Received: 31 August 2021 | Revised: 15 March 2022 | Accepted: 17 March 2022

DOI: 10.1002/hfm.20952

WILEY

Physical and mental well-being of cobot workers: A scoping review using the Software-Hardware-Environment-Liveware-Liveware-Organization model

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Funding information

Horizon 2020 Framework Programme, Grant/Award Number: 847926; Ministero della Salute, Grant/Award Number: Ricerca Corrente 2022 to Dr. E. Biffi

Abstract

The present scoping review investigated the current state of the art concerning factors affecting physical and mental health and well-being of workers using collaborative robots (cobots) in manufacturing industries. Each identified factor was classified using the SHELLO (Software-Hardware-Environment-Liveware-Liveware-Organization) conceptual model. Strengths and limitations of such an approach were outlined. A total of 53 papers were included in the scoping review and analyzed following PRISMA guidelines. In 35 papers at least one risk factor referred to the SHELLO Liveware-Hardware interaction, followed by factors concerning Liveware-Software (16 papers), Liveware-Liveware (11 papers), Liveware intrinsic factor (10 papers), Liveware-Organization (8 papers), and Liveware-Environment (8 papers). This work highlighted that methodological research is still primarily focused on traditional risk assessment and physical safety. However, several research directions concerning the design of cobots as active collaborators were identified, promoting workers' mental health and well-being, too. The SHELLO model proved to effectively highlight human factors relevant for the design of cobots and can provide a systemic approach to investigate human factors in other complex sociotechnical systems. To the best of our knowledge, this is the first time the model is applied in the field of human–cobot interaction.

KEYWORDS

cobots, health and well-being, human robot collaboration, SHELLO model, sociotechnical systems

1 | INTRODUCTION

1.1 | Industry 4.0 and cobots

The Fourth Industrial revolution, also known as Industry 4.0, refers to the profound digitalization and integration of information technologies into traditional manufacturing and industrial practices (Arnold et al., 2016), including internet of things, machine-to-machine communication, cloud-based systems, big data, additive manufacturing, and collaborative robots (Neumann et al., 2021). In this context, the role of human workforce in manufacturing processes is shifting toward supervision and collaboration with these new technologies (Reiman et al., 2021).

One of the most rapidly evolving aspects of this digital transformation is the increasingly advanced collaboration between humans and machines (Yilma et al., 2019). The concept of a collaborative robot, so-called cobot, was introduced two decades ago to describe a device enabling direct physical interaction between humans and computer-controlled manipulators (Peshkin & Colgate, 1999). The first cobots were passive and operated by humans, while modern cobots have evolved taking the form of light–weight robotic arms. Cobots are especially advantageous and most commonly used in assembly tasks, where the high payload and repeatability characterizing traditional robotic systems need to be combined with the skills and flexibility of human operators (Matheson et al., 2019). One of the classifications proposed to describe the different ways in which cobots can work with humans distinguishes four levels of increasing collaboration: coexistence, when operator and cobot only share the same physical space without interaction; synchronization, when operator and cobot share the same workspace, but work at different times; cooperation, when they work in the same workspace at the same time, but on separate tasks; collaboration, when they execute a task together, with one's actions having immediate consequences on the other (Vicentini, 2020). While early cobot implementations often only entailed removal of protective fences, in the near future applications involving full collaboration will increase, with operator and cobot increasing cognitive interaction through human actions and gesture recognition, voice command, and social acceptance (Hentout et al., 2019). In this context, the human operator and the cobot can be described as a dyad, capable of both physical and cognitive interaction (Schmidtler, Knott, et al., 2015). In view of the evolution of human–robot collaboration (HRC), it is necessary to understand the risks and the challenges that workers face when using cobots, in relation to both their physical and mental health and well-being.

1.2 | The role of human factors in workplaces adopting cobots

The complex and nonlinear relationship between work, technology, and health and well-being can be tackled by looking at modern workplaces as sociotechnical systems, where the social, organizational, and technical levels are strongly and dynamically interrelated (Carayon et al., 2015). Human factors and ergonomics (HFEs) studies are aimed at investigating human interactions with elements of these complex systems (Wilson, 2000). HFE is critical in contemporary industrial environments, because human beings are crucial players who allow smooth and physically safe workflows in workplaces filled with increasingly interconnected technologies. Until recently, however, HFE has been substantially overlooked in studies concerning industry 4.0 implementation (Bragança et al., 2019): cobots were primarily designed to promote optimal productivity performance by reducing uncertainty and instability in their cooperation with humans (Oliff et al., 2018), and research in collaborative robotics has been mainly focused on the development of technical solutions to implement human–robot physical interaction, to preserve workers' physical safety (Khalid et al., 2016). One of the most recent and comprehensive literature reviews looking at industrial collaborative robotics from an HFE perspective (Gualtieri et al., 2021) showed that the majority of studies still focus on classic safety issues such as contact avoidance or detection, or focuses on physical ergonomics such as motion planning and task scheduling. Research in cognitive ergonomics has been growing significantly in the last years but few studies were carried out so far.

1.3 | The Software-Hardware-Environment-Liveware-Liveware-Organization (SHELLO) model

In the field of HFE, many models for complex work systems have been proposed. Carayon classified these models based on the way they describe and “slice” these sociotechnical systems: vertically, functionally, or by domain (Carayon, 2006). To successfully describe these complex systems, all these models need to facilitate our understanding of the human–systems interactions.

