable	MWL Source 1	MWL Source 2	MWL Source 3	Findings
12	Etzi et al., 2020	Lab	Virtual robotic arm	Assembly	10	Subjective experience; EDA, HR, and performance	Cobot speed	x	==	==	Perceived pressure and stress, as well as excitement increase with higher robot motion speed
13	Zhao et al., 2020	Lab	Single arm	Assembly	31	Subjective experience; HRV and performance	Cobot role	==	==	x	Perceived stress is lower in the condition of reciprocal interdependence, in which the cobot works as a teammate to reach the shared goal
14	Rajavenkatanarayanan et al., 2020	Lab	Single arm	Assembly	25	HRV, EDA	Cobot role	x	==	==	Mental exertion increases with time constraints, such as following the robot speed
15	Bettoni et al., 2020	Field	Single arm	Moulding	4	Subjective experience, HRV and performance	Cobot role	x	==	==	Mental workload is lower when interacting with a robot able to dynamically assign tasks based on the worker's fatigue
16	Arntz et al., 2020	Virtual Scenario	Virtual single arm	Assembly	80	Subjective perceived stress	Augmented communication	==	x	==	Lower stress and higher positive affect are reported working with a robot-arm equipped with social communication interface
17	Hopko et al., 2021	Lab	Single arm	Surface polisthing	16	Subjective experience, HRV and performance	Cobot role	==	==	x	Perceived cognitive workload is lower in high assistant condition than low assistance.
18	Messeri et al., 2021	Lab	Dual arm	Assembly	15	HRV, EDA, and performance	Cobot speed	x	==	==	Lower stress and higher productivity are associated with robots' ability to adjust their pace to operators' stress level
19	Chacón et al., 2021	Lab	Single arm	Assembly	18	Subjective MWL and Performance	Task to perform	==	==	x	Mental workload during a high-demanding cognitive task is not increased by adding a secondary assembly task carried out with a cobot
20	Brun and Wioland, 2021	Field	n.a.	Packaging	8	Perceived stress	==	==	==	x	Lower stress, nervousness, and fatigue at the end of the day are associated with the introduction of cobots in the production line
21	Lagomarsino et al., 2022	Lab	Single arm	Pick and place	12	HRV, EDA, and performance	Cobot motion trajectories	x	==	==	Cognitive load is lower when working with a robot able to perform tasks autonomously, providing feedback about its ongoing actions, compared to a not autonomous machine. Automation is perceived more cognitively demanding by naïve operators than experts.

(*continued*)

Table 4. Continued.

N.	Study	Setting	Cobot	Task	Sample Size	Dependent Variable	Independent Variable	MWL Source 1	MWL Source 2	MWL Source 3	Findings
22	Fournier et al., 2022	Lab	Dual arm	Pick and place	54	Subjective MWL and performance	Cobot presence	x	==	==	No change in cognitive load levels was reported when working with a cobot compared to working alone.
23	Messeri et al., 2023	Lab	Dual arm	Assembly	33	HRV and performance	Cobot role	==	==	x	Stress is higher when in a collaborative task the operator follows the robot, rather than taking the lead

Notes. HRC = Human Robot Collaboration; MWL = Mental Workload; Cobot = Collaborative Robot; MWL Sources: 1 = Motions, predictability and proximity; 2 = Robot Communication skills; 3= Task organization.

(PASA; Gaab, 2009), adopted in Pollak et al. (2020), is designed according to the transactional stress theory. (Lazarus & Folkman, 1984). This instrument is aimed to measure threat and challenge as primary stress appraisals (PA) and perceived personal abilities and control expectancy as secondary appraisals (SA). It is composed by 16 items, rated on a 6-point scale (from strongly disagree to strongly agree; eight items assess PA and eight SA). In the selected paper including PASA (Pollak et al., 2020), two items referring to the event as stressful, challenging, or irrelevant were extrapolated from the primary appraisal subscale; similarly, two items concerning individual resources and options to deal with the stressor were selected from the secondary appraisal subscale. The Cohen's Perceived Stress Scale (PSS-10) (Chan & Greca, 2013; Cohen, 1994; Cohen et al., 1997), adopted in another study (Arntz et al., 2020) is a 10-item questionnaire that measures the frequency of stress perception in life events and situations, on a scale ranging between 0 and 40.

