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Human factors and cognitive ergonomics in advanced industrial human-robot interaction

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Human factors and cognitive ergonomics in advanced industrial human-robot interaction

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Table of contents

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Editorial: Human factors and cognitive ergonomics in advanced industrial human-robot interaction

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Editorial on the Research Topic
Human factors and cognitive ergonomics in advanced industrial human-robot interaction

1 Introduction

Collaborative robotics is a very promising technology for many industrial processes, including e.g., manufacturing, logistics, or construction. This new technology are also changing the environment for workers in industry. Research on human-robot interaction (HRI) will be crucial for enhancing the operator's work conditions and wellbeing, as well as production performance. In that regard, human factors, with a special emphasis on cognitive ergonomics are fundamental to implementing safe, fluent, and efficient collaborative applications.

This Research Topic gathers a range of contributions on the study of Human Factors and Cognitive ergonomics in user-centered and collaborative applications in industrial settings. Here, we summarize these studies from the perspective of three pivotal areas impacted by collaborative robotics: workers' *safety*, *performance*, and *wellbeing*. The Research Topic provides a timely analysis of the changing landscape of industrial HRI as we stand on the cusp of a new era in industrial automation, defined by the fusion of human ingenuity and robotic efficiency. The contributions within offer practical insights and forward-thinking perspectives on how collaborative robotics can transform industrial workspaces in the future, in addition to reflecting state-of-the-art research in the field. A different aspect of this intricate relationship is covered by each article in this Research Topic, from the social and psychological effects of incorporating robots into human-centered work environments to the complexities of design and implementation. Developing solutions that are both technologically sophisticated and human-centered requires a holistic approach, which is crucial for comprehending the complex nature of HRI.

Before delving into the particulars of each contribution, we invite the reader to this brief summary, briefly presenting each contribution to the Research Topic through the lenses of safety, performance, and wellbeing. We hope that this will support reflections on the wider societal implications of HRC development, in addition to their technical and ergonomic aspects. A harmonious balance between human needs and machine capabilities will be key to the future of industry.

2 Safety

In the field of Human Factors and Cognitive Ergonomics, introducing advanced collaborative robotic systems in production environments necessitates reevaluating safety from different perspectives, namely safety perceptions of workers, safety behaviours and mechanical safety. Integrating this technology in various industrial environments, such as manufacturing and logistics, prompts a critical examination of the interplay of the different elements interacting in the socio-technical system. As with any human-system interaction in the work context, a more ergonomic and anthropocentric system (characteristics that can be measured through optimisation of associated cognitive factors) implies greater safety in terms of prevention and mitigation of potential mechanical risk (understood as collisions, crushing, entrapment, etc.) and psychosocial risk as defined by Occupational Safety and Health Administration (OSHA) such as excessive workload, lack of control, job insecurity or insufficient communication. The present Research Topic includes diverse studies, each exploring different aspects of safety in human-robot collaboration.

The contribution by Mirnig et al. constitutes an excellent opening to the Research Topic. While focusing on automated material handling vehicles, Mirnig et al. discuss many design aspects that are applicable also to HRI more broadly, including contextual factors such as purpose and context of use, and many aspects of the interaction itself. The study by Onnasch et al. investigates how directing a worker's attention to specific targets with gaze communication can improve safety in human-robot interaction by, first of all, suggesting how robotic eye design could affect operator attention and perceived cognitive workload. Furthermore, the paper indirectly suggests how robotic eyes could potentially prevent mechanical risks like collisions and entrapments. According to research, an operator's situational awareness and capacity to anticipate and respond to possible hazards are enhanced when they focus on anthropomorphic robot eyes. This study highlights anthropomorphism's contribution to improving operator safety and attention, leading to safer and more conscious HRIs in industrial settings. On the effect of anthropomorphic features in collaborative robots, the paper by Roesler examines the impact of anthropomorphic versus technical framing of robots on operators' trust, particularly in the context of robot failures. The study concludes that although the general levels of trust between technically framed and anthropomorphically framed robots did not significantly differ, people perceived the anthropomorphically framed robots as being more transparent, particularly after understandable failures. Because it improves operators' awareness and skill in anticipating and responding to potential mechanical risks like collisions or entrapments, this increased perceived transparency and positive perception in the event of understandable failures by potentially contributing to increased safety in HRIs. In a complementary way, Freire et al. also addresses the importance of safety in human-robot collaboration, but through a different mechanism. Their proposed cognitive architecture incorporates a "Socially Adaptive Safety Engine," which dynamically adjusts safety parameters like distance and robot speed based on the worker's trust level and preferences. While Roesler's study emphasizes how transparency in robot behavior following failures can enhance safety, Freire et al. go further by actively modifying robot behavior in real-time to adapt to each worker's trust and comfort, creating a more personalized and context-sensitive safety environment. Together, these articles suggest that fostering both transparency and adaptability in robots—through anthropomorphic design and context-aware systems—can significantly enhance operator safety and wellbeing in industrial environments.

In a comprehensive perspective, Heinold et al. discusses various occupational safety and health (OSH) risks and benefits associated with the integration of robotic systems in industrial settings. These include both physical risks, such as collisions and mechanical failures, and psychosocial risks, including mental stress and job insecurity, which can arise from the use of advanced robotics in workplaces. The study also explores opportunities, such as the potential for reducing physical strain and improving long-term physical health by automating physically demanding tasks. The peculiarity of this manuscript lies in its comprehensive analysis of both physical and psychosocial OSH risks and opportunities, uniquely incorporating workers' expectations alongside evidence from the literature, offering a dual perspective on the safety implications of HRI. On a similar note, also addressing logistics and agricultural domains in addition to the manufacturing one, Pietrantoni et al. investigated experts' opinions regarding collaborative robotics safety considerations. Their study emphasized the critical role of tailored safety protocols, highlighting the need for advanced collision avoidance systems, failsafe mechanisms, and emergency stop protocols. Key aspects in agriculture include stability control and navigation on uneven ground for the safety and efficiency of workers. This sectoral approach completes the dual perspective taken by Heinold et al. in that it details how diverse industrial working contexts require tailor-made safety solutions to address both physical risks and ergonomic challenges and further promote the safe integration of robotics into complex work environments.

The impact of human autonomy and robot work pace on job quality in collaborative settings is examined by Van Dijk et al.. They find that higher human autonomy levels correlate with lower perceived workloads. The present article generally addresses some of the main working conditions leading to psychosocial risks according to OSHA, namely excessive workloads, lack of involvement in making decisions that affect the worker, and lack of influence over the way the job is done. This study shows that increasing human autonomy and modifying robot work pace can effectively reduce cognitive and temporal demands on workers. It compares scenarios of human-led work, fast-paced robot-led work, and slow-paced robot-led work. According to these results, reducing workload is linked to a lower mechanical risk because there is a lower probability of mistakes in HRI. This suggests that such measures optimise perceived workload and improve safety in collaborative scenarios.

In the context of an industrial defect inspection task, the article of Cymek et al. examines the phenomenon of decreased individual effort and attention in human–robot collaborative tasks. The study finds that individuals searching for defects with a robot partner may have been less focused and exerted more mental energy than those searching alone, who on average, found more defects. Because less alert workers may be more likely to overlook safety hazards in their environment. This lower level of attentiveness and operational performance in human-robot teams affects productivity and may increase exposure to mechanical risks.

Pluchino et al. examines how collaborative tasks involving robots affect senior workers' mental workload. The article's relevance is critical, considering that collaborative robotics is one of the most promising technology for retaining the ageing workforce and maintaining an appropriate quality of work. It finds that senior workers have a strong acceptance of technology and positive experiences during increased cognitive demand. As a result of increased mental demand during dual-task collaboration, the study found that task errors and duration increased despite these favourable perceptions. This might have detrimental effects on safety behaviours. While senior workers are generally open to working with robots, this increased cognitive workload—as indicated by eye tracking and cardiac activity—indicates that overburdening from collaboration may result in overwork and increase the mechanical risks in the workplace.

3 Performance

For human-robot interaction to be considered successful, assessing and supporting the performance of the system as a whole is of utmost importance. In fact, one might even say that successful performance of the system is a necessary requisite when arguing for its existence. Successful performance can be defined in many different ways but in essence it is the combination of two things; doing things accurately (effective), and being efficient while doing it. In the context of collaborative human-robot settings, this Research Topic investigates relations between human-factors and performance in terms of temporal performance and cognitive load (Van Dijk et al.; Pluchino et al.), collaborative setting and error rate (Cymek et al.), as well as collaborative setting and perceived workload (Van Dijk et al.). While all these papers are mentioned above in relation to safety, they also bring relevant results in relation to performance.

Van Dijk et al. show a positive correlation between temporal performance and cognitive load, comparing two conditions with a fast vs. slow scheduling for the HRC setup. Pluchino et al. analyze the performance in terms of errors and time on task of senior workers engaged in a sequential collaborative manufacturing task together with a cobot. A dual task condition where the subjects were challenged with a secondary mathematical assignment is compared to a single task (control) condition. Results show that the dual task condition lead to increases in both errors and time spent on task, which corresponded with higher levels of perceived mental effort. However, no differences in perceived performance, as assessed by the NASA-TLX questionnaire, were found between the conditions. Cymek et al. compares two versions of an inspection task, one collaborative where a human operator is working together with a robot, and one individual where the operator is working alone. Results show lower performance for the collaborative setting in terms of fewer identified defects during inspection, indicating an reduction in cognitive load compared to the individual condition.

As previously discussed, the effects on performance of different types of collaborative queues are investigated by Onnasch et al.. An indirect argument is made for faster reallocation of attention as a result of naturalistic attentional queues leading to increased performance. This paper also provides a brief argumentation that some queues used to improve collaboration, e.g., legible motion, may directly impact performance in a negative way, while robot eyes does not.

Finally, in their study of technical expert's opinions of HRC also mentioned earlier, Pietrantoni et al. found that the introduction of collaborative robots is expected to bring improved efficiency and better worker conditions, e.g. as a result of automation of physically demanding operations. While the participants in the study generally held a positive attitude towards collaborative robots, the increased efficiency was also linked to concerns of job displacement and the need for reskilling.

4 Wellbeing

A key concern of cognitive ergonomics is to reduce negative effects of work. This also specifically refers to deployed technologies at the workplace, like advanced robotic systems. However, a truly human-centered approach to workplace and technology design aims at developing a person's personality and fostering individual and organizational health in its broadest sense. A holistic understanding of health goes beyond the physical safety of humans, but includes mental and social wellbeing of humans. In the ever-evolving landscape of human-robot interaction, the integration of advanced robotics to different workplaces, raises critical questions about how the wellbeing of individuals might be affected. This Research Topic includes different publications, each shedding light on different facets of human-robot-interaction and its implications for the human experience thus potentially leading to wellbeing in the long-term.

As mentioned earlier, Heinold et al. address the question which psycho-social consequences are associated with a close interaction between humans and robots. By combining scientific perspectives through a literature review and insights from workers' expectations, the study provides a holistic view of the implications of task automation via robotic systems. The findings highlight the psycho-social impacts advanced robotics may have on workers. It becomes clear, that the aspects of task design and function allocation as well as the specific interactions design of systems as well as operation and supervision design are relevant sources potentially affecting the specific user experience and the wellbeing of workers in the long run.

When further considering potential psychological effects, assessing traditional workplace factors can be beneficial. From human factors research it is well understood, that the level of job control or autonomy within a given task is a strong determinant for job quality and wellbeing (Van Der Doef and Maes, 1999). This also applies to industrial tasks (Rosen and Wischniewski, 2019). As working tasks are newly allocated between humans and robots, human autonomy levels can change. The investigation of human autonomy and robotic work pace by Van Dijk et al. discussed earlier is also relevant from a wellbeing perspective. The research underscores the significance of autonomy and work pace in shaping job quality, emphasizing the importance of designing collaborative scenarios that prioritize human autonomy and adjustments to the robot's work pace to optimize workload and enhance overall wellbeing.

Exploring psycho-social effects more on a team level in this Research Topic is done by Cymek et al.. Their contribution focuses on the well-studied phenomenon of social loafing (Cymek et al.). Using a visual-search task, the presented study investigates whether reduced individual effort, the phenomenon in question, which is commonly observed in human teams, also occurs in human-robot teams. The findings suggest that working with a robot team partner may lead to less attentive task execution, highlighting the need to address mental effort and attention allocation in human-robot collaboration to ensure optimal performance and, consequently, wellbeing.

A human-centred technology design can contribute to a positive human-robot interaction and thus ensure a seamless workflow. One very relevant aspect of robot design which is touched upon in research is the application of anthropomorphic design features (Roesler et al., 2021). Two papers of this Research Topic explore the unique effects of anthropomorphic features in human-robot-interaction on different aspect of the distinct interaction quality and user experience. As mentioned earlier, Onnasch et al. examine how the design of predictive robot eyes influences human attention. The results indicate that anthropomorphic features contribute to a smooth interaction experience. Anthropomorphic robotic eyes trigger reflexive attention reallocation, hinting at a social and automatic processing of artificial stimuli, emphasizing the emotional and cognitive impact of such interactions on wellbeing. Through their analysis of anthropomorphic framing discussed earlier, Roesler show that an adequate level of trust within human-robot-interaction is also an important element contributing to a smooth interaction and a human-centered design. In this paper the perceived transparency of anthropomorphic robots emerges as a key factor, underscoring its role in shaping individuals' wellbeing.

A novel design approach in order to facilitate socially adaptive robot behaviour in industrial settings is presented by Freire et al.. The authors present a theoretical cognitive architecture for robotic actions control, highlighting modules that among others take into account human preferences and situational awareness and by thus can adapt to human needs. The presented cognitive architecture is integrated into a recycling plant use case for disassembly tasks showcasing the basic functionalities of the systems. In the piloted use cases, the architecture demonstrated key functionalities, such as turn-taking, personalized error-handling, adaptive safety measures, and gesture-based communication, making collaboration smoother and more efficient. The idea of incorporating human preferences and adapting to human needs already on a robot control level can be a promising way to enhance the overall human wellbeing in human-robot interaction.

5 Conclusion

In conclusion, this topic underscores the importance of Human Factors and Cognitive Ergonomics in the design and implementation of advanced industrial HRIs. The integration of robotics into industrial settings presents both opportunities and challenges, particularly in enhancing safety, performance, and worker wellbeing. Collaborative robotics can improve productivity and alleviate physical strain on workers, but it also raises concerns about psychosocial risks and job displacement.

The studies included in this Research Topic explore various dimensions of HRI, from safety concerns such as mechanical and psychological risks, to the cognitive demands placed on workers in collaborative environments. It highlights the need for designs that balance technological advancements with human-centric approaches, ensuring safety and wellbeing are not compromised in the pursuit of efficiency.

These papers collectively highlight the elaborate dynamics of human-robot interaction and its different facets each potentially contributing to an overall positive and smooth interaction quality which then eventually is related to an individual's wellbeing. These studies emphasize the importance of considering human factors at different stages, not only the design phase but also the implementation stage as well as considering newly designed working tasks carefully to ensure a positive impact on individual wellbeing in the workplace.

Future developments in HRI should prioritize interdisciplinary collaboration to develop solutions that consider both human and machine capabilities, promoting an adaptable, efficient, and safer industrial workspace. As industries evolve, a comprehensive understanding of the interaction between humans and robots will be essential for sustainable and productive future workplaces.

Author contributions

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Conflict of interest

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The potential of robot eyes as predictive cues in HRI—an eye-tracking study

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Robots currently provide only a limited amount of information about their future movements to human collaborators. In human interaction, communication through gaze can be helpful by intuitively directing attention to specific targets. Whether and how this mechanism could benefit the interaction with robots and how a design of predictive robot eyes in general should look like is not well understood. In a between-subjects design, four different types of eyes were therefore compared with regard to their attention directing potential: a pair of arrows, human eyes, and two anthropomorphic robot eye designs. For this purpose, 39 subjects performed a novel, screen-based gaze cueing task in the laboratory. Participants' attention was measured using manual responses and eye-tracking. Information on the perception of the tested cues was provided through additional subjective measures. All eye models were overall easy to read and were able to direct participants' attention. The anthropomorphic robot eyes were most efficient at shifting participants' attention which was revealed by faster manual and saccadic reaction times. In addition, a robot equipped with anthropomorphic eyes was perceived as being more competent. Abstract anthropomorphic robot eyes therefore seem to trigger a reflexive reallocation of attention. This points to a social and automatic processing of such artificial stimuli.

KEYWORDS

human-robot interaction (HRI), attentional processes, joint attention, anthropomorphism, robot design

1 Introduction

Industrial collaborative robots, or cobots for short, interact in direct temporal and physical proximity with a human partner (Restrepo et al., 2017). The accompanying elimination of safety barriers creates new requirements for coordination and action prediction between humans and robots. To date, however, cobots only provide limited information about future motion sequences, making it a hard task for humans to coordinate their behavior around the cobot–especially compared to how easy it is for humans to coordinate their interpersonal behavior. Explicit predictive cues would seem to be a good idea to make the robot's movements easier to understand. Yet, compared to social robots or other service robots, the design space offered by industrial cobots is quite a narrow one, as it is bounded rather by the specifications of the industrial task, performance metrics and a functional design, than by the affordances of a fluent human-robot interaction (HRI). If we want to implement predictive cues, we argue they have to meet at least three requirements. First, their implementation must not conflict with the robot's performance: e.g., Faria et al. (2021) proposed a solution to make robotic movements more legible to the operator, but this was at the expense of extra costs in motion planning. Second, the predictive cues need to fit into the functionalist design scope. Thus, a simple, straight forward approach would come to mind, like the use of arrows on a screen to indicate motion intention of a mobile robot (Shrestha et al., 2016), or projected arrows on the ground (Hetherington et al., 2021). Another design option that has been explored in this regard are moving lightbands to indicate motion intents of a mobile factory robot (Bacula et al., 2020). Third, as industrial human-robot coordination is not the main part of task fulfillment but rather a means to an end, the predictive cues should trigger resource-efficient mechanisms that do not require additional cognitive resources (Neider et al., 2010). This means that humans' attention shifts required to predict the robotic motion should happen as effortlessly as possible, i.e., automatically (Onuki et al., 2013; Khoramshahi et al., 2016). Arrows as indicators for robot movements might not fulfill this requirement as the interpretation of these cues needs an active consideration and therefore additional cognitive resources.

To find a solution integrating all these requirements, we think that functional anthropomorphic features, i.e., abstract forms of anthropomorphism that only aim to mimic certain functional aspects of human-likeness, are a promising suspect (Onnasch and Roesler, 2021). One such feature is the attention directing function of eyes and gaze. In human interaction, eye gaze is a key mechanism to engage in joint attention, which describes an automatic reallocation of one's attention to an object that another individual is attending to (Shepherd, 2010). This, in turn, enables us to understand, predict and adapt to the situation. The automaticity in joint attention is very resource efficient as it does not require an active interpretation of the directional gaze information and thereby does not interfere with other cognitively demanding activities. Accordingly, the implementation of abstract anthropomorphic eyes into robot design might be a resource efficient option to make robot movements more predictable. However, there is evidence that only social stimuli evoke joint attention in contrast to non-social stimuli like arrows (Ricciardelli et al., 2002; Friesen et al., 2004; Ristic and Kingstone, 2005). Whether abstract anthropomorphic eyes like robot eyes, trigger joint attention has therefore been the subject of several studies, which point to a great potential (Admoni and Scassellati, 2017). People have no problems reliably following a robot's gaze (e.g., Wiese et al., 2018; Onnasch et al., 2022), and use it to predict target positions before these are verbalized (Boucher et al., 2012). Even people's decision-making can be influenced by a robot's gaze. Mutlu et al. (2009) and Staudte and Crocker (2008) could show that although participants were told to only consider verbal cues, their attention allocation and object selection was biased by a robot briefly gazing at a certain object. Furthermore, human-like gaze trajectories implemented on a robot's display have the potential to make object handovers of a robotic arm more pleasant and fluid as well as time-efficient (Moon et al., 2014). Similarly, supportive gaze has been shown to improve performance in an interactive map-drawing task and to reduce the cognitive resources required by the human interaction partner (Skantze et al., 2013). However, also detrimental effects of robot eyes are possible when the eyes and according gaze behavior are purely decorative features and do not correspond to the robot's motion (Onnasch and Hildebrandt, 2021). In such cases, implementing abstract anthropomorphic eyes into robot design has the potential to distract people from their main task and to make interaction more difficult instead of supporting it.

Besides the growing body of evidence showing the effectiveness (or at least attention-grabbing effect) of robotic gaze, it is still unclear to what extent it is really automatic, i.e., to what extent abstract anthropomorphic gaze triggers reflexive attentional shifts. For example, Admoni et al. (2011) could not find a reflexive cueing for robotic stimuli. The study used the Posner paradigm (Posner, 1980), an experimental set-up for spatial cueing. Participants had to look at a fixation cross, which was then replaced by a spatial cue indicating the position of a subsequently following target stimulus to which participants had to react by an according key press as fast as possible (see also Figure 1). Results showed that participants could infer directional information from the robot's gaze, but they did not reflexively reallocate their attention to the cued position (Admoni et al., 2011). Other studies suggest an automatic attention cueing of robot gaze (e.g., Boucher et al., 2012). Specifically, Chaminade and Okka (2013) found that both human faces and those of a humanoid robot (Nao) led to automatic attentional shifts, Wiese et al. (2018) showed that eye movements of a social robot (Meka) triggered automatic attention-directing effects, and Pérez-Osorio et al. (2018) successfully replicated the gaze cueing effect using a humanoid robot (iCub). However, it is noteworthy that none of these studies explored an isolated use of eye movements, but a more ecologically typical integration of eye movements, head movements and/or pointing gestures. Some of them (Admoni et al., 2011; Chamindae and Okka, 2013) did not seem to use robots with moving or animated eye parts at all. The specific variance-explaining proportions of gaze thus cannot be determined. Mutlu et al. (2009) investigated the communication of behavioral intentions through robotic eyes without any head movements and found a positive effect of anthropomorphic eyes, but did not include a non-anthropomorphic control condition. Accordingly, it remains unclear whether abstract anthropomorphic robot eyes actually triggered automatic attentional shifts or whether positive effects were only due to the additional information compared to an interaction without any cues.

In summary, empirical evidence seems to favor the assumption of a beneficial effect of abstract anthropomorphic gaze cues. However, given the methodological characteristics of the existing research it remains unclear whether, in line with the cooperative eye hypothesis (Tomasello et al., 2007), eye movements of a robot are sufficient directional cues without head movements or point gestures. Further systematic research comparing anthropomorphic eye stimuli with non-anthropomorphic cue stimuli is therefore needed. In addition, there is a lack of studies specifically for the industrial application area and the associated special requirements mentioned above (functionalist design, straight forward implementation).

According to these requirements, we investigated in a previous study directional stimuli differing in their degree of anthropomorphism to facilitate attentional shifts for the potential use as robot eyes on an industrial robot (Onnasch et al., 2022). The online study used a modified version of the spatial cueing paradigm (Posner, 1980), using either arrows, abstract anthropomorphic eyes or photographed human eyes as directional stimuli. Attentional shifts were measured indirectly as the time from the target

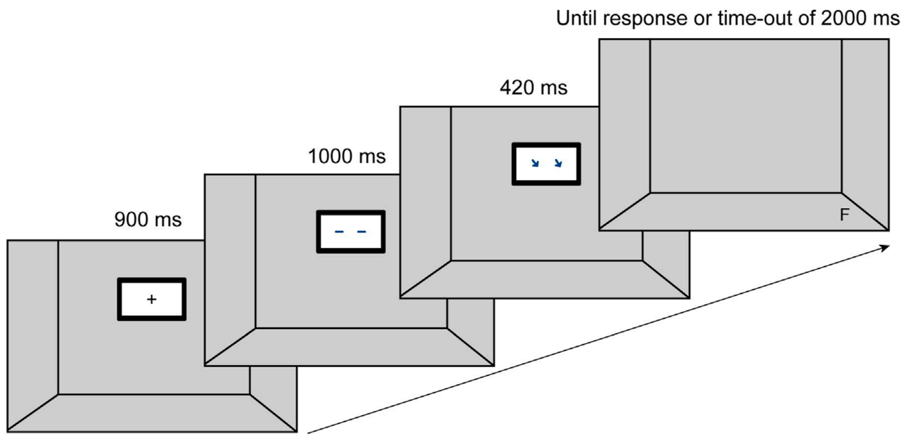

FIGURE 1
Set-up and sequence of events on a given valid trial. (Figure adapted from Onnasch et al., 2022).

onset (in that case the presentation of a single letter) until the according key press. Results supported the assumption that abstract anthropomorphic eyes have the potential to facilitate HRI, as they led to the fastest responses which is indicative for reflexive gaze cueing. Surprisingly and in contrast to hypotheses, the human eyes did not evoke reflexive attentional shifts as evidenced by longer response times. We suspected that the abstract anthropomorphic eyes elicited the desired effects because they were sufficiently human-like and at the same time much easier to perceive than human eyes, with the latter being due to the abstract anthropomorphic eyes' design featuring strong contrasts and clean lines. This is an interesting finding and may prove helpful for designing better HRI. However, to see whether this is in fact a solid basis for further conclusions and actions, those unexpected findings with regard to the superiority of anthropomorphic, non-human eyes, even in comparison to human eyes, call for a validation. Especially, because the implementation as an online-study comes with a lack of control in terms of standardized situational circumstances and hardware (light conditions, distraction, screen resolution, …). Moreover, the measurement of attention was only realized via covert measures in terms of reaction times. Thus, to further strengthen results and the interpretation that abstract anthropomorphic eyes induce reflexive gaze cueing, the aim of the current study was therefore to validate findings of the previous online study (Onnasch et al., 2022) in a highly controlled laboratory environment and to further deepen insights by introducing direct attentional measures via eye-tracking. We investigated how the design of highly abstract anthropomorphic eyes for a potential use on a collaborative robot should look like in order to reflexively trigger attention reallocation to improve the prediction of robot motion.

2 Materials and methods

The experiment was performed with ethical committee approval by the Institute of Psychology, Humboldt-Universität zu Berlin, and in accordance with the Declaration of Helsinki. Informed consent was obtained from each participant. We preregistered the study at the Open Science Framework (osf.io/wue6d).

2.1 Participants

A sample size of N = 80 was defined based on an *a priori* power analysis using GPower (Faul et al., 2007; Faul et al., 2009). Due to COVID-19 induced restrictions we had to halve the sample size and recruited 40 participants via the local online recruiting system of the Institute of Psychology, Humboldt-Universität zu Berlin. Participants either received course credit or a €10 compensation at the end of the experiment. One participant had to be excluded because of technical issues. We therefore conducted data analysis with a sample of N = 39 participants with German as native language or equal language abilities (M = 32.26 years, SD = 10.78 years, 27 females).

2.2 Apparatus and task

The experiment was conducted on a 27″ HD Dell Monitor (1,920 × 1,080 px) which was positioned at a distance of 67 cm to a chin rest. The latter was used to minimize artefacts of head movements for eye-tracking data. The setup was a modified version of a traditional spatial cueing paradigm (Posner, 1980; Figure 1) and corresponded to the setup of the previous online study (compare Onnasch et al., 2022). Each trial began with the presentation of a fixation cross in the center of a depicted display on the computer screen (see Figure 1). After 900 ms, a display appeared with a "gaze" facing to the front. 1,000 ms later the gaze averted to a position where the target appeared after a stimulus onset asynchrony (SOA) of 420 ms,. The target disappeared upon participants' reaction or a time-out of 2000 ms (description taken from Onnasch et al., 2022).

Figure 1 All central cue stimuli as well as the fixation cross were displayed at the subjects' eye level on the screen. The target stimuli appeared in a 3D-like image of a room. It seems noteworthy at this point that we intentionally designed a screen-based experiment instead of one using a real human-robot interaction. This has been done not only to exclude any confounding effects that the HRI might induce, but also to avoid parallax effects by making the angle between robot eyes and target positions, i.e., the stimulus geometry, absolutely invariant. Nevertheless, to increase ecological validity, we modeled the three-dimensional space with target positions in reference to a physical setup of a shared workspace with an industrial robot (Sawyer by Rethink Robotics). We measured the distances between actual target positions, i.e., positions that the robot could reach with its gripper, the robot's display, and the human co-worker. These distances were then scaled down and transferred as parameters into our model, that used HTML, JavaScript and raster graphics to render the virtual set-up. Eight different positions were determined for the target stimuli to appear in the experiment. Six target positions were located below the display on what appeared to be a floor (three positions in a front row, three positions in a back row), two target positions were on the side walls, one left and one right, each in a centered position. Implementing eight different target positions represents a significant change from the experimental gaze cueing setup which is conventionally distributed between two positions or a maximum of four positions (e.g., Admoni et al., 2011). This change was deemed necessary to approximate a real industrial HRI situation, thus further increasing ecological validity. The size of the frame in which the fixation cross and cue stimuli were presented centrally covered 7.91° × 4.81° in angle of view (AOV), which corresponds in its relative dimensions to the display of a Sawyer robot. The size of the display of the stimuli in angular degrees was determined approximately oriented to the mean value of previous studies. The cueing stimuli were either images of human eyes, arrows, or two different versions of abstract anthropomorphic eyes (pixel, cross). Following classical gaze cueing tasks, two black sans-serif letters F and T were presented as target stimuli (e.g., Friesen and Kingstone, 1998). These corresponded to 0.50° AOV in their presented size and were presented at a distance of 13.40°–22.75° AOV from the center of the fixation cross, depending on their position in space. The small size of the target stimuli in combination with the high degree of similarity in the typeface of the two letters was to ensure that no discrimination of the target stimuli was possible in the peripheral field of view. It should be necessary to shift the foveal field of view for task performance in order to trigger eye movements of the subjects. Table 1 summarizes the information on the AOV of the respective elements in the experimental set up.

For recording participants' manual responses to the cue stimuli, the Microsoft Xbox Wireless 1708 controller was used. For the recording of oculomotor movements, the screen-based remote eye tracker model RED500 from iMotion (Senso-Motoric Instruments GmbH, SMI) with a sampling rate of 500 Hz was used. The spatial accuracy of the device amounts to 0.40° for binocular recording, which was also chosen in this study.

2.3 Design

Two variables were systematically varied in the experiment. First, the cues were varied between-subject, representing either

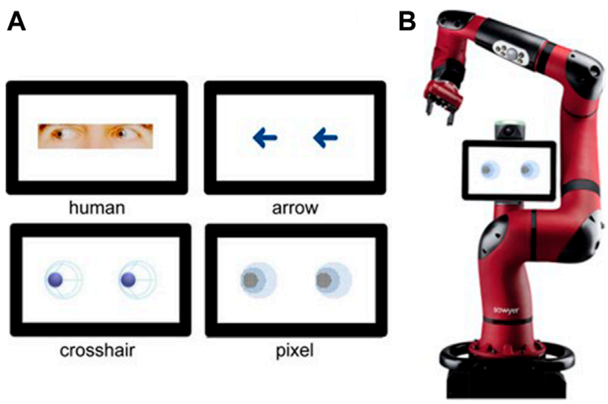

FIGURE 2
(A) The four stimulus types, labelled respectively. The top row includes the human (left) and arrow (right) stimuli. The abstract anthropomorphic robot eyes are presented in the second row. **(B)** Image of the collaborative robot Sawyer used in the questionnaire. In this case, presented featuring the pixel eye design. (Figure adapted from Onnasch et al., 2022).

human eyes, abstract anthropomorphic eyes, or arrow stimuli. For the previous online study, the anthropomorphic eyes were designed striving for a maximum level of abstraction while retaining the essential features of the human eye (e.g., visible pupil-sclera size ratio). This resulted in two different anthropomorphic eye designs, that were both exploratively compared in the online study and therefore also implemented in the current laboratory experiment (cross and pixel design, Figure 2). Second, the trial congruency was manipulated as a within-subject factor. From a total of 304 trials, the target stimuli appeared at cued locations in 80% of the trials (240 trials congruent), while in the remaining 20% of trials the target appeared at uncued locations (64 trials incongruent). The distribution of congruent and incongruent trials was defined with a random number generator and was the same in all four conditions. Overall, this resulted in a 4 (stimulus type) × 2 (trial congruency) mixed design. In the previous online study, a third factor was implemented which investigated the impact of paired vs. single stimulus representations (Onnasch et al., 2022). However, as this variation did not have an impact on reaction times, we decided to discard this factor for the follow up study.

TABLE 1 Summary of AOVs of the different elements used in the experimental set-up.

Element	Size in angle of view (AOV)
Frame representing the display	7.91° × 4.81°
Fixation cross	2.60° × 2.60° AOV
Photograph of the human eyes	5.80° × 1.73°
Arrows	1.58° × 1.50° each
Abstract eyes	2.61° × 2.61° each
Letters	0.50°
Distance between letter and fixation cross	between 13.40° and 22.75°

2.4 Dependent measures

2.4.1 Reaction time

We assessed the reaction times as a covert measure of attention and to evaluate the potential for reflexive cueing of the different stimuli. Reaction times were measured from the target onset to a key press (F or T) on the controller. We only included trials with correct answers (e.g., target F, key press F) as incorrect answers could have biased the results.

2.4.2 Gaze-cueing effect

We calculated the gaze cueing effect (GCE) by subtracting mean reaction times of congruent trials from the mean reaction times of incongruent trials.

2.4.3 Saccadic latency

As an overt attentional measure, saccadic latency was measured. This describes the time elapsing between the appearance of the target letter and the initiation of the orienting saccade away from the cue stimulus. It serves as an indicator of attention directing properties of the cue stimulus and describes how long a disengagement of attention from the cue stimulus took (e.g., Admoni and Scassellati, 2017). Fixations were detected using a dispersion based algorithm with 0.5° and 120 ms as spatial and temporal thresholds. Saccade initiation was defined as the first sample captured outside the fixation area (Nyström and Holmqvist, 2010).

2.4.4 Social attributes

On an explorative basis, we were further interested in how a robot having incorporated the stimulus designs would be perceived. A positive perception of the overall robot design is a crucial precondition for an implementation of such designs in terms of user acceptance. Accordingly, we presented the different stimulus designs as part of an image of an industrial collaborative robot (Sawyer, Rethink Robotics, Figure 2) and asked participants to fill in the Robotic Social Attributes Scale (RoSAS; Carpinella et al., 2017). The RoSAS consists of a total of 18 adjectives and three subscales: warmth, competence and discomfort. Participants have to indicate how closely each adjective is associated with the robot image on a 7-point Likert scale from 1 (definitely not associated) to 7 (definitely associated).

2.5 Procedure

Participants were randomly assigned to one of the four between-subject conditions. Upon arrival at the lab, participants received detailed information about the study and data handling. After giving their informed consent, they received instructions for the experiment and started with two training sessions that familiarized them with the task. The first training comprised 12 trials during which a letter (T or F) appeared centrally on the screen. Participants were instructed to place their index fingers on the directional pads of the controller (left shoulder key for F, right shoulder key for T) and to react upon seeing the letters, using the respective keys. The letter changed its color from white to green upon correct response and from white to red, indicating an incorrect reaction.The aim of this training was to get participants used to the key presses without having to shift their gaze to the controller. During the 40 trials of the second training, participants practiced the experimental task. They were told they would look into a room in which a display was hanging at the back wall (see Figure 1). The appearance of a fixation cross started a trial. After each trial an inter-trial interval of 200 ms elapsed before the next trial began. After completing the second training, the main test procedure started, consisting of 304 trials. The training did not include incongruent trials and participants were not told that there would be incongruent trails during the experiment. The time course followed in each trial of the second training and the test procedure is shown in Figure 1. Upon successful completion of the actual experiment, in a last step, participants were asked to fill in remaining questionnaires (sociodemographics & RoSAS). Only for the RoSAS, we presented a contextualized version of the stimulus design as part of the industrial robot Sawyer (Figure 2). The main test (spatial cueing paradigm) was done without depicting a robot but only a screen featuring the stimulus (Figure 1). The entire procedure took approximately 45 min.

3 Results

The descriptive data for all three dependent variables are reported for each stimulus condition in Table 2.

TABLE 2 Means (and SD) in ms for Reaction Time, Saccadic Latency and Gaze Cueing Effect.

	Reaction time				N
	Cued		Uncued		
Stimulus type	M	SD	M	SD	
Arrow	693.57	51,70	823,67	88,24	9
Pixel	683,28	64,83	802,14	66,81	10
Cross	641,82	66,81	781,23	80,00	9
Human	724,90	76,51	900,05	92,37	11
	Saccadic Latency				N
	Cued		Uncued		
	M	SD	M	SD	
Arrow	287,38	18,44	282,45	21,56	9
Pixel	267,63	21,53	297,29	21,39	10
Cross	273,37	11,17	283,07	19,46	9
Human	293,44	17,99	293,71	18,05	11
	Gaze Cueing Effect				N
	M	SD			
Arrow	133,95	45,55			9
Pixel	124,86	45,55			10
Cross	143,83	46,84			9
Human	181,54	61,14			11

3.1 Reaction time

Results are depicted in Figure 3. Reaction times were longer in incongruent trials (M = 829.89 ms; SD = 97.95 ms) compared to congruent trials (M = 687.82 ms; SD = 70.36 ms). This was supported by a main effect of trial congruency, F (1,70) = 61.91, $p < 0.001$, $\eta_p^2 = 0.469$.

The data also revealed a significant main effect of stimulus type, F (3,70) = 11.78, p = 0.001, η_p^2 = 0.200. In congruent as well as incongruent trials, the human eyes led on average to the longest reaction times (M = 812.47 ms; SD = 122.00 ms). The anthropomorphic cross condition elicited the fastest reactions (M = 711.52 ms; SD = 101.27 ms). No interaction effect was found ($F < 1$).

Bonferroni corrected *post hoc* comparisons showed that only the anthropomorphic cross design (mean difference −100.95 ms, p = 0.001) and the pixel design differed significantly from the human eye stimuli (mean difference −53.85 ms, p = 0.033) whereas no significant difference emerged between human eyes and arrow stimuli.

3.2 Gaze-cueing effect

The mean values for the GCE differed gradually, descriptively decreasing from human stimuli (M = 181.54, SD = 61.14) over anthropomorphic cross design (M = 143.83, SD = 46.84) and arrows (M = 133.95, SD = 45.55) to the anthropomorphic pixel condition (M = 124.86, SD = 45.55). The univariate ANOVA however did

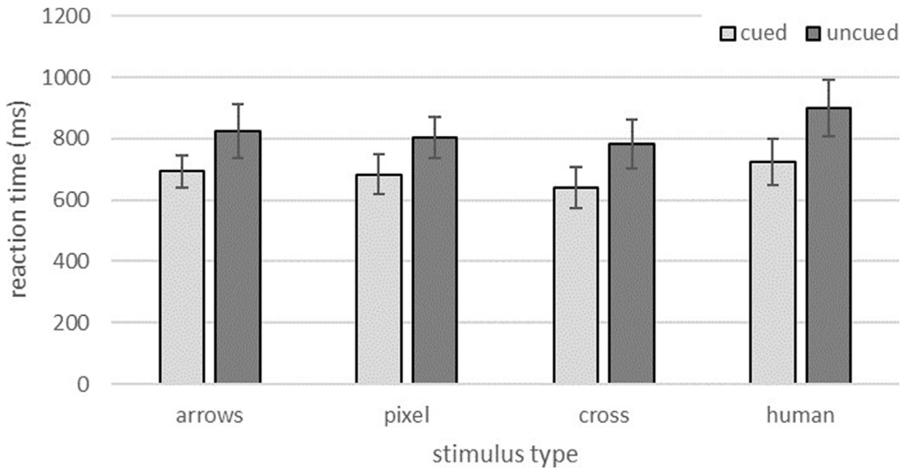

FIGURE 3
Reaction times for cued and uncued trials for the different stimulus type conditions. Error bars represent standard deviations.