In this domain, one of the few holistic models proposed to assess risks related to working conditions is the SHELLO (Software-Hardware-Environment-Liveware-Liveware-Organization) model (Chang & Wang, 2010) which is an evolution of the original SHEL model proposed by Edwards, which comprised three components (Software, Hardware, and Environment) interacting with humans, defined as *Liveware* (Edwards, 1972). Software refers to the rules and regulations that govern activities, but also includes procedures and computational code; *Hardware* concerns the physical elements in the setting; and *Environment* describes the physical location in which activities occur. The human being is considered as the core of the model, directly interconnected with the other components. The original model was developed to analyze the dynamics of aviation accidents (Licu et al., 2007). It was subsequently expanded to SHELL model (Hawkins, 1987), with the addition of a second *Liveware* factor referring to the person-to-person interaction, and used to investigate risk assessment and error management in other contexts, such as maritime settings (Chen et al., 2013), nuclear power plants (Kawano, 1997), community pharmacies (Croft et al., 2017), healthcare and rehabilitation services (Molloy & O'Boyle, 2005), industrial and railroad maintenance (Metso et al., 2016; Rizzo et al., 2000). The latest implementation is represented by the SHELLO model (Chang & Wang, 2010), including the Organization component and the Liveware-Organization interaction. As illustrated in Figure 1, the SHELLO model thus comprises a central human component (L) and five related interactions: Liveware-Hardware (L-H), Liveware-Software (L-S), Liveware-Environment (L-E), Liveware-Liveware (L-L), and Liveware-Organization (L-O). The SHELLO model allows for the assessment of risks related to each single component, including organizational issues, but it may also be used for other purposes, for example, to organize findings obtained in studies exploring the impact of introducing collaborative tasks in manufacturing scenarios, as exemplified by a case study conducted in a healthcare setting (Antunes et al., 2008). It may provide a useful conceptual framework to understand the interplay between elements influencing a complex sociotechnical system, including interaction with technology, social aspects, and organizational factors. Like the previous versions, this expanded model considers the human worker as the prominent component of the sociotechnical system, directly interconnected with all other components. We decided to use the SHELLO model as a conceptual HFE model in our work because of its demonstrated flexibility and applicability in many research areas, its holistic approach to risk assessment and its clearly defined interfaces providing the necessary structure to disentangle the many facets of collaborative work between humans and cobots.

1.4 | Aim and research questions

The overall aim of this study was to investigate the current state of the art in the complex and multifaceted research field of physical and mental health and well-being of workers in manufacturing industries, with a specific focus on collaborative robotics. Scoping reviews are a type of knowledge synthesis which can be used in pursuit of various goals, such as examining the extent and characteristics of evidence collected about a certain topic, or summarizing findings from a diversified body of knowledge (Tricco et al., 2018). Based on the overall aim, we performed a scoping review to answer the following research questions:

- Which factors affect physical and mental health and well-being of workers using cobots?
- What are these factors' implications on physical and mental health and well-being?

This study is contributing both to academia and practice: on the one hand, it may supports researchers in finding new topics and systematically address existing gaps in understanding consequences on health and well-being of risk factors during HRC. On the other hand, it may assist occupational health and safety (OHS) professionals in the manufacturing sector by proposing a categorization of risk factors within a sociotechnical system model (the SHELLO) to allow a better understanding of their major OHS issues, improve risk management and reduce risks during HRC.

2 | METHODS

Scoping reviews follow a systematic approach to comprehensively summarize and synthesize evidence from a specific field and are especially useful in emerging areas of investigation (Colquhoun et al., 2014). This study was conducted according to the PRISMA extension for scoping reviews guidelines (Tricco et al., 2018).

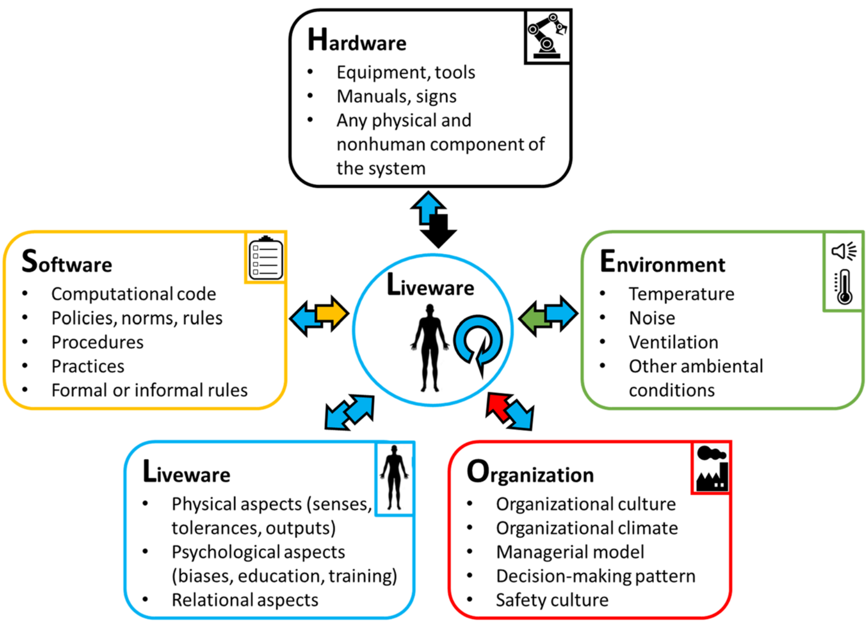


FIGURE 1 The SHELLO (Software-Hardware-Environment-Liveware-Liveware-Organization) model

2.1 | Search strategy

The current scoping review encompassed empirical studies with either qualitative or quantitative data, including conference papers but excluding literature reviews. A comprehensive search for relevant literature was conducted in June 2021 searching titles, abstracts and keywords for a combination of keywords commonly used to describe HRC ("cobots," "cobot," "collaborative robot," "robot"), medical subject headings pertaining to physical and mental health and well-being ("health," "safety," "mental health," "well-being") and terms associated with modern manufacturing workplaces ("industry 4.0," "workplace," "manufacturing," "enterprise"). The detailed search strategy is reported in Table 1. We searched four electronic databases (PubMed, Scopus, PsycINFO, Web of Science). Additional studies were identified through reference searching in various online research repositories and databases, and cross-referencing was applied to all papers, to identify further relevant studies.

2.2 | Inclusion criteria

Articles were considered for inclusion if they: (i) discussed potential factors affecting physical and mental health and well-being of workers in workplaces during HRC; (ii) were written in English; (iii) were published between 1st January 2011 and 30th June 2021, (iv) contained primary data and (v) were available online in full-text.