3.2.2. Physiological measures

Measures assessing operators' physiological response while executing a task allow for gathering continuous and objective data. Considered as highly sensitive to changes in workload, they are increasingly adopted in experimental settings, thanks to the evolution of sensor technologies (Longo et al., 2022). Physiological signals are also increasingly used to adjust cobots' behaviour to the operator's psychophysical state.

In 14 (60.9%) of the selected papers, physiological measures were used to assess MWL; more specifically, the electrodermal activity (EDA) was measured in six studies (26.1%; two of them also assessing heart rate signals), and heart activity (HR, Interbeat Rate or HRV) in 10 studies (43.5%).

The Electro Dermal Activity (EDA), or Galvanic Skin Response (GSR), also known as Skin Conductivity (SC), is one of the most accessible signals levered by the central nervous system. EDA is an effective indicator of physical and mental strain, as increased sweating of hand palms (typically characterizing mental strain) results in greater EDA and Skin Potential Response (SPR) spike amplitude and frequency (Arai et al., 2010; Fujita et al., 2010; Kato et al., 2010).

Electrocardiogram (ECG) can be used as a psychophysiological indicator of physical and mental stress through the evaluation of Heart Rate (HR) and Heart Rate Variability (HRV, the variation over time of the period between consecutive heart beats), both providing information on the person's level of relaxation versus activation. HR increases with higher task demands (De Rivecourt et al., 2008), whereas HRV comprises sympathetic and parasympathetic components. A condition of heavy MWL is associated with increased sympathetic control and reduced vagal tone, with a decrease in HRV (Delliaux et al., 2019; Hjortskov et al., 2004; Li et al., 2022; Wang et al., 2005). One of the most common indicators of HRV is LF/HF ratio (low frequency band/high frequency band), that represents the dominance of the sympathetic nervous system with respect to the parasympathetic one.

3.2.3. Performance measures

Performance measures are used to quantify how well an operator is performing the assigned task, based on the assumption that optimal levels of MWL are associated with performance maximization, while decrease in performance reflects suboptimal workload levels. To this purpose, primary and secondary task performance measures can be used (Cain, 2007). The former directly assess the operator's performance on the task of interest; the latter investigate the operator's remaining cognitive reserves while performing the primary task. The adoption of a dual tasking methodology allows for assessing performance in primary and secondary tasks, and cognitive interference between them. Researchers in the domain of robotics have investigated the effects of various factors on dual-task performance, including embodiment, virtualization of human-robot interactions, and haptic feedback during teleoperation of mobile robots (Corujeira et al., 2017; Iwasaki et al., 2022; Nenna et al., 2023).

Over half of the selected articles ($N = 13$; 56.5%) adopted one or more performance measures - productivity, task completion time, performance efficiency, task accuracy - in combination with other measurement approaches; all these studies except one (Chacón et al., 2021) used primary task performance measures.

3.3. Sources of mental workload

Findings from the selected studies revealed different factors associated with workers' MWL. Working side by side with cobots without any protective barrier can be demanding per se, especially in conditions of high speed and unpredictability of robots' movements (De Simone et al., 2022); the cobot's communication abilities and patterns, as well as its role in the collaborative task structure and organization can also contribute to operators' MWL and stress. In Table 4 the potential MWL sources investigated across studies are described in the column "independent variable"; in the same table, these sources are also classified into three typologies: Motions, predictability, and proximity; Robot Communication skills; Task organization. In the following paragraphs, a more detailed description of the related findings will be provided.

3.3.1. Motions, motion predictability and proximity

Closeness to moving cobots during collaborative assembly tasks can represent *per se* a source of psychophysiological strain (Arai et al., 2010; Fujita et al., 2010; Kato et al., 2010; Koppenborg et al., 2017), especially for naïve and less expert workers (Müller et al., 2017).