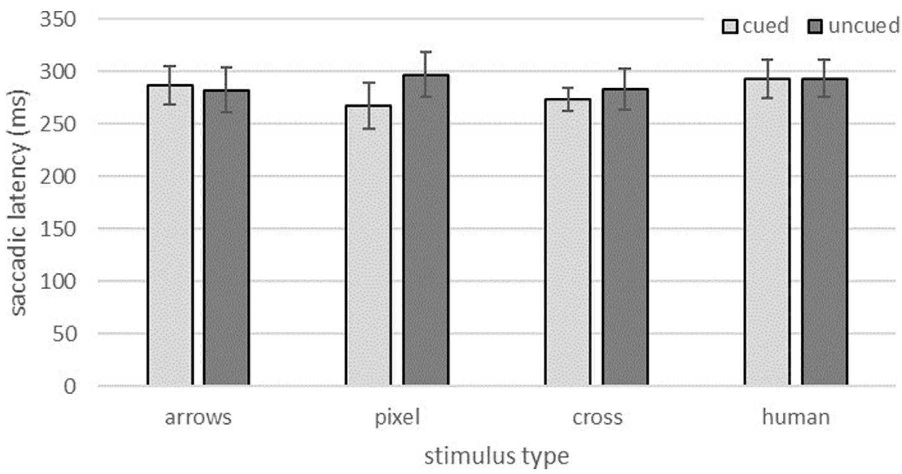

FIGURE 4
Saccadic latencies for congruent and incongruent trials for the different stimulus type conditions. Error bars represent standard errors.

TABLE 3 Cronbach's alpha, mean ratings (and SD) for the RoSAS.

	Warmth		Competence		Discomfort		
Cronbach's alpha	0.85		0.83		0.90		
Stimulus Type	M	SD	M	SD	M	SD	N
Arrow	2.00	0.77	4.77	1.14	2.11	0.86	9
Pixel	3.23	1.21	4.15	1.08	2.85	1.52	10
Cross	3.04	0.74	5.61	0.51	2.00	1.27	9
Human	2.79	1.35	4.88	0.95	2.33	1.08	11

not support this descriptive pattern as no significant main effect of stimulus type was found for GCE, F (3,35) = 2.16, p = 0.110.

3.3 Saccadic latency

Similar to the manual reaction times via key press, human eyes appeared to produce the longest (visual) reaction times in both congruency conditions (Figure 4; $M_{congruent}$ = 293.44 ms; $SD_{congruent}$ = 17.99 ms; $M_{incongruent}$ = 293.71 ms; $SD_{incongruent}$ = 18.05 ms). The descriptive data of the congruent trials also indicated the second longest times for the arrow eyes (M = 287.38 ms; SD = 18.44 ms) and, at some distance, the anthropomorphic stimuli both followed at about the same level with the lowest values (M_{cross} = 273.37 ms; SD_{cross} = 11.17 ms; M_{pixel} = 267.63 ms; SD_{pixel} = 21.53 ms). For incongruent trials, the difference between the arrow condition (M = 282.45 ms; SD = 21.56 ms) and the abstract anthropomorphic eyes (M = 293.71 ms; SD = 18.05 ms) appeared less evident. Overall, saccadic latency plausibly appeared to be independent of trial congruency.

The two-factorial ANOVA did not show a significant impact of trial congruency on saccadic latencies, F (1,70) = 0.94, p = 0.337, but a significant effect of stimulus type, F (3,70) = 4.40, p = 0.007, η_p^2 = 0.159. Bonferroni corrected *post hoc* pairwise comparisons detailed this effect and revealed significant differences only between the human stimuli and the anthropomorphic pixel design (p = 0.006). All other comparisons did not reach significance.

3.4 Social attributes

Results of the RoSAS are displayed in Table 3. On the *warmth* dimension, participants rated the two anthropomorphic stimulus designs highest while arrows received the overall lowest ratings. The ANOVA, however, did not reveal significant differences between the conditions, F (3,35) = 2.33, p = 0.091.

The perceived *competence* subscale showed substantial differences for the stimulus designs, F (3,35) = 3.72, p = 0.020, η_p^2 = 0.242. This was due to the high competence ratings of the cross design. Post hoc tests with Bonferroni correction further showed a significant difference of this design compared to the pixel design that was perceived least competent (p = 0.010).

With regard to the perceived *discomfort* of the overall robot's design, the different stimulus types did not significantly change participants' perception, F (3,35) = 0.93, p = 0.436.

4 Discussion

This study aimed to validate findings of a previous online study on the effectiveness of different directional stimuli regarding reflexive attention allocation (Onnasch et al., 2022) in a highly controlled laboratory environment and to further deepen insights by introducing direct attentional measures via eye-tracking. Both studies investigated how directional stimuli should be designed for a potential use on a collaborative industrial robot to enable human interaction partners to predict the robot's movements in a cognitively efficient way.

As expected, and in line with the previous online study, a congruency effect could be demonstrated for all four stimulus types. Subjects reacted faster to targets that were correctly indicated by the gaze direction of the stimuli (cued trials) than to those indicated in the opposite direction (uncued trials). This means that all stimulus types were essentially able to support the subjects' attentional orientation. Such a congruency effect has been demonstrated several times before for different directional cueing stimuli (e.g., Admoni et al., 2011; Chaminade and Okka, 2013; Wiese et al., 2018).

However, a closer look at the reaction times revealed surprising differences in how efficiently the guidance of the subjects' attention could be supported. Whereas no differences emerged for the GCE, the two abstract anthropomorphic eye designs each resulted in the shortest reaction times in cued trials. The current findings therefore support results from the previous online study, which also revealed the fastest reaction times for the abstract anthropomorphic eyes. In the current study, these findings were further underlined by the subjects' eye movements. For both anthropomorphic stimulus designs saccadic latencies were descriptively shorter compared to the arrows and the human eyes. A significant difference to the human eye design emerged however, only for the pixel design. Results of the current and the online study therefore conflict with studies that consider human eyes to be the strongest stimulus to reflexively direct the visual attention of an interaction partner due to their biological and social relevance (Tipper et al., 2008). The results also contradict studies that observed slower responses in direct comparisons of human and robotic eyes (Bonmassar et al., 2019).

Also, for the uncued trials, either of the anthropomorphic eye designs led to shorter reaction times compared to human eyes, and one of the anthropomorphic designs (cross) produced shorter saccadic latencies. Hereby results differ from the online study. As we did not change the stimuli it is hard to explain why the abstract anthropomorphic eyes supported attentional shifts in both, cued and uncued trials. This pattern of results is in contrast to the key mechanism of reflexive gaze cueing, which should always reveal shorter reaction times in cued trials compared to non-reflexive gaze cueing, but longer reaction times in invalid trials because of the higher effort to disengage attention (Ricciardelli et al., 2002; Friesen et al., 2004; Ristic and Kingstone, 2005). Thus, results still have to be further validated by future research to see whether abstract anthropomorphic eyes are the silver bullet in gaze cueing inducing only beneficial effects or whether the current results for the uncued trials do not represent a valid finding.

As was already discussed in more detail for the online study (Onnasch et al., 2022), the overall slower reactions to the human stimuli might have been due to a lack of saliency compared to the other stimuli because they were smaller (although the overall image size was the same) and less rich in contrast compared to the other cues. But this seems to be only half of the story, because if this was the exclusive driving force for the superior processing of the abstract anthropomorphic eyes then this should have also applied for the chunky, but purely symbolic arrows. Since this was not the case, it seems reasonable that the abstract anthropomorphic eyes combined best of both worlds. The anthropomorphic eye design triggered a social and therefore reflexive processing of the stimuli (Tomasello et al., 2007) while at the same time being easier to perceive than human eyes due the high contrast imagery.

To summarize results on reaction times and saccadic latencies, the findings are in favor of the abstract anthropomorphic eye designs as these eye gaze prototypes performed best in the cueing of attention.

The explorative analyses on the robot's overall perception with the according stimulus prototypes favor an anthropomorphic eye design, too. Whereas no stimulus design discomforted participants, they attributed more competence to a robot with an anthropomorphic cross eye design. The perceived warmth of the robot was not significantly different but again descriptively higher for the anthropomorphic designs.

A clear limitation of this study is the small sample size. We aimed at 80 participants for a sufficient statistical power but had to halve the sample size because of an ongoing lockdown due to the COVID-19 pandemic. Some of the reported results just missed the conventional level of significance, which could have been a consequence of the small sample. Further studies are needed to replicate the current design with sufficient power. Another drawback with regard to transferability of results is that we used a highly controlled computer-based paradigm instead of engaging participants in an interaction with an actual robot. Our results therefore have to be interpreted as a first step to identify directional stimuli for robot design that support humans' smooth attention reallocation in order to improve coordination in HRI. The current study did not represent a real human-robot collaboration. Naturalistic follow-up studies will have to validate the results in a real-world interaction and investigate whether the benefits of abstract anthropomorphic eyes persist and effectively ease the prediction of robot movements. In an actual working situation where people have to focus on other elements (such as assembly tasks), results may differ significantly which underlines the importance of more research. Another point to be considered in future studies is to parametrize and empirically explore the differences between the stimulus designs to better understand the underlying mechanisms leading to the observed effects. Lastly, since the stimulus condition was varied between subjects, no statement can be made about possible interindividual differences.

In sum, the current study supported previous findings of the online study, showing a clear tendency for superior processing of abstract anthropomorphic eyes. Both of the abstract eye gaze prototypes performed well in attentional cueing, yet, as the results were not consistent across all measures, neither of the prototypes stands out in particular. However, one of the designs received higher competence ratings, which makes it seem appropriate for the implementation in work-related settings. These insights on predictive visual stimuli are a first step to translate basic social mechanisms into useful design recommendations to ease the coordination in HRI.

Data availability statement

The raw data supporting the conclusions of this article are available at the OSF (osf.io/wue6d).

Ethics statement

The studies involving human participants were reviewed and approved by The Ethical Committee of the Institute of Psychology, Humboldt-Universität zu Berlin. The patients/participants provided their written informed consent to participate in this study.

Author contributions

LO, PS, and HS contributed to the conception and design of the study. HS collected the data. PS checked the data quality. Data analyses were conducted by LO and HS. All authors LO, PS, and HS contributed to the interpretation of findings. LO drafted the manuscript and LO and PS revised it. All authors contributed to the article and approved the submitted version.

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Conflict of interest

Author PS was employed by HFC Human-Factors-Consult GmbH. HS was currently employed by Land in Sicht—PROWO gGmbH, but was a master's student at Humboldt-Universität zu Berlin during the study implementation. The study was her master thesis which was conducted under the supervision of LO.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Anthropomorphic framing and failure comprehensibility influence different facets of trust towards industrial robots

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Introduction: Utilizing anthropomorphic features in industrial robots is a prevalent strategy aimed at enhancing their perception as collaborative team partners and promoting increased tolerance for failures. Nevertheless, recent research highlights the presence of potential drawbacks associated with this approach. It is still widely unknown, how anthropomorphic framing influences the dynamics of trust especially, in context of different failure experiences.

Method: The current laboratory study wanted to close this research gap. To do so, fifty-one participants interacted with a robot that was either anthropomorphically or technically framed. In addition, each robot produced either a comprehensible or an incomprehensible failure.

Results: The analysis revealed no differences in general trust towards the technically and anthropomorphically framed robot. Nevertheless, the anthropomorphic robot was perceived as more transparent than the technical robot. Furthermore, the robot's purpose was perceived as more positive after experiencing a comprehensible failure.

Discussion: The perceived higher transparency of anthropomorphically framed robots might be a double-edged sword, as the actual transparency did not differ between both conditions. In general, the results show that it is essential to consider trust multi-dimensionally, as a uni-dimensional approach which is often focused on performance might overshadow important facets of trust like transparency and purpose.

KEYWORDS

human-robot interaction, trust, multi-dimensional trust, anthropomorphism, failure experience

1 Introduction

Industrial robots are increasingly working hand in hand with their human coworkers. Hand in hand can be meant literally here, as close collaboration requires physical and temporal proximity (Onnasch and Roesler, 2021). For efficient collaboration, humans have to trust the robotic interaction partner (Hancock et al., 2011; Sheridan, 2016). While human-robot trust research is still an evolving field, trust has been studied extensively in human-automation and human-human interaction, both fields that are strongly related to human-robot interaction (HRI) (Lewis et al., 2018). Most theoretical models of trust in automation as well as trust in humans consider trust as multi-dimensional. For instance, for trust in automation, (Lee and See, 2004), performance, purpose, and process are described as separate dimensions of trust. Even though a transferability of these dimensions to human-robot trust is assumed (Lewis et al., 2018), recent research focused on using single-items of trust (e.g., Salem et al., 2015; Sarkar et al., 2017; Roesler et al., 2020; Onnasch and Hildebrandt, 2021) or uni-dimensional trust questionnaires (e.g., Sanders et al., 2019; Kopp et al., 2022). These approaches are not able to capture different dimensions, and thus cannot contribute much to a more detailed understanding of the underlying determinants of trust and trust dynamics in interaction with robots.

The multi-dimensional trust-in-automation questionnaire (MTQ) originally proposed by Wiczorek (2011) and translated, adapted, and validated by Roesler et al. (2022a) might also be used for investigating trust in HRI. Theoretically, it is based on the concept of Lee and See (2004) and assesses the dimensions performance, utility, purpose, and transparency. This allows for a more fine-grained assessment of trust in order to gain a better understanding of which trust dimensions are impacted from a given characteristic of a robot. Factors on part of the robot that influence trust can be classified as performance- and attribute-based characteristics (Hancock et al., 2011). In particular, performance-based factors such as reliability are the largest current influence on perceived trust in HRI. However, actual reliability is rarely correctly weighted for the formation of trust (Rieger et al., 2022). One decisive factor for this discrepancy could be the type of error experienced in the interaction (Madhavan et al., 2006). In particular, obvious failures made by a robot might dramatically reduce trust as expectations are violated (Madhavan et al., 2006). Based on this *easy-error hypothesis* in human-automation interaction, we hypothesized a comparable pattern in HRI. Thus, we assumed that comprehensible failures that might happen to humans as well are more forgivable than incomprehensible failures.

This effect could even be enhanced by one of the most popular design features in HRI—the application of anthropomorphic characteristics (Salem et al., 2015; Roesler et al., 2021). Anthropomorphism by design refers to the incorporation of human-like qualities and characteristics into the design and behavior of robots (Fischer, 2021). Anthropomorphic design extends beyond mere robotic appearances, encompassing elements such as communication, movement dynamics, and contextual integration (Onnasch and Roesler, 2021). Different factors collectively contribute to shaping perceived anthropomorphism of a robot. Even something subtle like an anthropomorphic framing of a robot can serve as a trigger that activates human-human interaction schemes (Onnasch and Roesler, 2019; Kopp et al., 2022). Due to the activation of humanlike expectations, failures that might have happened to a human as well [i.e., comprehensible failures (Madhavan et al., 2006)] could lead to less pronounced trust decrease in the anthropomorphically compared to the technically framed robot.

In addition to this presumed positive effect, anthropomorphism also comes with it potential pitfalls, especially in industrial HRI. In this application domain, anthropomorphism can undermine the perceived tool-like character of the robot, which can result in lower trust and perceived reliability (Roesler et al., 2020; Onnasch and Hildebrandt, 2021). The results in regard to anthropomorphic framing are currently mixed in task-related interactions (Onnasch and Roesler, 2019; Roesler et al., 2020; Kopp et al., 2022). Whereas studies which combined anthropomorphic framing and appearance in industrial HRI found negative effects (Onnasch and Roesler, 2019; Roesler et al., 2020), another study which investigated anthropomorphic framing without an exposure to an industrial robot found a positive effect on trust (Kopp et al., 2022). However, this was only the case if the anthropomorphic framing was combined with a cooperativeness framing (Kopp et al., 2022). As participants in this study were exposed to an actual robot and no additional framing in regard to the cooperativeness was given, it might be assumed that the possible mismatch of appearance, context, and framing reduces trust (Goetz et al., 2003; Roesler et al., 2022b). Thus, we hypothesized that anthropomorphic framing of an industrial robot leads to lower initial and learned trust compared to technical framing.

To investigate the joint effects of failure comprehensibility and anthropomorphic framing, we conducted a laboratory experiment. Participants collaborated with an industrial robot in a collaborative task. The robot either had an anthropomorphic framing or a technical framing based on perceived human-likeness framings used by Kopp et al. (2022). The dynamics of trust were investigated by measuring trust once initially before the actual collaboration started, after a period of perfectly reliable robotic performance, and after the experience of a failure, which was either comprehensible or incomprehensible.

2 Methods

The experiment was preregistered via the Open Science Framework (OSF) (https://osf.io/nvmqk) and approved by the local ethics committee. Also the collected data can be assessed via the OSF https://osf.io/2vzxj/.

2.1 Participants

The sample consisted of 51 participants (M_{age} = 26.94; SD_{age} = 7.72) who were recruited via the participant pool of the local university and online postings. Of those participants, 50.98% were female, 47.06% male, and 1.96% non-binary. Participants signed consent forms at the beginning of the experiment and received five Euros as compensation at the end of the experiment. Due to time constraints of the project, we were unable to achieve the intended sample size as planned and preregistered. Hence, it is crucial to consider the issue of limited statistical power.

2.2 Task and materials

The aim of the human-robot collaboration was to solve multiple times a four-disk version of the Tower of Hanoi together with the industrial robot *Panda* (Figure 1). In this mathematical game, a stack of disks has to be moved from the leftmost to the rightmost peg by carrying only one disk at a time and never dragging a larger disk on a smaller one in the fewest possible moves. The tower was situated in front of the robot vis-à-vis the participant. The

FIGURE 1
Photograph from a participant's perspective of the shared human-robot workspace (© W. Richter received via https://www.tu.berlin/themen/campus-leben/roboter-mit-fehlern).

required movement sequences of the robot were preprogrammed and included movements in the following chronology. First, the robot moved toward one peg as a sign to remove the top disk from this peg. Subsequently, the robot moved toward another peg as a prompt to place the previously picked disk there. Afterward, the robot moved back to the resting position to start the next sequence. The participant's task was to move the disks by following exactly the robot's directives to solve the Tower of Hanoi in an optimal sequence. Moreover, the participant had the task to monitor the robot's behavior by comparing the steps shown by the robot with an optimal procedure. The participants received a printed copy of the precise instructions of the Tower of Hanoi as can be seen on the table in Figure 1. Whenever the robot deviated from the optimal procedure, the participants needed to intervene by pushing a (mock-up) emergency button.

2.3 Dependent variables

Single items were used to assess general trust (How much do you trust the robot?) and reliability (How reliable is the robot?) both assessed on a scale from 0 to 100. In addition, the MTQ with four subscales (i.e, performance, utility, purpose, transparency) was assessed via 16 items (e.g., *The way the system works is clear to me.*) on a four-point Likert scale from *disagree* to *agree* (Wiczorek, 2011; Roesler et al., 2022a). Both the German and English versions of the questionnaire can be accessed through the OSF via https://osf.io/56cwx/.

To prevent confounding effects of participants' interindividual differences we included two control variables. First, the disposition to trust technology was assessed (Lankton et al., 2015). Second, we asked participants to fill in a 5-item short version of the Interindividual Differences in Anthropomorphism Questionnaire Waytz et al. (2010). The short version comprised solely of items that directly addressed technological aspects (*To what extent does technology—devices and machines for manufacturing, entertainment, and productive processes (e.g., cars, computers, television sets)—have intentions?*).

To test whether the manipulation of anthropomorphism via framing was successful we incorporated a self-constructed questionnaire with ten items that addressed aspects of anthropomorphic context (e.g., the character, task, and preferences of the robot). All items were rated on a 0%–100% human-likeness scale. The manipulation of failure comprehensibility was checked by asking the participants to rate on a five-point Likert scale whether they too could have committed the failure (Roesler et al., 2020).

2.4 Procedure

All participants were randomly assigned to one of the four conditions and received corresponding written instructions including the framing of the robot. After filling out the initial questionnaire compromising single items of trust and perceived reliability, participants were informed that they will be working together with the robot for three blocks each including three Towers of Hanoi. After the first fault-free block, again the single items of trust and perceived reliability were assessed. The next block started and in the second block, either a comprehensible failure (i.e., showing the wrong position of a disc without the violation of rules) or an incomprehensible failure (i.e., showing the wrong position of a disc and breaking the rule of never putting a large disc on a smaller one) occurred. After the failure experience, participants needed to push the (mock-up) emergency button. This was done to ensure that all participants realized the failure. Subsequently, the single items of trust and perceived reliability, the MTQ, sociodemographics, control variables, and manipulation checks were measured. After this, all participants were debriefed and obtained the 5 Euro compensation. The entire experiment lasted approximately 35 min.

2.5 Design

The study consisted of a 2 × 2 × 3 mixed design with the two between-factors robots framing (anthropomorphic vs technical) and failure comprehensibility (low vs high) and the within-factor experience (initial vs pre failure vs post failure).

The different robot framing conditions were implemented via written instructions (Kopp et al., 2022). In the anthropomorphic conditions, the robot was framed as a colleague and named Paul with humanlike characteristics. In contrast, in the technical conditions, the framing characterized the robot as a tool with some technical specifications and the model name PR-5. The framings can also be accessed via the OSF (https://osf.io/3xgcp). The failures were represented by wrong instructions on part of the robot. The comprehensibility was manipulated by the obviousness of the failure. In incomprehensible conditions, the robot suggested moving a bigger disk on a smaller one, which is forbidden by the general rules of the Tower of Hanoi. In the comprehensible conditions, the robot suggested a wrong position of a disk without breaking a general rule.

3 Results

3.1 Control variables

First, the variables regarding the individual differences concerning attitudes toward technology and tendency to anthropomorphize were analyzed between the four conditions using one-way ANOVAs. The analyses revealed no significant differences between the four groups in the disposition to trust technology ($F(3,47) = 1.25$; $p = .303$), as well as the tendency to anthropomorphize ($F(3,47) = 2.48$; $p = .072$).

3.2 Manipulation check

To investigate whether the manipulations were successful, independent t-tests were conducted. Surprisingly, the anthropomorphically framed robot was not perceived as significantly more anthropomorphic on the self-constructed scale compared to the technically framed one ($t(49) = 0.34$; $p = .732$). Moreover, the comprehensible and incomprehensible failures did not lead to a different understandability of the failure ($t(49) = -0.96$; $p = .341$).

3.3 Initial trust

Initial trust and perceived reliability were analyzed in regard to differences between differently framed robots via independent t-tests. The analyses revealed neither a difference in general trust ($t(49) = -0.63$; $p = .529$) nor in perceived reliability ($t(49) = 1.48$; $p = .145$) between the framing conditions.

3.4 Learned trust

General trust and perceived reliability were analyzed via 2 × 2 × 2 mixed ANOVAs with the between-factors framing (anthropomorphic vs technical) and failure comprehensibility (low vs high) as well as the within-factor failure experience (pre- vs. post-failure). The analysis of trust revealed only a significant main effect of failure experience ($F(1,47) = 40.73$; $p < .001$) with higher trust before ($M = 84.75$; $SD = 17.90$) compared to after the failure experience ($M = 64.31$; $SD = 24.65$). No further main or interaction effects were revealed in the analysis (all $ps > .068$). A comparable pattern of results was revealed for perceived reliability. Again, a significant main effect of failure experience was found ($F(1,47) = 71.15$; $p < .001$). Participants perceived the robot prior failure experience ($M = 93.51$; $SD = 8.94$) as significantly more reliable than after failure experience ($M = 66.16$; $SD = 23.65$). No further effects were revealed (all $ps > .349$).

As the MTQ was measured after failure experience 2 × 2 between-factors ANOVAs with the factors framing (anthropomorphic vs technical) and failure comprehensibility (low vs high) were used. Neither the analysis of the performance scale nor the analysis of the utility scale revealed any significant effects (all $ps > .132$). However, the analysis of the purpose scale showed a significant main effect of failure comprehensibility ($F(1,47) = 6.20$; $p = .016$) depicted in Figure 2 (left). Incomprehensible failures ($M = 3.05$; $SD = 0.54$) received significantly lower scores on this scale compared to comprehensible failures ($M = 3.38$; $SD = 0.35$). Moreover, the analysis of the

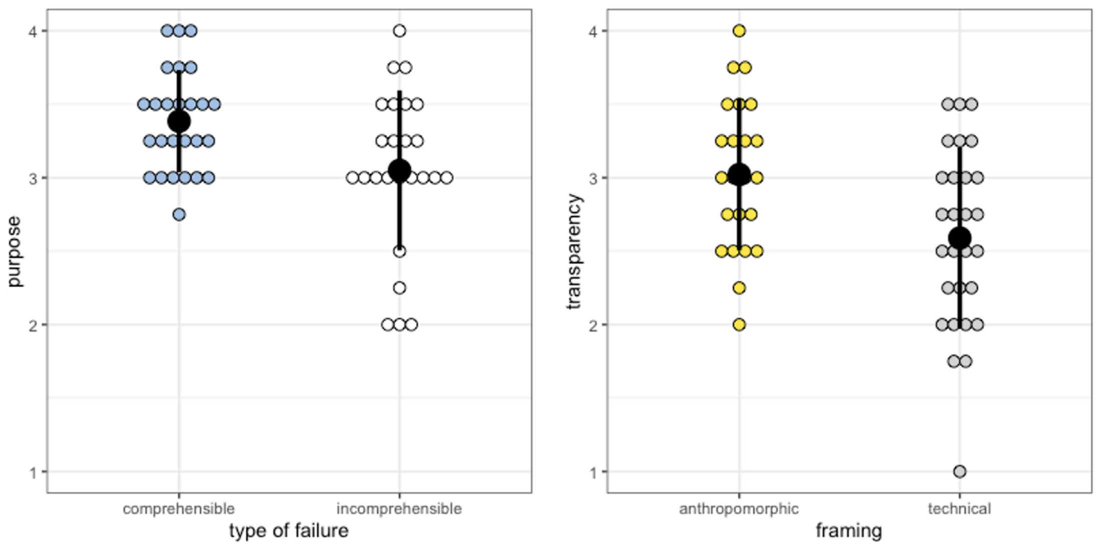

FIGURE 2
Means, standard errors and exact values of each participant for the type of failure concerning purpose (left) and the framing concerning transparency (right).

transparency scale revealed a significant main effect of robot framing ($F(1,47) = 7.08$; $p = .011$) as can be seen in Figure 2 (right). The anthropomorphically framed robot ($M = 3.02$; $SD = 0.52$) was perceived as significantly more transparent than the technically framed one ($M = 2.59$; $SD = 0.62$). No further significant effects were revealed for the purpose and transparency scale (all $ps > .161$).

4 Discussion

The purpose of the presented study was to examine the joint effects of anthropomorphic robot framing and the experience of more or less comprehensible failures on human trust in a realistic industrial human-robot collaboration. Based on previous research in task-related HRI (Onnasch and Roesler, 2019; Roesler et al., 2020; Onnasch and Hildebrandt, 2021) it was assumed that anthropomorphic framing would lead to lower trust and perceived reliability compared to a technical framing. The present results were not consistent with this claim, as no significant differences in initial and learned trust as well as perceived reliability were revealed. This might be explained by the interplay of framing and appearance. Earlier studies in industrial HRI manipulated framing and appearance together (Roesler et al., 2020; Onnasch and Hildebrandt, 2021). The comparison to the current results could indicate that the negative effect of the decorative anthropomorphism in industrial HRI might be mainly attributable to appearance rather than to framing. In addition, recent research of Kopp et al. (2022) showed a positive effect of anthropomorphic framing on trust in industrial HRI if the relation is perceived as cooperative. Even though it often remains unclear if and why people perceive the relation to an industrial robot in a cooperative or competitive manner (Oliveira et al., 2018), our interaction scenario was designed in a cooperative way. This might explain why anthropomorphic framing was influencing at least one facet of trust—transparency.

As anthropomorphism is assumed to activate well-known human-human interaction scripts, knowledge about the otherwise highly unknown novel technology is elicited (Epley et al., 2007). The imputation of human-like functions and behaviors can thus reduce uncertainty and, in this case, increase perceived transparency. Of course, this is a double-edged sword, as perceived transparency does not refer to actual transparency in this case. The illusion of higher transparency might even lead to unintentional side effects, such as a wrong mental model of the robot. In terms of future research, it would be important to consolidate the current findings by further examining the effect of anthropomorphic framing on transparency. However, the general effectiveness of framing in regard to human-robot trust should be interpreted with caution as no significant results were revealed for general trust and the other subscales of the MTQ. This pattern of results is consistent with a current meta-analysis showing no significant effect of context anthropomorphism for subjective as well as objective outcomes (Roesler et al., 2021). However, the meta-analysis has shed light on a notable research gap concerning anthropomorphic context, which has received comparably less attention than studying the effectiveness of robot appearances. The findings of this study, coupled with insights from Kopp et al. (2022) 's previous work, tentatively suggest a potential effectiveness of anthropomorphic framing for industrial HRI in regard to trust. The previous and current results underscore the necessity for further exploration and empirical investigation of possible benefits of anthropomorphic framing in industrial HRI.

Therefore, it might be not surprising that3no interaction effect of framing and failure comprehensibility was found. The possible effect might have been covered by the rather non-salient manipulations of both anthropomorphism and failure comprehensibility. This assumption is further supported by the non-significant manipulation checks for both variables. Nonetheless, the comprehensibility of failures did significantly influence the perceived purpose of the robot. Purpose refers to motives, benevolence, and intentions (Lee and See, 2004) and not to the performance of the interaction partner. This leads to the assumption that failure number and types affect different facets of trust.

Both the result that anthropomorphic framing and failure comprehensibility can affect different dimensions of trust but not general trust shows the importance to integrate multi-dimensional approaches to investigate trust in HRI. Uni-dimensional trust measures most commonly relate to performance aspects (Roesler et al., 2022b). Even though performance-attributes of a robot are one of the most important determinants of trust, they are by far not the only one (Hancock et al., 2011). Therefore, it is highly relevant to also include trust facets that go beyond performance. Thus, future research should include a multi-dimensional view at trust, particularly with novel embodied technologies like robots.

Although the generality of the current results must be established by future research, especially with bigger samples sizes to investigate the joint effect of both factors, the present study has provided clear support that uni-dimensional trust measurements might overshadow certain important facets of trust. Not only was anthropomorphic framing leading to higher transparency compared to technical framing, but more comprehensible failures to more perceived purpose of the robot compared to incomprehensible failures. Furthermore, this research opens up multiple avenues for future research to investigate more detailed different dimensions of trust.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://osf.io/2vzxj/.

Ethics statement

The studies involving humans were approved by Ethics Board of the Institute of Psychology and Ergonomics of the TU Berlin. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

The author confirms responsibility for the following: study conception and design, data analysis and interpretation of results, and manuscript preparation.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Lean back or lean in? Exploring social loafing in human–robot teams

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Introduction: Thanks to technological advances, robots are now being used for a wide range of tasks in the workplace. They are often introduced as team partners to assist workers. This teaming is typically associated with positive effects on work performance and outcomes. However, little is known about whether typical performance-reducing effects that occur in human teams also occur in human–robot teams. For example, it is not clear whether social loafing, defined as reduced individual effort on a task performed in a team compared to a task performed alone, can also occur in human–robot teams.

Methods: We investigated this question in an experimental study in which participants worked on an industrial defect inspection task that required them to search for manufacturing defects on circuit boards. One group of participants worked on the task alone, while the other group worked with a robot team partner, receiving boards that had already been inspected by the robot. The robot was quite reliable and marked defects on the boards before handing them over to the human. However, it missed 5 defects. The dependent behavioural measures of interest were effort, operationalised as inspection time and area inspected on the board, and defect detection performance. In addition, subjects rated their subjective effort, performance, and perceived responsibility for the task.

Results: Participants in both groups inspected almost the entire board surface, took their time searching, and rated their subjective effort as high. However, participants working in a team with the robot found on average 3.3 defects. People working alone found significantly more defects on these 5 occasions—an average of 4.2.

Discussion: This suggests that participants may have searched the boards less attentively when working with a robot team partner. The participants in our study seemed to have maintained the motor effort to search the boards, but it appears that the search was carried out with less mental effort and less attention to the information being sampled. Changes in mental effort are much harder to measure, but need to be minimised to ensure good performance.

KEYWORDS

human–robot interaction, team effects, motivation, social loafing, quality control, sequential redundancy

1 Introduction

Traditionally, robots have worked with little or no interaction with human colleagues for safety reasons. In the automotive sector, for example, the payload and speed of large single-arm robots handling body parts pose a serious risk to human workers. However, there is also an emerging trend to bring humans and robots closer together, both physically and temporally, offering a wealth of new applications (Restrepo et al., 2017). This structural shift from a separate workspace to a shared workspace with cooperative or collaborative facets resembles a paradigmatic change. While the human–robot relationship with conventional robots can be well described as a tool-operator relationship, the relationship with robots designed to work alongside humans increasingly resembles that of human teamwork, including its forms of interaction (Wiltshire et al., 2013; Lewis et al., 2018; Onnasch and Roesler, 2021). Examples of existing human–robot teams can be found in warehouses, where robots and humans work together to pick items for shipping, in complex final-assembly tasks in automotive manufacturing, or in quality control of manufactured goods. While such human–robot teaming can also help to compensate in sectors affected by a shortage of human labor (Wisskirchen et al., 2017), it is most often intended to increase the efficiency and ease of work for human workers (e.g., Lefeber et al., 2017; Neto et al., 2019). Moreover, some robots are specifically designed to complement human skills in order to optimize work outcomes (e.g., Wischmann, 2015). An example of such human–robot interaction (HRI) can be found in the increasingly digitized quality inspection of electronic components. Here, for example, robotic arms are used to scan welds and seams with profile sensors to detect cracks or other defects in the components (e.g., Brito et al., 2020). These systems are getting better and better, with powerful sensor technology that surpasses human vision, especially in terms of endurance, but sometimes also in terms of accuracy. Occasionally, however, these robotic vision systems can miss the finest cracks or mistake small grains of dust or oil residue for very fine cracks. These are conditions that humans can often distinguish relatively well. Using human–robot teams in a way that exploits the complementary strengths and skills of humans and robots therefore has great potential for optimizing work results in this case.

In addition, teamwork can improve work outcomes beyond simply combining complementary strengths. In human teams, where more than one person is responsible for completing a task, several positive effects on individual performance can occur. For example, people show increased levels of effort and performance when performing simple and well-trained tasks in the presence of others compared to when they are alone—a phenomenon called social facilitation (e.g., Triplett et al., 1898; Zajonc, 1965). Positive social-competition effects can also enhance performance in human teams, when individuals want to outperform each other on tasks where individual contributions to the task are recognizable (Stroebe et al., 2018). Such performance-enhancing team effects may also occur in human–robot teams, as it has been found that humans easily perceive computers as team partners (Nass et al., 1996) and tend to apply social rules, expectations, and behavioral patterns from human interaction also to human–computer interaction (Nass and Moon, 2000), such as gender categorization (Perugia et al., 2022; Roesler et al., 2022) or the use of forms of politeness (Liu et al., 2013; Salem et al., 2014; Babel et al., 2022). There are first studies that have investigated social facilitation in HRI (e.g., Woods et al., 2005; Riether et al., 2012; Wechsung et al., 2014; Hertz and Wiese, 2017). For example, Riether et al. (2012) compared task performance on simple and complex cognitive and motor tasks between individuals working alone or in the presence of a human or a robot. The results showed significant evidence for the predicted social-facilitation effects for both human and robot presence compared to an alone condition. This research shows that typical social effects of human groups can indeed occur in HRI as well.

However, in addition to these positive team effects, there can also be losses for teams. A well-studied phenomenon in human teams is social loafing (Latané et al., 1979; Harkins and Szymanski, 1989; Comer, 1995). It is defined as a lower individual effort on a task performed in a team than on a task performed alone (Karau and Williams, 1993). It has been found that this lower effort is not only a consequence of insufficient team coordination, but also of a change in motivation in shared task settings (Steiner, 1972; Ingham et al., 1974). Social loafing is strongly associated with a lower identifiability of individual contributions and reduced evaluation potential in teamwork, leading to a reduction in motivation (Karau and Williams, 1993). This effect is further moderated by factors such as task valence, coworker performance expectations, and uniqueness of individual task contributions (Karau and Williams, 1993). Specifically, social loafing is higher when the evaluation potential is low, when the task has low perceived value, when a coworker performs well on the task, and when task inputs of the group members are redundant. Social loafing in human teams occurs across different task types and group sizes—even in small teams consisting of only two people (Cymek, 2018; Cymek and Manzey, 2022). For example, in a study by Cymek and Manzey (2022), social loafing was found when two people double-checked the quality of chemical products one after the other. When individuals in the second position in the quality check experienced that the first person was working almost error-free, they checked the quality less often over time and therefore missed more undetected defects than individuals who did the quality check alone. This was expected because the individual performance of the preceding team partner was transparent to the person conducting the checks in the second position, so that the latter's effort, which is difficult to decipher from the team's performance anyway, provided only incremental benefit to task completion, thus reducing motivation.

The question of whether this tendency to withhold effort during a collective task with shared output is also relevant to HRI has not yet received much attention. Of course, social loafing may not occur in all forms of HRI. Schmidtler et al. (2015) distinguished three interaction classes of task-related HRI based on working time, workspace, aim, and contact. Coexistence incorporates only a minimum of proximity and dependency. It is characterized by overlapping working time and workspace of the human and the robot. In such a scenario, social-loafing effects should not occur because there is no shared task. Cooperation, in contrast, is additionally characterized by the same aim. Although both parties do not directly depend on each other because of a strict task allocation between humans and robots, the completion of the task by both parties is necessary to achieve the common aim. However, if the outcome of the task is not directly attributable to a particular

FIGURE 1
Experimental environment in the team condition. The white square represents the participants mouse while the red square represents a potential error marked by the robot. In the alone condition, the photo of the robot on the left is missing, the header says "Quality Control", and the images appear without any red mark.

group member, then social loafing becomes likely. The same applies to collaboration scenarios where humans and robots share the same subgoals and overall goals. When collaborating, both parties are dependent on each other's actions and work together to achieve a common task, which again opens up the potential for social loafing (Onnasch and Roesler, 2021).

Onnasch and Panayotidis (2020) have already investigated social-loafing effects in HRI. In this laboratory study, participants performed a speed-accuracy task once alone (while the robot also performed the task separately on its own) and once in cooperation with a human or a robotic team partner. Specifically, participants had to place a certain number and color of cotton balls in a gift bag and then place them in a collection box (which was a shared box in the team settings). According to Nass et al. (1996), this manipulation should be sufficient to induce team building in the team conditions, as a simple but credible clarification of whether one was working alone or together was provided (identity) and as team partners were informed that they were working towards a common outcome and would be evaluated together (interdependence). The authors hypothesized effects of social loafing in both team conditions, i.e., the collective human–human condition and the collective human–robot condition, compared to the alone condition. Furthermore, they assumed that social loafing would be more pronounced in the human–robot condition than in the human–human condition due to a reduced sense of being judged or a pressure to justify their performance level when working with a robot compared to a human partner (lower evaluation potential). While there were no differences in performance between the individual and teamwork conditions for either group in the objective performance data (number of filled bags per six-minute trial and number of incorrect filled bags), the subjective data showed a trend in the hypothesized direction. That is, participants in the robot-teamwork condition subjectively reported exerting the least effort compared to participants working with a human or in the solo condition. The authors suggested that the lack of objective social loafing could be due to insufficiently sensitive performance variables or to a low salience of the team setting.