2.3 | Study selection

Study selection was performed by two independent reviewers. First, titles and abstracts were screened removing duplicates and ineligible records according to the inclusion criteria. Then, both reviewers independently performed a preliminary eligibility check by reading the remaining full-text articles and screening them according to inclusion criteria. To ensure the appropriateness of the identified references, in a second detailed eligibility check both reviewers discussed papers which had not been selected as fitting to reach complete agreement.

2.4 | Data charting and reporting

A data-charting table was developed to determine the variables to be extracted from the included papers. We used a narrative descriptive approach to summarize and report the findings (Mays et al., 2005; Popay et al., 2006). In an iterative process, the reviewers independently charted the data, discussed the results, and updated the data-charting table until they finalized it. The following data were extracted from all papers: references, type of document, type of publication, and identified factors.

Potential factors influencing physical and mental health and well-being of workers were extracted from the qualitative synthesis and sorted into the relevant thematic categories according to the SHELLO Model: Liveware (L) and the five related interactions: L-H, L-S, L-E, L-L, and L-O. We decided to classify factors associated with the social aspects of HRC and interaction between collaborative robots and humans within the L-L interaction. This perspective is in line with research in social robotics, which aims at providing robots with a new set of skills related to natural interaction with humans (Cross et al., 2019). Each factor was also classified as having mainly physical, mental, or both physical and mental health implications for the workers, according to the point of view of the reviewed publications. The final overall classifications were decided through consultation with the review team and by referring to supportive data. It should be noted that the proposed subdivision is in no way univocal.

3 | RESULTS

3.1 | Descriptive data

A flowchart of the review process is provided in Figure 2. Database searching provided a total of 13,678 publications. Following the initial screening phase, 264 full-text papers were obtained. These papers were read and assessed independently by two reviewers. This preliminary eligibility check narrowed the initial list of publications to 141. After a second more detailed eligibility check, a total of 53 papers were selected for inclusion in the scoping review.

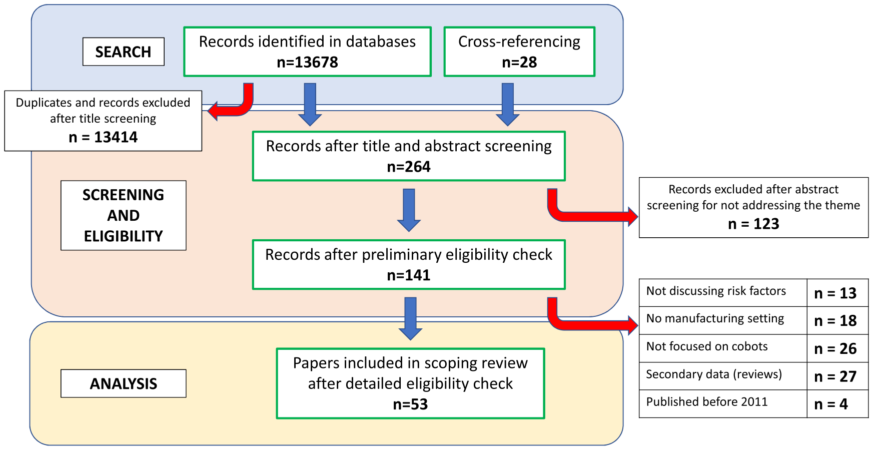
Only three papers published between 2011 and 2014 were included in the study, while paper publication per year increased significantly between 2015 and 2020, with over half of the included papers published from 2019 onwards. As shown in Figure 3, the majority of the documents were full-length journal articles (55%, 29 documents) and the remaining were conference proceedings papers (45%, 24 documents). Regarding the type of research, 36 papers (68%) investigated the topic of interest using an experimental approach to human participants, 17 papers (32%) were focused on methodology and technical issues.

TABLE 1 Search terms used for the scoping review

Word group 1: Robot and cobot	Word group 2: Physical and mental health and well-being	Word group 3: Workplaces
"Cobots" *OR* "Cobot" *OR* "Collaborative robot" *OR* "Robot"	"Health*" *OR* "Safety*" *OR* "Mental health*" *OR* "Well-being"	"Industry 4.0" *OR* "Workplace" *OR* "Manufacturing" *OR* "Enterprise"

Note: *Medical subject headings used in the Pubmed database.

FIGURE 2 Flow chart for study selection



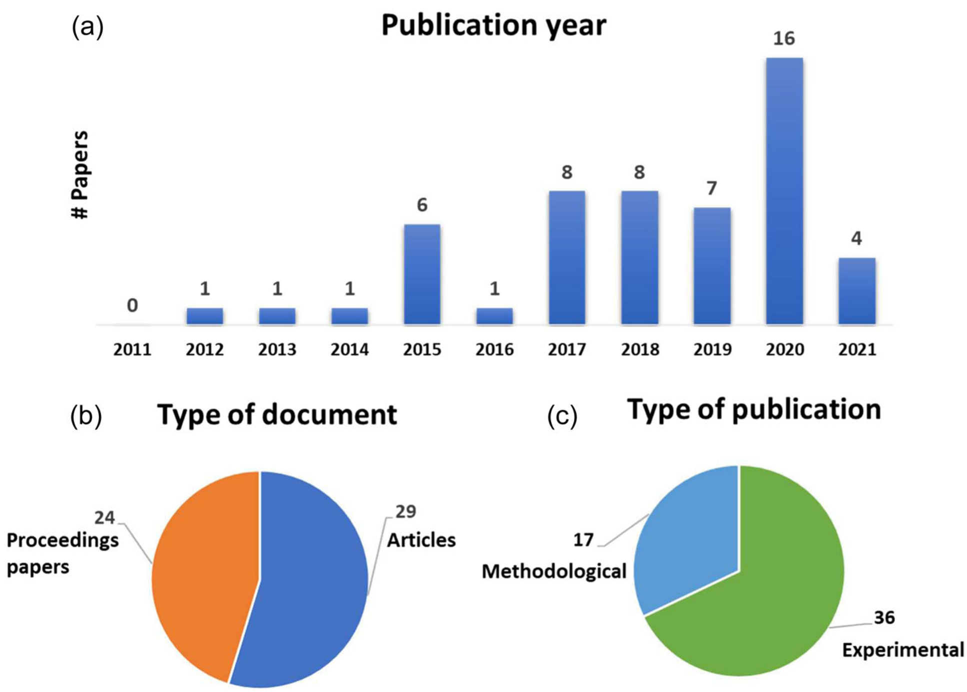


FIGURE 3 Distribution of analyzed papers (a) per year, (b) by type of document, and (c) by type of publication. Numbers in the pie charts indicate the number of papers