The combination of high speed and proximity was associated with participants' higher levels of physiological reactions (i.e. skin conductance), and stress (Arai et al., 2010; Fujita et al., 2010; Kato et al., 2010; Tan et al., 2009). Compared to slow-motion situations, fast cobot motions were associated with higher stress levels also during interaction with a virtual robot, even though physiological data did not mirror subjective stress perception (Etzi et al., 2020). Robots' higher working pace, posing time pressure on workers, also led to increased MWL (Bettoni et al., 2020; Rajavenkatanarayanan et al., 2020).

Motion trajectory is of great importance in HRC, as straight trajectories can increase stress and MWL compared to smooth ones (Arai et al., 2010; Fujita et al., 2010; Kato et al., 2010; Koppenborg et al., 2017). Unpredictable cobot motion can also increase stress, whereas providing workers with pre-knowledge and predictability cues can decrease it (Kato et al., 2010); low predictability of cobot motion was associated with higher risk perception, anxiety, mental workload, and a tendentially lower task performance in virtual settings as well (Koppenborg et al., 2017).

3.3.2. Robots' communication skills

Cobots endowed with social skills can contribute to lower MWL thanks to better communication and synchronization of movements with workers. To investigate this aspect, Rahman and Wang (2015) developed an affect-based robot able to express emotions coherent with the situation and the mental state of the co-workers. In their experiment, the robot's emotional ability resulted in better communication, smooth workflow, clearer operating roles between teammates, and lower cognitive workload (Rahman & Wang, 2015). Another study showed that equipping an HRC working cell with augmented communication channels can increase predictability of the robot's behaviour, thus decreasing workers' stress and frustration; lack of information about the robot's intentions may generate stress due to feelings of uncertainty and attempts to guess the machine's subsequent actions (Arntz et al., 2020). In the same vein, providing a picture of the product that participants had to assemble with the cobot was associated with lower MWL (Ustunel & Gunduz, 2017). It is important to notice that information about tasks can be helpful to workers only if provided in the proper quantity and through an appropriate support; otherwise it may generate an increase in MWL (Arai et al., 2010; Kato et al., 2010).

Robot performance and reliability seem to influence MWL as well: According to the mathematical model developed by Rabby et al. (2019), the association between human cognitive workload and task performance in an HRC framework varies according to task complexity and robot performance (i.e. human intervention required or not). Specifically, given a certain task complexity level, human cognitive workload decreases as the robot's performance improves. As concerns cobot's reliability, higher levels can reduce operator's cognitive workload (Rabby et al., 2019).

3.3.3. Task organization

The introduction of cobots inevitably brings about changes in the organization of work. First, cobots are designed to perform heavy, dangerous and repetitive handling tasks in collaborative cells (Brun & Wioland, 2021), while workers are assigned primarily mental tasks, such as monitoring robot operations, production flow and quality, and troubleshooting malfunctions; this multifaceted role contributes to increased cognitive load and stress (Chacón et al., 2021), but also satisfaction and engagement, if the cobot is programmed to adapt to the worker's needs (Brun & Wioland, 2021; Fournier et al., 2022). A robot able to offer proper support during collaborative activities may contribute to lower fatigue and MWL (Hopko et al., 2021). In addition, during the collaborative situation, study workers reported higher stress when they are assigned the role of task follower rather than task leader, most likely due to the perceived lack of control on the situation; the perception of control over the robot system is instead associated with lower stress levels (Pollak et al., 2020). Notably, in Messeri et al. (2023), and in Roncone et al. (2017), the productivity is higher when the robot guides the collaborative operations.