In the current study, we aimed to further investigate the question of the occurrence of social-loafing effects in human–robot teams. While social loafing in redundant quality control has already been demonstrated in humans (Cymek and Manzey, 2022), we wanted to know whether we would also find social-loafing effects in a quality-inspection task performed by a human–robot team, similar to the one described above for electronic components. If social loafing occurs in such a setting, the expected improvement in outcomes due to the redundant quality inspection may not materialize. In our laboratory study, we compared individuals who performed a quality inspection on circuit boards alone with individuals who processed them in a team with the industrial robotic arm Panda. In the latter condition, people performed the quality inspection after the robot and received the usually correct inspection results from the robot. In order to complete the task, participants had to inspect the circuit boards very accurately for defined defects. We hypothesized that the amount of effort that people put into the quality inspection, in terms of the area of the board they searched and the time they spent searching, would be less when working with the robot than when working alone. This reduced effort, if present, should also be likely to have a direct effect on the

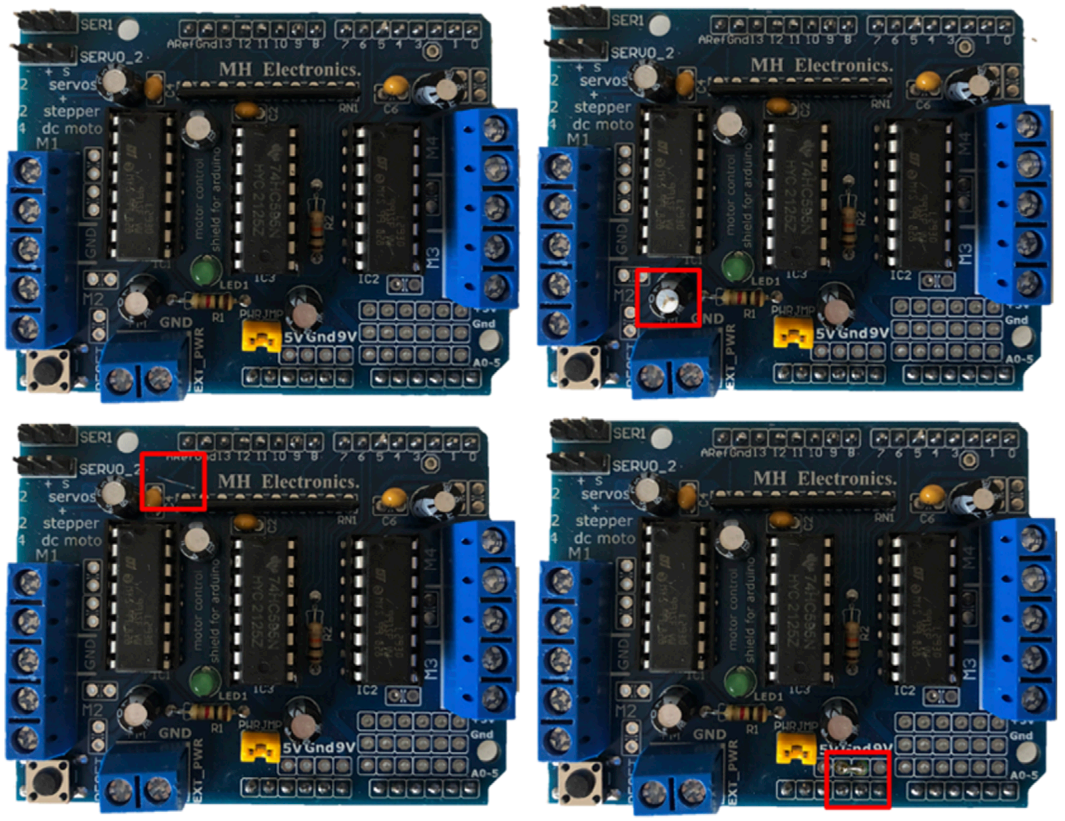

FIGURE 2
Overview of the error types. Top left: no error; top right: capacitator error; bottom left: scratch; bottom right: soldering error.

TABLE 1 Number of defects on circuit boards in each group with correctly marked defects (bold) and unmarked defects (!) by the robot in each block.

Condition block	1	2	3	4
Alone	24	24	24	24
Team	**24**	**24**	**24**	**19** & 5!

detection rate of circuit-board defects, which is why the performance of individuals working in teams with the robot should be worse than that of individuals working alone. Since the individuals working in a team with the robot experienced that the robot made few errors (expectation of high co-worker performance), we assumed that the effort invested should decrease over time due to the low cost-benefit ratio. The study was preregistered on the Open Science Framework and the data are available there (https://osf.io/njz2x/).

2 Materials and methods

2.1 Participants

A total of n = 44 people participated in the study. Based on a G*Power calculation (Faul et al., 2009), the sample size chosen should be sufficient to detect large between-subjects effects and moderate within-subjects and interaction effects in our ANOVAs (α err prob = 0.05, 1-β err prob = .95). However, two participants from the team condition had to be excluded from the data analyses based on prespecified criteria. One did not meet the inclusion criteria because he regularly worked with electronic workpieces, and another marked each robot mark on a circuit-board defect with another mark while not detecting any robot misses, indicating that she did not understand the experimental task. Thus, the final sample included in the data analyses consisted of n = 42 participants. Of these 42 participants, 21 identified themselves as female and 21 as male. All participants were students, had (corrected-to) good vision, spoke German at native-speaker level, and ranged in age from 22 to 30 years (M = 25.55, SD = 2.12). Participants were compensated with course credits.

2.2 Task

Subjects completed a visual-search task that simulated the quality control of circuit boards. Figure 1 shows the user interface of the experimental program. In the center, sets of four circuit-board images were displayed at a time. Each of them contained no, one, or two defects. There were defect capacitors, indicated by a crack in the top of the capacitor, surface scratches, which could potentially affect functioning, and soldering faults, which could potentially lead to short circuits (see Figure 2). The task was to find all of these

TABLE 2 Operationalization of dependent variables.

Dependent variable	Description
Uncovered area	Average percentage of image area revealed on each board per block via the computer mouse
Search time	Average time spent to examine each board with the computer mouse per block
Detection performance	Detection performance was operationalized as the performance in the five trials in which the robot missed defects in the last block
Subjective measures	Subjective rating on a 7-point Likert scale ranging from strongly disagree to strongly agree with the statements:
	"I put a lot of effort into the visual search."
	"I made a little less effort in the course of the search task."
	"I did a very good job on the search task."
	"I felt responsible for the task."

defects. The images of the circuit boards were initially blurred. To judge the images, participants had to reveal parts of the circuit board step by step. This was done by moving a small, white-framed square over the images with the mouse. Only the area within the moving square was sharp and could be evaluated. Participants were told that the "sharpening tool" would help them to focus during their visual search. This mouse-over approach made it possible to capture search behavior and to track how much of the stimulus participants uncovered. The size of the square was set to 20% of the image width. On the right side of the user interface, software functions such as setting a mark (left mouse click), removing a mark (right mouse click), and proceeding to new images (space bar) were displayed as reminders. On the left side of the board matrix, a reference circuit board without defects was displayed. The user interface varied slightly depending on the condition (team vs. alone). In the team condition, participants worked sequentially redundant with a robot that checked the boards first and set red marks around potential defects (see Figure 1, bottom-left quadrant). In the alone condition, participants worked in parallel, but independently of Panda, on different sets of circuit boards and saw no marks. Also, in the team condition, participants read the header "Double-Check", whereas in the alone condition the header said "Quality Control". Last but not least, a picture of Panda was displayed on the left side in the team condition, which was absent in the alone condition.

2.3 Design

The experiment used a 2 (condition) x 4 (block) mixed design. The first factor was varied between subjects and included two different conditions: either participants worked alone (while Panda worked simultaneously on different sets of circuit boards) or in the second position in sequential redundancy with Panda (where Panda worked at the first position and checked the circuit boards first). The second factor block was varied within subjects to investigate whether checking effort and/or possible social-loafing effects were influenced by time on task. All participants saw the same 320 images of scanned circuit boards. These were presented to the participants in four blocks of 80 images each. Each block contained 24 randomly distributed defects. In each block, three images contained two defects and 18 images contained one defect. Participants in the team setting saw all the defects correctly marked by Panda in the first three blocks, but could detect five misses of Panda in the failure block #4. The design is summarized in Table 1. In total, Panda detected 94.8% of the defects correctly during the experiment. Participants that worked alone on the task (with Panda working coactively but independently) did not see any defect marks in any of the four blocks.

2.4 Dependent variables

We defined four dependent variables: uncovered area, search time, detection performance, and subjective measures (see Table 2). The uncovered area is defined as the average percentage of image area revealed on each board per block. Search time is defined as the average time spent to examine each board with the computer mouse per block. Both variables (e.g., uncovered area and search time) are measures of objective task effort. Detection performance was operationalized as the performance in the five trials in which the robot missed defects in the last block. In addition, four subjective variables were measured with a survey that participants had to fill in after completing the task. It collected subjective ratings on a 7-point Likert scale ranging from strongly disagree to strongly agree. Specifically, participants were asked to rate how much they agreed with statements such as "I put a lot of effort into the visual search." and "I made a little less effort in the course of the search task." to learn about the perceived effort and effort over time. The third item measured subjective performance ("I did a very good job on the search task.") and the final item measured subjective responsibility for the task ("I felt responsible for the task.").

2.5 Procedure

The procedure is described in Table 3.

3 Results

3.1 Uncovered area

On average, a large proportion of the images were searched in both groups and across the blocks. The mean percentage of uncovered area varied within a narrow range of 87.5%–92.0%. A

TABLE 3 Procedure.

	Description
Study invitation	Participants were recruited from a university participant pool. Two separate studies were registered: a "Human–robot-collaboration study" (team condition) and a "Visual-inspection study" (alone condition). This was done so that people knew in advance whether or not they would be working with a robot or not.
Entrance	On entering the room, participants walked past Panda's workstation and sat down at a computer workstation that was visually separated from the robot by a partition.
Informed consent	Participants in each condition were informed about the experimental setting and their task, the procedure of the test session, and how the data would be kept anonymous. They then gave their informed consent.
Demographics	A short questionnaire asked for basic demographic information (age, sex, vision).
Group manipulation	Participants were briefly told that they would be inspecting circuit boards for defects and whether they would be working in a team with Panda or alone. In the team condition, participants were told that Panda's results would be forwarded to them for a double check and that they would need to find missed defects or deselect incorrect marks placed by the robot if necessary to achieve the best possible team result. In the alone condition, participants were told that they would be inspecting another set of circuit boards independently of the robot and that they had to find as many circuit-board defects as possible.
Panda demonstration and robot workspace	Panda was then demonstrated in both conditions. The experimenter briefly showed Panda's workstation and participants watched as the robot, holding a webcam in its gripper, (presumably) photographed and inspected a set of nine circuit boards placed on a tray in front of it. The robot moved from one board to the next, pausing about 10 cm above each one, pretending to take a picture of it. After inspecting the last board on a nine-board tray, the experimenter provided the next tray and the robot moved back to the first board position to begin inspecting the new tray. Two boxes were placed next to Panda, one of which, according to the label, contained "new" circuit boards that would be placed in front of Panda during the experiment to be analyzed, and the other of which, according to the label, would be filled with the "inspected" circuit boards. In addition, a cable connected the robot to the computer the participant was working on, to make the connection between the two workstations seem more plausible.
Written illustrated instructions	The participants read the illustrated instructions to familiarize themselves with the different types of defects. They received a printout of a correct circuit board and of three circuit boards showing the different types of defects. This printout was given to the participants to use it as a reference during the task.
Training	Participants practiced the task briefly. When the participants started training, the robot already started working on the task to get a head start. Thus, participants in the team condition did not have to wait for the inspected boards when they later started the experimental blocks. The experimenter stood next to the robot to supply it with new trays of circuit boards. The continuous supply could be heard but not seen by the participants.
Comprehension check	After the training block, participants had to find and mark one of each defect type on a printout to show that they understood the task.
Experiment	Once the experiment started, participants worked on the task for about 90 min without any feedback on their performance. However, the robot only took 30 min to scan all 320 circuit boards and was switched off at the end. After each experimental block, participants were required to take a short break of at least 1 minute to relax their eyes.
Post-task questionnaire	After completing the task, participants completed a post-test survey.
Debriefing	Finally, they were debriefed and told thank you and goodbye.

2 × 3 ANOVA was calculated for the percentage of uncovered area (excluding failure block #4). A highly significant block effect emerged, F (1.29, 51.63) = 12.66, p < .001, η_p^2 = .24, as all participants searched a smaller area with increasing time on task. No effect was found for the factor condition, F (1, 40) = 0.74, p = .395, η_p^2 = .02. As can be seen in Figure 3, participants working with Panda in a team checked a slightly smaller proportion of the images descriptively over time compared to the alone condition. However, the interaction effect of block and condition was not significant, F (1.29, 51.63) = 1.84, p = .180, η_p^2 = .04.

3.2 Search time

A further 2 × 3 ANOVA was calculated to analyze the time spent to search the images. Again, a highly significant effect of the factor block was found, F (1.17, 46.62) = 65.96, p < .001, η_p^2 = .62. No significant effect of the factor condition was found, F (1, 40) = 0.14, p = .708, η_p^2 < .01. The interaction was also not significant, F (1.17, 46.62) = 0.37, p = .578, η_p^2 = .01. Figure 4 shows that mean search time decreased across the blocks but was at the same level in both conditions. Participants took approximately 25 min to search the first block of 80 circuit board images (approximately 19 s per

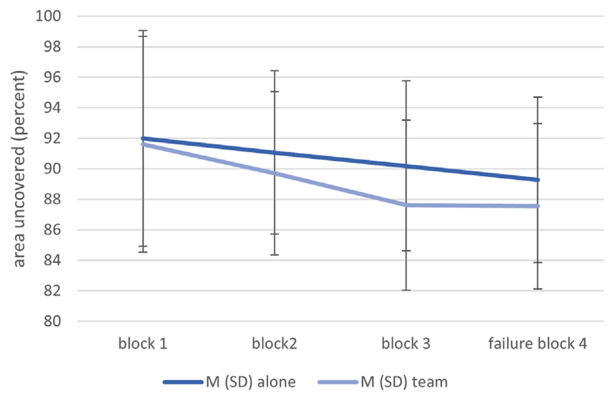

FIGURE 3
Means and standard deviations of the uncovered area in both conditions and across the four blocks.

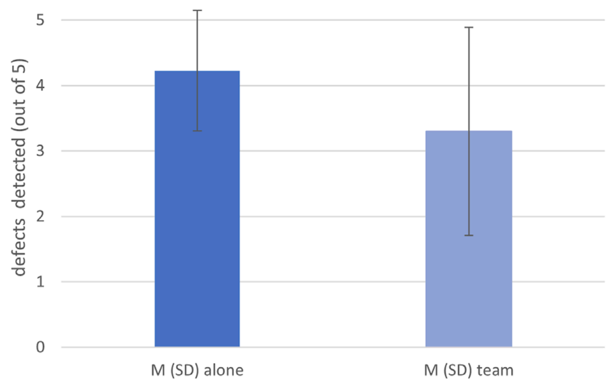

FIGURE 5
Means and standard deviations of detected defects in block #4 in both conditions.

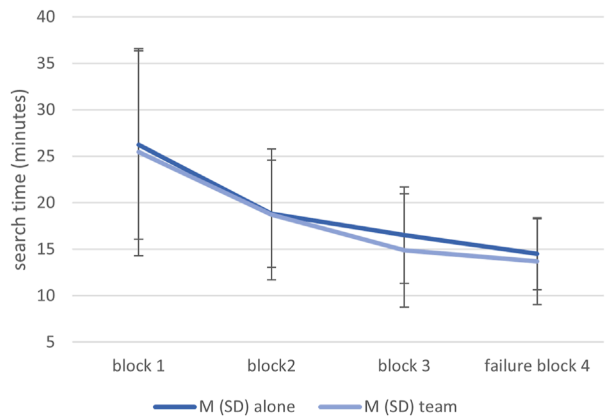

FIGURE 4
Means and standard deviations of the search time in both conditions and across the four blocks.

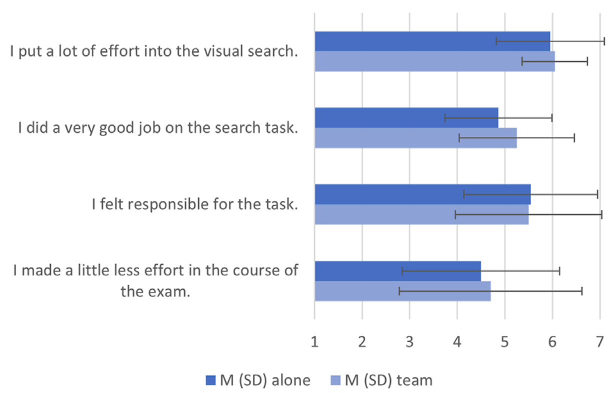

FIGURE 6
Means and standard deviations of subjective ratings in both conditions on a 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7).

image), 20 min for the second block, and 15 min for the third and fourth blocks (approximately 11 s per image).

3.3 Detection performance

In block #4, participants in the team condition could potentially miss five defects that were not marked by Panda. Correct detections out of these five potential defects were compared between the two conditions. In the alone condition, the mean detection rate was M = 4.23 (SD = 0.92), while in the team condition it was M = 3.30 (SD = 1.59) (see Figure 5). Due to non-normal data and unequal variance, a U-test was calculated. The results indicated that participants working in a team with Panda detected significantly fewer defects than participants working alone, $U = 148.5$, $Z = -1.83$, $p = .029$, $r = .292$.

Note that the people working alone also detected 80% of the defects over the whole experiment (M = 19.27 out of 96). The proportion of detected defects is thus comparable between the five trials and the detection performance in the overall experiment for the participants working alone.

3.4 Subjective measures

Simple t-tests were performed on the ratings of each statement. No significant differences were found, all $p > .14$. Figure 6 shows that participants in both conditions strongly agreed that they put a lot of effort into the visual search task, and that both groups thought they did a very good job on the task. They also confirmed that they felt responsible for the task and showed moderate agreement with the subjective reduction of effort over time.

4 Discussion

As interactions with robots increase, it is important to understand and predict the consequences of human interactions with them. Research on social facilitation has already shown that team processes that occur in human teams can be transferred to human–robot interactions and should be taken into account. The present study investigated whether working with a robot partner would lead to social-loafing effects. Therefore, an experiment was conducted in which participants worked either alone or in a team with a robot on a realistic quality inspection task. Our assumption was that the amount of effort people put into the quality inspection, i.e., the area of the board they searched and/or the amount of time they spent searching, would be lower when working together with the robot than when working alone on the quality inspection, similar to findings of redundant quality control in human teams (Cymek and Manzey, 2022). We also assumed that the individuals working in a team with the robot would reduce their effort over time more than the individuals working alone. In case of a more pronounced effort reduction in the team condition, we assumed that this could lead to a lower defect-detection performance of this group.

There were no group differences in the amount of effort invested in the task for any of the objective measures of effort (i.e., uncovered area, search time). At first sight, this suggests that social loafing did not occur in our experiment. Participants in both groups inspected almost the entire surface of the boards and took their time searching. Over the course of the experiment, participants in both conditions uncovered significantly less image area and accelerated their search. The small decrease in uncovered area may be due to learning that there were some areas of the board where defects did not occur. The large decrease in search time can also be explained by a learning effect. In general, the subjects spent a lot of time searching. In the beginning, they looked at a single image for an average of 19 s, which is a very long time. With more practice they became much faster, but still invested about 11 s per image.

The subjective measures of effort were consistent with the objective measures. Participants in both groups reported that they put a lot of effort into the task, that they felt responsible for the task, and that they performed well. In addition, both groups neither agreed nor disagreed with the statement "I made a little less effort in the course of the search task", suggesting that participants were aware that they were speeding up their search as time on task increased but were still quite engaged in the task.

We assumed that a reduction in effort might have an effect on the defect-detection performance. Apparently, we found no differences in our effort measures. However, when we compared detection performance on the five common occasions to miss a defect (the five defects in block #4 that were not marked by Panda in the team condition), we found a significant effect. Participants working alone detected on average $M = 4.23$ ($SD = 0.92$) of these five defects, whereas in the team condition on average a defect less was detected ($M = 3.30$, $SD = 1.59$). There could be several reasons for this disassociation of effort and performance measures. First, it could be that the search speed was too fast to detect the defects. However, this is unlikely as participants in the alone condition searched at a similar speed and found most defects during the experiment (approx. 80% of defects). It could also be that after experiencing a 100% reliable robot for the first three-quarters of the experimental session, participants in the team condition became less suspicious during their search in the last block. It seems as if the participants continued their search routine on the images, as they continued to look at almost the entire circuit board surface. However, they seem to have looked for defects less attentively than the participants who worked alone on the quality inspection.

In the light of these results, we need to consider a phenomenon from a study on cooperation with an automated assistance system. In this study by Manzey et al. (2012), people sampled the information necessary to detect an error, but still did not find it. They also had no idea what the information that had been uncovered actually was. The authors explained this by saying that people looked at the information but did not really process it consciously—in other words, they performed a kind of "inattentive processing" in cooperation with an assistance system. Similar effects have been found in pilots monitoring flight modes in the cockpit. In a study by Sarter et al. (2007), most pilots scanned the mode-annunciator display, but still failed to notice the inappropriateness of the active mode for the current flight context. The authors concluded that the experienced pilots did not process the mode changes thoroughly enough to understand their impact on the behavior of the aircraft. This kind of looking-but-not-seeing effect could have occurred in our experiment as well. Looking but not seeing is characterized by a lower mental engagement and less attentive processing of sampled information. The participants in our study seemed to have maintained the motor routine of uncovering the images with the mouse at a speed that increased slightly over time. So, the motoric effort did not change, the time spent did also not change between the groups, but it seems that the search was carried out with less mental effort and with less attention to the information being sampled. This kind of mental effort is harder to detect but could be measured in future studies using EEG measures such as the mental-engagement index used by Pope et al. (1995).

While Onnasch and Panayotidis (2020) found a tendency for subjective effort to be lower in human–robot teams, this study found lower defect-detection performance when working in a team with a robot. It seems that social loafing is a topic that deserves further investigation. However, as with human teams, it is not always easy to detect motivational losses in teams, such as social loafing, in a laboratory context (Price, 1993), as participants assume that their behavior is being observed and analyzed. Field studies could be an option to find larger effects and get a clearer picture of the impact of social loafing in HRI. It may be that social loafing is more subtle in the lab than in real life and that effect sizes are smaller in the lab. We therefore suggest that future studies try to use a larger sample. In addition, future studies should attempt to replicate our findings while trying to measure the mental effort involved in processing the sampled information.

Our study has several limitations. First of all, we chose an experimental setting that was unlikely to elicit very high levels of group feeling, as participants worked with Panda while visually separated by a partition wall and without the need for communication or direct interaction with the robot. However, participants were told that they would be working in a team, saw the robot as it (presumably) inspected a set of circuit boards before they started their own work on the task, heard the robot's movements as they worked, had a picture of the robot displayed on their monitor, and saw the marks it (presumably) made, thus constantly reminding participants of the teamwork. Future studies should directly measure the perception of working in a team (e.g., as in Nass et al., 1996) and could investigate the occurrence of social loafing in low, moderate, and high team-perception settings.

Second, social-loafing effects are more difficult to detect when participants are highly aroused (Price, 1993) or when they feel that their individual performance is being evaluated (Karau and Williams, 1993). It is difficult to avoid this completely in a laboratory experiment. Participants need to feel comfortable, well informed, and guided throughout the experiment in order to relax during the test session. Interacting with a friendly and patient experimenter, reading the written instructions at their own pace, and having the opportunity to practice and ask questions should have all helped to reduce participants arousal a bit. In order to reduce the feeling of being evaluated, we chose a set-up where the experimenter could not see the participants while they worked. Also, we did not use eye-tracking, but a more subtle way of measuring where and for how long attention is distributed using our mouse-over approach.

Third, in our experiment, Panda did not actually inspect the circuit boards. To do this, Panda would have needed to be equipped with some kind of vision-analysis software—perhaps based on machine learning—to classify the visual input. Machine learning, such as deep neural networks, are algorithms that can detect patterns they have previously been trained on. We believe that deep neural networks might be well suited to detect production errors on circuit boards. In our setting, we have just claimed that Panda can not only scan the boards but also analyze them for specific defects. Our participants, who all had a human-factors background, did not express any doubts. Although the visual-search task we used seems suitable for machine-learning applications, we chose to work with an embodied robot team partner. We did so because robots are usually perceived more as social agents due to their physicality, and various "social effects" have already been found here (e.g., Woods et al., 2005; Riether et al., 2012). Therefore, we assume that if there is social loafing in human–machine interaction, it should be particularly the case for embodied and autonomous agents. Future studies should investigate social loafing in interaction with non-embodied AI, as the effects could in principle also be conceivable here.

Robots are becoming increasingly important in many industries and can take over more and more tasks. However, they are often not yet capable of working fully autonomously and without supervision. For this reason, in many industries and for many tasks, human supervision or augmentation of the robot's work will be required for some time to come. Combining the capabilities of humans and robots obviously offers many opportunities, but we should also consider unintended group effects that might occur in human–robot teams. When humans and robots work redundantly on a task, this can lead to motivational losses for the human team partner and make effects such as social loafing more likely. Social loafing should therefore be taken into account.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://osf.io/njz2x/.

Ethics statement

The studies involving humans were approved by the Ethik-Kommision des Instituts für Psychologie und Arbeitswissenschaft der Technischen Universität Berlin. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

All authors contributed to conception and design of the study. AT collected and organized the data. DC and AT analyzed the data. DC and LO wrote the initial draft of the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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OSH related risks and opportunities for industrial human-robot interaction: results from literature and practice

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Robotic systems are an integral component of today's work place automation, especially in industrial settings. Due to technological advancements, we see new forms of human-robot interaction emerge which are related to different OSH risks and benefits. We present a multifaceted analysis of risks and opportunities regarding robotic systems in the context of task automation in the industrial sector. This includes the scientific perspective through literature review as well as the workers' expectations in form of use case evaluations. Based on the results, with regards to human-centred workplace design and occupational safety and health (OSH), implications for the practical application are derived and presented. For the literature review a selected subset of papers from a systematic review was extracted. Five systematic reviews and meta-analysis (492 primary studies) focused on the topic of task automation via robotic systems and OSH. These were extracted and categorised into physical, psychosocial and organisational factors based on an OSH-factors framework for advanced robotics developed for the European Agency for Safety and Health at Work (EU-OSHA). To assess the workers' perspective, 27 workers from three European manufacturing companies were asked about their expectations regarding benefits and challenges of robotic systems at their workplace. The answers were translated and categorised in accordance with the framework as well. The statements, both from literature and the survey were then analysed according to the qualitative content analysis, to gain additional insight into the underlying structure and trends in them. As a result, new categories were formed deductively. The analysis showed that the framework is capable to help categorise both findings from literature and worker survey into basic categories with good interrater reliability. Regarding the proposed subcategories however, it failed to reflect the complexity of the workers' expectations. The results of the worker evaluation as well as literature findings both predominantly highlight the psychosocial impact these systems may have on workers. Organisational risks or changes are underrepresented in both groups. Workers' initial expectations lean towards a positive impact.

KEYWORDS

human-robot interaction, OSH risks and benefits, cognitive ergonomics, robotic systems, workplace automation, user expectations

1 Introduction

Interactive robotic systems have become a frequent occurrence in Europe's workplaces over the last years. More and more workers find themselves working alongside a wide range of robotic technologies that assist them with their everyday tasks. These tasks can range from a robotic arm holding a heavy work piece for an industrial worker, to an automated guided vehicle which navigates the hospital hallways to deliver medicine (Kyrarini et al., 2021), tasks in the agricultural sector, like weeding, land preparation (Benos et al., 2023) or working more closely alongside humans assisting with the detection of fruit and vegetables, grasping and detaching (Vasconez et al., 2019). There are also robots working alongside waiters in restaurants (Lu, Zhang and Zhang, 2021). The areas of application are ever expanding. This way, robotic systems have contributed to creating more ergonomic and efficient work places (Jungmittag and Pesole, 2019). While the percentage of companies that use robotic systems capable of safe interaction with human operators is still comparatively low (Hämäläinen, Lanz and Koskinen, 2018), the International Federation of Robotics (IFR) reports an increase in annually installed robotic systems for the sixth year in a row. A trend which they predict to continue (Müller, 2022). The third European Survey of Enterprises on New and Emerging Risks (ESENER III) conducted by the European Agency for Safety and Health reveals that 28% of all human-robot interaction (HRI) applications were found in the manufacturing sector (Wischniewski et al., 2021). While other sectors are still gaging possible applications for these systems, the industrial sector already uses them actively and expands continuously in their use.

The relationship between occupational health and safety of workers and robotic systems can be multifaceted and complex. Industrial robots have traditionally been utilized for physically demanding tasks that can have negative effects on the health of a worker and may have a heightened risk of workplace accidents. Automating these tasks or larger parts of a manufacturing job through a robotic system has benefited workers by helping to prevent injuries (Haddadin et al., 2009) and adverse health effects that arise from working in hazardous conditions, such as musculoskeletal disorders caused by repetitive motions (Colim et al., 2020). However, if the robotic system is not used correctly and necessary standards for a safe interaction are not upheld, the technology may increase the risk for accidents (Yang et al., 2022) or introduce new hazards (Matthias et al., 2011). Even though, modern, interactive robotic systems are more commonly associated with their potential to remove workers from hazardous situations, and thus benefiting their safety and health (Kim et al., 2017), there is growing concern regarding the potential negative impact of human-machine interaction on the mental health of workers. Studies suggest that this relationship could have negative effects on workers' wellbeing, while also becoming an additional source of stress in modern manufacturing workplaces (Robelski and Wischniewski, 2018; Körner et al., 2019). The increasing prevalence of robotic systems as a means of task automation can also increase stress (Venkataramani et al., 2020) and cause anxiety over potential job loss (Bhattacharyya, 2023). Moreover, it was found that implementing a robotic system to a workplace may trigger higher stress levels during the initial introduction (Wisse and Sleebos, 2016), and spike fear of job loss in the early days (Tuomi et al., 2021). Both effects seem to subside over time, bringing up the question how workers expect robotic systems to impact their work, not only in the short- but also in the long-term.

Evidently, the relationship between robotic automation and occupational safety and health (OSH) is complex, especially once the psychosocial implications are considered. While workers may see some OSH benefits related to automating a task, there may also be concerns regarding OSH related issues like job loss, the robots' safety and their effect on workload (Wisse and Sleebos, 2016). The attitude and expectations of workers towards a technology can be a major contributor in the success of its implementation. Knowing about these factors before installing the technology offers the opportunity to adapt measures to address the mentioned issues. For this reason, existing studies, theoretical concepts and taxonomies are used in practical application to assess potential OSH related opportunities and risks when introducing robotic systems. One recently published report by EU-OSHA focusses on OSH impacts of advanced robotics in relation to the (semi-)automation of tasks. The authors of this report developed an OSH-factors framework for advanced robotics by defining dimensions that impact OSH during the introduction and use of robotic systems, as a means to assess possible risks and opportunities (Rosen et al., 2022).

This article focusses on whether and how these dimensions apply for the automation of physical task within the manufacturing industry. This will be assessed by considering both, a subsample of a systematic literature review as well as results from an evaluation of workers' expectations within this field. We will analyse to what extent the OSH related dimensions and effects of robotic systems according to the OSH-factors framework for advanced robotics apply for the automation of physical tasks in the manufacturing sector. Moreover, we give an overview of the workers' long- and short-term expectations towards the impact of robotic systems on their work and analyse whether workers primary expectations towards the system were positive or negative.

2 Industrial human-robot interaction and OSH

Robots capable working alongside humans are a comparatively new development, and represent only ion form of human-robot interaction. Onnasch Roesler, (2021) created a taxonomy to classify human-robot interaction in three distinct categories: coexistence, cooperation, collaboration. Coexistence describes an episodic encounter between humans and robots where the interaction is limited in terms of time and space, like passing a transport robot in the hallway. During a cooperation, robotic system and human worker work towards an overarching common goal. A robotic system performing a sorting task, while the worker uses the sorted parts to finish a work piece would be an example for this form of interaction. Collaboration describes an interaction in which both human and robot share an overarching task as well as sub-goals here. Their actions need to be coordinated and assigned consecutively. Human-robot collaboration is the most complex form of interaction. Industrial workers are at the forefront of jobs likely to come in contact with or get automated through robotic systems (Kadir et al., 2019; Dobra and Dhir, 2020; Gualtieri et al., 2021). Numerous sources report on robotic automation being used to automate tasks in the industrial sector (Gholamian and Ghomi, 2007; Iqbal et al., 2016; Enríquez et al., 2020). This includes tasks like pick-and-place or sorting tasks, holding work pieces, welding, assembly, paint spraying, packaging and arranging, cutting, moving, and sanding (Iqbal et al., 2016) as well as heavy lifting, precise physical activities and, specifically in a manufacturing context, the production of small volume assembly items in a high mix of products/precision works (Krzywdzinski, 2021). Traditionally, industrial robots operate spatially separated from shop floor workers. However, modern robotic systems are capable of working safely and efficiently alongside humans. This has allowed for new forms of human-robot interaction to arise. Robots which share an unfenced workspace with humans do require specified safety standards. Recommendations for collaborative robots (cobots) are summarized in the technical specification ISO/TS 15066 (Robots and robotic devices—Collaborative robots) (ISO, 2016).

There is evidence that these technologies impact the occupational safety and health of industrial workers. Both safety and efficiency are expected to increase through human-robot interaction (Gualtieri et al., 2021). Workers benefit from a decrease in physical strain through the automation of physically demanding tasks and increased safety of the work environment (Gualtieri et al., 2021). Recent publications on risk factors for human-robot collaboration also shine a light on emerging socio-technological risks, as well as on new ground with robot-centric ethical considerations and cybersecurity (Brex et al., 2022).

A growing number of workers now find themselves in the position that a robotic system has recently been introduced to their work place, or will be in the near future. This naturally triggers expectations towards the robot and the changes it brings to their work life. Not only regarding its impact on safety and health but more broadly speaking, its impact on their work overall, both long-term and short-term.

2.1 Worker expectations towards robotic systems

For an effective use it is advisable that a robotic system and the workers' expectations towards it align. This typically relates to the robot's features, functionalities or patterns of movement when it comes to direct interaction (Eyssel et al., 2011). However, looking at the larger picture, it is very rarely researched what general expectations there are towards how a robotic system will impact their workplace. In order to enhance the workplace interaction and long-term usage of the technology, it is important to consider the workers' perspectives. This encompasses the expectations of workers prior to the robot's introduction, which should not be limited to only its functionalities, but the larger impact that is expected. Without considering human factors during the implementation, however, the introduction of such systems tend to fail (Fletcher and Webb, 2017). Few publications address general expectations towards robotic systems from a workers' perspective, and equally few investigating the workers' specific expectations towards OSH with regards to the robotic system (Wurhofer et al., 2015; Aaltonen et al., 2017; Elprama et al., 2017; Kildal et al., 2018; Willems et al., 2023). This article is therefore an enrichment to the current scientific discourse, as industrial workers' expectations were assessed and analysed using global categories as proposed by the OSH-factors framework for advanced robotics (Rosen et al., 2022).

One study which does address workers' expectations in the manufacturing sector is conducted by Wurhofer et al. (2015). They studied workers' expectations prior to the introduction of robotic systems to a semi-conductor factory and accompanied the workers throughout the process. Within their study, statements of uncertainty as well as scepticism and rejection were the most frequent. However, positive expectations were also present. While OSH relevant factors were mentioned, it was not in the foreground of workers' expectations. These results align with further studies on the topic. Workers expect interactive robotic systems to lighten their mental and physical workload (Elprama et al., 2017). Other studies found, that workers expect physical workload to decrease, and safety to increase, however, they also expect their workload to increase along the robot's productivity (Aaltonen et al., 2017; Kildal et al., 2018). Kildal et al. (2018) asked potential robotic users from robot related industries for their expectations towards the technology. The participants expected the impact of robots as a whole to be positive (productivity, quality, competitiveness, safety, costs and working conditions). The most negative expectations were centred on job loss (Kildal et al., 2018).

Within this limited body of studies, we see that workers tend to have mixed expectations towards the change robotic systems might bring. While the physical changes are primarily expected to be positive, both psychosocial and organisational changes that are brought up lean towards the negative. Additionally, a varied time perspective is rarely explored. Instead, in many cases, a timeframe is not defined and the studies are focusing on the most immediate expected changes. Incorporating short- and long-term expectations from workers and interpret them within the dimensions of OSH impacts in advanced robotics yields an opportunity to broaden the understanding about the most prevalent factors from a worker's perspective, in order to facilitate successful long-term use of the technology.

3 OSH-factors framework for advanced robotics

To provide meaningful advice for the implementation of robotic systems in the workplace, all relevant components of a work system should be considered. This includes the physical and psychosocial context as well as the social and organisational work environment (Leka and Jain, 2010). In a recently published report on the OSH impacts of advanced robotics for the (semi-)automation of tasks, the authors present an overview of OSH relevant dimensions (Rosen et al., 2022). They utilize three foundational categories (*physical*, *psychosocial* and *organisational*) and subdivide them into eight sub-categories (physical alteration of the workplace, function allocation, task design, interaction design, operation and supervision, introduction process, change management, training) representing areas of OSH relevance in this context (Figure 1). Based on an extensive literature review, the authors found that these facets may result in different positive or negative OSH outcomes. The presented categories may all effect OSH during the introduction and interaction with the robotic system. The framework provides a comprehensive categorisation of relevant

FIGURE 1
EU-OSHA Framework of OSH relevant dimensions for the introduction and use of robotic systems.

aspects and has proven to be an adequate framework to assess OSH related risks and benefits while taking specific task and technology characteristics into account. It was created with considerations regarding automation type as well as relevant OSH characteristics, in order to suite the automation of tasks through robotic systems. This sets it apart from non-robot specific OSH frameworks for the automation of tasks for a wider variety of technologies and the automation of tasks more generally (e.g., Nickel et al., 2020). While this framework presents one possible set of categories to base an analysis on, there are others attempting the same thing. Berx et al. (2022) also created a categorisation based on a systematic literature review, which resulted in five overarching groups (Human, Technology, Collaborative Workspace, Enterprise and External). Content wise these categories are parallel the OSH-factors framework by Rosen et al. The category External may be especially useful, for research that aims to include the wider context of robot use. The following section provides an overview of the different dimensions and their subcategories as described in Rosen et al. framework. These form the foundation of a content analysis on whether and how the OSH related dimensions and effects of robotic systems apply for the subset of physical task automation in the manufacturing sector as well as their suitability to categorise worker expectations.

3.1 OSH dimensions

3.1.1 Physical

The automation of tasks via robotic systems is especially associated with changes in the physicality of tasks or the working environment. Changing a physically straining task to be supported by a robotic system can impact physical OSH. The actual OSH benefits and risks that an advanced robot brings to a workplace is highly dependent on the use case and technology and are not limited to physical effects. For example, removing a worker from a dangerous environment does decrease the risk of physical harm, however it may also lighten the psychological stress associated with working in a dangerous surrounding.

3.1.1.1 Physical alteration of the workplace

Robotic systems are predominantly used to automate physical tasks, and thereby change the physical workspace and job demands of workers (Rosen et al., 2022). Robots may also physically support workers in tasks that cause repeated physical strain (Kyrarini et al., 2021), possibly reducing work-related musculoskeletal pain and injuries. However, the introduction of advanced robotics may also introduce new OSH risks to a workplace, like collisions. In order to not introduce new physical risks, contact avoidance measures, motion planning, and sensor systems play a significant role in ensuring the operators' safety.