3.2 | Risk factors and SHELLO classification

All factors identified in the papers as influencing HRC from a health and well-being perspective were extracted and classified within the SHELLO model (Chang & Wang, 2010). Most of the studies (35 papers, 66.0%) identified at least one risk factor that we classified within the L-H interaction. The second most frequently investigated risk factors were included in the L-S interaction (16 papers, 23.2%), followed by factors associated with the L-L interaction (12 papers, 22.6%) and those associated with the Liveware (L) intrinsic component (7 papers, 13.2%). Finally, the least common risk factors were classified in the L-E and L-O factors (5 papers each, 9.4%). Figure 4 graphically shows paper distribution based on the types of investigated risk factors classified using the SHELLO model: papers dealing exclusively with factors associated with the L-H interaction were the relative majority (26 papers, 49.1%). Only 4 out of 12 papers investigating factors concerning the L-L interaction mentioned other types of factors. By contrast, no papers investigated L-O factors alone without considering any further factors.

3.3 | Risk factors and health

As shown in Figure 5, most papers discussing factors that we classified within the L-H component of the SHELLO model mentioned exclusively their impact on the physical health and well-being of the cobot workers (20 factors, 57.1%). However, there were also papers discussing the impact of L-H factors only on mental

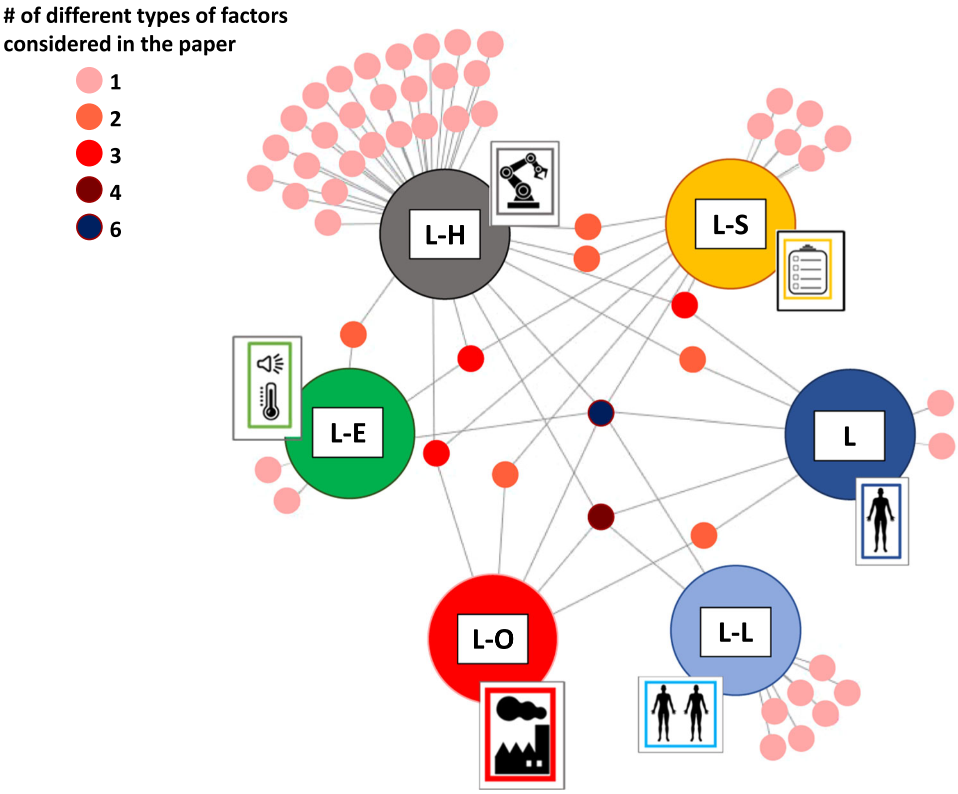


FIGURE 4 Graphical representation of paper distribution based on the type of investigated factors classified using the Software-Hardware-Environment-Liveware-Liveware-Organization (SHELLO) model. Each paper is represented by a small dot. L-H, Liveware-Hardware; L-S, Liveware-Software; L-E, Liveware-Environment; L-O, Liveware-Organization; L, Liveware; L-L, Liveware-Liveware. Image is drawn using Di Venn (Sun et al., 2019) website (https://divenn.tch.harvard.edu/)

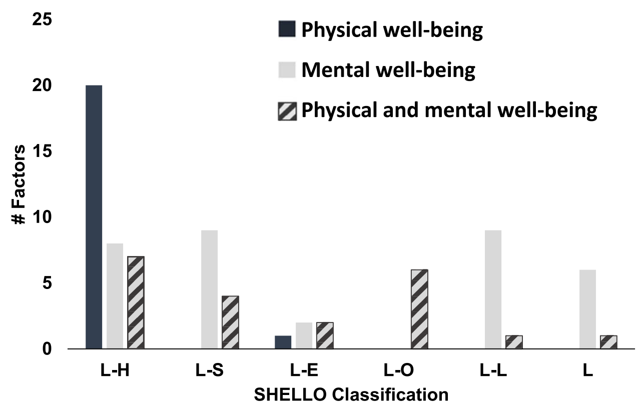


FIGURE 5 Factors identified in the reviewed papers are classified according to as either impacting physical, mental, or both aspects of health and well-being

health and well-being (eight factors, 22.9%), or both physical and mental aspects (7 factors, 20.0%). Factors related to the L-S interaction were associated mainly to mental health and well-being aspects (9 factors, 69.2%), with only 4 factors (30.8%) being associated to physical health and well-being, too. Of the 5 identified factors that were classified within the L-E interaction, 1 factor was associated to physical well-being, 2 factors to mental well-being and 2 factors to both physical and mental aspects. The 6 factors classified in the SHELLO model within the L-O interaction were associated by the authors of the papers as impacting mental health and well-being. Among factors associated to the L-L interaction, 9 factors were associated to the workers' mental health and well-being, while only 1 also mentioned physical implications. Similarly, factors classified in the L intrinsic component were almost exclusively linked to mental health and well-being, with only 1 out of 7 factors which also considered physical implications. A summary of all factors identified in the reviewed papers and classified according to the SHELLO model is shown in Table 2.