The level of interdependence, that is the extent to which one team member's actions affect the performance of the other one, was also investigated by Zhao et al. (2020) as a potential source of MWL variations, leading to the identification of three types of interdependence: Pooled interdependence (robot and worker complete tasks separately), sequential interdependence (robot and worker complete tasks together in a pre-defined order), and reciprocal interdependence (each partner specializes in a certain skill or specific aspect of the task). Participants in the reciprocal interdependence condition (i.e. in which humans perceived cobot as a teammate with shared responsibilities and goals) reported lower levels of stress compared to the other two conditions. Moreover, in the reciprocal interdependence condition, participants reported higher freedom in setting their work pace, at the same time perceiving collaboration with the robot, compared to sequential interdependence (Zhao et al., 2020).

3.4. How to reduce MWL: Solutions from the selected studies

The studies included in this review suggest that collaboration with cobots is intrinsically characterized by specific demands, that may increase human partners' cognitive load, with detrimental effects on their mental health and task performance (Fallahi et al., 2016; Midha et al., 2022; Minowa, 2000; Shao et al., 2020). It is therefore crucial to design HRC systems capable of maximizing productivity while maintaining workers' MWL levels within a healthy range (Baltrusch et al., 2022). Some of the selected papers propose solutions to this problem.

Bettoni et al. (2020) implemented a smart decision maker system able to balance productivity and a general reduction of the workers' mental and physical workload, based on physiological data gathered from operators through three different wearable devices: chest strap, wristband, and a smartwatch. The continuous monitoring of workers' physiological parameters allows the system to adjust cobots' actions to humans' conditions along the entire production process, for example by proposing a different allocation of tasks to the workers, who can accept or refuse it through the touch screen of their smartwatches (Bettoni et al., 2020). This solution, tested at a manufacturing company on a workstation with four workers, was associated with globally lower mental and physical workload, higher job engagement, and less perceived monotony (Bettoni et al., 2020).

Another solution is represented by RobotAssist (Rajavenkatanarayanan et al., 2020), a multi-sensory minimally invasive HRC system that enables the cobot to assess the cognitive load of the human partner through ECG and EDA sensors, and to analyse and model them based on machine learning techniques.

The joint evaluation of the worker's stress and productivity is the core of another potential solution (Messeri et al., 2021). Through an online control strategy, a learning automation system can modify the robot's work pace over time, to guarantee the best compromise between mitigation of human stress and maximization of productivity. In another paper, a decision-making algorithm was developed to optimize productivity and mental fatigue based on HRV signals (Lagomarsino et al., 2022). The tuning algorithm allows for adapting robots' motion characteristics and pace to workers' mental states, regulating MLW and ensuring an optimal level of productivity. A similar solution is represented by a transparent task planner, embedded on a dual arm robot, able to perform basic evaluations of role assignments and task allocation (Roncone et al., 2017). The system introduces a shift in task allocation from human to robot based on the task completion time, freeing the operator from reasoning about the task, and leading to reduction in task completion time. Study participants expressed their preference for this allocation system compared to a traditional one, in which they were fully responsible for task definition, emphasizing that the reduction in cognitive load relieved them from the need to remember steps by heart and to waste less time in making decisions (Roncone et al., 2017).

4. Discussion

This scoping review was aimed at identifying the approaches adopted to investigate mental workload, and the prominent sources of mental workload detected in the literature concerning collaboration with cobots.

Almost all the selected studies were performed in laboratory settings, participants were volunteers, and the sample sizes were rather small (82.6% of the studies involved less than 50 participants; 52.2% less than 20). Moreover, the cobots used in laboratory experiments were equipped with single or dual robotic arms, thus reproducing a specific type of robot used in factories to perform assembly and pick and place tasks. Finally, the tasks in which the participants were engaged were generally short and isolated, and did not reflect the prolonged, continuous HRC operations that are commonly observed in industrial settings. Furthermore, the experimental design of the selected studies often lacked a multimodal approach, which further limits the generalizability of the findings to real-world industrial scenarios. These features limit the generalizability of the laboratory findings to real-world industrial settings. Further research with larger samples and longer task duration is needed to fully understand the impact of HRC on mental workload in real industry settings.