3.1.2 Psychosocial

Psychosocial effects include a range of phenomena relating to a worker's mental, emotional, or social state. Based on the dimensions of the OSH-factors framework for advanced robotics (Figure 1), these four categories are most likely to expect changes due to the implementation of robotic systems at workplaces. Depending on how these categories are executed, they may affect workers strongly on a psychosocial level.

3.1.2.1 Function allocation

Function allocation in task automation involves determining the division of tasks between humans and robotic systems based on the specific task requirements (Robelski and Wischniewski, 2018; Tausch et al., 2020). While static task allocation is a common approach, as robotic systems become more flexible and capable, task scheduling becomes more dynamic. The resulting distribution of tasks holds implications for occupational safety and health regarding various psychological factors, including but not limited to perceived process control, mental effort, fairness, task identity, acceptance, flow, and self-efficacy (Tausch et al., 2020).

3.1.2.2 Task design

The process of function allocation results in direct consequences for the task design. How a task is designed may change once a robotic system is installed in the workplace. If tasks are predominantly designed around robotic performance and speed, it can result in the workers' pace being determined by the robotic system. This may result in negative psychosocial effects, including but not limited to emotional exhaustion, nervousness, irritability, worse mental wellbeing, and reduced job satisfaction (Robelski and Wischniewski, 2018; Rosen and Wischniewski, 2019). A concern regarding the introduction of advanced robots into workplaces and the changes they trigger in task design is possible work intensification, as described in the Job-Demand-Resources Model (Demerouti et al., 2001). It might manifest as increased work demands and higher expectations placed on workers, a quickened work pace or an increased quantity of work. It may also manifest as reduced autonomy or the expectation to multitask.

3.1.2.3 Interaction design

The interaction between workers and robotic systems can influence a number of OSH related factors. This can relate to, among others, the way they handle interaction, as well as how transparent and comprehensive the interaction is perceived by the user. Another aspect of interaction design that needs to be considered in HRI, is the transparency of the system. When transparency is lacking and the operator is left without the necessary information to follow the underlying reasoning, a robot might be perceived as unreliable (Kim and Hinds, 2006). However, more information is not always better. An overabundance of information might even decrease transparency, leading to difficulties in selecting crucial information by the worker (Finomore et al., 2012). Furthermore, the interaction with the robotic system should be designed in such a way, that its users perceive the system as safe. Transparency is one of several factors influencing this, alongside familiarity, predictability, sense of control and trust (Akalin, Kristoffersson and Loutfi, 2022).

3.1.2.4 Operation and supervision

Operation and supervision refers to the management and oversight of the day-to-day activities and processes when working with a robotic systems. A number of topics fall into this category such as the allocation of resources and monitoring of performance. One psychosocial factor that should be taken into account during the introduction of robotic systems to the workplace is the attitude and experience towards and with robots present in the workers. A lack of familiarity may shape initial attitudes (Sanders et al., 2019). Moreover, it was found that trust and acceptance tend to increase as workers are exposed to the systems (Hancock et al., 2011) while negative attitudes decrease over time (Nomura et al., 2011). The fear of job loss is one of the most thoroughly researched topics in the context of robotic automation (McClure, 2018) and given that approximately 40% of workers will experience significant changes in their work due to the introduction of robotic systems to the workplace (Pouliakas, 2018), it represents another important psychosocial factor. More so in light of the evidence that job insecurity is linked to the risk or presence of depression, anxiety and emotional exhaustion, as well as to low satisfaction with life (Llosa et al., 2018).

3.2 Organisational

The effects of introducing a new technology to a workplace can reach further than the physical or psychosocial aspects of OSH. In some cases, it leads to OSH related organisational changes, or the introduction itself needs to be preceded by specific processes to maximize the OSH benefits of the technology.

3.2.1 Change management

Change management in a company refers to the structured approach aimed at preparing and implementing organisational changes. Effective communication and active participation are crucial for a successful introduction of a new technology. Informing and involving employees in workplace changes can have positive effects on acceptance and enhanced commitment (Bordia et al., 2004). Change management encompasses the company culture around the process and how they deal with problems that may arise. If change management fails for a technology that was intended to bring OSH benefits to workers, they may now not experience these positive effects. Unsuccessful change management may also result in feelings of uncertainty, stress (DeGhetto et al., 2017), while successful change management may increase them (Chien, 2015).

3.2.2 Introduction process

The introduction process of a new technology falls under the umbrella of change management. It is, however, more specific to the technology being implemented. It includes the involvement of all stakeholders in the process, but also pilot testing, risk assessment, training, as well as pre and post assessments. Factors like proper risk assessments are vital to OSH. However, the involvement of effected parties can be influential on OSH as well. Communicating future changes to employees can reduce feelings of uncertainty towards the rationale behind the change and promote change supportive behaviour (Bordia et al., 2004). Employee participation and involvement play a part in the acceptance and the implementation and outcomes of technological transformations in the workplace (Krutova et al., 2022). Increased worker participation also correlates with better risk assessments and more effective preventive measures, especially concerning psychological strain (Popma, 2009).

3.2.3 Training

For many workers, advanced robotic systems are still a new technology with which they have little to no prior experience. Changes in the work equipment or work routine might incite the need for workers to acquire new skills or change their overall skill portfolio, some skills even might become dispensable. Some organisations predict that the automation of tasks will lead to skill polarization in the workplace, where available jobs are extreme in complexity, either very high or very low, with little available middle ground (ILO, 2017). Specialized training specific to the robotic technology and work situation may be necessary to ensure effective and safe use of the systems. While this offers the potential for workers to perform more interesting tasks, continuous learning may also pose a new cognitive strain on the workers.

4 Methodology

The data for this publication was collected via two methods. The data sources were a subset of studies from a systematic literature review and a worker survey, the results of which were then subjected to qualitative content analysis and interrater reliability using Fleiss kappa was calculated. All calculations were performed with IBM SPSS Statistics Version 29 (IBM, 2022).

The original literature review was performed as part of a larger research project funded through the European Agency for Safety and Health at Work. The original review aimed to create an overview of policies, research and practices in relation to advanced robotics and AI-based systems for automation of tasks and occupational safety and health; which is a much wider scope than this research paper addresses. Part of the author team of this article was involved in the creation of the framework used in this article. The worker survey was part of the EU-funded project “Socio-Physical Interaction Skills for Cooperative Human-Robot Systems in Agile Production” (SOPHIA, Funding Agreement No. 871237).

4.1 Systematic literature review

Two systematic literature reviews were conducted with a focus on systematic reviews and meta-analysis only, examining human-robot interaction and the automation of tasks within EU-OSHA's original publication (Rosen et al., 2022). Their publication focuses on the central question where current research activities regarding advanced robotic and AI-based systems lie, whereas our analysis focusses on the question what OSH implications are addressed in the manufacturing sector with regards to advanced robotics specifically. We aim to investigate whether and how OSH related dimensions and effects of robotic systems apply for the subset of physical task automation in the manufacturing sector as well as their suitability to categorise worker expectations. Hence, we specifically selected the subset of publications that focused on the automation of physical tasks in the manufacturing sector, which featured OSH relevant findings. The selection process from each search is illustrated in Figure 2. The literature review was conducted in scientific and complementary databases (IEEEexplore, Ebscohost, WebOfScience, PubMed, and Google Scholar). An additional systematic literature review focused on the automation of tasks, independent from any specific technology. Supplementary literature was obtained through additional desk research using the same data bases, in order to elaborate on the previous results. A comprehensive combination of search terms was developed following the PEO-scheme (Population—Exposure—Outcome). The complete search strings, as well as a more detailed description of the review process can be found in the publication Rosen et al. (2022). The review only included publications meeting set criteria. They had to be meta-analysis or literature reviews, focussing on human-robot interaction. For the initial quantitative reporting, they did not have to include OSH specific results, for the second step of analysis in Rosen et al., only publications with OSH related insights were included. Rosen et al., aimed to create an overview of the state of research, hence they did not limit the sector or type of task the publications had to address, as long as they included a work-related application of an AI-based system or advanced robotics. For our publication the selection was narrowed down, significantly, by enforcing additional selection criteria. For our analysis, five publications met the selection criteria of focusing on the automation of physical tasks in the manufacturing sector, or being applicable to this field, while containing OSH relevant outcomes (Prewett et al., 2010; Kadir et al., 2019; Dobra and Dhir, 2020; Rauch and Dallasega, 2020; Ötting et al., 2022). Major outcomes from these studies were extracted to be analysed in this study. An overview of the included studies can be found in Table 1.

4.2 Worker survey

To assess the workers' perspective, we performed a survey as part of the SOPHIA project that included workers from three European companies. They were asked about their expectations regarding changes, benefits and challenges of robotic systems at their workplace. All three companies are part of the manufacturing industry but differ in size, core business and country of origin (Germany, Netherlands, and Slovenia). Twenty seven workers were asked about their expectations regarding a robotic system that was planned to be implemented at a workstation at their company. The number of potential participants was limited in order to survey workers with a high level of experience and therefore expertise at the selected workplace. All the workers who took part in the survey had at least 1 year of experience of working at the chosen workstation. The workstations considered were selected by the companies after identifying a suitable task that could be facilitated by a robotic system. All selected workstations involved repetitive tasks that had recently been performed manually: the unloading of steel laminates after an annealing line, the manufacturing process of gear cutting and the attachment of a rubber seal to the car body.

The questionnaires and surveys were conducted over a period of 2 weeks in small online groups, due to the pandemic restrictions in autumn 2020. The focus was set on workers' expectations regarding aspects related to the usability of the respective robotic system. Ethical approval was obtained beforehand, and a data protection declaration was carried out and approved by the organization's data protection officer. Participating in the study was voluntary during their working hours. Each round of the survey lasted approximately one to one and a half hours. The workers completed paper and pencil versions of the survey, which were returned by post to the responsible scientists for analysis.

The aim of the study was to gather data on workers' expectations before developing a specific robotic system, they were asked to

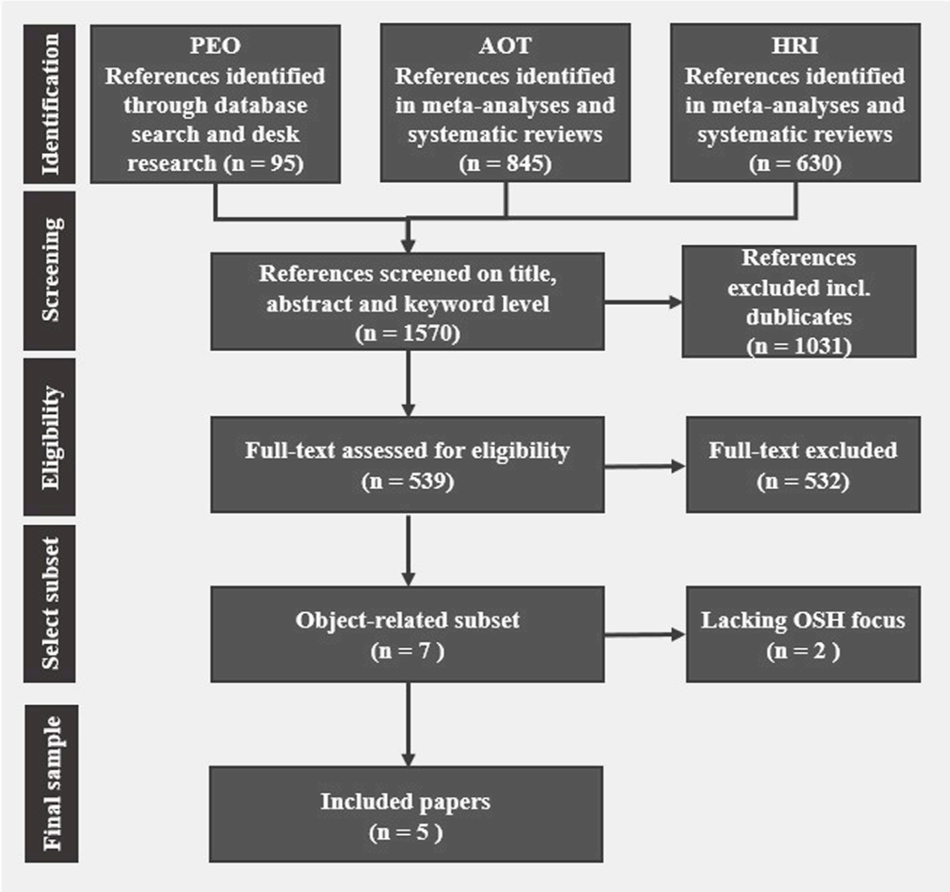

FIGURE 2
Literature review process.

imagine working with a robot that could perform various tasks to support their daily work. To give the employees a better idea of the intended scenario, they were shown a picture of the intended workstation and a picture of the chosen base platform for the development of a robot as an anchor example for the collaborative robots. In one company the robotic system had been introduced a few weeks before the survey, so the workers were already familiar with it. Therefore, the participants were asked to imagine that the functionality of a robotic system would exceed the level of the current system, with the aim of gathering expectations of robotic systems from a more general point of view. Besides well-established questionnaires on system usability, acceptance, strain and job control, open format questions were included, asking the workers to express their initial expectations towards the changes brought by the robot: How do you think your task will change by using the robot?; Do you expect benefits from using the robot (in the short- and long-tern)?; Where do you see potential problems when using the robot (in the short- and long-tern)? For this article, we analysed theses open-ended questions. By this, we aimed to gauge if the primary association with the technology from workers is positive, negative or neutral. Their statements were not limited to a specific number of expectations to express or to OSH related changes.

4.3 Content analysis

Central questions to the analysis were whether and how the OSH dimensions and effects laid out in the OSH-factors framework for advanced robotics apply for the automation of physical tasks in the manufacturing sector. Furthermore, we wanted to find out if the results of the literature match the expectations of the surveyed workers and if tendencies (positive or negative) can be identified for the respective categories.

To elevate the collected statements from both literature and the worker survey, we performed a Qualitative Content Analysis (QCA) (Mayring and Fenzl, 2019), which is a commonly used methodology to analyse qualitative data. QCA concentrates on describing and reducing or summarizing the collected material focussing on the particular analysis object as well as the material context (Mayring, 2014). Since objective criteria, common in quantitative studies to assure a high research quality, are not easily transferable to qualitative research, it is important to focus on methodological consistency (Corbin and Strauss, 2014). Equally important is iterative data collection and analysis, enabling a comprehensive consideration of different perspectives and contexts. Ideally, there is a balance between following a systematic approach and discussion-based consensus (Strübing, et al., 2018). Therefore,

TABLE 1 Overview of the included studies.

Author	Year	Study	Number of primary studies	Technology	NACE-sector
Dobra and Dhir	2020	Technology jump in the industry: human-robot cooperation in production	87	Industrial robots	Manufacturing
Kadir et al.	2019	Current research and future perspectives on human factors and ergonomics in Industry 4.0	90	Industrial and collaborative robots	Manufacturing
Prewett et al.	2010	Managing workload in human-robot interaction: A review of empirical studies.	113	Robotic systems	Manufacturing
Rauch et al.	2020	Anthropocentric perspective of production before ad within Industry 4.0	58	Industrial robots	Manufacturing
Ötting et al.	2022	Let´s work together: A meta-analysis on robot design features that enable successful Human-Robot interaction at work	81	Industrial robots	other

decided on a structured analysis approach for which the underlying code were the categories of the framework (*physical*, *psychosocial* and *organisational*) including its subcategories with the above written descriptions (Figure 1). These deductive categories provided the guideline for the initial analysis.

On this basis, three independent raters categorised both the literature and worker statements to relate to either *physical*, *psychosocial* or *organisational* changes. The raters were part of the research team and are considered experts in the field of robotic systems and human factors with academic backgrounds in psychology, sociology, cognitive science and computer science. In a second step they also assigned each statement to one of the OSH-factors framework subcategories. Furthermore, they had the option to withdraw a statement from the selection should it not contain information that could be attributed to a category (for example, "*I do not think the robot could do my job successfully*"). Once each rater had independently categorised the statements, the results were compared and the researchers discussed any points of controversy. When all raters assigned a statement to the same primary category it was classified as an agreement. An overlap of two out of three raters in the subcategory was also seen as an agreement on the subcategory level. Any remaining disagreements were discussed and resolved among the raters. All statements that were not made in English were translated using DeepL, and translated back, to reduce loss of information. In total, 16 statements made by workers were excluded from further analysis (plus three who choose not to answer the question). During the process of discussion, the raters noticed repeating patterns in the assignment of categories. Hence, they decided to form new, inductive subcategories on the basis of the existing framework.

5 Results

In the following section, we present the results of the content analysis. The OSH-factors framework's categories were considered as a basis to assign major insights of the selected research papers into the categories, where possible. The first section presents selected results from the literature review, while the second, greyed, section presents exemplary replies of the workers (Table 2). It was possible to categorise both, the worker statements as well as the excerpts from literature, using the primary categories of the OSH-factors framework for advanced robotics. Several statements, however, were categorised as too ambiguous to be assigned a definitive subcategory by the raters. The sample included only 25 male and 2 female participants, of whom 72% were working directly at the production line, 24% were craftsmen and one person was in middle management. In order to ensure the anonymity of the participants, data on age was not collected.

5.1 Interrater reliability

Fleiss' kappa was calculated to determine if there was agreement between the raters on the primary categories assigned to the statements from literature and the worker survey. The base categories were taken from the OSH-factors framework, namely, *physical*, *psychosocial* and *organisational*. For the statements extracted from literature, the kappa regarding the primary categories was $(\kappa) = 0.624$, a 95% confidence interval (CI) between 0.478 and 0.770. The result was statistically significant ($p < 0.001$) and represents a substantial strength of agreement between the raters. For the worker

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TABLE 2 Categorisation of statements.

Physical		
Subcategory	**Risk**	**Opportunity**
Physical alteration of the workplace	- Close human robot collaboration evokes safety concerns	
	- Residual risk/unreliability cannot be eliminated completely	- A [robot] cannot always avoid colliding with humans. Safety sensors reduce the force of impacts and stop the robot movement when bumping into a human, but the residual risk remains
	- Some operators experience mental stress because of safety concerns during close collaboration with robotic systems	- Robots can help compensate physical limitation of human workers
	- […]	
		- "Ergonomic improvement, increase of occupational safety"
		- "Less physical load as a result of which in an older age you have fewer complaints or would never get worse from them"
	- "Combining human and robot safety at work and detection of border pieces"	- "Less suffering joints and muscles"
	- "Space around the machine, weight of the products"	- "No more heavy physical work"
	- "More space by the machine" (room)	- "Preservation of your physical condition. Less physical complaints"
		- "Protection of body and psyche"
		- […]
Psychosocial		
Function allocation		- "Multiple machines save more time"
Task design		- "Facilitate/simplify the work"
		- "Less repetitive work and therefore less work pressure"
		- "Makes work more interesting"
		- "More time left for maintenance and other important things"
		- "Setting up the robot cost time in the beginning, but later you benefit from it because the programs already exist and you can therefore do other things"
		- […]
Ambiguous (Task design or Function allocation)		- Robots and collaborative robots can perform easy, repetitive, monotonous and straining manual tasks (dull tasks) instead of humans
		- Hybrid production systems [incl. robots] can bridge the gap between humans and machines abilities
		- Cobots can perform unsafe, repetitive, or boring tasks so workers can perform other more value-added tasks

(Continued on the following page)

TABLE 2 (***Continued***) **Categorisation of statements.**

Physical		
Subcategory	**Risk**	**Opportunity**
Interaction design	- Working with an advanced socio-technological system can result in a degree of uncertainty	- Autonomous robots might be able to identify and adapt to a worker's individual strengths and needs
	- Audio feedback while controlling a multi-robot set up increases reaction time	- The interface design of a robotic system can significantly influence performance, cooperation and satisfaction, by increasing feature visibility and giving feedback
	- Lack of confidence in sensory systems for physical contact [during HRI]	- Minimize injury through viscoelastic coverings, mechanical absorption systems, lightweight structures and collision detection systems
		- […]
	- "High error rate, complicates handling"	
	- "Perishability of the robot and its repair	
	- the consequences of a delay in production"	- "The simple handling"
	- "I foresee many technical problems in the human-machine-robot collaboration."	- "That it works"
	- "Prone to failure, acceptance of the workforce"	
	- […]	
Operation and supervision	- Residual risk/unreliability cannot be eliminated completely	- Reliable automation can improve operator performance
		- Automating tasks through robotic automation might lessen operator workload, if the technology is reliable
	- "Older" persons have fear of failure, problems of understanding"	- "Increase work performance"
	- "Elimination of personnel by machinery use"	- "Increasing productivity through daily operation in the service, healthcare"
	- "Replacement of employees"	- "More productivity"
	- […]	- "More profit for the company"
Ambiguous (Interaction design/Operation and supervision)	- As system complexity increase, so might the cognitive workload of operators	
	- Controlling more than two robotic systems can decrease performance and increase error rate	- Effective HRI is achieved by considering both humans and robots [abilities]
	- "Difficulties in examining the use, not related to the technology"	- The mental status of the human partner plays an important part in the collaboration […]. [It is proposed to] adjust the human workload according to the stress level of the operator
	- "Service and manipulation in production"	
Organisational		
Training	- Cognitive overload of workers [due to constant need for learning]	
	- [Industry 4.0 incl. robots] is driven forward more quickly than training and education institutes are able to adapt the qualification profile of existing and future workers	
	- "Knowledge when using it"	
	- "Problem in robot learning (use)"	

(Continued on the following page)

TABLE 2 (*Continued*) (*Continued*) **Categorisation of statements.**

Physical		
Subcategory	**Risk**	**Opportunity**
Change management	- Without effective human leadership, and material resources operators will struggle to be effective	- Robots will support demographic and diverse team structures
	- Fear, that increasing digitization will result in a large wave of unemployment	- Participation, communication, manager support, training, worker empowerment and existing process [are process enabler when introducing a robotic system]
	- Union membership, awareness of process complexity, manual process variability and [scarcity of] resources [are barriers]	
	- "Destruction of many jobs, chance for a basic income"	- "When we manage to implement it in the environment it certainly picks up the acquisition of the yield, the work done"
		- "Not in the short-term. Think that a lot of time is needed for the work on the shop floor"
Introduction process		

statements Fleiss' kappa (κ) = 0.755, a 95% confidence interval (CI) between 0.679 and 0.835. The result was statistically significant ($p < 0.001$) and represents a substantial strength of agreement between the raters (Landis and Koch, 1977).

5.2 Categorisation

After the initial round of analysis which resulted in the categorisation (Table 2), it became apparent, that the categories of the framework are quantitatively and qualitatively addressed to varying degree in the workers' replies as well as in the literature statements, and present a varied image towards the risks and opportunities associated with robotic systems in industrial workspaces. Regarding the category of *physical* factors, and its only subcategory *physical alteration of the workplace*, physical closeness to the machine was a concern, however, literature indicates that only a residual risk of physical complications remains. This is strengthened by the listed opportunities, which highlight that new, advanced sensors allow safe and close interaction. Workers highlight the reduction of physical load and health complications, especially in the long-term ("Less physical load as a result of which in an older age you have fewer complaints"). Regarding the category of *psychosocial* factors, the raters assigned most statements unanimously to the primary category, however in the subcategory there were two clusters of statements that were labelled as too ambiguous to be assigned to one of the four subcategories. *Function allocation* was assigned near to no statements from either workers or literature. *Task design* only contained opportunities or positive expectations workers, no statements from literature. Workers expect their tasks to become "less repetitive" and "more interesting." Several statements from literature were assigned to a distinct subcategory, as they could reasonably describe *function allocation* or *task design*. Content wise however, they mirrored workers expectations (e.g., Cobots can perform unsafe, repetitive, or boring tasks so workers can perform other more value-added tasks). These statements contained facets of both how the task would be effected as well as who would perform it. The raters discussed this overlap and came to the consensus, that while *task design* and *function allocation* are distinguishable in a theoretical context, when analysing workers' experiences and expectations it is a too high level of detail to apply. However, the importance of both topics was recognized by the raters, so the researchers propose to combine the two categories into shared one called "*function allocation and task design.*" A similar situation emerged when it came to the categories of *interaction design* and *operation and supervision*. Depending on the perspective applied to the statements, both categories were applicable and assigned by at least one rater. A statement from the workers perspective can be interpreted to relate more to the expected interaction with a technology, whereas from a company perspective, it would be more related to *operation and supervision*. Hence, the categories were ultimately combined into one group called "*interaction design, operation and supervision*". Statements that were categorised as related to primarily *interaction design* from literature, focussed primarily on how interface and interaction modalities effect the interaction, both in a positive and possibly negative direction. Workers mainly anticipated malfunction from the robot. In the category *operation and supervision*, literature highlighted reliability or unreliability as a determining factor for the effectiveness of a robotic system in the industrial sector. Workers positive expectations leaned towards increased productivity, while they negatively anticipated job loss, and demographic challenges with regards to learning new, robotic related skills. The *operation and supervision*, literature highlighted reliability or unreliability as a determining factor for the effectiveness of a robotic system in the industrial sector. Workers positive expectations leaned towards increased productivity, while they negatively anticipated job loss, and demographic challenges with regards to learning new, robotic

TABLE 3 Initial expectation of change from workers.

Positive	Neutral	Negative
- Reduced work intensity (2)		
- Improved physical ergonomics (5)		
- Increased task variability (2)	- General expectation of change (2)	
- Reduction of strenuous tasks	- Uncertainty about what could change	- No changes expected
- Overall improvement (7)	- They do not see a robotic system as applicable for their workplace (2)	- General negative changes expected
- Higher efficiency in the production (5)		
- Upskilling of workers		

related skills. The *organisational* factor and its subcategories were the least populated among the three. Both literature and workers only listed risks regarding *training*. They both described the challenges of re-education and the cognitive demand this poses on workers. *Change management* was represented nuanced in both sources. Literature stressed ineffective leadership as curtail in enabling people to work effectively with the technology, and point out the potential for a more inclusive workplace. Workers perspectives included statements addressing a potential development towards universal income and more long-term developments on the shop floor. Noticeably, neither literature nor worker statements addressed the *introduction processes*.

5.3 Changes, short- and long-term expectations by workers

The survey asked workers about their general expectations of changes. By keeping the initial question of this set open, we aimed to gauge if the primary association with the technology from workers is positive, negative or neutral. These results can deliver an indication if workers had a primarily positive, neutral or negative outlook towards the changes brought by the technology. However, focusing too strongly on the quantity of the expectations named might result in a skewed representation, as workers were not limited to a specific number of expectations to express. To provide a comprehensible overview, statements relating to the same general topic (e.g., "*lifting fewer heavy objects*" and "*work will become less physically demanding*") were summarized under group names presented below (Table 3). After every group we provide an indication how many statements were included in it.

To further illustrate these finding, Figure 3 displays the named positive, negative and neutral expectations towards robotic systems. The size of each word is relative to the frequency the category was mentioned. Green writing indicates positive aspects, yellow neutral and red negative aspects. Next, workers were specifically asked what types of effects they expect the robotic system to have in the short- and long-term. Differentiating between the immediate and continuous impact of a technology may grant insight into a more layered opinion of workers on the technology. Table 4 provides an overview of the workers responses to both the short- and long-term category. Participants were again not limited in how many expected benefits or problems they could name.

6 Discussion

The introduction of advanced robotic systems at an industrial workplace can change working conditions drastically for the employees. These changes can permeate aspects regarding physical, psychosocial and organisational factors concerning, but not limited to, occupational safety and health. While it is vital to consult research on possible effects such a technology can have on workers, it is also important to assess the expectations of those who will be directly affected by the technology. Using existing frameworks like the OSH-factors framework for advanced robotics can provide a basis for comparison and further analysis.

6.1 Content analysis

The selected literature focusses on OSH related risks and opportunities for industrial human-robot interaction. All five studies contain various outcomes that describe how OSH is affected by advanced robotic systems in an industrial setting. The results show that these studies cover a vast variety of factors. When it comes to opportunities, the analysed literature does not provide any insight regarding the categories of *task design, organisation and supervision* as well as *training*. With regards to possible risks the category of *change management* was underrepresented. Furthermore, the category *introduction process* was neither addressed regarding any opportunities nor risks. The analysed literature only presents a small, yet specific subsample of all available literature on robotic systems. The present distribution may still be used as an indicator of areas which are in need of more focused research in the future. The worker statements were similarly distributed, with the greatest focus on physical effects followed by how their direct task might change. The fewest statements were assigned towards organisational aspects. Possibly, because the effect of organisational changes is

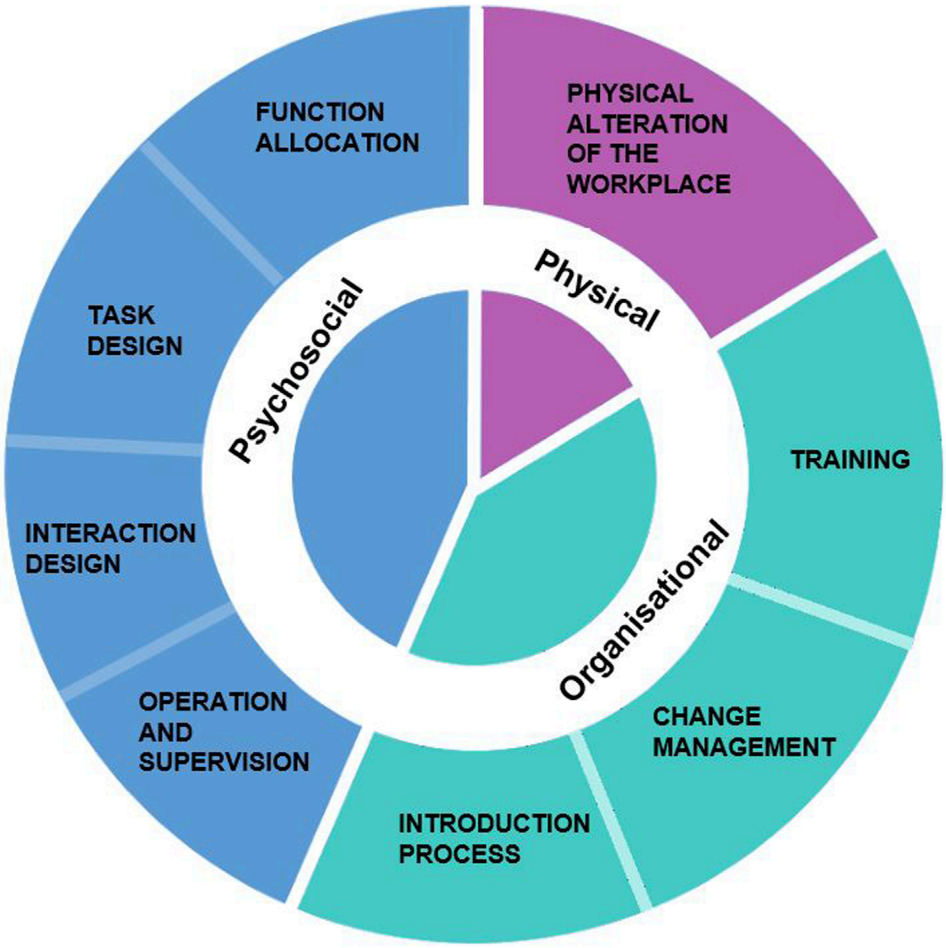

FIGURE 3
Visualisation of positive, neutral and negative expectations towards robotic systems.

the furthest removed from their area of influence. Even though neither literature nor worker statements addressed the introduction processes, the topic is of major relevance. The distribution supports the findings of Berx et al. (2022), where Technological and Human related OSH factors were noticeably more present in their reviewed literature as in the Enterprise category. The underrepresentation of the organisational category on the workers' side might be due to the framing of the survey. The questions were phrased in such a way that it could be assumed, the robotic system had already been installed and the introduction process finished. Future studies could consider investigating workers expectations towards the introduction process specifically, to gain insight on the needs and expectations of workers during this time of change. When focussing on the content both sources provided, we can see that they align in some categories, while others focus on different aspects of the topic.

During the categorisation of statements, a few points of discussion came up. One that was repeatedly raised between the raters, was the perspective under which any given statement should be analysed under. Depending on that, the category that was considered fitting for a statement changed among the rater. For example, "*Personalized, adapting systems could result in continuous monitoring, which raises concerns for privacy*" was categorised as applicable for *interaction design*, *operation and supervision*, and *change management*. The categorisation depended on where the focus was being set and if they were seen to relate to the worker perspective, developers' perspective or the company's perspective. This change of category depending on the mikro- or meso-view of a working situation poses a challenge for this type of content analysis.

The OSH dimensions and effects laid out by the OSH-factors framework for advanced robotics largely apply for the automation of physical tasks in the manufacturing sector regarding advanced robotic systems, especially when looking at the three main categories proposed. However, as working situations become more complex, which is that case for advanced robotic systems, using a framework with highly granular categories can be less effective. In our analysis, not all categories were represented. This does not necessarily indicate that these categories hold no importance to the automation of physical tasks through robotic systems, but more so that these are currently neither at the forefront of workers expectations nor the primary focus of research. In order to better represent the

TABLE 4 Short- and long-term risks and opportunities expected from workers.

Short-term	Long-term
- Technological failures (2)	
- Unclear task allocation	
- Reduced physical workspace (3)	- Job loss (4)
- Reduced product quality	- Decreased productivity
- High error rate (3)	- Increased monotony
- Stress (2)	- Malfunctions and errors
- Low acceptance	
- (Lack of) training (2)	
- Safety concerns	
- Increased job control	- Increased task variability (2)
- Reduced work intensity	- Improved time control
- Increased productivity (2)	- Improved physical ergonomics (7)
- Reduced monotony	- Improved physical and cognitive ergonomics
- None (2)	- Reduced long-term health complications (3)
- Improved wellbeing	- Economic growth
- Reduced work intensity	- Job transformation (2)
- Improved physical ergonomics (3)	- Increased productivity
- Improved cognitive ergonomics	- Overall improvement (2)
- Overall improvement (4)	

statements analysed in this study, researchers decided to combine the categories "*task design and function allocation*" as well as "*interaction design, operation and supervision.*" Future analysis may have a greater benefit from using the primary categories (*physical*, *psychosocial* and *organisational*) and then derive their own sub-categories, while using publications like the OSH-factors framework for advanced robotics as a guideline (Rosen et al., 2022).

6.2 Positive—neutral—negative expectations

When comparing the initial expectation of change towards the robotic system, as displayed in Table 3, one can observe two general tendencies. Firstly, the replies heavily lean towards positive changes. The most frequently named expectations related to unspecified changes was "*overall improvement of the work situation.*" This goes along with the second most named category, namely, "*improved physical ergonomics.*" This was as frequently addressed as the expectation for the robotic system to increase the efficiency in production. Other positive changes that were also named were a reduction in work intensity, an increased task variability and that the introduction will lead to an upskilling of workers. The initial positive expectations align with the impact robotic systems typically have on a workplace according to literature (improved efficiency (Evjemo et al., 2020), and ergonomic improvements (Colim et al., 2020). Looking at the neutral and negative responses, workers either expected a general increase of their work, explicitly express that they are uncertain what will change, or doubted the applicability of robotic systems at their workplace. This might indicate a lack of knowledge about automation, the capabilities or intended uses. Overall, we see a similarly mixed distribution of expectations as in previous studies on this topic (Wurhofer et al., 2015; Kildal et al., 2018) with a slight lean towards positive change.

The technology as well as public perception and media reporting on it, may have changed over time, influencing workers' answers (Riemer and Wischniewski, 2019). While it is not possible to conclusively determine the reason why this sample's initial expectations were more positive than in prior studies (Wurhofer et al., 2015), it underlines that it is valuable to assess these expectations in workers. Not only to gauge if their expectations are realistic, but also to identify any distrust or fears related to the technology, as these can have a negative influence on the implementation process and later use of the robot (Hancock et al., 2011; Marangunić and Granić, 2015).

6.3 Opportunities and risks on a time frame

The follow-up questions of the general change workers expected from the technology were targeted at short-term as well as long-term risks and benefits. Literature shows that people consider distant or immediate consequences of potential behaviours or events differently (Strathman et al., 1994). Moreover, the Construal-Level Theory of Psychological Distance states that the further removed something is from direct experience, the more abstract the level of construal of the matter (Trope and Liberman, 2010). Hence, results should indicate a greater level of detail in the expected short-term changes, compared to the long-term consequences, which matches our findings.

6.3.1 Short- and long-term changes

When workers were asked to give specific examples on short-term opportunities and risks, they provided a variety of answers with varying depth. The most named opportunity was an overall improvement of the work situation without any further specifications, followed by the expectation that the robot will improve physical ergonomics. However, a number of other OSH related factors were named in greater detail. From the named opportunities (Table 2), the workers' expectations for the system in the short-term were that it will benefit their working conditions by alleviating both physical and mental strain. Workers were able to formulate their short-term expectations in great detail. Workers expect the robot to have errors or produce work at a lower quality. There is minor concern about the physical safety of the system but a stronger focus on the machine taking up too much space in the current workplace. When OSH related factors were named by workers, they focus on psychosocial factors like increased stress, unclear task allocation or a low acceptance for the technology which literature shows can spike during the early days of use (Wisse and Sleebos, 2016; Tuomi et al., 2021). We also see that a lack of training is mentioned in the short-term, which could potentially contribute to the expected errors and in the long run, job loss. Interestingly the short-term risks indicate that while workers are aware that the robotic system will alter their physical workspace and has residual physical risks, they name negative psychosocial effect more frequently than physical.

Regarding the long-term changes, there were fewer risks than opportunities named and those exhibited a lower level of detail. Workers name primarily OSH related long-term opportunities, like an increased task variability, prevention of long-term health consequences and the improvement of both physical and cognitive ergonomics at the workplace, which aligns with literature findings (Kim et al., 2017; Kadir et al., 2019). The most dominant group here is the improvement of physical ergonomics. However, there were also contributions from individuals who expected opposing effects: an increase in task variability or more monotony. The most commonly named long term-risk was job loss; the fear of which triggered by automation at the workplace is well documented (Bhattacharyya, 2023). Malfunctions, too, were named as a long-term phenomenon of the technology, however to a lesser degree than in the short-term. Overall, the long-term consequences were formulated to a lower level of detail, which generally aligns with the Construal-Level Theory of Psychological Distance (Trope and Liberman, 2010).

This comparison of both short- and long-term risks and opportunities highlights that worker are well aware of the potential impact a robotic system can have on them and their work environment, not just imminently, but also over time. Long- and short-term expectations from workers towards robotic systems, OSH related and non-OSH related, is a highly under researched area. Few studies on the OSH impact take an explicit timeframe into consideration, with the exception of long-term physical strain effects like MSD (Haddadin et al., 2009). None of the above included publications specified the effects to a certain time frame.

7 Limitations

While great efforts were made, to uphold high scientific standards, some limitations still apply to the results of this research. The worker survey took place in their mother tongue, however the results had to be translated for further analysis. While a high standard of translation was aimed for, linguistic nuance was inevitably lost in translation. Furthermore, the surveyed workers had different levels of experience, specifically the German subsample, as they had already worked with the robot by the time the survey took place. This may have informed their replies to the survey. Although a large proportion of employees in the workplaces surveyed participated, the overall sample size is moderate. Regarding the analysis of short-term and long-term consequences, it has to be noted that some participants gave identical answers for both, leaving it open to interpretation if they expect the effect to be persistent, or to change over time.

8 Future research

The present study has provided a comprehensive examination of the multifaceted risks and opportunities associated with robotic systems in the context of workplace automation, particularly in industrial settings. However, to further enhance the depth and applicability of our findings, there is a need for future research. An important next step could be a validation of our findings through expert consensus assessment by involving experts in the fields of robotics, occupational safety and health (OSH), and industrial automation. By gauging the level of agreement among experts, it would be possible to ascertain whether our conclusions align with a broader expert consensus. Another research avenue that can be explored is, preforming the above demonstrated procedure in other sectors that are likely to see increased robot usage in the near future, like the agricultural or medical sector. This would allow a broader comparison between the sectors, possibly unveiling critical overlap or discrepancies between the expectation and OSH factors between the sectors.