3.4 | L-H factors

The L-H interaction described in the SHELLO model is crucial for maximizing safety, as it concerns the relationship between the worker and the physical features. Physical safety of humans during HRC has been extensively investigated as a key aspect of ergonomics and OHS (Vicentini, 2020), and is nowadays incorporated in many industrial regulations and international standards, such as the ISO/TS 15066 (2016), ISO 10218-1 (2014), ISO 10218-2 (2006), and ISO 8373 (2012). In fact, much of the science of ergonomics is concerned with this interface, and, not surprisingly, risk factors associated with this interaction were frequently investigated by papers included in this

TABLE 2 Included studies, investigated risk factors, and SHELLO classification

References	Doc	Pub	Investigated factors	SHELLO components						Well-being component	
				L-H	L-S	L-E	L-O	L-L	L		
Kim et al. (2021)	A	Exp	Excessive torques at shoulder and elbow joints							P	
Rojas et al. (2020)	A	Met	Smoothness and speed of robot arm trajectories								M
Vogel et al. (2013)	C	Met	Safety space around the cobot							P	
Reddy et al. (2019)	C	Exp	Risk of collision							P	
Anand et al. (2018)	C	Met	Presence of the worker in the robot work cell							P	
Mateus et al. (2019)	A	Met	Sub-optimal collaborative assembly sequences							P	M
Mohammed et al. (2017)	A	Met	Collision between the cobot and the human							P	
Long et al. (2018)	A	Met	Trade-off between task efficiency and physical safety							P	M
Leitao et al. (2020)	C	Exp	Gap in technical skills (Artificial Intelligence and Software development) and nontechnical skills (capacity to adapt to new situations, continuous development, problem solving)							P	M
Hietanen et al. (2020)	A	Met	Tradeoff between task efficiency and physical safety							P	
Schmidtler, Knott, et al. (2015)	C	Exp	Background-to-robot-arm chromatic contrasts							P	M
Pang et al. (2021)	C	Met	Injuries due to collisions							P	
Kong and Yu (2014)	C	Met	Risk of collision							P	
Gombolay et al. (2017)	A	Exp	Situational awareness, workload influence, workflow preferences							P	M
Koppenborg et al. (2017)	A	Exp	Robot movement speed and robot movement predictability							P	M
Meissner et al. (2020)	A	Exp	Mental underload due to waiting periods, low speed of the robot, decreased efficiency due to safety restrictions, physical safety, design of the robot							P	M

(Continues)

			Increased dependence to a collaborative workflow, process reliability, adjustability of the robot to tasks		■						M
			Adjustability of the robot to the external environment			■					M
			Organizational change: downsizing, excessive work requirements, trust in executives				■				M
			Less exchange with colleagues					■			M
			Knowledge and experience, trust and interest in robots, personality and moral values						■		M
Biermann et al. (2021)	A	Exp	Robot design (anthropomorphic vs functional)	■							M
Petruck et al. (2019)	C	Met	Arbitrary actions of the robot; low adaptability of the robot's behavior	■						P	M
			Lack of physical ergonomic principles when designing the workplace			■				P	
Oliff et al. (2018)	C	Exp	Disparity in capability between robotic operators and their human counterparts					■		P	M
Eimontaite et al. (2019)	A	Exp	Instructional information through graphical signage		■						M
Pearce et al. (2018)	A	Exp	Task allocation between human and robot, assignments and schedules in human-robot teams		■					P	M
Brun and Wioland (2021)	C	Exp	Collisions with mechanical moving parts	■						P	
			Allocation of attentional resources due to changing role				■			P	M
Fletcher et al. (2019)	A	Exp	Accidental collisions, robot speed	■						P	
			Adaptability of automation/robotics to varying production demands		■						M
			Adaptability of automation/robotics to meet varying environmental conditions (light, noise)			■				P	M

Rosen and Wischniewski (2018)	C	Exp	Production task design features								M
			Job rotation								M
Zhao et al. (2020)	C	Exp	Task interdependence during human-robot teaming								M
Tausch and Kluge (2020)	A	Exp	Task allocation processes and mechanisms during HRI interaction								M
Rajavenkatanarayanan et al. (2020)	C	Exp	Cognitive load due to time constraints during human-robot cooperation								M
Cerqueira et al. (2020)	A	Met	Work-related musculoskeletal disorders due to postures							P	
Hu et al. (2020)	A	Exp	Robot unanticipated physical actions							P	M
Ore et al. (2019)	A	Met	Risk of collision, biomechanical load							P	
Pollak et al. (2020)	A	Exp	Manual and autonomous cobot modes								M
Lindblom and Alenljung (2020)	A	Met	Action and intention recognition between humans and robots								M
Fratczak et al. (2020)	C	Exp	Speed and unexpected movements of the robot								M
Welfare et al. (2019)	C	Exp	Health and safety issues							P	
			Scheduling concerns, task selection								M
			Job displacement								M
Kadir et al. (2018)	C	Exp	Collisions							P	M
			Difficult during task implementation								M
			Distrust of the worker due to lack of flexibility								M
Charalambous et al. (2015)	A	Exp	Communication of the change, employee participation in implementation, senior management commitment and support								M
			Training and development of the workforce								M
Corrales et al. (2012)	A	Exp	Risk of collisions							P	
El Makrini et al. (2017)	C	Met	Movements of the robot								M

(Continues)