Discrepancies emerged in the relationship between cobot behaviour and human MWL levels in the four studies adopting virtual scenarios: In two of them (Koppenborg et al., 2017 and Rabby et al., 2019), results were consistent with those derived from real-world scenarios; in the other two studies (Arntz et al., 2020; Müller et al., 2017), mental workload levels were lower or unrelated to robot behaviour. Virtual environments may not always replicate the complexities of real-world scenarios, and related results should therefore be interpreted with caution when generalizing to real-world settings (Wijnen et al., 2020; 2020). Further investigation is required to fully comprehend the impact of HRC on mental workload in real-world industrial settings.

As concerns the assessment of MWL, the most frequently used objective measure was EDA, characterized by high sensitivity and low intrusiveness. NASA TLX was instead the most common self-report instrument adopted to evaluate the subjective perception of MWL. Despite repeated acknowledgements that only a multimodal approach, including physiological, task-performance, and self-report measures, can adequately capture the complexity of HRC (Cain, 2007; Longo et al., 2022; Miller, 2001), only six of the selected studies adopted this strategy.

As concerns sources of mental workload, the most relevant factors that can negatively impact on both productivity and workers' mental conditions were patterns of cobot motion and interaction with the human worker, as well as task organization and procedures. However, in two studies (Chacón et al., 2021; Fournier et al., 2022) collaboration with robots was not associated with an increase in perceived cognitive load. This heterogeneity of findings calls for further investigation; to this purpose, it is important to notice that most of the selected studies were conference proceedings, suggesting that human mental functioning during HRC is still a young and expanding research field (Storm et al., 2022).

As for possible solutions to reduce workers' cognitive load during HRC, five of the selected studies proposed methods to dynamically control cobot actions in response to workers' mental stress during collaborative tasks. Overall, their authors converged on acknowledging the need for designing cobots sensitive to human mental resources and functioning, equipped with the ability to adjust their behaviour to workers' psychophysical states through regulation of speed and pace, and variations in task allocation. The current technological advancements, allowing for the continuous assessment of MWL related physiological data through increasingly sensitive and non-invasive sensors, could enable cobots to use information about workers' mental state as a basis for defining and modulating collaboration patterns.

This scoping review is not exempt from limitations. Despite efforts to make it exhaustive, it is possible that relevant publications were not included because of the selection criteria or involuntary omissions in the screening phase. Another limitation is related to the generalizability of the findings, which were predominantly obtained in simulated laboratory settings from small samples of volunteers, often students or university staff. Finally, at the methodological level the selected studies widely differed in quality, an issue related to the still limited literature available on HRC.

5. Conclusion and future directions

This scoping review summarized the literature investigating cobot and task related factors that may contribute to increase workers' mental workload, and the potential solutions to address this problem. Cobot motion patterns, speed, and pace, as well as the cobot's role in task allocation during HRC were associated with higher MWL. These findings have been primarily interpreted through the transactional theory of stress (Lazarus & Folkman, 1984), a psychological model derived from the investigation of the interplay between environmental demands and individual resources. It is interesting to notice that most of the studies included in this scoping review were designed and conducted by researchers working in the domain of engineering or robotics, suggesting that multidisciplinary collaboration is not yet the rule in this area of investigation. Moreover, although all the studies were focused on workers' psychological functioning, only seven papers (30.4%) involved psychologists as co-authors. This lack of interdisciplinary collaboration is a potential risk when dealing with HRC, an intrinsically relational condition jointly involving humans and machines (Dautenhahn, 2007; Gervasi et al., 2020; 2020; Meissner et al., 2020; Tsai et al., 2022). The involvement of researchers with specific expertise in human psychological functioning and relational needs may help identify the most appropriate methods and measures to investigate such a complex interplay, as well as open novel pathways to explore it, fruitfully integrating the perspective of experts in technology and robotics.