Lastly, a topic which is continuously growing in relevance and prominence, when it comes to the integration of robotic systems into the world of work at large, as well as the industrial sector specifically, are the ethics and legislative challenges these technologies create. Their expanding capabilities in perceiving their work environment are already in focus of matters regarding data privacy and personal data collection. Future research should focus on the specific ethical challenges for the industrial sector as well as the world of work at large.

9 Conclusion

More and more workers are expected to interact with robotic systems at their workplace. In order to create a human-centred workspace, it is necessary to be aware of worker expectations as well as current research on the risks and opportunities these technologies may bring. In order to gain a better understanding of research results, both theoretical and from worker surveys, it can be helpful to use existing models or frameworks to create a common ground for analysis. The OSH-factors framework for advanced robotics divides the topic into physical, psychosocial and organisational facets. Central question to our paper was whether and how these OSH dimensions and effects apply for the automation of physical tasks through interactive robotic systems in the manufacturing sector, represented by literature as well as a worker survey. Furthermore, we analysed tendencies (positive or negative) in workers expectations in the long- and short-term, as this is a critically under researched topic. We found that the framework is applicable to the reviewed data with limitations. The three main categories could be applied to the statements with high interrater reliability, showing that they are suitable as a baseline for further analysis. Most of the subcategories provide additional nuance to that analysis. However, not all subcategories are distinct enough and show significant overlap. Combining the categories may help better represent the underlying data. There are several categories in the framework that are underrepresented, both in literature, as well as the worker survey. Especially the lack of focus on the introduction process offers potential for future research.

Regarding expected short- and long-term changes, both the positive and negative details are prevalent expectations. Both short- and long-term opportunities focus on physical ergonomics, however, they also contain detailed suggestions on how workers expect their jobs to change towards less monotonous work, and more control over their time and decision making. Short- and long-term risks were highly varied and addressed topic relating to physical, psychosocial and organisational aspects.

The results of the study highlight the predominantly positive impact of robotic systems on physical factors, including reduced physical strain, removal from unsafe work environments and long-term ergonomic improvement. From the literature perspective, there is a lack of long-term study results on the impact of these technologies. The interviews however indicate that workers do approach these technologies with the expectation of long-term health benefits. However, both the literature and the workers' perspective also identified potential psychosocial risks, including an increase in cognitive demands and concerns about job loss.

Overall, this article provides insights for researchers, practitioners, and policymakers involved in the design and implementation of robotic systems in the workplace. While the results suggest an overall positive impact expectation of robotic systems on occupational safety and health in the manufacturing sector, it also highlights that workers expect negative changes to come from the technology. Further research is needed to assess long-term effects and ensure that workers' wellbeing is prioritized in the process of automation.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by the ethics committee of the Federal Institute for Occupational Safety and Health. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

EH: Conceptualization, Formal Analysis, Investigation, Methodology, Visualization, Writing–original draft. MF: Conceptualization, Investigation, Methodology, Writing–original draft. SN: Writing–review and editing, Visualization. PR: Conceptualization, Writing–review and editing. SW: Supervision, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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The effect of human autonomy and robot work pace on perceived workload in human-robot collaborative assembly work

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Collaborative robots (in short: cobots) have the potential to assist workers with physically or cognitive demanding tasks. However, it is crucial to recognize that such assistance can have both positive and negative effects on job quality. A key aspect of human-robot collaboration is the interdependence between human and robotic tasks. This interdependence influences the autonomy of the operator and can impact the work pace, potentially leading to a situation where the human's work pace becomes reliant on that of the robot. Given that autonomy and work pace are essential determinants of job quality, design decisions concerning these factors can greatly influence the overall success of a robot implementation. The impact of autonomy and work pace was systematically examined through an experimental study conducted in an industrial assembly task. 20 participants engaged in collaborative work with a robot under three conditions: human lead (HL), fast-paced robot lead (FRL), and slow-paced robot lead (SRL). Perceived workload was used as a proxy for job quality. To assess the perceived workload associated with each condition was assessed with the NASA Task Load Index (TLX). Specifically, the study aimed to evaluate the role of human autonomy by comparing the perceived workload between HL and FRL conditions, as well as the influence of robot pace by comparing SRL and FRL conditions. The findings revealed a significant correlation between a higher level of human autonomy and a lower perceived workload. Furthermore, a decrease in robot pace was observed to result in a reduction of two specific factors measuring perceived workload, namely cognitive and temporal demand. These results suggest that interventions aimed at increasing human autonomy and appropriately adjusting the robot's work pace can serve as effective measures for optimizing the perceived workload in collaborative scenarios.

KEYWORDS

cobot, perceived workload, industrial assembly work, autonomy, work pace, job quality

1 Introduction

The fourth industrial revolution, conceptualized in Industry 4.0, has led to the introduction of various new technologies that digitize, connect, and automate procedures. Despite this ever-increasing level of automation, human involvement is still crucial due to their adaptability, dexterity, and cognitive abilities. To make optimal use of the strengths of humans within a highly automated environment new solutions are needed. The development of the collaborative robot or cobot, allowed humans and robots to work closely together as a flexible and efficient team (Lenz et al., 2008). A key characteristic of human-robot collaboration is the interdependency between human and robot actions (Hoc, 2000).

The benefit of human-robot collaboration (HRC) is the possibility to make optimal use of human and robot strengths and mitigate weaknesses. HRC can improve efficiency through concurrent motion of robots and humans (Lasota and Shah, 2015). The potential benefit for humans in HRC is that it can reduce physical and cognitive workload (Singh et al., 2013; Cherubini et al., 2016). On the other hand, working in collaboration with a robot can also have negative effects for humans. To facilitate human robot collaboration, more focus on the human is needed, instead of automation alone (Kolbeinsson, Lagerstedt, and Lindblom, 2019).

To measure and access the quality of jobs the OECD developed the framework for job quality (Cazes, Hijzen, and Saint-Martin, 2015). Within this framework, the quality of the working environment is the dimension that deals with the non-economic aspects of the work. A good working environment balances job demands and job resources. This balance originated from the job-demand-control model (Karasek, 1979). According to this model operator wellbeing depends on the balance between the level of job demands, and the level of control the operator has to cope with these demands. The introduction of robots in the workplace alters both demands and control. The demands change when tasks are reallocated between the human and the robot, or the robot changes the working pace. The level of control changes when the robot takes over decision making tasks from the human. In the design of HRC applications, numerous task distributions and robot work paces can be considered, offering an opportunity to optimize the HRC implementation and enhance working conditions. In this research, we focus on the robot work pace and the human autonomy, i.e., the level of control an operator has to select and initiate actions.

Human autonomy in HRC is conceptualized in the levels of automation that describe ten levels between fully manual and fully automated behavior (Parasuraman, Sheridan, and Wickens, 2000). According to this study, an automation level should be chosen that optimizes performance. A metastudy Onnasch et al. (2014) shows a preference to increase automaton until a tipping point is reached where the unwanted effects from mistakes overtake. HRC studies by Gombolay et al. (2015) and Schulz et al. (2017) have shown that humans prefer working with a robot with a relative high level of automation. This seems to suggest that operators are willing to sacrifice autonomy if there is a considerable advantage in demand. The opposite has been argued by Weiss et al. (2011) who stated that operators might perceive a negative change in their working conditions when part of the control and task load is taken over by the robot. In line with this Pollak et al. (2020) found that manual control over the robot improved the wellbeing of the operator.

The effect of pace and synchronization of human and robot actions has been captured in the concept of fluency for which a set of subjective and objective metrics is available. The objective metrics include the relative portion of functional and non-functional delays of the human and robot, and the amount of parallel work (Hoffman, 2019). Fluency is generally improved by minimizing delays, especially for the worker. This promotes a fast-paced robot that finishes tasks early in anticipation of human tasks. However, two studies revealed that a high moving speed of the robot leads to high cognitive workload, significantly increasing fear, surprise and discomfort (Arai, Kato, and Fujita, 2010; Fujita, Kato, and Tamio, 2010). These results might also be explained in part by the fact that faster moving robots increased the sense of time pressure.

The aforementioned studies seem to make conflicting statements about the role of human autonomy and time pressure. There are several explanations for this. First, the change in human autonomy or work pace is paired with other factors that have influenced the outcomes. For example, time pressure and robot speed might be influenced at the same time (Arai, Kato, and Fujita, 2010; Fujita, Kato, and Tamio, 2010), or the change in autonomy also entails a change in the task load (Fournier et al., 2022). Second, many studies are intended as a proof of concept and only involve a small (<10) number of subjects (Baltrusch et al., 2021).

To properly study the effects of time-pressure and autonomy, the conditions should be kept uniform in terms of task load. Such a standardization might also benefit industrial applications. Many industrial processes, such as assembly work, are characterized by repetitive tasks that must be completed in a prescribed cycle time (Cohen et al., 2022). This cycle time is linked to the task at hand and also to other tasks in the process and customer demand. HRC solutions that improve workload at the expense of cycle time are likely to be rejected in practice.

This study aims to identify the effect of human autonomy and robot work pace in the context of industrial assembly work. The following research questions are formulated:

1. What is the impact of increasing human autonomy on the perceived workload of industrial operators?
2. What is the impact of slower robot pacing on the perceived workload of industrial operators?

We have set up an experiment to answer the stated research questions. In the experiment, participants worked together with a robot on a manual assembly task. The task simulates a typical industrial assembly task. During the experiment the level of human autonomy and the robot work pace of the robot could be controlled such that multiple conditions were created that provided the data to answer the research questions.

2 Methods

2.1 Participants

In this study 20 participants were included (15 men and 5 women, 39 std 14 years old). Participants were recruited via flyers and personal contacts at the BIC Manufacturing Campus, Eindhoven, Netherlands and from the research groups at TNO and HIVA KU Leuven. As such, a diverse group of participants

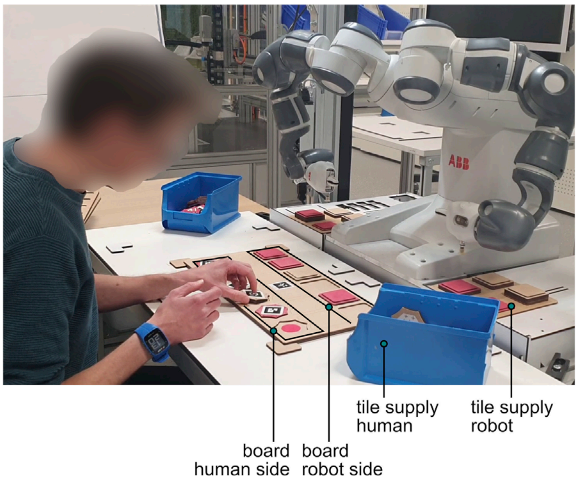

FIGURE 1
Experimental set-up of the manual assembly task.

was found, 4 participants had secondary education or an associate degree, 4 had a bachelor's degree, and 12 had a master's degree or higher. 6 participants were students, 14 had a job. This research complied with the tenets of the Declaration of Helsinki and was approved by the Institutional Review Board at TNO, Leiden, Netherlands (application 2020-063). Informed consent was obtained from each participant.

2.2 Experimental set-up

The participant and the robot performed collaborative manual assembly tasks in a shared workspace (Figure 1).

The collaborative task comprised placing pink and brown tiles on a board. Each board had two rows with six slots and ten of these boards were made per condition. The human and the robot each filled a different row with tiles (Figure 2). The participant and the robot were instructed to place the tiles such that opposing tiles had the same color. Each participant collaborated with the robot in three different conditions. For each condition the way the tiles had to be placed on the board was different: human in the lead (HL), slow-paced robot in the lead (SRL), fast-paced robot in the lead (FRL). The actor that was in the lead, determined the placement order of the tiles and triggering the actions of the other actor (human or robot). The HL *versus* the FRL condition tests the effect of human autonomy (high *versus* low human autonomy). The SRL *versus* the FRL condition tests the effect of robot work pace. The robot work pace was changed by altering the onset of the robot movement. The robot speed was constant across conditions. The different conditions are visualized in Figure 3. A video of the conditions is available as Supplementary Material.

2.2.1 Human in the lead (HL)

The participants initiated the task, by selecting a tile from their supply and placing it in one of the slots on the board (Figure 2A). In this condition the slots were marked pink or brown and the participant was instructed to place tiles in the slots with matching colors. Each board had a different color pattern to prevent that a participant learned a sequence. The participant could select its own placement pattern, i.e., the order in which the slots were filled. When the participant placed a tile, the robot picked a tile of the same color and placed it in the matching slot on the opposite side of the board. The human did not have to wait for the robot to continue to the next tile, so the participant and the robot worked in parallel.

2.2.2 Slow-paced robot in the lead (SRL)

The robot initiated the task, by selecting a tile from its supply and placing this tile in one of the slots on the board (Figure 2B). Then participants had to pick a tile of the same color and placed it in the opposing slot on the board. The robot waited until the participant had placed a tile before placing its next tile. The participant and the robot worked serially on the task. The robot had a limited set of predefined placement patterns, to prevent that a participant learned a sequence.

2.2.3 Fast-paced robot in the lead (FRL)

This condition was the same as the SRL condition with one exception. In the FRL condition the robot was allowed to work one tile ahead of the human so the participant and the robot worked in parallel without waiting times between human and robot tasks.

2.2.4 Cognitive task

To assure, for each condition, that the task time of the robot was shorter than the task time of the human, the participants had to perform a small cognitive task before placing the tile. The participant had to count the number of “T”-signs in an arrangement of “T” and “+”-signs on the back of each tile (Figure 4). Each tile had between 2 and 8 “T”-signs on the back.

The front side listed multiple possible answers (2-8). The participant had to place the tile with the correct answer on top the board. To assure that the participant placed all the tiles correctly. The tiles had an unnoticeable small asymmetry, such that the tiles only fitted in the slots when the correct answer was on top. When the participant noticed the tile did not fit, the participant had to correct the counting error before proceeding with the next tile. This approach effectively mitigated the possibility of errors at task completion.

2.2.5 Robotic setup

The robotic setup consisted out of a dual armed YuMi cobot (IRB 14000, ABB, Zürich, Switzerland) and an auxiliary camera (Logitech C920 HD Pro Webcam). The board and robot-tiles supply had fixed positions and the robot was programmed to place tiles from its tile supply to the board using its build in suction cups. The position and color of the tiles that were placed on the board by the participant were detected by the camera that tracked the square AR markers that were put on the tiles and board. The detection of a new placement triggered the robot actions. The synchronization of tasks performed with custom scheduling software (Pupa, Van Dijk, and Secchi, 2021). The robot motions were programmed in ABB RAPID software. The markers detection

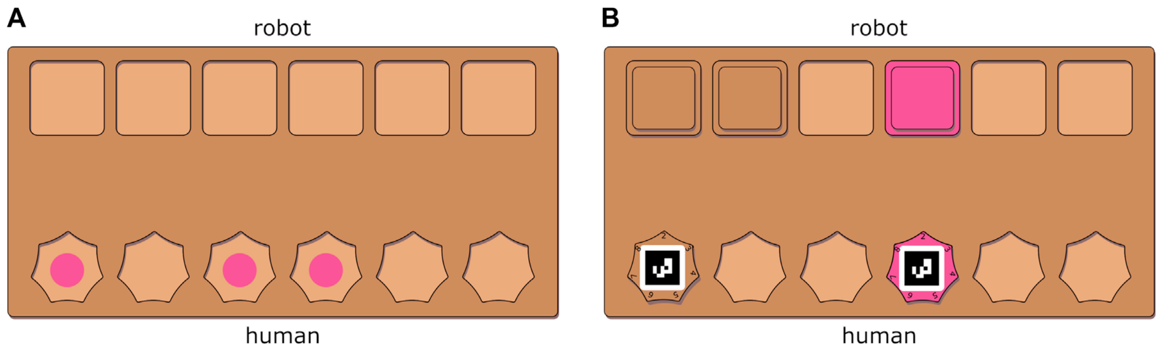

FIGURE 2
Tile boards for the collaborative tasks. **(A)**: tile board for the HL condition without tiles. Note that for the HL conditions the dots in the middle in the bottom rows indicate the color of the tile that needs to be placed. **(B)**: tile board for the FRL and SRL conditions with 3 robot tiles and 2 human tiles.

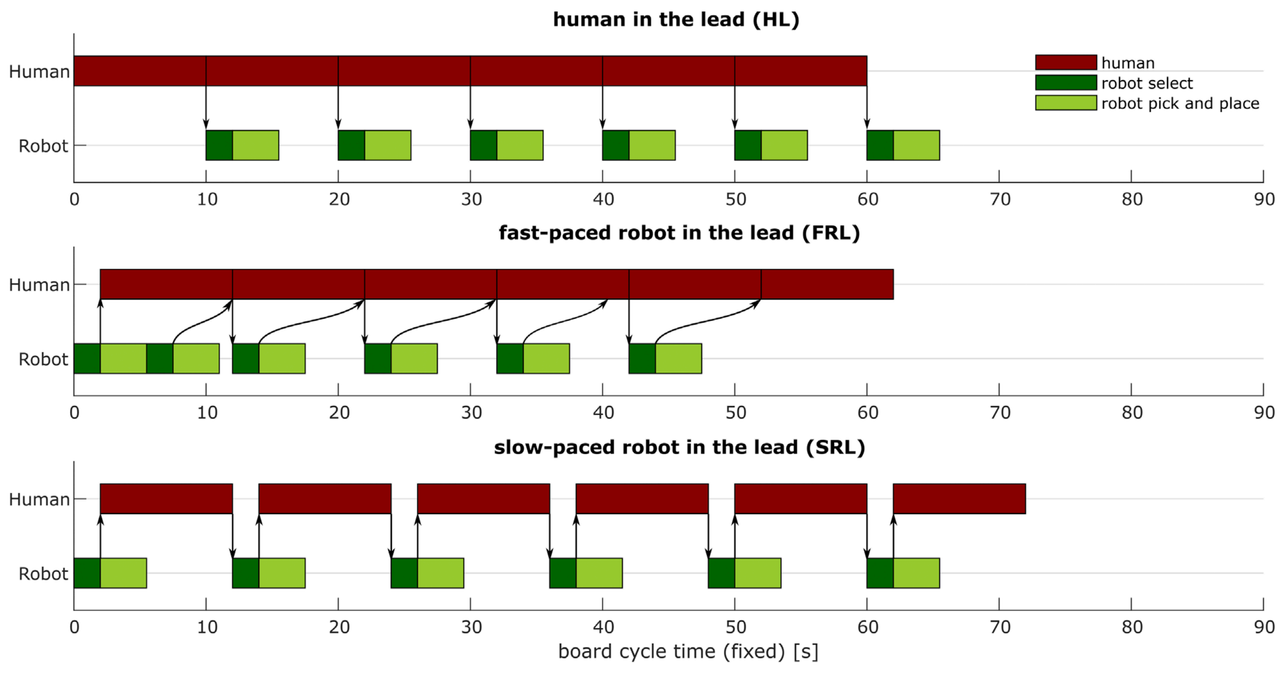

FIGURE 3
Timeline of the three conditions (HL, FRL, SRL). Task times are indicative for flawless task execution without delays or mistakes. The board cycle time, the time to finish one board, is fixed to 90 s. Arrows denote a dependency between an ending and a starting task. Note that when a human task is dependent on a robot task, the human can start as soon as the robot has selected a tile, and the human does not have to wait until the robot has completed the task.

was programmed in ROS (kinetic) using the ar_track_alvar package.

2.3 Experimental procedure

Before the start of the measurement participants were requested to fill in a questionnaire on personal characteristics, gender, age, highest completed level of education and type of employment. After a short explanation of the experimental set-up, each participant started with a try-out where each condition was tested for a brief period. During this try-out the participants could get familiarized with the robot and the task. Subsequently, the participant performed the manual assembly task in the three different collaboration conditions (Figure 2). Each condition consisted of the assembly of ten boards in a row. The assembly of a board consisted of placing the tiles, removing the tiles placed by the robot, putting away the current board, and placing a new board on the table. The board cycle time, i.e., the time a participant had to finish one board, was fixed at 90 s. The board cycle time was established during a pilot and allowed the subjects to work at a comfortable pace. If the participant finished early, the participant waited until the 90 s were passed. If the participant was not ready in the allotted time the participant was allowed to finish the task before starting the next cycle. After

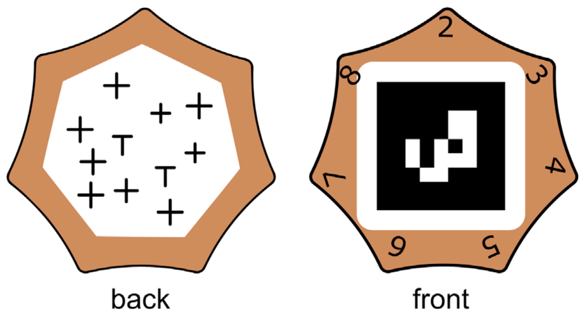

FIGURE 4
Back and front view of a tile that was placed by the human. The correct answer (2) is on top.

each condition with ten boards, participants filled a questionnaire for assessing perceived workload and perceived performance. The sequence of conditions was systematically varied to prevent order effects.

2.4 Measurements

2.4.1 Perceived workload

The NASA Task Load Index (TLX) (Hart and Staveland, 1988) was used to score the perceived workload on 6 scales: cognitive demand, physical demand, temporal demand, effort, frustration and perceived performance. A copy of the questionnaire in Dutch and English is available as Supplementary Material. Since objective performance was fixed through the board cycle time across conditions, the perceived performance score will serve an indicator of whether subjects perceived their performance as similar across conditions. The other factors are indicators for the change in perceived workload.

2.4.2 Objective task performance

The board cycle time was kept constant (see Section Experimental set-up), while the tile cycle time had the potential to vary. To ensure that large variations in tile cycle time were not present across conditions, the tile cycle time was recoded. The tile cycle time was recorded as the time between placing two tiles by the participant. Any waiting time for the participant due to the robot was included in the cycle time. For each participant and condition the median cycle time was calculated. The placement of the first tile was discarded because it often had some irregularities in the recording and in the HL condition involved a vocal "go" from the experiment conductor which did not exactly line up with the start of the recording.

2.4.3 Statistics

To test for statistical differences in collaboration conditions, the scale values of the TLX were compared between the conditions, using the non-parametric Wilcoxon test. The results will report the comparison between HL vs. FRL and SRL vs. FRL that relate to respectively research questions one and two. p-values below 0.05 were marked as statistically significant. Results will report the relevant findings.

3 Results

3.1 Perceived workload

The perceived workload (cognitive demand, physical demand, temporal demand, effort, frustration) and perceived performance are shown in Figure 5, a full report on the outcomes of the statistical tests is available as Supplementary Material.

Increased human autonomy (HL vs. FRL) led to a significant decrease in all perceived workload factors (cognitive demand $p < 0.001$, physical demand $p = 0.011$, temporal demand, $p = 0.007$, effort $p = 0.03$, frustration $p = 0.032$). Decreased robot work pace (SRL vs. FRL) led to a significant decrease in cognitive demand ($p = 0.026$) and temporal demand ($p = 0.008$). The same trend was observed in the other perceived workload factors, physical demand, effort, and frustration, but without significant differences. The difference in perceived performance between all collaboration conditions was small and not significant.

3.2 Objective performance

The tile cycle time, the time between two tiles placed by the human is shown in Figure 6.

Increased human autonomy (HL vs. FRL) led to a 9.2% decrease in tile cycle time (6.8 s vs. 7.5 s). Decreased robot work pace (SRL vs. FRL) led to an 12.5% increase in tile cycle time (8.5 s vs. 7.5 s). These differences were significant.

4 Discussion

4.1 Experimental validity and limitations

The experiment aimed to keep performance constant across conditions by fixing the board cycle time. Despite this, small (<15%) but significant differences in the tile cycle times were observed, which affected the waiting time between boards. However, these differences in tile cycle time did not lead to significant differences in perceived performance among participants. Furthermore, the increase in perceived workload was not directly associated with an increase in tile cycle time, as observed in the HL vs. FRL comparison but not in the SRL vs. FRL comparison. The tile cycle time is therefore not considered as a primary indicator for perceived workload. Still, the tile cycle time differences will be considered when interpreting the other results.

After the experiment the participants were asked if they were able to systematically improve their task execution with something they discovered in the experiment. First, they were asked after the experiment whether they recognized the predefined placement patterns of the robot, which was not the case. Secondly, participants

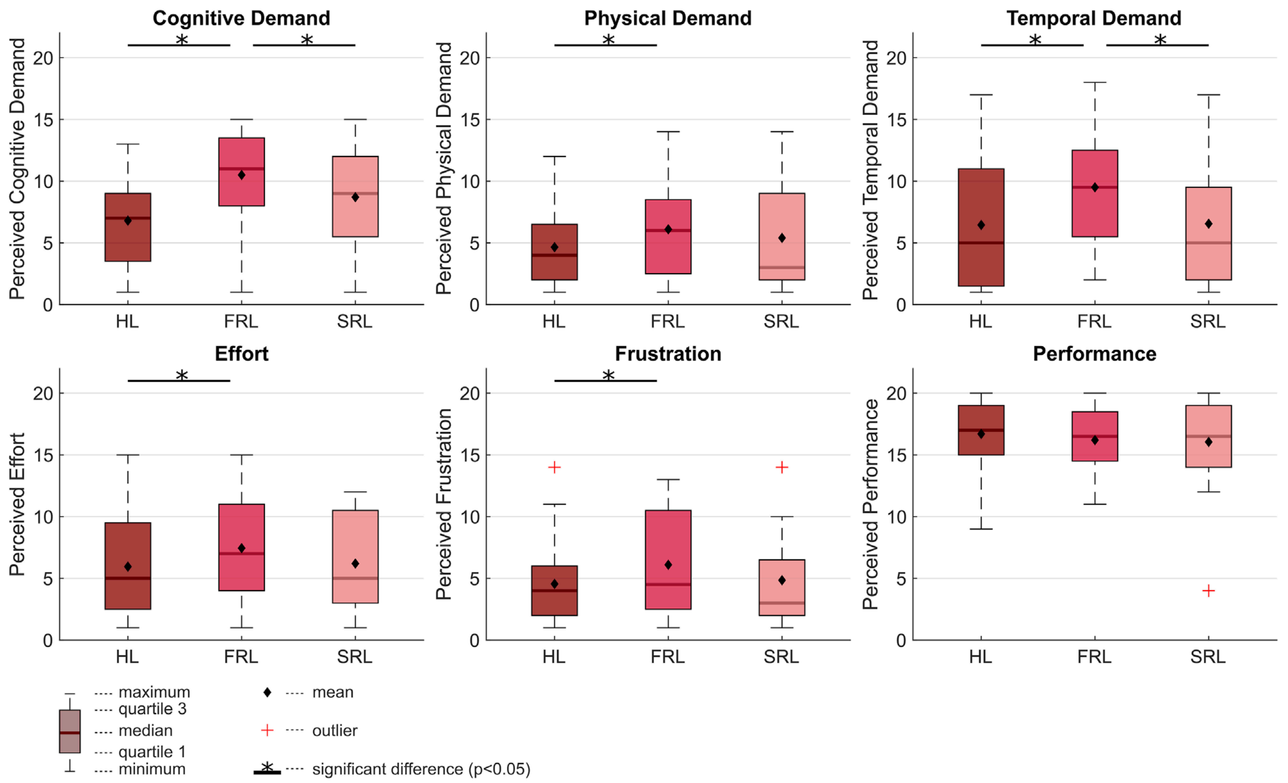

FIGURE 5
Perceived workload in the three collaboration conditions: Human in the lead (HL), Slow-paced robot in the lead (SRL) and Fast-paced robot in the lead (FRL).

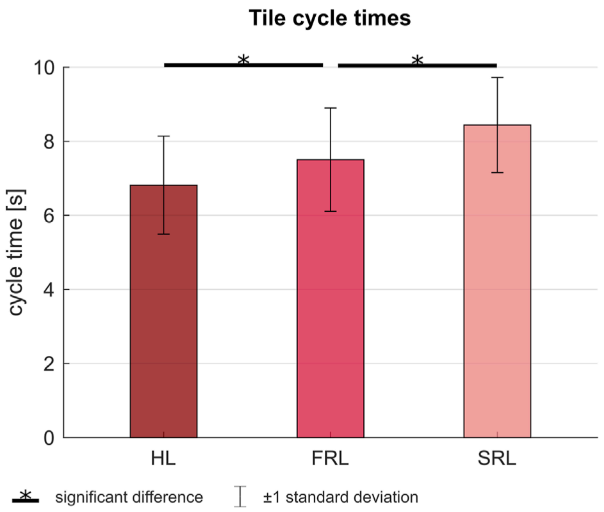

FIGURE 6
Average tile cycle times.

were asked whether they discovered strategies that let them work more efficient, e.g., counting strategies for the cognitive tasks. Participants reported a wide range of strategies. However, they did not experience one strategy to be much more efficient that other strategies. Therefore, it is unlikely that placement patterns of the robot or the development of task strategies led to instantaneous changes in performance and influenced the outcomes of the experiment.

There are limitations to consider in this study. Firstly, our experiment focused solely on a single task resembling an industrial assembly task. The perceived workload, measured using the TLX, served as a proxy for job quality, but this relationship is non-linear. Extreme workload levels, either too low or too high, can lead to performance decline, following a U-model (Young and Stanton, 2002). Therefore, the findings should be interpreted within the context of industrial assembly work and may not be generalizable to other tasks, such as monitoring or high-load tasks. Also, factors of the TLX tend to correlate (Hart, 2006). This study reports the outcomes on all six factors. Due to the correlation between factors, it is difficult to isolate the effects on different types of perceived demands which might also be reflected in the results. For example, the perceived physical demand changed along with the other factors even though the real physical demand did not change.

Another limitation is that a fixed delay was chosen between human tasks, ensuring all participants experienced the same waiting time. This delay was effectively zero in FRL and HL conditions and small in the SRL condition. Consequently, participants were unable to adjust the waiting time by working at a faster or slower pace. In situations where the waiting time between tasks is dependent on the working speed of the human, the relation between working pace and perceived workload may differ.

Furthermore, the experiment involved modifying human autonomy by allowing participants to initiate tasks and select the execution order, which slightly altered their task load. The primary components of task load were manual handling and cognitive counting. However, minor variations in task load existed across the conditions. These limitations emphasize the need for caution when extrapolating the results, particularly to other types of work.

4.2 Human autonomy (HL vs. FRL)

The study results indicate that, in the assembly task, increased human autonomy reduces perceived workload. The increase in human autonomy (HL vs. FRL) was achieved by letting the human start the tile placement sequence and letting the human select the order in which the tiles were placed instead of the robot. This relatively small change in human autonomy was sufficient to lead to a significant decrease in the selected five perceived workload factors. This is in line with the findings of Pollak et al. (2020) that promotes manual control over the robot. This finding is also in line with the Karasek's job-demand-control model (Karasek, 1979; De Spiegelaere et al., 2015). According to the model, when the operator has the job control (i.e., autonomy to initiate a new cycle) to tackle a matching job demand (i.e., work pace) the perceived workload will be lower. Thus, it should be noted that leaving a task for the operator to perform does not automatically increase perceived workload. On the contrary, take away a task which helps the operator control the job demands, and the perceived workload will likely increase. In contrast, the result of the present study conflicts the findings of (Gombolay et al., 2015; Schulz, Kratzer, and Toussaint, 2017) that promote automation. A difference between this study and Schulz et al. (2017) and Gombolay et al. (2015) is that these studies is that a pro-active involvement of the cobot resulted in clear task performance advantages, such as reduced execution time or less re-scheduling.

It was also observed that the tile cycle time in the FRL condition was slightly higher than in HL condition. This was not caused by increased waiting time of the human since the robot always worked ahead of the human (Figure 3). The change in autonomy also entailed a change in dependency between the robot and the human tasks. In the HL condition there was no direct dependency of the human tasks on the robot tasks, i.e., the human could work without noticing the result of the robot's task. In the FRL condition, the human did have to watch the outcome of the robotic tasks, i.e., observe the color and the location of the tile placed by the robot. The dependency on robot tasks in the FRL condition might have caused that the participant felt an increased need to actively follow the robot's actions. It could have also been caused by the fact that since the robot took the initiative, it was perceived as less predictable. The predictability of robot motions has been positively associated with trust and perceived safety (Dragan et al., 2015). Both factors might have led to an increase in attention to the robot's actions which might have caused the increased cognitive and temporal demand in the FRL condition.

4.3 Robot work pace (SRL vs. FRL)

This study indicates that decreased robot working pace reduces workload. In the SRL condition, participants experienced a fixed delay between their tasks. They had to wait with picking a new tile until the robot selected a tile color by picking a new tile from the supply. This contributed to the observed increase in the tile cycle time. In the FRL condition the new tile from the robot was already on the table since the robot worked one step ahead. This change led only to a significant change in two factors, cognitive and temporal demand, and is thus less prominent as the human autonomy related effect.

The finding that workload indicators are lower in the SRL condition competes with the findings of Hoffman (2019) who found positive associations between objective fluency (i.e., minimizing delays) and factors such as trust and bonding which favor the FRL condition. However, if reducing workload is the goal, it can be achieved by decreasing the robot pace, which aligns with the SRL condition. Other studies (Arai, Kato, and Fujita, 2010; Fujita, Kato, and Tamio, 2010) have shown that faster moving robots increase mental strain. It must be noted that in their studies the moving speed of the robot was increased. This study changed pace, i.e., the timing of the onset of robot actions, alone and the robot moving speed was constant. Changing the moving speed of the robot might have a separate effect on perceived workload.

5 Conclusion

The study demonstrates that human-robot collaboration (HRC) in industrial settings creates interdependence between humans and robots, which can impact job quality. Based on The OECD Job Quality Framework and Karasek's job-demand-control model (1979), human autonomy and robot work pace were selected as key factors that might affect the perceived workload. The experiment manipulated these two factors across three conditions.

Increasing human autonomy by assigning decision-making tasks to humans resulted in a decrease in perceived workload, even for small decision-making tasks typical in industrial assembly. This finding aligns with the notion that higher levels of human autonomy which match corresponding job demands contribute to improved job quality.

Lowering the work pace of the robot, such that it creates small waiting times between tasks for the human, led to a reduction in perceived workload. This finding supports previous research suggesting that a high working speed of the robot can increase mental strain. Interestingly, this finding contradicts the fluency principle, which emphasizes minimizing waiting times for both humans and robots.

These findings have practical implications for various industrial HRC processes that involve a sequence of human and robot tasks. The level of human autonomy can be adjusted by determining task initiation and execution order responsibilities between humans and robots. Similarly, the robot's pacing can be modified by altering the timing of its actions. Importantly, these changes can be implemented independently of the primary task distribution between humans and robots, without significant consequences for productivity. Based on the study's results, two design guidelines are proposed to optimize HRC applications:

- Encourage a design that allows operators some freedom to initiate tasks and choose the execution order.
- The work pace of a robot can be optimized by balancing fluency, cognitive demands, and temporal demands (time pressure). Lowering the robot pace can be an effective strategy to reduce cognitive and temporal demands.

By following these design guidelines, industrial HRC processes can be optimized to enhance working conditions, improve job quality, and mitigate workload-related challenges.

Data availability statement

The datasets presented in this article are not readily available because the data involves human subject data. This data should only reported on group level. Requests to access the datasets should be directed to wietse.vandijk@tno.nl.

Ethics statement

The studies involving humans were approved by the Institutional Review Board at TNO, Leiden, Netherlands. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

WD created the first concept for the study. WD was responsible for the design of the robotic setup. SB acquired the ethical approval for the study. WD and SB executed the experiment. SB performed the statistical analysis. WD and SB wrote the first draft of the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frobt.2023.1244656/full#supplementary-material

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Advanced workstations and collaborative robots: exploiting eye-tracking and cardiac activity indices to unveil senior workers' mental workload in assembly tasks

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Introduction: As a result of Industry 5.0's technological advancements, collaborative robots (cobots) have emerged as pivotal enablers for refining manufacturing processes while re-focusing on humans. However, the successful integration of these cutting-edge tools hinges on a better understanding of human factors when interacting with such new technologies, eventually fostering workers' trust and acceptance and promoting low-fatigue work. This study thus delves into the intricate dynamics of human-cobot interactions by adopting a human-centric view.

Methods: With this intent, we targeted senior workers, who often contend with diminishing work capabilities, and we explored the nexus between various human factors and task outcomes during a joint assembly operation with a cobot on an ergonomic workstation. Exploiting a dual-task manipulation to increase the task demand, we measured performance, subjective perceptions, eye-tracking indices and cardiac activity during the task. Firstly, we provided an overview of the senior workers' perceptions regarding their shared work with the cobot, by measuring technology acceptance, perceived wellbeing, work experience, and the estimated social impact of this technology in the industrial sector. Secondly, we asked whether the considered human factors varied significantly under dual-tasking, thus responding to a higher mental load while working alongside the cobot. Finally, we explored the predictive power of the collected measurements over the number of errors committed at the work task and the participants' perceived workload.

Results: The present findings demonstrated how senior workers exhibited strong acceptance and positive experiences with our advanced workstation and the cobot, even under higher mental strain. Besides, their task performance suffered increased errors and duration during dual-tasking, while the eye behavior partially reflected the increased mental demand. Some interesting outcomes were also gained about the predictive power of some of the collected indices over the number of errors committed at the assembly task, even though the same did not apply to predicting perceived workload levels.

Discussion: Overall, the paper discusses possible applications of these results in the 5.0 manufacturing sector, emphasizing the importance of adopting a holistic human-centered approach to understand the human-cobot complex better.

KEYWORDS

human factors, ergonomic workstations, collaborative robots, mental workload, psychophysiology

1 Introduction

The rapid evolution of technology has had a profound impact on the manufacturing industry. Specifically, collaborative robotics (or cobotics) has gained attention for increasing accuracy and efficiency in manufacturing activities (Liu et al., 2022; Lorenzini et al., 2023). In this framework, innovations such as the Internet of Things (IoT) and the Industrial Internet of Things (IIoT) have enabled data-sharing between tools, sensors, and actuators, optimizing working activities and predicting maintenance needs (Wollschlaeger et al., 2017; Khan and Javaid, 2022). Artificial Intelligence (AI) is also being leveraged to enhance processes and ensure quality control (Jan et al., 2022; Morandini et al., 2023), while Big Data analytics is being used to identify trends and support supply chain management (Bag et al., 2020; Koot et al., 2021). Despite these technologies have a clear relevance for the manufacturing sector, their introduction into the industrial routines needs to be carefully implemented to avoid a low level of workers' acceptance (Lu et al., 2022) and trust (Charalambous et al., 2016) towards such working technologies, that would otherwise result in a reduced use. Eventually, operators need to understand that these recent and advanced tools have not been considered as a replacement but instead as a support in carrying out the daily working activities.

The shift in the conceptualization from Industry 4.0–5.0 has in fact brought to light the centrality of human beings, their individual characteristics and needs (e.g., ageing and consequent physical or cognitive decline). In this view, besides the strong interest in the digital transition, the introduction of cutting-edge hardware and software solutions and AI-driven technologies must be carefully considered, on the one hand, to support efficient and flexible industrial productivity, and on the other hand, to back individuals and society. To pursue the latter point, technologies must adapt to the needs and individual features of industrial workers (Lu et al., 2021; Lu et al., 2022), while adhering to the principles of social fairness and sustainability inherent in Industry 5.0 (Xu et al., 2021; Huang et al., 2022; Ivanov, 2023). This human-centric approach is also endorsed by the European Commission (Breque et al., 2021) and is essential for creating accessible, inclusive, and safe working environments that enhance physical and mental health, wellbeing, and the quality of working life.