			Difficult communication due to noise								M
Elprama et al. (2016)	C	Exp	Amount of social cues used by the cobot								M
Elprama et al. (2017)	C	Exp	Concern of robots taking jobs								M
			Decreased amount of contact with other colleagues								M
Flacco et al. (2015)	A	Met	Risk of collisions							P	
Magrini et al. (2020)	C	Met	Risk of collisions							P	
Marvel and Norcross (2017)	A	Met	Risk of collisions							P	
Messeri et al. (2020)	A	Exp	Impact of leader-follower collaboration strategies on human-cobot team's performance								M
Müller et al. (2017)	A	Exp	Anthropomorphic characteristics of the cobots								M
			Cobot's quality of collaboration								M
Terzioğlu et al. (2020)	C	Exp	Physical appearance, trajectories of the cobot								M
Wurhofer et al. (2015)	C	Exp	Shift in social environment								M
Lasota & Shah, 2015)	A	Exp	Movement trajectories of the cobot							P	M
Etzi et al. (2019)	C	Exp	Kinematic aspects of robot's motion within a human-robot collaboration								M
Kildal et al. (2018)	C	Exp	Physical safety							P	
			Knowledge and training of the workforce								M
Landi et al. (2018)	A	Exp	Sub-optimal human-cobot interaction								M
Mühlemeyer (2020)	A	Exp	Body posture, body movement, manual handling of loads, dynamic muscle workload							P	
			Unchallenging work, repetition of work-tasks								M
			Contact with colleagues								M
			Concentration, visual space and acuity, fine motor skills								M

Sauppé and Mutlu (2015)	C	Exp	Robot's physical appearance, social elements of the robot's design, worker perceptions of the robot and their work together								M
Maurtua et al. (2017)	A	Exp	Risk of collisions							P	

Note: Colors in table 2 are associated to the corresponding interaction of the SHELLO model.

Abbreviations: A, article; C, conference proceeding; Doc, type of document; Exp, experimental study; M, mental health and well-being; Met, methodological study; P, physical health and well-being; Pub, type of publication.

scoping review. The most common factors classified within the L-H interaction were those related to the risk of collisions between cobot and worker. Collision avoidance is a classic research topic, extensively studied by researchers, and promising technologies for preventing human-cobot impacts during HRC activities include virtual fencing systems based on passive infrared sensors (Anand et al., 2018), projection-based safety system (Maurtua et al., 2017; Vogel et al., 2013), augmented environments using computer vision (Mohammed et al., 2017), inertial measurement units combined with global localization systems (Corrales et al., 2012) and depth sensors (Flacco et al., 2015; Hietanen et al., 2020; Magrini et al., 2020). Many papers mentioned generic physical harm or physical safety as a risk factor to be considered when designing collaborative interactions between humans and robots (Kong & Yu, 2014; Marvel & Norcross, 2017; Ore et al., 2019; Reddy et al., 2019), including studies on minimization of injuries if a collision occurs. Injury minimization after an unwanted collision can be pursued through mechanical compliance systems aiming at reducing impact energy or strategies involving contact detection (Pang et al., 2021). Robot speed and movements were also often mentioned as risk factors, potentially impacting on workers' psychological conditions. Excessive physical effort during HRC, leading to musculoskeletal disorders was also mentioned in papers proposing methods to minimize joint loading (Kim et al., 2021) or smart garment for real-time ergonomic risk assessment (Cerqueira et al., 2020). Most of the methodological papers reviewed in the present work mentioned at least 1 of the L-H factors, highlighting that the classic approach concerning physical safety is still very common. However, a growing area of research is also focusing on the psychological consequences of the L-H factors. Especially movement predictability, smoothness, and speed (Etzi et al., 2019; Fratczak et al., 2020; Hu et al., 2020) have been shown to impact on mental health and well-being: methods were proposed to design trajectories allowing for less stressful movements, reducing anxiety and increasing perceived safety (Koppenborg et al., 2017; Lasota & Shah, 2015; Rojas et al., 2020) and to detect stressful situations that may require adapting the behavior of the cobot (Landi et al., 2018). A paper proposing dynamic security zones demonstrated that the system was deemed less stressful by cobot operators with respect to static security zone systems (Long et al., 2018). A recent paper also showed that different (anthropomorphic vs. functional) designs of the cobot may have an impact on trust (Biermann et al., 2021).

3.5 | L-S factors

The L-S interaction represents the relationship between humans and the nonphysical components of the system, such as policies, norms, rules, procedures, checklists, and codes (Rizzo et al., 2000). Most of the factors emerging in the papers and classified within this interaction are related to the design of the collaborative task, which should be performed safely and efficiently, minimizing risks for procedural omissions or mistakes. In this context, experimental studies have proposed optimization frameworks able to support process engineers in generating task assignments balancing both time and ergonomics (Mateus et al., 2019). Studies focusing on psychological aspects of task allocation suggest that autonomy in decision-making increases workers' satisfaction and task identity (Tausch & Kluge, 2022). Thus, increased attentional resources may be needed owing to the changing role of the worker (Brun & Wioland, 2021). An experimental study on workflow preferences during human–robot teaming confirmed that situational awareness might be compromised as the degree of robot autonomy increases (Gombolay et al., 2017). Different cobot modes (autonomous and manual) can also influence psychological and physiological stress in human workers (Pollak et al., 2020). Clear instructional information through graphical signage has also demonstrated its usefulness in positively impacting on user feelings and performance during human-cobot interaction (Eimontaite et al., 2019). Another aspect considered in the reviewed papers is the limited flexibility of the cobot technology in responding to human and environmental inputs. Hence, the creation of adequate standard operating procedures is crucial for improving work efficiency and quality (Kadir et al., 2018; Pearce et al., 2018). Cobots should be designed to favor teaming with the worker, adapting their behaviors both to the performed task and the worker's state, with potential effects on higher productivity as well as higher social recognition (Rosen & Wischniewski, 2018). Another study showed that quality of collaboration also influences stress levels of the human coworker (Müller et al., 2017). This evidence confirms the relevance of designing truly collaborative tasks, where human workers and cobots interact in ways enabling workers to perceive task execution as challenging, motivating, and not frustrating, thus contributing to fostering their health and well-being.