To define the features of a positive and effective human-robot interaction, however, more refined information should be collected from the workers, besides MWL or stress indicators. A promising though still novel area of research in this domain is the real-time repeated assessment of the experience reported by operators during HRC in the factory setting. This emerging area opens new research and intervention avenues, including the implementation of new work patterns, new manufacturing workplaces and new roles for cobots, with the goal of protecting and promoting workers' mental health. To this purpose, a new type of cobot is currently under development by a multidisciplinary consortium of researchers within the European H2020 "MindBot" project, aimed at designing collaborative robots able to interact with the human operator in ways that promote optimal experiences and foster positive mental health (Nicora et al., 2021). The conceptual and empirical model guiding the MindBot project is Flow Theory (Csikszentmihalyi, 1975, 2000). "Flow" or "optimal experience" is a state of well-being characterized by high concentration, involvement, control of the situation, perception of high stakes and clear goals, positively balanced mood, and perceived intrinsic reward. It is "a state in which people are so involved in an activity that nothing else seems to matter; the experience itself is so enjoyable that people will do it even at a great cost, for the sheer sake of doing it" (Csikszentmihalyi, 1990, p. 4). A vast literature highlighted that a key prerequisite for flow onset is the perception of high challenges in the task at hand, matched with adequate personal skills in facing them (for a review, see Delle Fave et al., 2011). In the work domain, flow was found to be positively associated with higher work performance (Demerouti, 2006) and positive mental functioning (Csikszentmihalyi, 1997; Csikszentmihalyi & LeFevre, 1989; Fullagar et al., 2017; Llorens et al., 2013). In HRC settings, fostering the onset of flow experiences based on the challenge/skill balance may promote optimal MWL levels, thus preventing workers' exposure to mental overload, derived from the perception of challenges exceeding workers' skills, and mental underload, generated by the perceived lack of significant challenges. By means of their flexibility and adaptability, cobots could be a relevant resource to this aim, as they could become active partners in promoting a functional match between job task challenges and workers' skills, thus supporting human motivation and work engagement. Cobots can be designed to meet both task demands and worker's needs, through the tuning of their speed and motion patterns according to workers' MWL levels, and through enhanced communication features, making HRC a source of optimal experiences. Monitoring a worker's MWL levels and deviations from optimal mental states in real-time can be used by the cobot as trigger to adopt strategies aimed at achieving a better match between task demands and the worker's skills.

Over and above technological implementations, projects aimed to endow cobots with features that may facilitate workers' actions, speed up the pace of work, and promote a better HRC should rely on a multifaceted approach, including industry-specific institutional and regulatory changes, broader policy changes, and workplace organizational efforts (Hammerling, 2022). Interdisciplinary support and counselling may be the most appropriate way to create cobot increasingly able to maximise performance and productivity, at the same time respecting and even promoting humans' mental health.

Almost all the selected physiological data in the industrial context raises ethical concerns regarding privacy and informed consent (McAleenan et al., 2019). The disclosure of these data could convey potential benefits, such as the identification and resolution of workers' health problems before they become more serious; at the same time, however, it could entail the risk of violating workers' rights to privacy and equal treatment, as this information could be used by employers to make decisions about employee performance or promotions, or to discriminate workers based on their health status (Bernhardt et al., 2021). In addition, workers may feel forced to provide their consent to this type of monitoring when, for example, it is presented as a prerequisite for hiring. In order to prevent these problems, workers should get thorough and transparent information about the type of data collected, their use, and the access policy (Bernhardt et al., 2023; Tindale et al., 2022). The implementation of technologies able to gather and understand physiological and behavioural data from human workers is not enough to promote a better HRC; it is also necessary to define clear policies and guidelines on the use of these data (Wullenkord & Eyssel, 2020). Workers should be able to refuse this type of monitoring if they so wish, without negative consequences on their job status; respect for workers' rights to privacy and informed consent should be granted, in order to properly exploit the benefits of this technology in the workplace (Jacobs et al., 2019).

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Notes

1. Statista Research Department. (2021). Collaborative robots' share of the worldwide industrial robot market 2017-2019. Available at: https://www.statista.com/statistics/897655/cobot-industrial-robot-market-share
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Data availability statement

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