In the manufacturing sector specifically, advanced ergonomic workstations and collaborative robots play a pivotal role in this shift toward a human-centric focus. These enabling technologies are designed to work alongside human operators, providing ergonomic features and promoting user-centered design (Panchetti et al., 2023). In cobotics, operators and cobots share time and workspace, directly interacting to perform tasks (Hopko et al., 2022). The introduction of these technologies typically increases acceptance, intention of usage, and actual usage among end users (Weiss and Huber, 2016; Meissner et al., 2020).

These advanced workstations offer various ergonomic features, such as adjustable height, smart lighting, pick-to-light systems, and torque reaction arms to improve the operator' comfort, safety and acceptability. Furthermore, there are relevant differences between traditional robots and cobots. For instance, traditional industrial robots do not allow the human-robot direct physical interaction, and therefore do not need any safety features to ensure the physical integrity of the worker. Differently, cobots allow a shared workspace and close actions of humans and cobots. To ensure workers' safety when closely interacting with these technologies, cobots are equipped with several sensors (e.g., proximity, smart cameras) and safety features (i.e., force and speed limiting and collision avoidance systems; Sherwani et al., 2020). This heightened level of safety measures enables cobots to interact securely with human workers in close proximity. They effectively bridge the divide between the physical limitations that traditional industrial robots entail. By assuming responsibility for physically demanding and repetitive tasks while concurrently minimizing the risks of errors, waste, injuries, and accidents, cobots reveal their substantial advantages for human workers, with particular significance for senior workers.

The human-cobot framework is thus characterized by a symbiotic relationship that combines human expertise, creativity, and the ability to handle unforeseen situations, in conjunction with the precision and unwavering performance of robots. According to Kopp et al. (2021), the effectiveness of a human-cobot dyad can be influenced by three elements: worker's skills, cobot performance, and their mutual interaction. Remarkably, there is recent literature that highlights how, by bringing the focus on humans within the human-cobot interplay, the study and assessment of human factors become essential. For instance, Paliga and Pollak (2021) and Paliga (2022), proposed the concept of fluency in human-robot collaboration, which seeks to replicate the seamless interactions observed in human teams. Furthermore, physical ergonomics, trust, acceptance, user experience and usability of these working tools, and the level of operators' mental workload are crucial aspects that must be measured in order to introduce cutting-edge workstations and collaborative robotics in the workplace effectively (for a review, see

Faccio et al., 2023). All these factors, along with the aging factor that is central in our investigation, are detailed in the following paragraphs.

Concerning **physical ergonomics**, researchers such as Gualtieri et al. (2021) and Gaultieri et al. (2020a) have explored the assessment of anthropometric data, focusing on workbench heights and the positions of tools, including dispensers. To accomplish this, both virtual and real prototypes have been employed to determine the correct positioning of workers' arms, shoulders, and backs, often using wearable devices. The objective was to mitigate the risk of musculoskeletal problems (Colim et al., 2021a). In certain scenarios, these ergonomic risks can be alleviated by delegating specific assembly phases to robotic counterparts, thereby reducing the strain on operators' hands and wrists (Colim et al., 2021b). This approach not only lessens physical fatigue but also optimizes overall body posture (Lorenzini et al., 2019). Further research underscored the significance of task allocation and increased collaboration with cobots in comparison to entirely manual work processes (Liau and Ryu, 2020). Ultimately, reducing physical risks for workers can be achieved by entrusting manual handling of heavy components and repetitive tasks to collaborative robots (Gualtieri et al., 2020b; Cardoso et al., 2021).

Other fundamental factors to account for are **trust and acceptance** of cobots (Rossato et al., 2021a; Panchetti et al., 2023). In fact, these working tools can be seen as a threat or an opportunity. The former can lead, for example, to a reduction in work motivation related to the fear of employment loss, while the latter can be characterized, for instance, by a decrement of physical and mental strain (Meissner et al., 2020). Furthermore, research suggests that cobots must be related to a positive working experience and characterized by high levels of usability to influence the perceptions of workers favorably (Hopko et al., 2022; Faccio et al., 2023), for example, by permitting the workers to customize the cobot behavior (e.g., speed, type of interaction; Fraboni et al., 2022) or choosing the interaction modality (i.e., direct physical interaction or mediated by a control interface; Rossato et al., 2021a). Nonetheless, so far, there are more studies focusing on the acceptance of healthcare and assistive robots but yet not enough research in the industrial domain (Savela et al., 2018).

Concerning the **human mental/cognitive workload** (Van Acker et al., 2018), previous studies have quantified this factor by processing various psychophysiological indices that can affect human-cobot interactions or by collecting and analyzing self-reports. For instance, some researchers have considered indices related to eye behavior, such as fixation duration/number (Matthews et al., 2015; Wu et al., 2020) or blink rate/duration (Nenna et al., 2023). Others have analyzed cardiac activity, for example, heart rate or heart rate variability (Charles and Nixon, 2019; Lagomarsino et al., 2022; Lin and Lukodono, 2022), which can reflect fluctuations in the level of mental workload while performing working tasks. To explore the mental workload in experimental settings, the scientific literature has outlined how the manipulation of experimental tasks (e.g., dual task, time pressure, etc.) can induce elevated levels of mental load and negatively influence participants' performance and subjective experiences (Galy and Mélan, 2015; Shaw et al., 2018; Vasquez et al., 2019). Similarly, the subjective perception of participants' cognitive workload (i.e., NASA-TLX; Chacón et al., 2021; Rossato et al., 2021a) or the decrement in work performance are also typically used for measuring the human mental/cognitive load. For instance, longer time on task or higher error rate are indicative of increased mental demand (Rossato et al., 2021a; De Simone et al., 2022; Fraboni et al., 2022; Panchetti et al., 2023).

Finally, considering the extension of working life, the **age of operators** (i.e., >50–55 years) is a human factor that is recently gaining increasing importance. This element can significantly influence operators' perception and interaction with cutting-edge working tools such as cobots. Several studies have investigated the senior workers-cobot interaction and overall experience (Bogataj et al., 2019; Rossato et al., 2021a). Bogataj et al. (2019) outlined the need to invest in workplace ergonomics and cobots to reduce the fatigue and mental stress of old operators, which can mitigate the decrement in their working abilities (e.g., speed, physical strength). A recent literature review (Calzavara et al., 2020) described several benefits related to the introduction of cobots considering the management of ageing workforce. Specifically, they mentioned how simplifying tasks, assigning to cobots the non-ergonomic activities, and enhancing the quality of work output (i.e., human-cobot co-monitoring) are the most beneficial aspects. Rossato et al. (2021a) showed that senior workers perceived the cobot as more supportive than a sample of adult workers. These last reported high levels of satisfaction, cobot's perceived ease of use, and besides high pleasantness when they had the opportunity of interacting physically with it. Recent studies (Rossato et al., 2021a; Rossato et al., 2021b), reported various primary elements that can affect the aged operators' acceptance of advanced workstations equipped with cobots, such as perceived utility, sense of safety, and the need for proper training to use these technologies. Indeed, operators' ageing can make it difficult to ensure high knowledge and skills to deal with advanced technologies.

Taking all this, the main objectives of the present study are to: a) evaluate the subjective perceptions of senior workers in terms of technology acceptance (before and after both post-tests), perceived wellbeing and working experience with an advanced workstation and a cobot and the estimated social impact of this integrated working technology in the industrial sector; b) assess whether the human factors considered in the present research (i.e., task performance, subjective perceptions, eye tracking indices and cardiac activity) variate significantly under dual-tasking (i.e., under higher mental load); c) explore the predictive power of the collected measurements over the number of errors committed at the work task and over the perceived mental demand. For clarity, we have provided a table (i.e., Table 1) collecting all the acronyms used along the paper.

2 Materials and methods

The study was carried out with ethical committee approval by the Ethics Committee of the Human Inspired Technology Research Centre (HIT) (Protocol number: n.2019_58).

2.1 Participants

Fifteen workers (M_{age} = 55.21, SD_{age} = 3.65, F = 4) were recruited for the experiment. The inclusion criteria were that the

TABLE 1 Acronyms used along the paper.

Full term	Acronym
Collaborative robots	cobots
Internet of Things	IoT
Industrial Internet of Things	IIoT
Collaborative robotics	Cobotics
Artificial Intelligence	AI
Assistive Assembly System	AAS
Smart Manufacturing Manager	SMM
Hardware	HW
Software	SW
Heart Rate	HR

age was equal to or higher than 50 years old, normal or corrected-to-normal vision, and no heart diseases, and that participants were active workers in the industrial domain. Participants received compensation for partaking in the trial (i.e., 25 euros). Eleven participants (M_{age} = 54.72, SD_{age} = 4.05, F = 4) were considered in the statistical analyses. Indeed, four participants were excluded for low accuracy of the eye-tracking and/or cardiac activity data. Participants were recruited by an agency, that was a sub-contractor of the Co-Adapt H2020 EU project, with experience in recruiting senior workers within the industrial/artisanal sectors.

2.2 Experimental design

A within-participants design was adopted for the experiment. All participants had to accomplish a single and a dual task (counter-balanced order). Following a dual task paradigm, we manipulated the task difficulty (i.e., independent variable) by adding a secondary task (i.e., mathematical) to the main one (i.e., assembling task).

2.3 Tasks

In the single task condition, participants had to accomplish an assembly task conceived in collaboration with BNP Srl company to have an ecological working activity carried out in a laboratory setting. Typically, an assembly task is a manufacturing or production process that involves the assembly of various components, parts or materials to create a finished products or subassembly. The same assembly task was performed four consecutive times.

In the first step, following the instructions presented on the monitor, participants had to choose a green plate (step 1; i.e., a green metallic plate, "*Retrieve a green plate*") and manually tighten the screws (step 2; i.e., "*Pick up and screw in six pillars and six screws onto the green plate, taking them one at a time from the steel tray. Ensure with your hands that all six pillars are tightened*"). Next, they had to place the plate inside a specific area delimited by pieces of plexiglass tightened with screws on the workbench (step 3; i.e., "*Position the green plate between the stops on the right side of the table. Press the "next" button at the top right of the workstation screen*"; Figure 1).

Then participants had to choose a transparent plate (step 4; i.e., "*Take a transparent plate*") and place it in the cobot's area (step 5; "*Place it below the cobot on the supports*") on two supports. Following, they had to pick up a black plastic plate (step 6; i.e., "*Retrieve a black plastic mold with the same letter as the green plate*") and a set of colored plastic pieces (step 7) to form a puzzle (step 8; i.e., "*Complete the puzzle using the components in the blue boxes following the pattern in the illustration*" Figure 2), while the cobot pretended to glue the transparent plate.

When the cobot finished its task, it passed the transparent plate to the participants (step 9; i.e., "*Take the transparent cover that the robot brought to you. Press the "next" button at the top right of the workstation screen*"). They placed it on the semi-assembled block of components (step 10). Finally, senior workers picked a red metallic plate (step 11; i.e., "*Retrieve a red plate with the corresponding letter and position it above the semi-assembled block of components and press the "next" button at the top right of the workstation screen*") and used an electric screwdriver to tighten the screws following a specific sequence detailed in the instructions presented on the Assistive Assembly System (AAS) monitor (step 12–13; i.e., "*Retrieve the screws one at a time from the steel tray and perform the screwing in the indicated order and use the screwdriver located on the arm to your right and press the finish button when you have completed the screwing task*"). The final assembled object is depicted in Figure 3 (step 13).

In the dual task condition, participants had to carry out a mathematical task aloud simultaneously. They had to subtract seven from 800 and again from the result until the main assembly task was completed (4 times). We asked participants to be accurate and fast as much as possible while performing both experimental tasks. A familiarization phase (see Procedure Section 2.5 for details) was considered for both types of tasks (i.e., assembly and mathematical).

2.4 Equipment and materials

An advanced workstation equipped with a collaborative robot (Assistive Assembly System; AAS) was exploited in the experiment. The integrated working tool is graphically depicted in Figure 4. The collaborative robot is installed aside from the workbench.

The AAS comprises several hardware (HW) and software (SW) components as follows:

HW:

- collaborative robot (Universal Robot UR10e) with its teach pendant (control interface);
- adaptive workbench with adjustable height;
- smart lighting system;
- gesture detection and safety smart camera;
- LCD touch screen (on which the task instructions were displayed);
- force reaction system and a comfortable electric tightener;
- RGB Pick-to-Light smart system;
- Wearable eye-tracking glasses;
- Amplifier and non-invasive surface electrodes for monitoring cardiac activity.

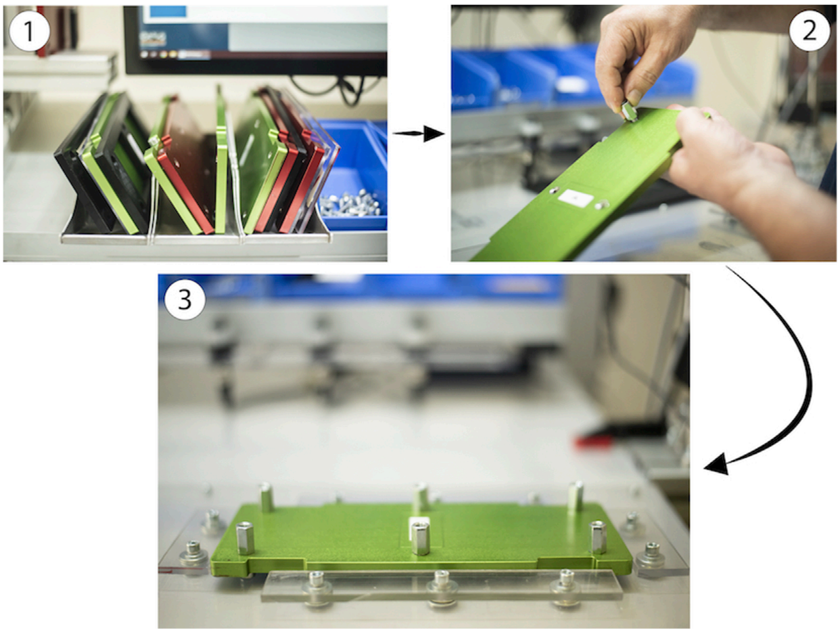

FIGURE 1
Participants had to choose the metallic plate (1), tighten the screws (2), and place the first plate on the AAS workbench (3).

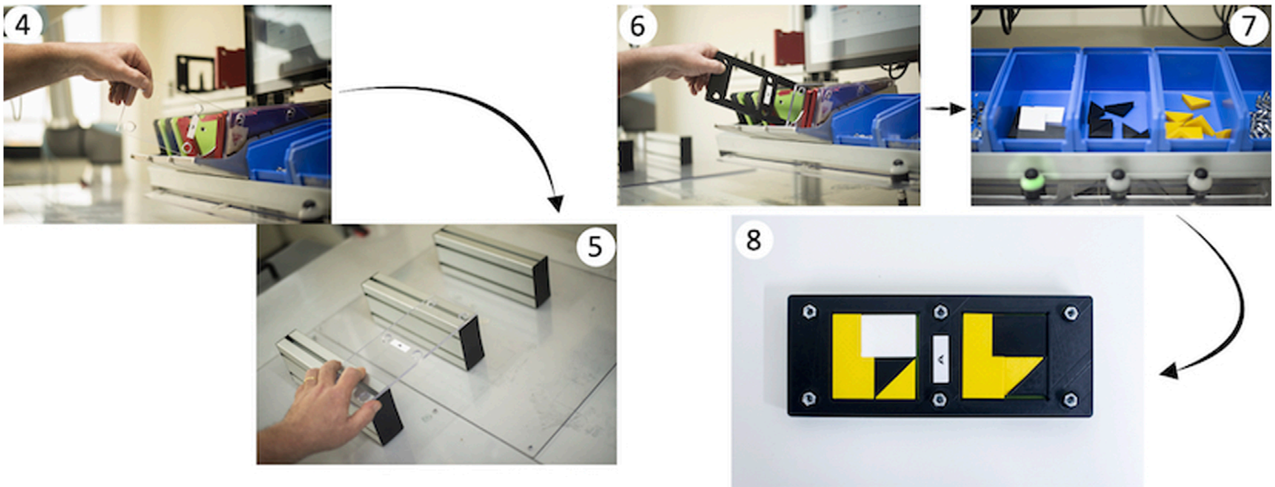

FIGURE 2
Participants chose a transparent plate (4), placed the plate in the cobot area (5), picked up the plastic plate (6) and pieces (7), and formed a puzzle (8).

SW:

- Smart Manufacturing Manager (SMM), offering real-time interactive multimedia instructions;
- Integration of the eye-tracking and physiological software API/SDK for synchronizing the data acquisition.

We utilized a collaborative robot (UNIVERSAL ROBOT; UR10e) which adheres to a stringent set of safety standards as outlined in ISO/TS 15066:2016, making it suitable for operation in close proximity to human workers. It boasts a considerable payload capacity of 10 kg and exhibits remarkable versatility in reaching diverse positions on the workbench. The robot system comprises a robotic arm, complemented by a user-friendly interface installed in a "teach pendant", i.e., a tablet device. This interface empowers users to establish virtual boundaries around the cobot, serving as a proactive safety measure to prevent inadvertent collisions with other objects or surfaces. Besides, the UR10e is equipped with an automatic safety feature that halts its movement if any attempt is made to breach these pre-defined safety boundaries. In this particular setup, we employed

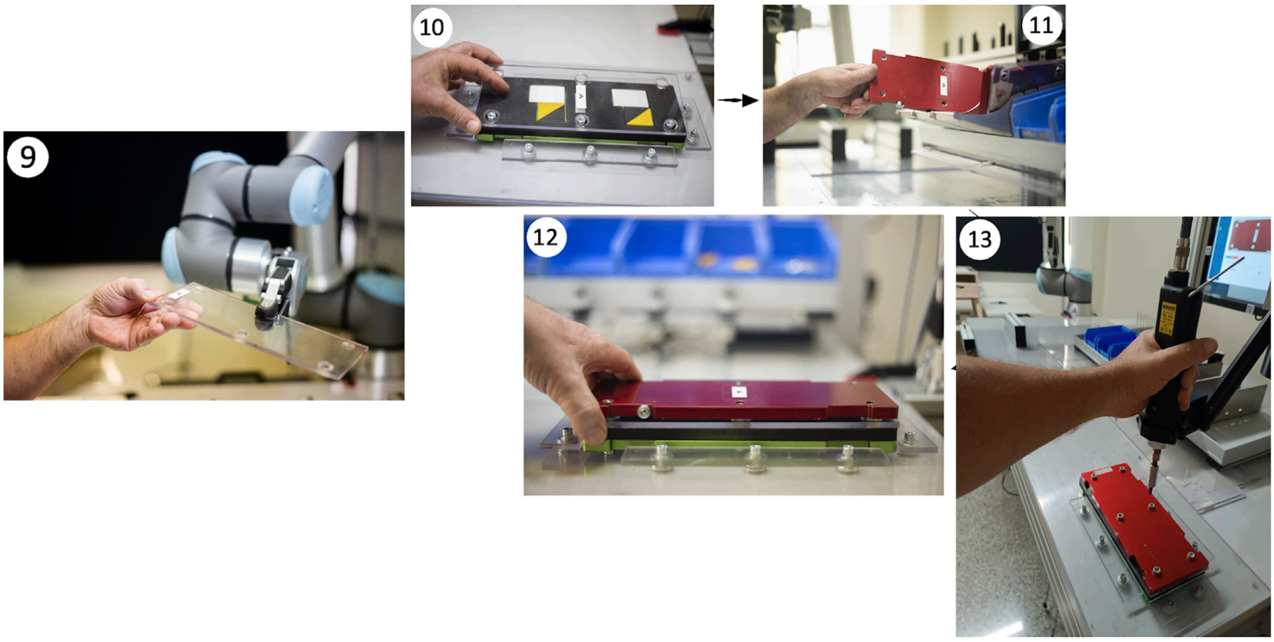

FIGURE 3
Cobot passed the plate to the participants (9), they placed the plate on the semi-assembled piece (10), took a red metallic plate (11), and tightened the screws (12–13).

FIGURE 4
The Assembly Workstation with cobot, eye tracker, and surface electrodes on the workbench.

a gripper as the end effector, facilitating the robot's capability to grasp and release assembly components. The teach pendant permitted the programming of all the cobot movements in the collaborative task.

Besides, participants wore a pair of eye-tracking glasses (i.e., Pupil Labs; maximum sampling frequency of 120 Hz, accuracy of 0.5 visual angle degrees) during the whole experimental session. This tool allowed the collection of fixations and blinks data (i.e., duration and frequency) and pupil diameter. An MSI laptop (Intel Core i7-6700HQ, screen resolution 1920 × 1080) was connected using a USB cable to the eye-tracking glasses, permitted to perform the calibration phases and store the eye-tracking data.

A portable amplifier (ProComp5 Infiniti; © 2022 Thought Technology Ltd.) and its software (i.e., BioGraph Infiniti; © 2022 Thought Technology Ltd.) installed on a second MSI laptop (Intel Core i7-6700HQ, screen resolution 1920 × 1080) were utilized to gather physiological data related to the cardiac activity. The amplifier comprises five channels (i.e., it can record up to 2,048 Hz). For the present purpose surface electrodes were used, and the sampling rate was set at 256 Hz.

Two 4K cameras (Value HD Corporation©) were positioned in the laboratory to allow the video recordings (acquired with the software WMIX HD Edition) of all the experimental sessions.

Recording user interactions with technology in complex settings, such as workplaces, has been widely embraced (Heath and Luff, 2018; Blackler et al., 2018). Researchers can scrutinize the recorded behaviors pertinent to their investigations, employing lucid, observable criteria to ensure impartiality and mitigate bias (Bakeman and Quera, 2012; Guo et al., 2015).

The WMIX HD Edition software was employed to process and synchronize footage captured by each camera resulting in a unified video. Subsequently, these videos were imported into BORIS software, and a coding scheme was independently devised by two researchers based on the observed behavioral patterns. Discrepancies were addressed through discussion, thereby diminishing subjectivity. Subsequent analysis, executed with the concurred-upon coding framework, revealed that certain manual errors (e.g., errors in selecting the correct plates; screw tightening sequence) were infrequently committed by participants. For this reason, the errors were included in a single final category. The refined coding scheme is presented in Table 2.

TABLE 2 Coding scheme.

Coded event	Description
Time on task	The time spent in completing each task (i.e., single task, dual task)
Error in the assembly process	These errors occurred each time the participant failed in some operations of the assembly process
Error in the math task	These errors occurred each time the participant failed in the -7 task

The following self-reported tools were administered:

- Demographic questionnaire (PRE), this tool aimed at collecting background information (e.g., gender, age, experience with collaborative robots, etc.).
- NASA-TLX (POST), the NASA-Task Load Index (Hart and Staveland, 1988; Hart, 2006) was used for assessing the task load in the different experimental sessions. This tool comprises the following six sub-scales: mental, physical, and temporal demands, perceived performance, effort, and frustration. Each sub-scale presents a response based on a 20-step bipolar scale (i.e., range: 5–100). It is possible to evaluate each scale (Galy et al., 2018) independently or consider an overall score by merging the scores of the individual scales.
- TAM 3 (PRE-POST). We adapted the TAM3 questionnaire (Venkatesh and Bala, 2008) considering 16 items and the following constructs: Perceived Usefulness (PU; 4 items), Perceived Ease of Use (PEOU; 4 items), Perception of External Control (PEC; 3 items), Perceived Enjoyment (PE; 3 items), and Behavioral Intention (BI; 2 items). All items were measured on a 7-point Likert scale (i.e., from 1, strongly disagree, to 7, strongly agree).
- *Ad hoc* wellbeing and working experience questionnaire (PRE-POST). This instrument comprises a total of 14 items considering the following dimensions: work satisfaction (4 items), motivation (3 items), engagement (3 items), and overall working experience (4 items). A 5-point scale was used to respond (i.e., from 1, not at all, to 5, extremely).
- Social impact (PRE-POST). This dimension was assessed utilizing a single item (Gervasi et al., 2020). We asked, "which will be the introduction of our workstation in the industrial sector?". The response options were: it will cause the dismissal of workers; it will positively affect the working activities but it will not cause the dismissal of workers; and it will not produce any effect on the working activities.

2.5 Procedure

The experimental sessions were carried out in a quiet and isolated laboratory. Upon participants' arrival they were administered with the informed consent and an informative note. They had to fill out a battery of pre-test questionnaires (i.e., demographic, TAM 3, Social impact, and Wellbeing and working experience).

According to Rossato et al. (2021a), the height of the workbench, where participants were asked to accomplish the various tasks, was meticulously adjusted to conform with precise ergonomic standards, such as ensuring that the workbench's height corresponds to the height of the bent elbow aligned parallel to the ground, minus 150 mm. Afterward, participants were asked if they found comfortable the workbench height to reach various locations shown by the experimenter, that were linked to the actual assembly activity and to use the tools of the workstation (e.g., electric tightener). Thus, in case of an affirmative response the first set of pre-recorded instructions was presented. This information was provided prior to each experimental condition. Nevertheless, researchers were available to clarify any doubt to participants.

A familiarization phase (10–15 min) allowed participants to learn how to perform the assembly task utilizing the cobot, the Smart Manufacturing Manager (SMM) control interface, and the electric tightener. Following this, the experimenter helped participants wearing eye-tracking glasses, and three non-invasive surface electrodes were placed on their chests. The eye tracker was calibrated following a standard procedure using external markers. Afterward, participants were still maintaining their gaze on a cross made of two tapes that were located on a wall at a specific distance from the chair (2.5 m). This phase was carried out to acquire the baseline of their gaze behavior and cardiac activity in a resting condition. The baseline permitted in the pre-processing phase to set the threshold for considering an eye closure as a blink and to avoid artifacts in the data (e.g., not a real blink but a moment in which the eye was ajar).

After the baseline, participants began the experimental tasks. The first condition (e.g., single task) was equal for all participants. They had to perform an assembly activity utilizing the AAS equal to the task of the familiarization phase four consecutive times. In the second condition (e.g., dual task), participants had to simultaneously perform a secondary task: mathematical counting. Participants while performing the assembly task, had to simultaneously subtract seven from 800 and again from the obtained result up to when they accomplished 4 times the assembly task. At the end of each condition, a set of questionnaires was administered. Participants had to complete the NASA-TLX, TAM3, and the Social Impact questionnaire. Single and dual task were counterbalanced across participants (i.e., a sub-group of participants performed first the single task, and then the dual task the other sub-sample first accomplished the dual task and then the single task). Participants carried out the various assembly tasks without speed pressure or a pre-specified time interval. Additionally, to mitigate fatigue-related effects, scheduled intervals of rest were incorporated between the completion of the questionnaires and the beginning of the subsequent task, which were tailored to the needs of each participant. The overall experiment lasted around 45 min. A graphical depiction of the procedure is presented in Figure 5.

2.6 Measures

The following dependent variables were considered, related respectively to performance, subjective perceptions, eye behavior, and cardiac activity:

- Performance (i.e., n° of errors in the assembly and percentage of accuracy in the mathematical task, time on task in sec);

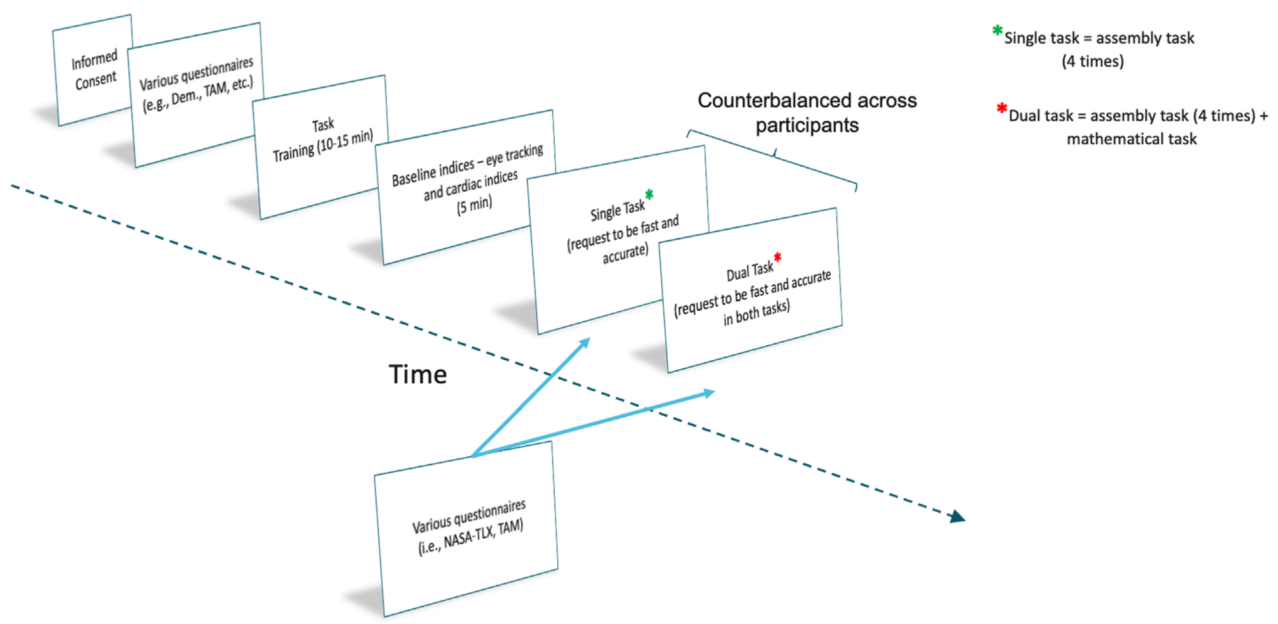

FIGURE 5
Experimental procedure.

- Pre- and Post-test questionnaires scores (e.g., NASA-TLX, acceptance, wellbeing and working experience);
- Fixations duration (ms) and frequency (min);
- Blinks duration (ms) and frequency (min);
- Heart Rate (HR; bpm).

3 Results

For the sake of brevity, in the following sections, only the analyses that showed significant differences among the experimental conditions are reported. All analyses were conducted using the software RStudio (R Core Team, 2022).

In the case of data normally distributed, ANOVA analyses were performed. Differently, non-parametric (i.e., Wilcoxon tests) analyses were considered, and the Benjamini and Hochberg (1995) correction was applied to adjust p-values. Regarding the parameters enclosed in parentheses, we provide the following explanations for clarity: t/V = respectively the value of a t-test or Wilcoxon test; d = Cohen's d effect size value; r = effect size value for Wilcoxon tests (Field et al., 2012; Page 665); and R^2 = r-squared of the model.

3.1 Performance

3.1.1 Errors

A difference emerged ($t = -2.87$, df = 10, $p < 0.05$, $d = 1.28$). Participants committed a higher number of errors in the dual task ($M = 5.64$) compared to the single task ($M = 0.81$; Figure 6). On average, participants performed well on the secondary task (M = 77.23%), reflecting the mental workload imposed by the dual task condition.

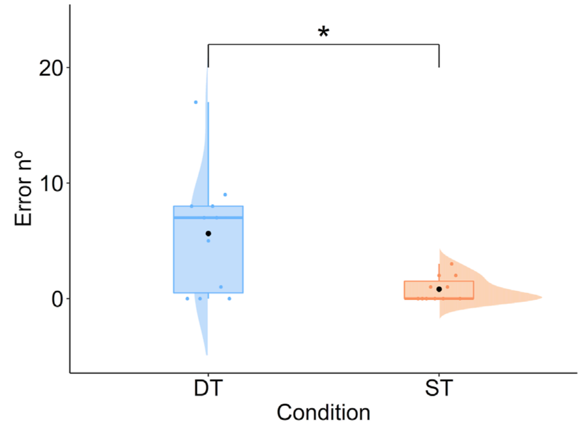

FIGURE 6
Mean number of errors in the assembly task as a function of condition. Note: DT, Dual Task; ST, Single Task.

3.1.2 Time on task

A difference emerged ($V = 0$, $p < 0.001$, $r = 0.99$). Participants were faster in performing the single task (M = 806.82 s) compared to the dual task (M = 966.84 s; Figure 7).

3.2 Subjective perceptions

3.2.1 NASA-TLX

Several Wilcoxon tests were carried out considering the NASA-TLX sub-scales (20-step bipolar scale, range: 5–100). Regarding the mental demand sub-scale, a difference was highlighted ($V = 0$, $p <$

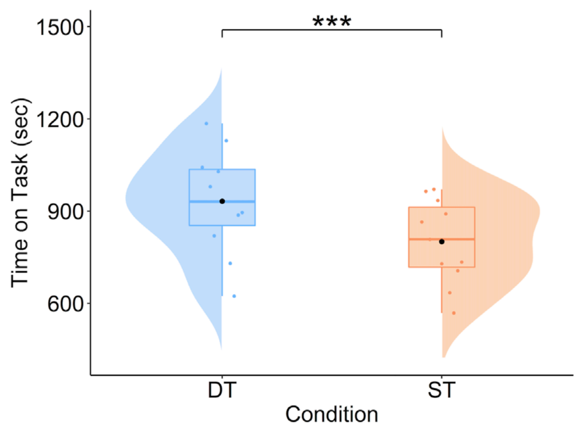

FIGURE 7
Mean Time on Task (seconds) in the assembly task as a function of condition. Note: DT, Dual Task; ST, Single Task.

0.05, r = 0.87). Participants reported a higher level of mental load in the dual task (*Mdn* = 100) compared to the single task (*Mdn* = 45). Besides, considering the effort sub-scale, a difference was shown ($V = 0$, $p < 0.05$, $r = 0.79$). Senior workers reported a higher effort in the dual task (*Mdn* = 95) compared to the single task (*Mdn* = 60).

3.2.2 TAM

No differences emerged considering all the TAM dimensions (all $p_s > 0.05$). Nevertheless, Table 3 shows that all the mean and median (in parentheses) scores were above the scale median (i.e., 4; 7-point Likert Scale, strongly disagree-strongly agree).

3.2.3 *Ad hoc* wellbeing and working experience

No differences emerged considering all the dimensions (all $p_s > 0.05$). Mean and median (in parentheses) scores are reported in Table 4. Wellbeing and working experience questionnaire (scale median = 3; 5-point scale, not at all-extremely).

3.2.4 Social impact

Overall, participants reported a positive perception regarding the potential effect of introducing an AAS equipped with a cobot in an Industrial context. Indeed, more than 90% of the participants at pre-test and both post-tests choose "it will positively affect the working activities, but it will not cause the dismissal of workers." Only 10% of participants in both post-tests selected "it will not produce effects on working activities" (Figure 8).

3.3 Eye tracking

3.3.1 Fixation duration

Considering fixations duration, three t-tests were performed. No difference emerged between single and dual task conditions ($p > 0.05$; respectively, single task: M = 142.15 ms; dual task M = 139.47 ms). Differently, both experimental conditions (resting vs. single task: $t = 5.43$, $df = 10$, $p < 0.001$, $d = 2.47$; resting vs. dual task: $t = 5.96$, $df = 10$, $p < 0.001$, $d = 2.58$) showed a significant reduction in the average duration of fixations compared to the resting condition (M = 325.50 ms).

3.3.2 Fixation frequency

Pertaining to the frequency of fixations, a series of t-tests did not highlight any difference between single and dual tasks. The mean fixation frequency per minute was similar among the resting phase and the experimental conditions (resting: M = 140.49; single task: M = 146.00; dual task: M = 147.21).

3.3.3 Blink duration

Regarding the blink duration, t-tests were carried out. No difference was shown between the experimental conditions ($p > 0.05$; respectively, single task: M = 379.78 ms; dual task: M = 424.69 ms). Nonetheless, in both experimental conditions (resting vs. single task: $t = -3.06$, $df = 10$, $p < 0.05$, $d = 1.79$; resting vs. dual task: $t = -2.39$, $df = 10$, $p < 0.05$, $d = 0.97$), the duration of blink was longer than in the resting condition (M = 239.65 ms).

3.3.4 Blink frequency

Concerning the blink frequency, a difference was underlined ($t = -5.03$, $df = 10$, $p < 0.01$, $d = 0.70$) between experimental conditions. Participants blinked more frequently in the dual task (M = 23.30 blink/min) compared to the single task (M = 14.87 blink/min; see Figure 9). Besides, only the dual task condition differed from the resting conditions (resting: M = 9.12 blink/min; resting vs. dual task: $t = -4.84$, $df = 10$, $p < 0.01$, $d = 1.37$).

3.4 Cardiac activity

No difference in heart rate was shown between single and dual task conditions ($p > 0.05$). The average heart rate was similar in the experimental sessions (single task: M = 101.25 bpm; dual task: M = 100.05 bpm), while, both conditions differed from the resting phase (resting: M = 78.05; resting vs. single task: $t = -5.50$, $df = 10$, $p < 0.001$, $d = 1.78$; resting vs. dual task: $t = -3.01$, $df = 10$, $p < 0.05$; $d = 1.31$).

3.5 Multiple linear regressions

A first multiple linear regression analysis was carried out to assess if the implicit measures (i.e., time on task, fixation duration, fixation frequency, blink duration, blink frequency, and heart rate) could predict task accuracy in the assembly task (explicit measure) including in the model also all the interactions between the implicit measures and the condition. This model (m1) was overall not significant [F (13, 8) = 2.41, $p = 0.11$, $R^2 = 0.47$], although some of the predictors and interactions were significant. For this reason, we refined the model (m2) by removing the variables (i.e., time on task, heart rate) and the corresponding interactions that were not contributing to the predictive power of the model (James et al., 2013). The second model was significant (F (9, 12) = 4.68, $p < 0.01$, $R^2 = 0.61$). Besides, the reduction in the residual standard error from m1 to m2 (respectively from 3.24 to 2.76) suggested that m2 is better fitting the data. We further analyzed the individual predictors. The fixation duration (B = 0.33, $t = 3.78$, $p < 0.01$), fixation frequency

TABLE 3 TAM questionnaire dimensions and scores.

TAM dimensions	Pre-test	Post ST	Post DT
	Mean (Median)	Mean (Median)	Mean (Median)
Perceived Enjoyment	4.27 (4)	5.45 (6)	4.64 (5)
Perceived Usefulness	5.68 (5.5)	6.41 (6.5)	5.50 (6)
Perceived Ease of Use	4.73 (4.5)	5.95 (6)	4.59 (4.5)
Behavioral Intention	5.82 (6)	6.32 (6.5)	5.64 (6)
Perceived External Control	5.36 (6)	6.00 (6)	5.55 (5)

Note. ST, Single Task and DT, dual task.

TABLE 4 Wellbeing and working experience questionnaire dimensions and scores.

WB Dimensions	Pre-test	Post ST	Post DT
	Mean (Median)	Mean (Median)	Mean (Median)
Motivation	3.14 (3.5)	3.82 (4)	3.50 (3.5)
Engagement	3.18 (3)	3.64 (4)	4.05 (4)
Satisfaction	2.91 (3)	3.91 (4)	3.03 (3)
Work/Task Experience	2.86 (3)	3.59 (3.5)	3.12 (3)

Note. ST, Single Task and DT, dual task.

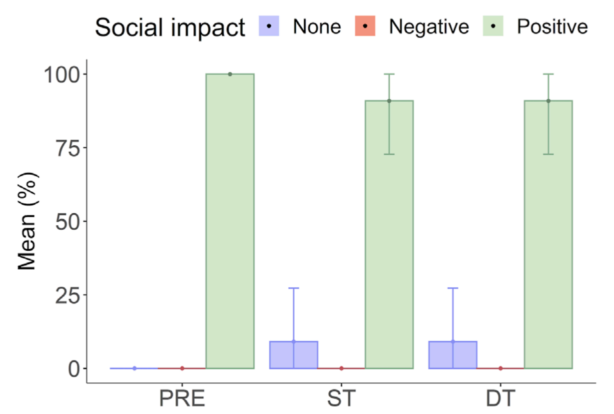

FIGURE 8
Mean responses (%) concerning the perceived social impact of the AAS as a function of the experimental phase. Note: PRE, Pre-test; ST, Single Task; DT, Dual task.