3.6 | L-E factors

The positive and negative effects of the physical environment on job performance and health have been extensively investigated in other contexts (Kegel, 2017; Vischer, 2007). Some papers highlighted that shop-floor conditions such as ventilation, noise, temperature, humidity, and light may represent risk factors during complex HRC tasks (Fletcher et al., 2019). El Makrini et al. identified a potential risk in communication difficulties between the worker and the cobot owing to noise, proposing a novel collaborative architecture for human–robot assembly tasks mainly based on face and gesture recognition (El Makrini et al., 2017). Interestingly, the chromatic contrast of the robotic arm against the background was also investigated as a potential distractor during HRC (Schmidtler, Sezgin, et al., 2015). Research focusing on factors grouped in the L-E interaction suggest the necessity to consider how the introduction of a cobot may produce an inadequate setting that can affect worker's physical and mental health and well-being if these aspects are not considered (Petruck et al., 2019).

3.7 | L-O factors

The L-O interface—the interaction between the worker and the organizational aspects of the system—concerns workload allocation, management of the organizational structure, political environment, financial constraints, resource management, and safety culture (Croft et al., 2017). Previous research has highlighted the systematic oversight of organizational human factors, hindering full exploitation of new technologies (Charalambous et al., 2015). The most common potential L-O risk factors identified in the reviewed papers were related to job displacement, reconfiguration, or loss owing to the introduction of cobots in production lines (Rosen & Wischniewski, 2018; Welfare et al., 2019). An experimental study exploring the relationship between work attributes and automation (Elprama et al., 2017) showed that workers express some concern about robots taking their jobs, but they also acknowledge robots' contribution to reducing their mental and physical workload. Another qualitative experimental study (Meissner et al., 2020) highlighted that employees perceive the introduction of robots as a more drastic organizational change compared to other technologies. Findings from the reviewed papers suggest that the L-O interaction factors play a fundamental role especially in the early stage of cobot adoption, when significant organizational challenges require a transition in the way business is done, ultimately affecting human workers. Comprehensive training programs for the workforce are also proposed, since inappropriate preparation of the employees may negatively affect organizational performance and effective use of the equipment (Charalambous et al., 2015; Welfare et al., 2019).

3.8 | L-L factors

For the purposes of this analysis, the L-L interaction was looked at from two main viewpoints: the effects of the cobot implementation on the social environment, and the potential role of the cobot as a social agent within an extended social environment. Regarding the first facet, the impact of cobots on the relations among colleagues has often been analyzed in the reviewed papers in negative terms, as entailing the risk of reducing human-human interactions, and favoring social isolation (Elprama et al., 2017; Mühlemeyer, 2020; Welfare et al., 2019; Wurhofer et al., 2015). However, this type of socially protected environment might facilitate workers with specific conditions, such as people with autism spectrum disorders (Khalifa et al., 2020). Teamwork dynamics could also be affected with cobots taking the role of team operatives, while humans are engaged in leadership and supervision tasks (Bergman et al., 2019; Messeri et al., 2020; Zhao et al., 2020), or mutual action and intention recognition between human workers and cobots (Lindblom & Alenljung, 2020).

The second facet of the L-L interaction is based on the view of the cobot as a potential coworker, thus capable of socially interacting. In relation to this, the factor that was most frequently investigated in the reviewed papers was the introduction of social elements in the cobot. A study applying principles from character animation to enhance HRC highlighted that social capabilities may increase likeability and perceived sociability (Terzioğlu et al., 2020). In an interesting experimental pilot test in a factory, cobots exhibiting more social cues elicited workers' increased willingness to work with them (Elprama et al., 2016). Another study investigating the effects of social cues in HRC showed that workers in a manufacturing setting rely significantly on social cues to understand the robot's behavior (Sauppé & Mutlu, 2015). It is interesting to note that these social elements do not only have an impact on workers' perceived trust, but may also increase feelings of physical safety and protection (Bergman et al., 2019).

3.9 | Liveware factors

Liveware (L), representing humans and their intrinsic characteristics, is the most flexible component of the SHELLO model (Croft et al., 2017). It includes all factors intrinsically related to the human operator, and not necessarily associated to a specific interaction. In the modern industrial framework, despite high automation, the role of the human worker remains crucial to grant an optimal workflow and avoid unsuccessful implementation of new technologies, which lead people to feel neglected, frustrated, and overpowered (Bragança et al., 2019). The intrinsic factors affecting the Liveware component investigated in the reviewed studies are both physical and cognitive. The most frequently mentioned factors were related to mental processes, especially the ability to adapt to new situations and cognitive load (Rajavenkatanarayanan et al., 2020). Knowledge and training of the workforce are also mentioned (Kildal et al., 2018). An online questionnaire completed by workers from different industries identified soft skills such as continuous development and problem-solving as crucial (Leitao et al., 2020). Meissner et al. suggested that knowledge and experience, trust and interest in robots, personality, and moral values are also important to increase acceptance of HRC in assembly environments. Trust in robots is also a vital aspect of the HRI relationship. Cobot workers should trust the safety strategy adopted during a task, and should also have confidence that cobots will not harm their welfare and interests (Kadir et al., 2018).

4 | DISCUSSION

In the Industry 4.0 era, manufacturing enterprises are facing the challenge of aligning themselves to a new digital transformation without moving the human worker from the central role he/she deserves. We reviewed existing literature with the aim of investigating the state of the art related to physical and mental health and well-being of workers interacting with collaborative robots. We identified a list of factors discussed in recent publications, and we provided a sociotechnical systems perspective by proposing a possible classification using the SHELLO model. As confirmed by recent literature on HFE, such a socio-technical perspective may help to overcome the traditional techno-centric approach to HRC, focused mainly on physical and safety-related aspects and less on the implications related to the nature of the collaborative work, where the "coagency" is the unit of analysis (Adriaensen et al., 2021).