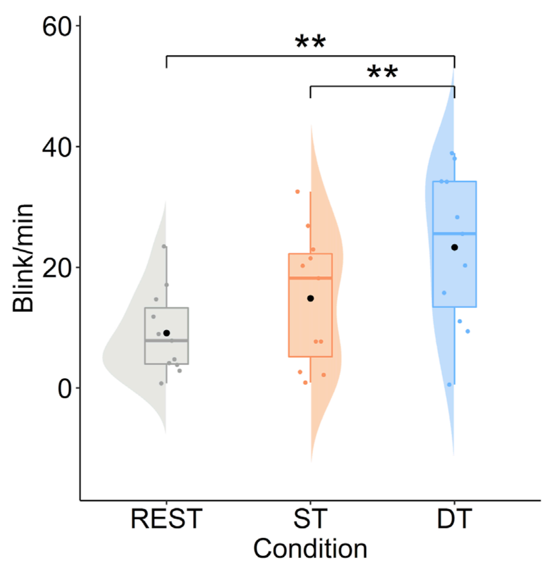

FIGURE 9
Mean blink frequency/min as a function of condition. Note: REST, Baseline resting condition; ST, Single Task; DT, Dual Task.

(B = −0.21, $t = -4.40$, $p < 0.001$), blink duration (B = 0.02, $t = -3.98$, $p < 0.01$), and blink frequency (B = 0.23, $t = 2.84$, $p < 0.05$) were able to predict the accuracy in the assembly task significantly. Besides, three significant interactions emerged (Figure 10): fixation duration X condition (B = −0.34, $t = -3.75$, $p < 0.01$), fixation frequency X condition (B = 0.21, $t = 3.72$, $p < 0.01$), and blink duration X condition (B = 0.02, $t = 2.7$, $p < 0.05$).

We carried out a second a multiple linear regression analysis to predict the task performance in terms of time on task on the basis of the implicit metrics including in the model all the interactions between the implicit measures and the condition. The first model

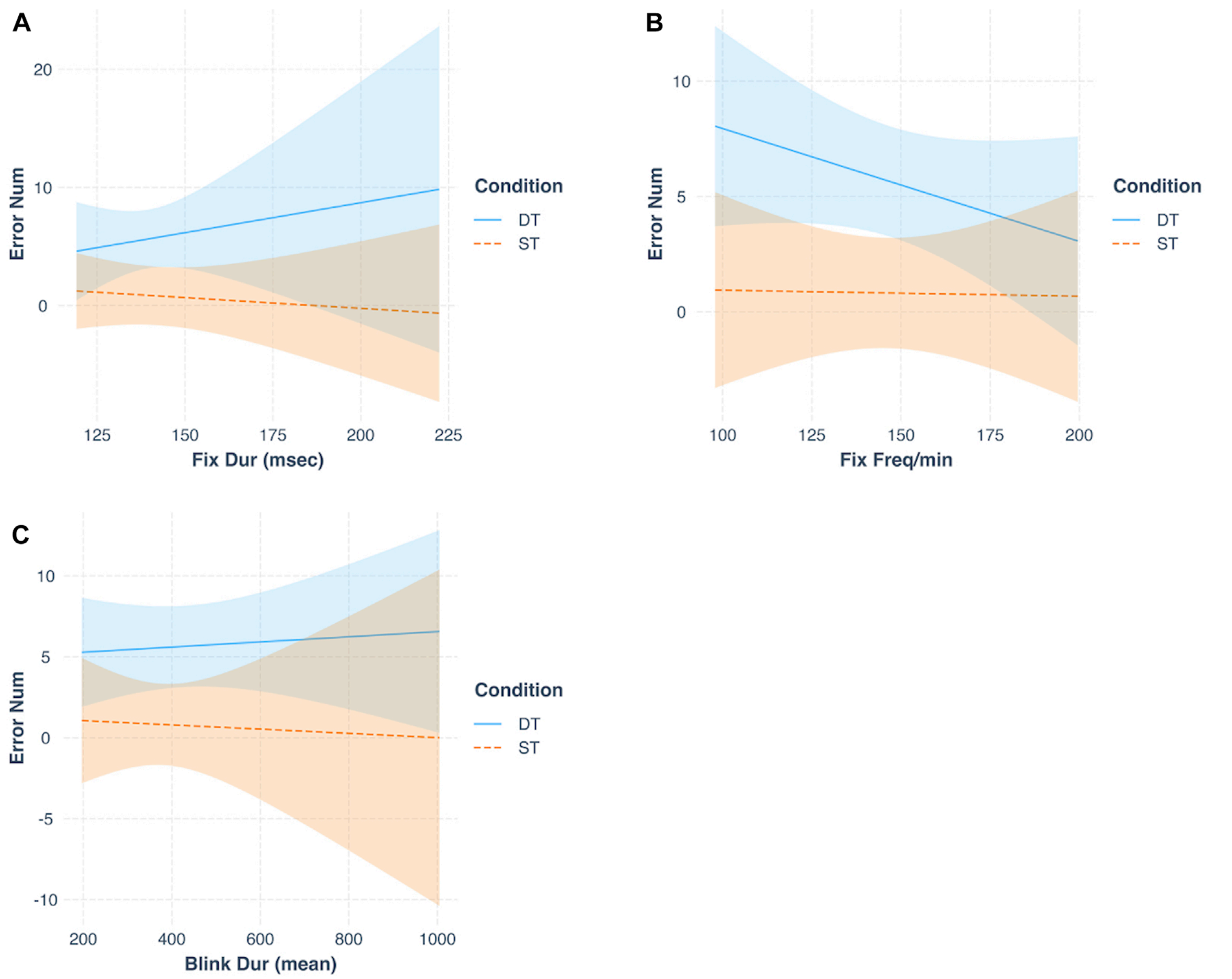

FIGURE 10
Multiple linear regressions showing the predicting power of Fixation duration **(A)**, Fixation Frequency **(B)**, Blink duration **(C)** over the Number of errors in the two experimental conditions. Note: DT, Dual task; ST, Single Task; Fix Dur, Fixation Duration; Fix Freq/min, Fixation Frequency; Blink Dur, Blink Duration.

was overall not significant [F (13, 8) = 1.13, p = 0.44, R^2 = 0.08], and all the predictors and interactions were not significant (all $p_s > 0.30$).

Besides, a series of multiple regressions was performed to analyze if the implicit measures could predict the scores assigned to the different NASA-TLX subscales. The outcomes of the first regression model, which considered mental demand as the dependent variable, did show a significant collective effect between the considered predictors [F (15, 6) = 7.64, $p < 0.01$, $R^2 = 0.83$]. Nonetheless, the predictors or their interactions with the condition did not predict the mental demand scores (all $p_s > 0.05$). Considering the other multiple linear regressions they did not show collective effects [i.e., physical demand: F (15, 6) = 0.97, $p > 0.05$, $R^2 = -0.02$; temporal demand: F (15, 6) = 1.87, $p > 0.05$, R^2 = 0.38; performance: F (15, 6) = 1.72, $p > 0.05$, $R^2 = 0.34$; effort: F (15, 6) = 2.23, $p > 0.05$, $R^2 = 0.47$; frustration: F (15, 6) = 3.41, $p > 0.05$, $R^2 = 0.63$].

4 Discussion

The present experiment aimed at a thorough analysis of a series of human factors in a cutting-edge manufacturing setting, which involved an advanced ergonomic workstation and a cobot. By following the Industry 5.0 conceptualization, we proposed a human-centered study. We specifically targeted senior workers, as this population is particularly inclined to a decrement in their working abilities and, therefore, would particularly benefit from the introduction of supportive and collaborative systems such as cobots in their daily work life (Bogataj et al., 2019). The main objective of this study was thus to provide a broad assessment of various human factors (e.g., senior workers' mental workload and task accuracy) during the execution of an assembly task in collaboration with a cobot, installed on an assistive assembly workstation. More specifically, the following human factors were analyzed: task performance (i.e., number of errors and time on task), subjective perceptions (i.e., the perceived workload reported at the NASA-TLX, the cobot acceptance assessed via TAM, the level of wellbeing and work experience, the social impact of using cobots), eye tracking indices (i.e., blink and fixation frequency and duration), and the cardiac activity. A dual task paradigm was used to manipulate the task difficulty, and therefore, the participants' mental loads.

As a first objective, we wanted to provide a broad assessment of human perceptions regarding the integration of a cobot within a work environment, including technology acceptance, wellbeing, and working experience as well as the broader social impact of this integrated technology in the industrial sector. Our senior participants' scores were high (>4.3) above the scale median (4) both after the single task and after the dual task condition, demonstrating that they enjoyed working with the AAS, they found it useful and easy to use, they expressed the intention to use it if available, they perceived to have control over the system, and they possess the necessary skills to utilize it. Furthermore, at both post-tests, the wellbeing and work experience scores (>3) showed high reported motivation, engagement, satisfaction, and positive work/task experience. Finally, most participants reported that the AAS would have a positive effect on the working activities and would not cause the dismissal of workers if implemented in a real-world scenario. It is important to highlight that these findings were observed in older workers, who might have less experience and skills with advanced technologies compared to a younger population. This observation is in line with Rossato et al. (2021a), who found that older workers viewed the cobot as being more helpful than a group of younger adult workers did.

As a second objective, we aimed at evaluating if the human factors examined in this study (e.g., task performance, subjective perceptions, eye tracking measures, and cardiac activity) significantly changed during dual tasking with increased mental load. On this regard, the level of AAS acceptance, wellbeing, and work experience scores did not differ in the dual task compared to the single task. These findings thus suggest that the cobot was actually supportive and well-accepted even during dual tasking when handling a new technology while under mental strain could have introduced an additional challenge.

Concerning the performance measures, as predicted, both performance indices were modulated. Indeed, the increment in difficulty (dual task; i.e., assembly task + concurrent mathematical task) resulted in a higher number of errors and a longer time on task compared to the condition in which participants had to accomplish the assembly task only. These results align with previous literature using dual tasking to increase task difficulty (Galy and Mélan, 2015; Shaw et al., 2018; Vasquez et al., 2019).

Furthermore, as regards the perceived workload, participants showed a higher level of perceived mental demand and effort while accomplishing the dual task. This result confirms that our manipulation successfully also increased the perceived level of mental demand in the users, and it is in line with previous research (Rubio et al., 2004; Mansikka et al., 2019; Mingardi et al., 2020; Lowndes et al., 2020; Panchetti et al., 2023). Concerning the physical demand, the absence of single vs. dual task difference simply due to the nature of the secondary task being predominantly cognitive (i.e., mathematical), did not affect participants' perception in terms of physical strain. Regarding the temporal demand, a difference was not shown insofar as senior workers were expected to execute the tasks in the various experimental condition with both speed and accuracy, albeit without adhering to a predefined time constraint. Participants reported a similar level of perceived performance, suggesting that they may not have been aware of the disparity in difficulty and, as a result, inadvertently committed more errors in the dual task condition. Finally, the dual task condition was not associated with a higher level of perceived frustration. This finding also substantiates the lack of awareness regarding their actual performance in the two conditions. In fact, being conscious of committing more errors in the dual task would have been expected to be related to a higher sense of frustration. In the context of advanced workstations and collaborative robotics, failing to recognize performance deterioration can result in increased operational risks, higher error rates, compromised quality control, and adverse effects on workers' health and wellbeing. Therefore, it is crucial to explore and study the implementation of monitoring technologies that can quickly identify performance decline, especially in individuals who may be more prone to it due to factors like age. This area deserves further investigation in future research.

Regarding the implicit measures, instead, we did highlight a difference in one of the eye behavior metrics. Indeed, blink frequency associated with the dual task condition was higher than in the single task condition. It thus seems that, based on previous literature (Faure et al., 2016; Tao et al., 2019; Mingardi et al., 2020), participants experienced a higher level of mental load in the dual task compared to the single task. Nonetheless, the fixation frequency and duration, as well as the blink duration and also cardiac activity, did not demonstrate to change significantly under dual tasking. On this matter, it is possible that these indices were not sensitive to the mental load fluctuations during our assembly task, while they demonstrated to be sensitive to mental load fluctuations in different work tasks (e.g., a manual screwing task, Mingardi et al., 2020). This generates new questions about whether the psychophysiological indices' sensitivity to mental load in such ecological work contexts is task-dependent, a question that is worth investigating in future research.

Finally, we investigated the predictive capacity of the gathered measurements on task-related errors and perceived mental demand. Our results from the first linear regression analyses demonstrated how all the measured eye behavioral indices (i.e., fixation duration and frequency, and blink duration and frequency) successfully predicted the number of errors committed at the assembly task. Interestingly, these indices had a stronger predictive power on the committed errors in the dual task condition compared to the single task one, suggesting that the higher the mental demand, the more these indices differ with varying error rates at the task. This could be related to the fact that eye blinks and fixations are known to respond to different levels of task complexity and mental demand (Matthews et al., 2015; Mingardi et al., 2020; Wu et al., 2020; Nenna et al., 2023). Therefore, even though we only found a significant effect of dual tasking over blink frequency, the eye indices might show significant modulations under higher mental strain particularly. More specifically, we found that an increase in the number of errors committed at the assembly task is related to an increase in the fixation duration and the blink frequency, and with a decrease in the fixation frequency. Future works might extend research on the predictive power of eye indices over work task accuracy, similarly to what was done with workload estimation (e.g., Novak et al., 2015), and consider the possibility of implementing eye measures to actively predict the increase rate of task errors online, during the interaction with cobots.

Otherwise, the second series of linear regression analyses showed that task accuracy and the implicit measures were not capable of predicting the scores of the NASA-TLX sub-scales. A suitable explanation is that participants were not aware of their actual performance. Indeed, differences in both task accuracy and time on task (i.e., higher error rates and longer time in the dual task condition) were not related to a discrepancy in the NASA-TLX sub-scale of perceived performance. This outcome is very relevant regarding work safety insofar as not being aware of a decline in performance due to a more demanding working activity could potentially be related to a diminution of overall attention and the adoption of unsafe behaviors.

Some limitations of the study could be underlined. Firstly, we considered a small sample size ($N = 11$), so we must exercise caution when generalizing the findings of the current study. Secondly, more ecological tasks must be considered, especially in terms of duration that could be similar to a phase of a real working shift to also have reliable data, for instance, to assess work-related stress exploiting heart-rate variability (HRV; Gervasi et al., 2020).

Overall, this paper contributes to the literature by proposing a human-centric perspective and a thorough analysis of various human factors to shed light on the feasibility of integrating advanced ergonomic workstations and cobots within industrial manufacturing contexts. While the benefits of these technologies for industrial production are well-known, our study uniquely examines their impact on human factors by adopting a multi-method approach that includes various data sources (performance, self-report, eye-tracking and heart rate data). In a future perspective, the relationships between implicit measures acquired while participants were performing the tasks (e.g., eye-tracking indices) and the working performance could be exploited to inform advanced workstations equipped with wearable sensors (e.g., eye trackers, chest bands) that could adapt their functioning based on the detection of variations in the level of mental load (i.e., overload), with the intention of assisting the workers when they are dealing with more mentally demanding working activities. For instance, future directions might involve adapting these systems for the effective detection and mitigation of worker overload states in diverse industrial environments. This may encompass the development of tailored interventions and the integration of adaptive technologies to enhance worker wellbeing and productivity while maintaining safety standards. However, to implement such a flexible system, it is first imperative to understand human needs. In this respect, we here assessed technology acceptance and perceived wellbeing among senior workers, shedding light on their experiences with these integrated technologies in industrial settings. This holistic approach advances our understanding of the complex interplay between humans and technology, paving the way for safer, more inclusive, and efficient working environments in the evolving manufacturing landscape.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors upon specific request.

Ethics statement

The studies involving humans were approved by Ethics Committee HIT (Human Inspired Technology Research Centre). The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

PP: Conceptualization, Data curation, Formal Analysis, Methodology, Visualization, Writing–original draft, Writing–review and editing, Supervision. GP: Data curation, Investigation, Writing–original draft, Writing–review and editing, Methodology. FN: Data curation, Visualization, Writing–original draft, Writing–review and editing, Formal Analysis. MM: Data curation, Formal Analysis, Investigation, Writing–review and editing. AB: Data curation, Writing–review and editing, Writing–original draft. DB: Writing–review and editing, Data curation, Formal Analysis. AS: Supervision, Writing–review and editing, Writing–original draft. GJ: Funding acquisition, Supervision, Writing–review and editing. AR: Methodology, Writing–review and editing, Software. LM: Methodology, Software, Writing–review and editing. CP: Writing–review and editing, Methodology, Software. LG: Writing–review and editing, Conceptualization, Funding acquisition, Methodology, Resources, Supervision.

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Conflict of interest

Authors AR and LM were employed by BNP Srl. CP is the CEO of BNP Srl. BNP Srl was a partner of the Co-Adapt project.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The authors declared that they were an editorial board member of Frontiers, at the time of submission. PP was Review Editor for Frontiers in Organizational Psychology Employee Well-being and Health and Frontiers in Psychology for Clinical Settings. This had no impact on the peer review process and the final decision.

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A design space for automated material handling vehicles

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Material Handling Vehicles (loaders, excavators, forklifts, harvesters, *etc.*) have seen a strong increase in automation efforts in recent years. The contexts such vehicles operate in are frequently complex and due to the often very specific nature of industrial material handling scenarios, know-how is fragmented and literature is not as numerous as, for example, for passenger vehicle automation. In this paper, we present a contextual design space for automated material handling vehicles (AMHV), that is intended to inform context analysis and design activities across a wide spectrum of material handling use cases. It was developed on the basis of existing context and design spaces for vehicle and machine automation and extended via expert knowledge. The design space consists of separate context and interaction subspaces, that separately capture the situation and each individual point of interaction, respectively. Implications, opportunities, and limitations for the investigation and design of AMHV are discussed.

KEYWORDS

vehicle automation, material handling, interaction design, design space, human in the loop

1 Introduction

Along with the continuous automation of public and private transport as well as manufacturing environments, material handling is another context that sees increasing automation efforts (Machado et al., 2021a; Machado et al., 2021b; Li et al., 2018; Efthymiou and Ponis, 2019). Not only does the number of employed front loaders, excavators, bulldozers, forwarders, mobile cranes, and other material handling vehicles increase, but their degrees of automation do as well (Ha et al., 2018; Heath, 2018; Frank, 2019), thus increasing in-context complexity on two levels. Even without automation factored in, material handling is a complex context by itself: Not only does it involve navigation from one point to another, but destinations are usually also changing as tasks progress or are finished (e.g., moving from stack to stack as they are gradually filled at the same location or transitioning from one location to another entirely). On top of that, there is the non-navigational handling operation, e.g., grabbing, dredging, lifting, *etc.*, all mediated through higher degrees of freedom (e.g., cranes with multiple junction points) and resulting complex controls. In addition, material handling is needed in a wide variety of environments, many of which are not regular on-road environments (e.g., construction sites, farmland, gravel pits, forests, *etc.*). By adding automation to this already demanding mix, the additional challenge of adequately keeping the *human in the loop* (Gil et al., 2019) receives greater relevance.

It is unlikely that any given material handling situation is limited to a single handling operation of quantity X of material Y to a point Z. Rather, material handling exists along a process chain, often at multiple points, and in interaction with other agents, which can and often are themselves material handlers (e.g., loading containers via crane onto a train, then unloading container contents via forklift for a very common example with already three vehicle handlers involved). Depending on the levels of individual automation of each handler as well as the automation of the entire handling chain, properly calibrating the human-in-the-loop is not trivial: At which points in the handling flow does a human need to observe/verify/intervene? Which capacity/qualification does the human need to have, mediated by the task that needs to be performed? At which physical point does the interaction happen and does it need to be done on-site or can it be done remotely? Can the interaction be prompted by a system or must it be human-initiated? These and similar questions need to be answerable in order to properly and safely operate heavy machinery within a material handling context (Heath, 2018).

In Human-Computer Interaction (HCI), one of the best ways to properly capture a context is via a *design space*. A design space essentially is a "space of possibilities", which organizes design opportunities and constraints along specified dimensions (Heape, 2007; Beaudouin-Lafon and Mackay, 2009; Biskjaer et al., 2014; MacLean et al., 2020). A comprehensive design space thus should capture and structure a given interaction context, including related stakeholders, points of interaction, and any variables that can influence the interaction between stakeholders and machines or devices within the context. The goal and purpose of a design space is then to show where within the space activities can be done, whom they will likely affect, and conversely what they are mediated by. This greatly aids interaction designers in planning where, when, and for whom to design - an essential step before the actual interaction design begins.

Currently, there is no such design space for automated material-handling vehicles. There are numerous related design spaces, including in-car interaction (Kern and Schmidt, 2009; Haeuslschmid et al., 2016; Wiegand et al., 2019) and external communication of automated vehicles (Colley et al., 2017; Colley and Rukzio, 2020). The transferability of these design spaces to material handling is limited, as material handling involves specific task types and interaction chains, driving maneuvers, and handling actions combined, as well as greater contextual variability due to the great variety of material handling scenarios. Due to the industrial nature of material handling use cases, there is quite a good number of automation projects with significant funding behind them, yet there is also little knowledge exchange between these projects, which would enable a common material handling automation knowledge base.

Thus, a design space for material handling would be both desirable and beneficial to 1) capture and categorize current efforts and 2) structure, guide, and help align future design and development efforts. In this paper, we present such a design space that was derived from components of related design spaces and enriched with aspects specific to material handling. The multidimensional design space structures the automated vehicle handling space via the dimensions *task and purpose*, *automation setting*, *situation*, and *interaction*. The design space allows specification of driving and handling tasks, mapping them to individual interaction points, and defining the role of the human not only in relation to the interactive device but also via levels of autonomy of (a) the vehicle, (b) the material handler, and (c) the operative process.

2 Related work

Heavy material handling vehicles are primarily or exclusively used on private, off-highway grounds - be it construction and mining grounds, industrial production sites, agricultural fields, or logistics areas. The higher control over processes, traffic, and lower regulatory demands have made material handling vehicles pioneers for automated transport. Automated Guided Vehicles (AGV) have been used for decades in specific industrial contexts (Wankhede and Vinodh, 2021), and these are increasingly used in one-to-many relationships through the remote management of driverless vehicle fleets (Fottner et al., 2021). There is a high business interest and considerable growth prospects with regard to achieving higher autonomy levels (Krug et al., 2019; Gupta et al., 2022). The strive for automatizing material handling vehicles is also motivated by ongoing driver shortage (Costello and Suarez, 2015), the need to increase the attractiveness of work within harsh environments, as well as to reduce safety risks (Machado et al., 2021b). However, despite the longstanding experience and growing relevance of such systems for automated handling of heavy materials, there is surprisingly little open scientific literature available about contextual factors and HMI design, and if available, it is scattered across different sub-disciplines (Krug et al., 2019; Machado et al., 2021b). For such situations with little knowledge about the context variables, general scope, and design alternatives, a design space can help to provide a generic means of orientation. In the following, the state of the art of design spaces is summarised. Then, taxonomies for describing the level of automation and contextual factors are described.

2.1 Design spaces in HCI

Design spaces have been used in architecture, computer science, and especially in Human-Computer Interaction as a complement to standards and guidelines, to inspire design decisions and innovations (Simon, 1975; Card and Mackinlay, 1997; Shaw, 2012; Haeuslschmid et al., 2016; Halskov et al., 2021). Their primary use is to structure and group designs and parameters according to a set of design dimensions. Each design option is ideally represented as a point within that space, thus defining the parameters for each of its constituting dimensions (Simon, 1975). While early work focused on fundamental classifications of input devices (Buxton, 1983; Card et al., 1991) and information visualization (Card and Mackinlay, 1997; Chi, 2000), important contributions have also been provided for specific types of interaction, such as mobile phone input (Ballagas et al., 2008), public displays or multimodal interaction (Müller et al., 2010). Since Kern's and Schmidt's design space for the car cockpit (Kern and Schmidt, 2009), further more specific automotive user interface aspects were addressed, such as augmented reality (Tönnis et al., 2009; Haeuslschmid et al., 2016; Wiegand et al., 2019), conversational interaction (Braun et al., 2017), multimodal interaction (Wang et al., 2022) as well as application contexts like the mobile office (Li et al., 2020). With regard to design support of automated driving, however, design spaces for the internal design of automated vehicles are still rare, but for the external communication of automated vehicles (Colley and Rukzio, 2020) and teleoperation, first proposals have been made

(Graf et al., 2020). While surveys on interaction issues with AMHV have been put forward (Hoffmann and Chan, 2018), no design space is available to support the development of human-automation interaction for this category of systems.

2.2 Level of automation

With the constant penetration of automation and robotics in industrial contexts, the nature of human tasks and involvement with technology is changing (Chen and Barnes, 2014; Gil et al., 2019). The increasing intelligence and sophistication of systems enables human operators of AMHV to not only manually operate them ("in-the-loop"), but also to transition into a supervisory role ("on-the-loop"), where fleets of vehicles are monitored over a distance [see related definitions in Merat et al. (2019)] Various models within and across application areas to categorize the degree of automation and human involvement therein have been proposed [see Vagia et al. (2016), for a comprehensive overview). While for automation of passenger cars, the SAEJ3016 taxonomy of automation levels (Taxonomy, 2021) has become a *de facto* standard (despite other existing standards (Hopkins and Schwanen, 2021)], automation taxonomies for heavy machinery or load handling vehicles are mostly specific to application fields, such as agriculture (Benos et al., 2020), constructions sites (Lee et al., 2022), or mining (Rogers et al., 2019). Only recently, Machado et al. (Machado et al., 2021a) proposed an approach that makes reference to several preliminary models (Heath, 2018; Heikkilä et al., 2019; Krug et al., 2019), which is essentially constituted of a 2-dimensional matrix, where both for driving and for handling (or "manipulation") the six levels of the SAEJ3016 are applied.

2.3 Contextual factors

Interaction design choices for AMHV will have to take account of various contextual factors, in order to achieve optimal system control and perception, worksite communication, and decision making. Only a few scientific accounts, notably all of them from the research area of Automotive UI, include contextual factors like the traffic situations and involved traffic participants, thus actually extending towards contextual design spaces (Wiegand et al., 2019; Colley and Rukzio, 2020; Graf et al., 2020; Colley et al., 2022). Taxonomies of context have a long tradition, as documented in the standard definition of "context of use" in ISO 9241-210 and ISO 20282-1 (for Standardization, 2010; ISO, 2006; Bevan et al., 2015) and 20 years of discussion on context-aware computing (Schmidt et al., 1999; Bradley and Dunlop, 2005; Bauer and Novotny, 2017; Dey, 2018). However, there is no dedicated taxonomy of physical, social, or organizational context factors for material handling vehicles, let alone related to their automation.

3 Methods

While there is no standard method for creating design spaces, we used a systematic procedure for developing the design space that consisted of a literature review as well as two design and evaluation cycles. The purpose of the initial literature review was to identify existing relevant design spaces to use as a basis. We used two iterative cycles so that we could do one in-depth evaluation and fundamental iteration and then a second refinement afterward, following a standard iterative approach. For practical relevance, we focused on the AMHV domains of construction, agriculture, intralogistics, and manufacturing, which are frequent subjects of automation efforts.

After defining the scope, we conducted the initial literature review across the ACM Digital Library and IEEE Xplore. These two data sources were chosen for literature review work since both ACM Digital Library and IEEE Xplore feature a wide selection of reliable HCI works. We used the following search queries in August 2022 in English-language publications: "automated/automation material handling vehicle", "automated/automation crane", "automated/automation forklift". This resulted in a total of 908 publications (633 publications in ACM Digital Library and 275 publications in IEEE Xplore). After having the database, we screened the papers that met our criteria. First, we looked for papers that potentially had an example of design space by searching through their title, authors' keywords, abstract, and introduction with the keywords "design space". Second, as we found no single design space paper for any automated material handling vehicle, we instead focused on publications dealing with the automated vehicles. Third, we focused on detailed descriptions or full overviews of design spaces for the analysis and, therefore, targeted full conference or journal papers only. Any formats that can be expected to only mention or superficially describe design spaces, such as proposals, panels, workshops, or doctoral consortium papers, were excluded. After a metadata-screening for relevance and removing duplicates, the number was reduced to 30 publications. A manual screening in the full text of the publications with the goal of identifying the most directly related design spaces resulted in seven final publications (Kern and Schmidt, 2009; Colley et al., 2017; Mahadevan et al., 2018; Wiegand et al., 2019; Colley and Rukzio, 2020; Graf et al., 2020; Wang and song, 2022). We used the design spaces described within them as inspirations for initial dimensions and categories. We then enriched them with features specific to capture automation as well as the human-in-the-loop characteristics to arrive at the first draft of the contextual design space.

We then evaluated this draft through a series of in-depth expert interviews with three AMHV domain experts. These experts were selected for their experience and expertise in material handling vehicles ranging from technical competence such as automation aspects to process competence that demonstrates the interrelation of various stakeholders. Experts had on average 4 years of experience working with material handling vehicles in the areas of logistics or mobility. Each interview lasted approximately 2 h, excluding preparation time. Before the interview, each interviewee was instructed to prepare a use case of their choice from within their application domain. They were free to do so in any possible way, as long as they would be able to fully describe the case and all relevant actors during the interview. The interview itself then consisted of three parts: an introduction, the design space population, and then a final feedback and comments session.

During the introduction, the interviewee was informed about the purpose of the interview as well as its duration and agenda and was then introduced to the design space, its overall purpose, as well as all dimensions and categories. They were then explicitly asked to raise questions regarding anything that was not clear before moving on to the next part. The introduction lasted 10–15 min. Then, the interviewee was asked to populate the design space with the use case they had prepared. We conducted a semi-structured interview, where the interviewer asked several predetermined thematic questions based on each part of the design space "E.g., How many individuals are involved in the overall process and which roles do they have?". As the interviewee answered, the interviewer completed the dimensions of the design space in an Excel Sheet. This step took approximately 60–70 min. In the final phase of the interview, the interviewee was asked to reflect on the completed design space and comment on any aspects of the design space that had not been situated in the use case at all or only incompletely. They were also asked to highlight incomplete or inappropriately named labels, category errors, or any other issues that came to their mind.

On the basis of the interview results, we created an iterated version of the design space. This version was then validated in a second round of interviews with seven human-machine interaction experts. We selected our sample respondents by identifying the target population as experienced HCI designers and researchers with at least 4 years of professional experience in the field of automated vehicles. While selecting more experienced individuals might exclude the viewpoints of early-career HCI practitioners, our goal was to provide a comprehensive design space by highlighting the practical and industry-oriented insights that are crucial for the implementation of automated material-handling vehicles. These interviews were shorter, with a duration of 30–40 min each, and the interviewees were no longer asked to prepare a use case description beforehand, as this round of interviews primarily emphasized the design perspective. Instead, the interviews consisted of a very short introduction (5 min), after which the interviewer reviewed the design space together with the interviewee, asking for each dimension and its categories regarding relevance, comprehensibility, cohesion, and completeness. This part took 20–30 min. At the end, the interviewee was asked to provide a final valuation of the design space's appropriateness as well as sum up the definitive needs for improvement, if any. The results from this second round of interviews were collected and then integrated into the final version of the contextual design space (see Table 1 for an overview of the main implications from the subsequent phases of the development of the design space).

4 Design space

In this section, we describe the design space that resulted from the iterative process described in the previous section. The design space consists of two main parts or "spaces": *Context Space*, and *Interaction Space*.

The two spaces complement each other and also serve to reduce the complexity of any given context that is captured via the design space. The Context *Space* serves to capture all factors pertaining to the material handling context, including surface and weather constraints, machines and their automation levels, user roles and task types, *etc.* It is to be defined once for any given scenario or use case.

The *Interaction Space*, on the other hand, defines any *interaction point* within the context. An *interaction point* is any (physical) instance where a machine or human interacts. E.g., a simple context with two machines, each with one set of direct controls each as well as a fleet management workstation would result in three *interaction points* overall. The *Interaction Space* then defines in- and output for each of these points but maps back to the *Context Space* to the previously defined task types, user roles, automation setting, *etc.*

By doing so, the overall design space can efficiently capture complex human-in-the-loop scenarios with many different machine types, several control interfaces, different automation levels and intervention capabilities, without increasing exponentially. In the following, we describe the sub-space (e.g., automation setting), dimensions (e.g., driving), categories (e.g., level of autonomy), and their characteristics (e.g., semi-automated) for each space in detail.

4.1 Purpose/task

Although there are two primary purposes that we cover for automated material handling vehicles, that is, driving and handling, we subdivided the purpose subspace into three scope elements: driving, handling, and support tasks (see Figure 1, left side). Driving tasks are those related to maneuvering the vehicle. Handling tasks are about handling the material such as loading/unloading the cargo. Lastly, coordination and support tasks are non-related driving or handling tasks such as management of fleet scheduling, vehicle allocation, and maintenance.

4.1.1 Task abstraction

As Table 1 indicates, the scope or abstraction of a task has emerged as a relevant dimension from our first interview round, but notably, it has so far not been proposed by previous design spaces summarised in section 2. We identified three abstraction levels of driving and handling tasks, based on Michon's model (Michon, 1979). Strategic tasks are those that plan the goal of the action such as navigation. Tactical tasks are those that facilitate the accomplishment of the task, for instance, detecting an obstacle. Operational tasks are those activities that aim to maintain and sustain a system such as loading the lattice box.

4.1.2 Degree of freedom

A factor of primary relevance was found to be the physical direction in terms of movement. In order to capture this for the design space, the degree of freedom has been incorporated as a dimension of the design space. Notably, this aspect so far has not been presented as part of previous related design spaces mentioned in section 2. The most generic way to specify the target direction along their trajectories is to specify degrees of freedom, separately for the driving, handling, and support tasks (e.g., for directing vehicle charging or maintenance personnel). It has to be noted that the technical movements to be done by the handling components are typically highly complex and fine-grained (Hamid et al., 2016; Martin and Irani, 2021), thus in principle entailing many degrees of freedom. However, from the perspective of task and purpose specification, the actual defined movement targets can be specified with significantly fewer degrees of freedom, essentially reducing it towards three independent directions (x,y,z) in space.

TABLE 1 Overview of the implications from the literature review and the two rounds of expert interviews.

Space	Sub-space	Dimension	Main implications from the evidence collected during the design space creation process		
			Literature review	1st interview round	2nd interview round
			Previous work adopted for first draft	Resulting revisions of design space	Evidence for the finalization of the design space
Context Space	Purpose/task	General	Machado et al. (Machado et al., 2021a): Main Driving and handling ("manipulation") as main categories	Refined (3rd category of coordination added)	Confirmed
		Task abstraction	-	Refined (task types and steps)	Consolidated (Michon's model implemented, based on expert feedback (Michon, 1979))
		Degree of Freedom	-	Refined (introduced different types of DoF: actual and translated)	Consolidated (simplified DoF options)
		Duration	Wiegand et al. (Wiegand et al., 2019) introduced duration "travel time"	Introduced	Confirmed
	Automation Setting	General	-	Refined (levels of automation)	Confirmed
		Level of Automation	SAEJ3016 as widely accepted taxonomy for automated driving (Taxonomy, 2021), Machado expand this for the LoA of material handling vehicles (Machado et al., 2021a)	Refined (summarizing SAE automation levels 1/2 and 3/4)	Confirmed
		Human operator location	-	Refined (Added option "no human operator location")	Consolidated (simplified the categories)
	Situation	General	ISO 9241-210 taxonomy for social and physical context (for Standardization, 2010); Colley et al. 's design space contains physical and social context variables (Colley and Rukzio, 2020)	Confirmed	Confirmed
		Social	Different user/operator roles adopted from (Graf et al., 2020; Colley and Rukzio, 2020)	Refined (added user role "maintenance")	Consolidated (final grouping of user roles)
		Physical	Physical context aspects are broken as categories in ISO 9241-210 (for Standardization, 2010), and related to automated driving in Colley et al. (Colley and Rukzio, 2020). Soil categories were taken from (Deatherage et al., 2004). Other environmental factors, such as temperature and light intensity, were taken from (Yamazaki et al., 1998)	Refined (introduced "Dynamicity" dimension, added "sunlight" and "storm")	Refined (Added dimension "Loading dock type"), consolidated

(Continued on the following page)

TABLE 1 (*Continued*) **Overview of the implications from the literature review and the two rounds of expert interviews.**

Space	Sub-space	Dimension	Main implications from the evidence collected during the design space creation process		
			Literature review	1st interview round	2nd interview round
			Previous work adopted for first draft	Resulting revisions of design space	Evidence for the finalization of the design space
Interaction Space	Human-Automation Interaction	Scope elements Input/Output	Multiple design spaces with a differentiation of input and output (Nigay and Coutaz, 1993; Frohlich, 1992; Kern and Schmidt, 2009; Graf et al., 2020; Wang and song, 2022)	Confirmed	Confirmed
		User role profiles	-	Refined (added user role “maintenance”)	Consolidation (consistency with user role in social dimension)
		Communication type	Communication messages of automated vehicles to road users proposed by Colley et al. (Colley and Rukzio, 2020)	Confirmed	Confirmed
		Modality	Design spaces with modality as a key dimension (Detjen et al., 2021; Colley et al., 2022; Graf et al., 2020; Ahmad et al., 2018)	Confirmed	Refined (added variation “biometrics” for input modality)
		Device Type	Graf et al. propose partly propose device types, as part of their interaction space (Graf et al., 2020)	Refined (added variation “pedal”)	Confirmed
		Locus	(Detjen et al., 2021; Colley et al., 2022)	Confirmed	Confirmed
		Degree of Freedom	-	Introduced	Confirmed

4.1.3 Duration

This dimension distinguishes between short or long duration of a task [adapted from Wiegand et al. (2019)]. According to the duration of task performance, additional interaction with the vehicle would be required. For instance, a long duration may require charging the vehicle.

4.2 Automation setting

For the characterization of the automation setting targeted for a certain AMHV use case, we again analyze the vehicle's driving and handling, as well as the coordination and support activities.

4.2.1 Level of automation

For categorizing automation levels for driving, handling, and coordination, we took reference to the SAE automation levels (Taxonomy, 2021) [similarly to Machado et al. (2021a)], in a condensed form.

- No automation: human operator is in direct control and performs the tasks manually (equivalent to L0 SAE J016 level).
- Partial automation: operator in direct control, but supported through partial automation (SAE L1+L2).
- Supervised automation: system is operated in an automated way, but operator should be available to intervene (SAE L3+L4).
- Full automation: system is running autonomously with interventions only in case of system errors (SAE L5).

This taxonomy is similar to the level of automation (LOA) of decision and action selection (Sheridan et al., 1978), e.g., no automation is equivalent to LOA scale 1, partial automation to LOA 2-4, supervised automation to LOA 5-9 and full automation to LOA 10.