Recent reviews in the field of HFE and cobot implementation have focused on specific interactions which take place in socio-technical systems: for example, two reviews focused on the applications and features of HRC from a task planning and operations management perspective, that we classified as L-S interaction (Hashemi-Petroodi et al., 2020; Tsarouchi et al., 2016). Another review demonstrated that HFE issues are rarely considered as requirement when designing collaborative robotic workstations, suggesting that further work should be undertaken to create a comprehensive framework to allow an assessment of both physical and mental workload during human-cobot interaction (Cardoso et al., 2021). Several authors reviewed methods to ensure physical safety in industrial HRC applications (Reddy et al., 2019; Robla-Gomez et al., 2017), without considering aspects related to mental health. Matheson et al. (2019) identified 35 case studies of industrial applications, grouping them into three broad categories based on their focus: productivity, safety, or human–robot interaction. A further classification of research themes in industrial collaborative robotics was performed by Hentout et al. (2019), who grouped the reviewed papers into 7 categories and 39 subcategories ranked from an architectural vantage point, including safety, and cognitive human–robot interaction. A review focused on poorly designed human-machine interactions as potential risk factors for emotional and mental stress (Robelski & Wischniewski, 2016), suggesting that future research should focus on a detailed description of human–machine systems to gain a comprehensive understanding of their interactions. In one of the most recent and comprehensive reviews, Gualtieri et al. (2021) looked at emerging themes in safety and ergonomics in industrial collaborative robotics, identifying risks such as contact avoidance, detection and mitigation (L-H factors), task scheduling, and motion planning (L-S factors), minimization of work-related psychosocial risks including acceptability of the collaborative systems by human coworkers. The authors conclude that the most developed research category is safety, even though cognitive and organizational ergonomics have been growing significantly in the last years. This has been confirmed by a recent experimental study looking at human factors during the implementation of cobots in distribution centers, focusing specifically on resistance to change, organizational culture, and leadership (Lambrechts et al., 2021).

Looking at the larger picture of Industry 4.0, a review highlighted that most articles focus on the technologies driving this revolution, rather than on worker's health and safety: Kadir et al. (2018) applied a broader search for contributions in the field of HFE applied to Industry 4.0 and found that only a minority of the 40 papers reviewed were journal articles. Our review, too, included a significant number of conference proceedings, confirming that the quality of literature looking at mental and physical aspects of HRC is still growing (Kadir et al., 2018).

Compared to the mentioned reviews, our study classified all identified factors into a model such as the SHELLO to provide a more comprehensive picture of the sociotechnical system in which the HRC occurs. Our grouping is in no way univocal but it allowed to identify which aspects received greater attention in the scientific literature. Our review confirms that safety issues related to the physical interaction with the cobot, which we classified into the L-H SHELLO interaction, are the predominant topic. However, a growing research area on motion planning and predictability and its influence on the psychological state of the worker has also emerged. We also showed that there is a need for more research into factors affecting mental health and well-being, which are still poorly investigated and mostly address the remaining SHELLO interactions. The systemic human factors approach given by such a socio-technical perspective provides insights for the design, implementation and operation of cobot systems that may not be achieved through traditional nonsystemic methods.

4.1 | The SHELLO model: Value and limitations

The SHELLO model helps to identify and examine the individual psychological and behavioral elements that play an important role in complex sociotechnical systems (Croft et al., 2017; Metso et al., 2016). This global and systemic investigation approach is in line with the Reason model of error (Reason, 2000), highlighting the complexity of human–system interactions (Molloy & O'Boyle, 2005).

The SHELLO allowed to achieve a further aim of this study, which was to establish how the classification of within- the model factors would relate with the implications for physical and/or mental health that were discussed in each of the reviewed papers. Our findings suggest that factors associated to the interaction between the human operator and the physical components of the system (the L-H interaction) are predominantly investigated in view of their impact on physical safety and are still influenced by a classic "hard-safety" approach, while factors classified in all other SHELLO components were predominantly associated to mental and psychological health and well-being.

We also identified drawbacks and limitations concerning the use of the SHELLO model. The classification of factors was not always straightforward, and considerable discussion was needed to reach a consensus among authors regarding some of these factors. In addition, the aspect of social interaction between the cobot and the worker was hardly classifiable using the classic SHELLO subdivision. We decided to extend the definition of *Liveware* to include this facet, but we acknowledge the potential limits of such approach. Finally, the SHELLO is a broad descriptive model, allowing for a structured classification of data but not providing a systematic methodology to analyze and sort the classified factors.

Further limitations of the present work concern methodological aspects. The search strategy could be improved by including the terms "human factors" and "ergonomics" to better address HFE aspects. In addition, the use of the term "Industry 4.0" as an alternative for within the word group associated to workplaces may be misleading since it is not strictly synonym, but rather a phenomenon and trend of modern industrial reality.

We also decided to exclude secondary sources such as reviews from the literature search to focus exclusively on the scientific basis provided by primary sources. However, for this reason, some relevant papers may not have been considered in the present review.

5 | CONCLUSIONS

The overall aim of this study was to provide a global view of factors highlighted in the scientific literature as affecting physical and mental health of workers during HRC, by taking into account social and organizational aspects, too. In the current scenario of human–cobot interaction and collaboration, our work confirmed that methodological research is still primarily focused on traditional risk assessment and physical safety, which are major issues for cobot producers and users. However, the present scoping review highlighted several research directions concerning the design of cobots as active collaborators which also promote workers' mental health and well-being. We believe that the systemic approach characterizing the SHELLO model can be useful for the classification of factors affecting workers' health in modern industries using cobots, and can assist researchers in finding new topics and systematically addressing existing gaps.

ACKNOWLEDGMENTS

The project leading to this review has received funding from the European Union's Horizon 2020 research and innovation programme, under grant agreement No 847926 (Mindbot: Mental Health promotion of cobot Workers in Industry 4.0). This study was also supported by the Italian Ministry of Health (Ricerca Corrente 2022 to Dr. E. Biffi).

DATA AVAILABILITY STATEMENT

The data that supports the findings of this study are available in the supplementary material of this article.

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How to cite this article: Storm, F. A., Chiappini, M., Dei, C., Piazza, C., André, E., Reißner, N., Brdar, I., Delle Fave, A., Gebhard, P., Malosio, M., Pena Fernández, A., Štefok, S., & Reni, G. (2022). Physical and mental well-being of cobot workers: A scoping review using the Software-Hardware-Environment-Liveware-Liveware-Organization model. *Human Factors and Ergonomics in Manufacturing and Service Industries*, 32, 419–435. https://doi.org/10.1002/hfm.20952