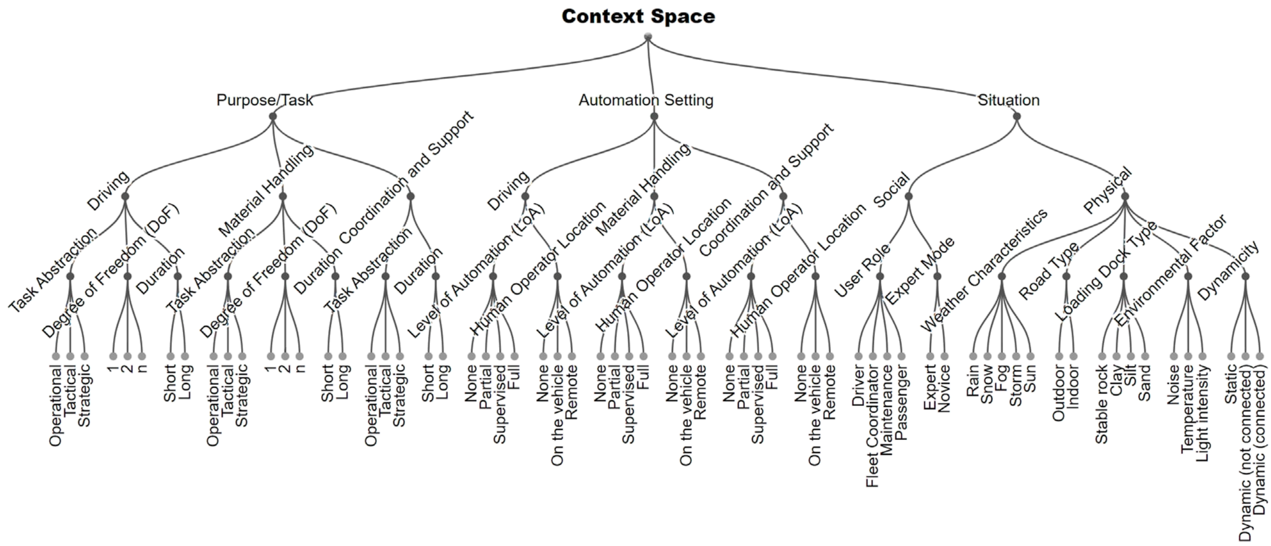

FIGURE 1
Human-Automation Context Space for AMHV (see description in sections 4.1–4.3).

4.2.2 Human operator location

The location of operators to material handling vehicles can be either on the vehicle or distant from the vehicle, which results in different design requirements. Also in case of coordinating or supporting actions, it makes a significant difference whether the scheduling or charging is done with the vehicle in sight. This dimension emerged during the first round of interviews and was refined in the second round.

4.3 Situation

The situation in which the operation is undertaken will entail significant constraints on the design options for AMHV interfaces. Referring to context models from HCI and pervasive computing (ISO, 2006; for Standardization, 2010; Schmidt et al., 1999; Bradley and Dunlop, 2005; Dey, 2018), as well as to previous design spaces that had already adopted contextual dimensions (Colley et al., 2017; Wiegand et al., 2019; Colley and Rukzio, 2020; Graf et al., 2020), we include the following main elements for the situation sub-space: social and physical context (see Figure 1, right side). The first two dimensions - user roles and expertise - are related to the social context and the other five are about the physical context (weather characteristics, road type, loading dock type, environmental factor, and dynamicity).

4.3.1 User role

A user is any person who is actively or passively engaged with the AMHV. The most common roles of these persons who need to be supported by AMHV user interfaces are direct control of a vehicle (driver), monitoring and coordination of (fleets of) vehicles, regular technical support, and interventions in situations of malfunction (maintenance), and passive use of a vehicle (passenger). This dimension has also been part of other design spaces (e.g., Colley and Rukzio, 2020), and the categories have been specified by means of the first round of interviews.

4.3.2 Expert mode

Depending on the user interacting with the AMHV, information may embrace different degrees of detail. While the criteria in assessing expert models of operators can vary depending on the industry, equipment, and specific task, here we define expertise as the extent of specialized knowledge and skills in operating a material handling vehicle (Hetmański, 2018). This could be based on a history of successful completion of similar tasks or relevant certification or training in material handling operations. In order to capture this important difference, we identify two modes, i.e., expert and novice [adapted from Graf et al. (2020)]. For instance, a novice operator who requires the supervision of a superior is considered a novice, while an experienced operator is an expert.

4.3.3 Weather characteristics

Weather as a relevant contextual dimension has been proposed for external HMIs of automated vehicles (Colley and Rukzio, 2020). We identified different characteristics such as rain, snow, and fog [adapted from Colley and Rukzio (2020)] that affect the sensor functionality. Furthermore, we added two weather characteristics that are particularly important for handling activities that emerged from the interviews: storm and sunlight.

4.3.4 Road type

AMHV operation strongly depends on the road type, especially whether activities are being performed indoors or outdoors. In this regard, an indoor road can be part of a warehouse, whereas an outdoor road is outside, for instance at a construction site.

4.3.5 Loading dock type

This dimension is discussed by reviewed publications. Previous work lacks a description of the soil at the loading dock (i.e., pick up

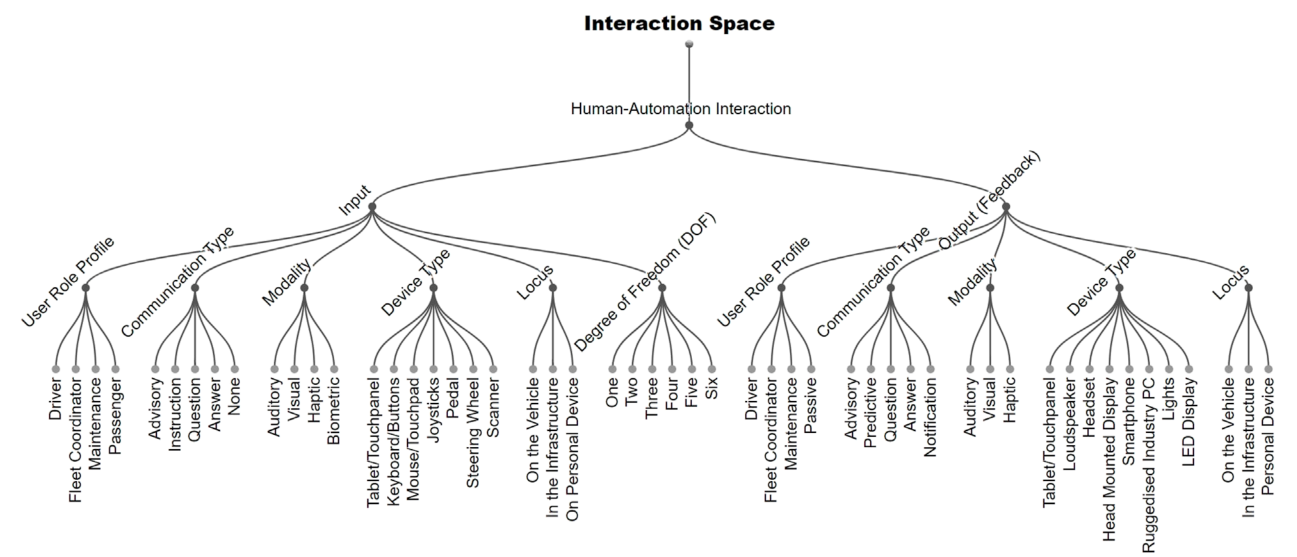

FIGURE 2
Human-Automation Interaction Space for AMHV (see description in section 4.4).

or drop-off points), therefore we add a new category for specification of soil type, since loading or unloading the material can take place in locations outside of a warehouse. According to a taxonomy by the OSHA (Occupational Safety and Health Administration, Department of Labor), we identify four characteristics such as solid rock, clay, silt, and sand (Deatherage et al., 2004).

4.3.6 Environmental factor

Similar to Colley and Rukzio (2020), we incorporated this category for environmental aspects that can affect the vehicle's performance in terms of energy efficiency, component reliability, and communication interference. Two characteristics of temperature and light intensity were added to noise (Yamazaki et al., 1998), due to the relevance of this category in material handling.

4.3.7 Dynamicity

This dimension is introduced during the first round of interviews. We added this category to distinguish static and dynamic environments. It influences the design of communication protocols and methods of data gathering. As AMHVs are expected to communicate with other vehicles or with infrastructure via wireless technologies, we further categorize the dynamic environment into non-connected and connected.

4.4 Human-automation interaction

As Figure 2 shows, we propose the following dimensions to describe human automation interaction with AMHV. For both input and output, the following dimensions are proposed.

4.4.1 User role profile

This dimension reflects any active (e.g., driver) or passive user (e.g., passenger) who engages in an interaction with AMHV. The most common users are the driver, who is in charge of operating the vehicle. A truck driver could also communicate with the operator, e.g., by requesting to park the AMHV at a specific destination in relation to the truck. Other users, e.g., fleet coordinator and maintenance, to some degree might interact with the AMHV. Also, a system such as a fleet management system can be considered as an active user, in case AMHV is connected to infrastructure or other machinery. Furthermore, passive users can also be considered as interacting partners. Passengers, for instance, might be informed about the activity that the AMHV is about to undertake (e.g., parking).

4.4.2 Communication type

The communication type contains the elements advisory, instruction, question, answer, notification, and prediction. These characteristics are adapted from Colley and Rukzio (2020). Advisory and instruction are both guiding behaviors, however, instruction has a relatively top-down approach. Question is demanding information, while answer is providing information. Predictive is a special type of answer when the provided information contains an extent of probability. Notification is giving notice for instance about the intent of the AMHV or possible failure in executing an action such as a warning.

4.4.3 Modality

This dimension is discussed by reviewing design spaces and refined during the second round of interviews. Based on previous works [e.g., (Detjen et al., 2021; Colley et al., 2022)], we identified three main interaction modalities, i.e., auditory, visual, and haptic. Auditory inputs are, for instance, speech control and non-speech sounds. Alarm or warning sounds are examples of auditory feedback. Visual inputs such as laser point or gesture are efficient for a simple command (such as selecting an option from a given alternative) (Ahmad et al., 2018). Anything displayed on the monitor or the color of vehicle lights are examples of visual feedback. Haptic controls such as pedals and the steering wheel are fixed, installed at a particular spot. Vibrations are a common example of haptic feedback (Detjen et al., 2021). Furthermore, we also include the biometric as an additional input modality for determining physical and behavioral characteristics, e.g., mental fatigue and stress of the operator (Graf et al., 2020).

4.4.4 Device type

Depending on the modality of interaction, different devices can be used. For input modality, we identified tablet, keyboard, mouse, joysticks, pedal, wheel, and scanner. For the feedback modality, tablet, loudspeaker, headset, head-mounted display, smartphone, ruggedized industry PC, lights, and LED display can be listed.

4.4.5 Locus

Due to the different physical positions that team members can have in relation to the vehicle, depending on the role (confer the different roles specified in the context space) and operator location (e.g., remote or on the vehicle), user interfaces may be located at different locations. Based on Mahadevan et al.'s design exploration of external communication for automated vehicles (Mahadevan et al., 2018), the locus of the interaction device can be on the vehicle, in the infrastructure, or on a user's personal device.

4.4.6 Degree of freedom

For system inputs, the degree of freedom that an interaction device offers or requires is regarded as the number of defined modes in which users can move the device to specify the command input (Albertson and Womack, 1968). For instance, the rotary knob has only one degree of freedom but a traditional mouse has two degrees of freedom. The degree of freedom has so far not been proposed as a dimension in related design spaces introduced above.

5 Illustrating the design space

The contextual design space introduced previously is intended to support the design of concrete instances within a flow of activities. In the case of the example of a *forestry use case* where a flatbed logging truck equipped with a z-crane is driven to a log pile in the forest and the driver uses the automated crane to load tree trunks onto the flatbed, the context is first to be specified. Table 2 lists the context parameters, highlighted in red, that apply to this use case. While driving is an operational task that occurs with three degrees of freedom and takes a long time to complete, the material handling device (i.e., the z-crane) is mechanically equipped with 6 degrees of freedom. Loading the truck with this type of handler is considered an operational task, but it takes a short completion time. Coordination and support are only necessary in the event of a fault (i.e., a defect) and can therefore be classified as an operational (manual) factor with a relatively short time impact (i.e., repair on-site). In the selected use case, the approach to automation of driving is still manual, with the driver performing the task. However, the material handling is carried out autonomously under the supervision of the user at the vehicle, while other tasks (e.g., maintenance, repairs on site) require the human to be in control of the handler or vehicle (no automation). Since in this case automation is only applicable to the handling level, the user still needs to have expert knowledge of the situation. Furthermore, the physical conditions, like weather conditions (i.e., rain or sunshine), loading dock type (i.e., silt), and environmental disturbance factors (i.e., light intensity) as well as a static dynamicity of the situation, in which the automated material handler is only communicating with the user directly, are prominent properties within the shown contextual design space.

As shown in Table 3, on another example of a logistics use case, where lattice boxes are to be picked up by an automated forklift in a production area and then to be transported to and parked at a drop-off spot, the context can be specified following the same scheme. In this case, the operational task of driving an AMHV is relatively short in duration, but it has a medium-range degree of freedom (DOF) due to the technical and functional range of motion of the vehicle. Similar parameters also apply to the material handling and coordination tasks, although their task abstraction is classified as strategic (i.e., preventive maintenance and allocation of vehicles). A further specialty of this contextual instance is that the technical material handling scope only reflects a small range in the degree of freedom parameter field, due to the technical conditions of the material handling device (i.e., forklift). For the chosen context instance, the AMHV is assumed to have highly automated driving behavior without a human in the loop, while in the material handling task, a human is assumed to act as an external (remote) supervisor for any necessary checks and safety measures.

In terms of the situational context in this specific logistics use case, the role of an expert user is to monitor the system, communicating over a wireless network. The situational context is furthermore characterized as dynamic, due to the changing locations of goods and other vehicles, but not as connected, as here machines are not communicating with each other. As regards the environment, the forklift operates in an indoor environment, on a stable surface such as tar or concrete. Thus, in this case, external weather characteristics are not prominent, but sunlight (shining through warehouse windows) may still be a factor of relevance, also expressed by the environmental factor of light intensity. As can be seen, the provided categories of our design space are neither exclusive nor independent. For instance, the road type for the discussed use case is both indoor and outdoor, as the boxes are handled inside a warehouse but sometimes the drop-off point is outside the warehouse building.

Based on the specified context, the possible options for human-automation interaction can be specified. Table 4 shows a task flow matrix on the example of a logistics use case. This matrix has been adapted from (Prati et al., 2021) and is completed as a result of a use case interview. As shown in Table 4, first the temporal sequence of the tasks to be performed and the actors of the actions and tasks (e.g., driver or AMHV) are defined. In our example, this process starts with the worker bringing the lattice box to the pick-up point and ends with an AMHV moving back to the parking area. In the next step, for each interaction between the user and an AMHV, the modality, device, its locus, and degree of freedom are clarified. Based on this information, designers can be supported in the exploration and allocation of a proper interplay of human actions and automated system behaviors.

At the very right column of the task flow matrix in Table 4, standards are provided, which have to be considered or followed

TABLE 2 Context parameters of example forestry use case.

Space	Sub-space	Scope element	Dimension	Variation									
Context Space	Purpose/task	Driving	Task abstraction	Operational				Tactical			Strategic		
			Degree of Freedom (DoF)	1	2	3	4	5	6	7	8	9	10
			Duration	Short			Long						
		Material Handling	Task abstraction	Operational			Tactical				Strategic		
			Degree of Freedom (DoF)	1	2	3	4	5	6	7	8	9	10
			Duration	Short					Long				
		Coordination and Support	Task abstraction	Operational				Tactical			Strategic		
			Duration	Short	Long								
	Automation Setting	Driving	Level of Automation (LoA)	None			Partial		Supervised			Full	
			Human operator location	None			On the vehicle					Remote	
		Material Handling	Level of Automation (LoA)	None			Partial		Supervised			Full	
			Human operator location	None			On the vehicle					Remote	
		Coordination and Support	Level of Automation (LoA)	None			Partial		Supervised			Full	
			Human operator location	None			On the vehicle					Remote	
	Situation	Social	User roles	Driverr			Fleet coordinato		Maintenance			Passenger	
			Expertise	Expert	Novice								
		Physical	Weather characteristics	Rain		Snow	Fog		Storm			Sun	
			Road type	Outdoor				Indoor					
			Loading dock type	Stable rock		Clay	Silt			Sand			
			Environmental factor	Noise			Temperature			Light intensity			
			Dynamicity	Static			Dynamic (not connected)			Dynamic (connected)			

TABLE 3 Context parameters of example logistics use case.

Space	Sub-space	Scope element	Dimension	Variation									
Context Space	Purpose/task	Driving	Task abstraction	Operational				Tactical			Strategic		
			Degree of Freedom (DoF)	1	2	3	4	5	6	7	8	9	10
			Duration	Short			Long						
		Material Handling	Task abstraction	Operational			Tactical				Strategic		
			Degree of Freedom (DoF)	1	2	3	4	5	6	7	8	9	10
			Duration	Short					Long				
		Coordination and Support	Task abstraction	Operational				Tactical			Strategic		
			Duration	Short	Long								
	Automation Setting	Driving	Level of Automation (LoA)	None			Partial		Supervised			Full	
			Human operator location	None			On the vehicle					Remote	
		Material Handling	Level of Automation (LoA)	None			Partial		Supervised			Full	
			Human operator location	None			On the vehicle					Remote	
		Coordination and Support	Level of Automation (LoA)	None			Partial		Supervised			Full	
			Human operator location	None			On the vehicle					Remote	
	Situation	Social	User roles	Driverr			Fleet coordinato		Maintenance			Passenger	
			Expertise	Expert	Novice								
		Physical	Weather characteristics	Rain		Snow	Fog		Storm			Sun	
			Road type	Outdoor				Indoor					
			Loading dock type	Stable rock		Clay	Silt			Sand			
			Environmental factor	Noise			Temperature			Light intensity			
			Dynamicity	Static			Dynamic (not connected)			Dynamic (connected)			

TABLE 4 Task flow matrix of example logistics use case, used for setting the parameters for dimensions of the interaction space.

Task	User/Actor	Communication type		Modality	Device	Locus	DoF	Applicable standards
		Input	Output					
Bringing the lattice box to the pick-up point	Driver	Instruction		Haptic	Scanner	in the infrastructure	Six	EN 894
Turning on at parking area	AMHV		Notification	Visual	PC (via FMS)	in the infrastructure		EN 61310-1
Moving to the pick-up point	AMHV		Notification	Auditory	Speakers	in the infrastructure		EN 61310-1, SAE J3134
Positioning in the pick-up area	AMHV		Notification	Auditory	Speakers	on the vehicle		EN 61310-1, SAE J3134
Scanning/detection of lattice box	AMHV		Question	Visual	PC (via FMS)	in the infrastructure		EN 61310-1
Checking the lattice box for loading	Driver	Answer		Haptic	Touchpad	in the infrastructure	Two	-
Loading the lattice box	AMHV		Notification	Visual/Auditory	PC/headset	in the infrastructure		EN 61310-1
Securing the lattice box	Driver	None		Haptic	Touchpad	in the infrastructure	Two	OSHA 2236
Transporting with lattice box to the drop-off point	AMHV		Notification	Auditory	Speakers	in the infrastructure		EN 61310-1, SAE J3134
Positioning in the pick-up area	AMHV		Notification	Auditory	Speakers	on the vehicle		EN 61310-1, SAE J3134
Detecting the free spot to unload	AMHV		Advisory	Visual	Lights	on the vehicle		-
Confirming the unloading spot	Driver	Instruction		Haptic	Touchpad	in the infrastructure	Two	EN 894, EN 61310-1
Unloading the lattice box	AMHV		Notification	Visual/Auditory	PC/headset	in the infrastructure		EN 61310-1
Moving back to parking area	AMHV		Notification	Visual	PC (via FMS)	in the infrastructure		EN 61310-1, SAE J3134

when addressing the interaction design regarding a certain task, and thus these can impose potential design constraints. The referenced standards include design requirements for heavy machinery, such as principles for visual, acoustic, and tactile signals (European Machine Directive, EN61310-1 (for Electrotechnical Standardization, 2008a)), for visual displays and control actuators (EN 894-1:1997 + A1:2008 (for Electrotechnical Standardization, 2008c)), and for indications, actuation and marking (EN61310-2 (for Electrotechnical Standardization, 2008b)). Also, standards applying for the general scope of automated driving are to be considered, most importantly the SAE J3134 for vehicle lighting towards other road users (SAE, 2019). As regards operational health standards for the material handling domain, respective standards like OSHA 2236 (Safety and Administration, 2002) also need to be taken into account in the design process.

6 Discussion

In the following, we discuss the in-practice application of the design space, as well as two related aspects, namely, the capturing of human-in-the-loop aspects as well as the feasibility of strict separation of the design space constituents.

6.1 Making use of the design space

The primary purpose and intended use of the design space is to situate any given interaction context or specific challenge within it and then identify the most suitable design options in a structured way. In doing so, one can reveal, identify, and categorize all relevant aspects (objects, actors, or parameters) that can (a) be subject to or targets of design activities, (b) influence interactions, including the success of interaction designs within the context (Dove et al., 2016). This aligns with the notion of a design space also being able to serve as a practical foundation for promising and novel, but also challenging and still insufficiently structured interface classes or application areas (Ballagas et al., 2008; Kern and Schmidt, 2009; Tönnis et al., 2009; Haeuslschmid et al., 2016; Braun et al., 2017; Wiegand et al., 2019; Colley and Rukzio, 2020).

While only recently previous design spaces have started to add contextual variables (Colley and Rukzio, 2020), the AMHV context space necessarily had to be more comprehensive, given the multitude of possible situations, automation settings, and allocated tasks. Mapping out an entire use case within a specific context can be time-consuming, which is why the space is modular and should be used as such: The *Context Space* can be used on its own to capture possible influences on any given design activity and be used as a design aid even when the interaction space is not being used. Users can already gain all relevant information regarding contextual variables, possible task types, controllability of machines, and their degree of automation, as well as elementary user characteristics.

The *Interaction Space* can be used to finely detail any given interaction situation. It is intended to be detailed for any given point of interaction, e.g.,: if there are two machines, a fleet management interface for both, and each with its own on-machine control interface, then that results in three interaction points overall. As a result, a full capturing of this space would entail specifying input and output three times, separately for each interaction point. Thereby, the interaction space is specified in accordance with both the level of interactional complexity in the specific use case as well as the design needs - if the design for a specific interaction point is out of the scope of the current activities, then that one can be omitted.

6.2 Capturing the human(s) in the loop

Describing the involvement of humans in automated processes in the area of material handling is especially complex, as work roles and team allocations are currently evolving (Cimini et al., 2020). One of the bigger challenges of creating the design space was thus to capture the human role within various scenarios of automation, without introducing needless complexity into the design space, as the space needs to be easily readable and graspable in order to serve its primary purpose (Halskov et al., 2021). Since the context space is defined once for a given use case and the size of the interaction space is proportional to the number of interaction points, we aimed to contain the human in the loop within the context space as much as possible, in order to keep complexity low.

In our approach, we captured the aspects relevant to the position of the human in the loop via the level of abstraction as well as the automation setting for each task (driving, handling, coordination, and support). While this does not result in detailed human-machine-interaction workflows with exact indicators as to when and where the human is involved to which capacity, it does provide a similar result once the interaction space maps back to it: Since the level of automation–and with it, the degree of human involvement—are specified in the context space, this information does not need to be repeated for every single interaction point. Even high-level task durations are already specified in the context space already. Also, the human operator location is specified for the driving, handling, and coordination and support tasks, which gives, in combination, an overall impression of the distribution of human-automation task distribution among the team. Thus, by mapping the interaction to the context space, any given interaction is specified regarding the Where, When, and How of the Human-in-the-Loop.

This approach does have two drawbacks: The temporal component is high-level and specific task durations or times when certain tasks are performed are not supported by this design space. In addition, it is not possible to specify different levels of involvement within the same interaction point and user role, which can occur in individual cases (e.g., different levels of experience between two individuals sharing the same role leading to different involvement). Especially the latter is very specific and out of the scope of a typical design space (Simon, 1975; Halskov et al., 2021). Still, both are relevant to finely specify the role and position of the Human-in-the-Loop, thereby also suggesting a limit as to how far this can be specified within a design space alone.

6.3 Managing definitions and delimitations

A design space, at least in its classical understanding (Shaw, 2012), implies that its dimensions are independent and that parameters along these dimensions should be discrete. However, in system types such as mechanical material handling vehicles, delicate interdependencies need to be considered (Halskov et al., 2021). We encountered a fundamental example of this during the creation of the AMHV design space, as we were separating driving from handling as the two elementary task categories. While both involve movement to some extent, focus and challenge are different: Movement is primarily a matter of (two-dimensional) trajectory planning, steering maneuver execution, and dealing with different surface types. Material handling, however, involves trajectories in a three-dimensional space, with challenges more related to picking up and putting down, and also concerned with the type and quantity of material to be handled, as well as generally shorter trajectories. In addition, there is also frequently a clear physical distinction between a machine's driving and handling means (e.g., wheels vs. crane boom).

We had separated the two categories like that in the initial draft already and the division held until the final version, with iterations mainly concerning the dimensions and their refinement. What became clear, however, was that a clear separation was sometimes more challenging in practice and the term "movement" could sometimes be misleading. Two machine types where this came up more frequently were forklifts and swap-body trucks. Forklifts do have a clear separation between fork movement and forklift steering controls. However, part of the picking-up motion is purely driving: The forklift is first, via the regular driving controls, maneuvered into position so that the fork is positioned below the stillage. Only then is the fork moved upwards. The question is then - how should the initial maneuvering be classified: as movement or material handling? Swap-body trucks face a very similar challenge. Such trucks simply dock at a loading station, where their body is then loaded automatically. A truck can dock onto any loaded body and drive out for delivery, hence the term "swap body". The question is whether the driving into the docking station constituted a driving or a material handling task.

One possible solution to this problem could be to further define tasks specific to their purpose. This could mean that if an action is executed primarily for the purpose of handling or preparing to handle material, then it would be classified under material handling, even if it uses driving controls and maneuvers only. If, on the other hand, the primary purpose is the navigation of the entire machine from point A to point B, then it would be classified under driving. The challenge with this solution is the clear delineation in specific cases - where does the driving end and how much of the approach of, e.g., the forklift to the hall where the stillages are, is handling? Given that there is no clear intrinsic distinction, this would need to be defined at least on a machine-level separate for each machine type, perhaps even on a contextual level (storehouse types, *etc.*), which would defeat the purpose of a design space that should not impose unnecessary restrictions and enable consistency.

Instead, we decided and subsequently suggest to separate the task categories on the control level instead. If the task is executed via driving controls and entails moving the machine, it is of the driving type. If it is executed via non-driving controls and either directly involves or has the immediate purpose of handling material (including repositioning), then it is classified as the material handling type. This means that both the initial maneuvering of the forklift, as well as the entire docking operation of a swap body truck, would be classified as driving. On the interaction level especially, this renders the distinction clear, as there is no switch from driving to handling on the same set of controls. For the swap body trucks in particular, it would seem that this categorization then misses the material handling component entirely. However, the actual material bulk of the material handling challenge in these cases happens during the container loading operation, where the truck is simply not involved, and not during docking. As such, the categorization also more adequately reflects the extent of material handling involved, which is minimal to nonexistent in these cases.

7 Limitations

The design space was based on a foundation of existing design spaces and was iterated on the basis of expert inputs from professionals working in AMHV contexts as well as HCI. Due to the often closed nature of industrial AMHV use cases and the resulting difficulty of stakeholder access, gathering the ten experts involved was already very challenging. While in line with or even above the number of experts involved when creating a design space (Braun et al., 2017; Wiegand et al., 2019; Colley and Rukzio, 2020), it still means that the number of individuals involved was on the lower end. While the application domains we focused on (construction, agriculture, intralogistics, and manufacturing) represent a broad spectrum of material handling applications, we do expect that applications outside of the investigated domains will yield further requirements or extensions for the design space. To this end, one should keep in mind that a design space should serve as a design aid that should be adaptable along each tackled design project (Heape, 2007). A particularly promising area of further extending the AMHV design space has been proposed by (Steckhan et al., 2022), suggesting the extension of lower-level abstractions (e.g., functional driving dynamics as cues for interventions) and user satisfaction as target functions. Another limitation lies with our separation of task types between driving and material handling and delineating the two on the control level. While this solution does lead to a clearer distinguishability and reflects the involved actual material handling well, it cannot appropriately capture some corner cases, such as, e.g., using a crane boom to push oneself away, thus constituting movement rather than any type of handling operation. While such actions are typically outside of the intended scope (and unsafe as well as nonpermitted as a result), capturing non-intended use can be very valuable for accurately describing design contexts (Satchell and Dourish, 2009) and we consider this potential room for improvement.

8 Conclusion

In this paper, we presented a design space for AMHV. The design space is based on six existing design spaces for either automation or material handling and is the first design space that captures both aspects and enables AMHV contexts to be fully situated within. The design space consists of two sub-spaces—the Context Space and the Interaction Space. This division enables efficient definition of each interaction point in the Interaction Space by mapping back to the contextual factors (user roles, task types, level of automation, *etc.*) that are globally defined in the Context Space. The design space can be used to support targeted design efforts that in configurations are characteristic of automated material handling use cases, including extended process chains and multiple interaction chains across several machines that involve different user roles, remote vs. on-machine operation, as well as different degrees of automation and corresponding intervention or monitoring capabilities. It is the first dedicated design space specific to AMHV and shall serve to be a useful tool for future design efforts as well as provide a consistent framing for AMHV contexts going forward.

9 Future work

One of the main goals of this design space was to provide a tool to structure any given context in order to then situate one's design activities within it and to identify correct devices, locus, users, *etc.* We plan to conduct prototyping-oriented research with the help of the proposed design space, specifically focusing usability and acceptability of fleet monitoring interfaces in multi-machine contexts. We use the design space to mainly capture the type and levels of automation and controllability for each machine involved, then identify and design for the user roles that require access to the fleet view, with the eventual goal of defining views with separate indicators and different levels of detail, depending on physical location and which user roles access it.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

AM: Formal Analysis, Writing–original draft, Conceptualization, Writing–review and editing. PF: Conceptualization, Formal Analysis, Writing–original draft, Writing–review and editing, Project administration, Validation. SZ: Formal Analysis, Writing–original draft, Writing–review and editing, Investigation, Methodology. MG: Conceptualization, Software, Visualization, Writing–original draft. LK: Conceptualization, Visualization, Writing–review and editing. MT: Supervision, Writing–review and editing.

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Socially adaptive cognitive architecture for human-robot collaboration in industrial settings

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This paper introduces DAC-HRC, a novel cognitive architecture designed to optimize human-robot collaboration (HRC) in industrial settings, particularly within the context of Industry 4.0. The architecture is grounded in the Distributed Adaptive Control theory and the principles of joint intentionality and interdependence, which are key to effective HRC. Joint intentionality refers to the shared goals and mutual understanding between a human and a robot, while interdependence emphasizes the reliance on each other's capabilities to complete tasks. DAC-HRC is applied to a hybrid recycling plant for the disassembly and recycling of Waste Electrical and Electronic Equipment (WEEE) devices. The architecture incorporates several cognitive modules operating at different timescales and abstraction levels, fostering adaptive collaboration that is personalized to each human user. The effectiveness of DAC-HRC is demonstrated through several pilot studies, showcasing functionalities such as turn-taking interaction, personalized error-handling mechanisms, adaptive safety measures, and gesture-based communication. These features enhance human-robot collaboration in the recycling plant by promoting real-time robot adaptation to human needs and preferences. The DAC-HRC architecture aims to contribute to the development of a new HRC paradigm by paving the way for more seamless and efficient collaboration in Industry 4.0 by relying on socially adept cognitive architectures.

KEYWORDS

cognitive architecture, social robotics, human-robot collaboration, industry 4.0, distributed adaptive control

1 Introduction

The increasing automation in the industry over the past decades has been partially driven by the adoption of robots, which have proven to be valuable tools for handling heavy, risky, and repetitive tasks. By automating these tasks, robots have helped alleviate the burden on human workers, contributing to improved safety, efficiency, and productivity Mazachek (2020) and Cette et al. (2021). However, robotic solutions have their own limitations; they tend to have restricted operational capacity in terms of degrees of freedom and decision-making and therefore they do not perform well outside of highly controlled and structured environments Vysocky and Novak (2016). As a result, complete automation might be neither feasible nor desirable Charalambous et al. (2015), Weiss et al. (2021), a discussion further amplified by recent advances in AI Verschure et al. (2020).

Instead, the future of Industry 4.0 Lasi et al. (2014) lies in the collaboration between humans and robots, capitalizing on the strengths of both in a manner that is both beneficial for the health and wellbeing of the workforce and productive for companies. Human-Robot Collaboration (HRC) is poised to become a key component of Industry 4.0 Baratta et al. (2023), with the primary goal of creating a safe environment for humans and robots to collaborate effectively. This transition from traditional automation to Industry 4.0 will be marked by a transformation involving the use of the latest advancements in information and communication technologies (ICTs) Robla-Gómez et al. (2017).

However, the transition to HRC in industrial settings faces several technical and scientific challenges Inkulu et al. (2021). Physically close collaboration between human workers and industrial robots has been limited so far, primarily due to safety concerns, such as potential collisions causing injury to human operators Robla-Gómez et al. (2017), Vysocky and Novak (2016). Recent advances in collaborative robotics, including the emergence of cobots, now allow for safer and closer interactions between humans and robots Weiss et al. (2021). Other technological advances come from transformative ICTs like artificial intelligence (AI) and the related field of machine learning (ML). In Semeraro et al. (2023), the authors review the impact of AI and ML in HRC, highlighting the shift towards cobots (collaborative robots) designed for safe, close-proximity work with humans. The authors emphasize the potential of ML to improve HRC by enabling robots to better understand and adapt to human behavior. Most approaches have relied on vision-based ML to handle objects and perform collaborative assembly in a safe manner. In addition, neural networks have been used to recognize human actions for the robot to assist the human when needed. Furthermore, reinforcement learning has shown great promise in decision-making during collaborative tasks that require outcome-dependent switching between the human and the robot. An example of an AI-based HRC solution in an industrial setting is outlined in Dimitropoulos et al. (2021), where the authors introduce an AI system with three modules to enable seamless human-robot collaboration by understanding the environment and operator actions, providing customized support, and adapting robot poses for better ergonomics, demonstrated through an elevator manufacturing case study. However, despite all these advances, Lemaignan et al. (2017) point out that advanced HRC will actually require robots to possess more advanced cognitive capabilities, such as common sense reasoning for context-aware decision making, which is not achievable yet. These advances in collaborative technologies call for novel paradigms to design collaboration in hybrid industrial settings that are in line with the ambitions of Industry 4.0.

One prime example of such a setting has been the implementation of a hybrid human-robot system in a recycling plant for Waste Electrical and Electronic Equipment (WEEE) products under the umbrella of the EU-funded HR-Recycler project Axenopoulos et al. (2019). This type of environment poses a unique set of challenges for human-robot interaction (HRI) and collaboration (HRC) Robla-Gómez et al. (2017), Vysocky and Novak (2016).

- Noise. Tasks carried out in a recycling plant involve actions such as hammering, cutting, grinding, and transporting heavy pallets, which makes the workplace a highly noisy environment where verbal communication is hampered if not completely disrupted.
- Task hazardousness. WEEE material disassembly involves the manipulation of sharp and heavy materials that during their processing may produce hazardous metal shavings and sparks during processing. To ensure the integrity of the workers, WEEE recycling requires safety measures such as wearing Personal Protective Equipment and maintaining a large distance between co-workers that, at the same time, limits the collaboration between counterparts.
- Dynamic environment. Plant configuration constantly evolves. The continuous processing of WEEE material involves piles of WEEE devices disappearing and new piles arriving at different locations, workers leaving their workbenches to attend to other assignments, surfaces getting covered by metallic dust, light conditions changing along the day, etc. This prevents cobots from following fixed routines.

In parallel, the specific tasks involved in the recycling process demand physically close collaboration and interaction between workers and robots, requiring human-robot collaboration to be socially adaptive.

To achieve social adaptability, HR-Recycler builds on the new dimension that human-robot collaboration (HRC) takes in Industry 4.0, becoming a complex sociotechnical system where agency—the capacity to act—is not solely attributed to humans. Instead, it is shared among humans and non-human agents, such as machines, robots, sensors, and software Weiss et al. (2021). This paradigm shift is crucial as it acknowledges the increasing demand for more interactive roles between humans and cobots within industrial settings and, therefore, the need to develop new control systems that accommodate this emergent reality. Additionally, this shift also highlights the rise of novel configurations of shared control and distributed agency, which are key aspects of this new industrial paradigm.

To address the challenges posed by Industry 4.0, including the integration of collaborative robots (cobots) in hybrid industrial environments, this paper introduces a novel systems-level control paradigm for designing and implementing cognitive architectures tailored for Human-Robot Collaboration (HRC). Accordingly, we present DAC-HRC, a novel cognitive architecture that is specifically designed to facilitate socially adaptive human-robot collaboration within industrial contexts. In the next sections of the introduction, first, we outline the key principles for human-robot collaboration upon which the cognitive architecture is based, with and special emphasis on the notions of joint intentionality and interdependence. We then introduce the Distributed Adaptive Control perspective for building HRC and highlight how each of the specialized modules of the DAC-HRC cognitive architecture is related to these principles and the state-of-the-art of each implemented functionality.

1.1 Principles for human-robot collaboration in industrial settings

To develop an effective socially adaptive cognitive architecture within the context of a hybrid recycling plant, we reviewed state-of-the-art Human-Robot Collaboration principles for industrial settings aiming to conciliate the perspective of different authors that have explored this in the past. As a result, the following principles were considered:

- Implicit Switch Modes: The system must fluidly alternate between various interaction modes, adapting to the human worker's context without burdening them Bauer et al. (2008).
- Natural Cues: Intuitive interaction is facilitated by leveraging humans' inherent understanding of natural signals, enabling humans to communicate with robots using familiar gestures and symbols Goodrich and Olsen (2003).
- Direct World Manipulation: Interactions are designed to serve the ultimate purpose of task completion in a tangible world, allowing humans to directly influence robotic behavior to navigate the unpredictable physical environment of industrial settings Adams (2005).
- Information Manipulation: Information presented by the robot must be actionable, supporting the human worker's decision-making processes and promoting goal-oriented collaboration Goodrich and Olsen (2003).
- Attention Management: The design of HRC interactions should cater to the cognitive limitations of human attention, ensuring that critical information is highlighted and that potential attentional lapses are mitigated Adams (2005).
- Situational Awareness: Maintaining an acute awareness of the robot's internal and external state is paramount, enabling human workers to anticipate robotic actions and intervene when necessary Goodrich and Olsen (2003).
- Safety: Paramount to any HRC system is the unwavering commitment to human safety, ensuring that robots can navigate the potential hazards of industrial tasks without endangering human collaborators Goodrich and Olsen (2003).

1.1.1 Joint intentionality and interdependence as core principles for industrial HRC

Beyond the general HRI principles described above, the DAC-HRC architecture incorporates two core principles coming from our current understanding of the origins of human collaboration: interdependence and joint intentionality.

Joint intentionality refers to the shared mental states and cooperative activities that arise when individuals engage in collaborative endeavors. Research on social cognition posits that shared intentionality is a unique feature of human cognition, setting us apart from other primates Tomasello et al. (2005). It manifests in the form of shared goals, joint attention, and mutual knowledge among individuals working together. For instance, when two people collaborate to lift a heavy object, they share a common goal (i.e., moving the object) and are aware of each other's intentions, roles, and actions.

This concept is particularly relevant in the context of Human-Robot Collaboration (HRC), as it emphasizes the importance of mutual understanding, communication, and coordination between human workers and their robotic partners. In industrial HRC, developing systems capable of exhibiting joint intentionality is essential for ensuring more efficient and safer interactions between human workers and robots. In this context, developing shared intentionality in artificial and hybrid collaborative systems would imply the ability to (1) detect and predict human intentions, actions, and goals, (2) communicate its intentions, actions, and goals to human workers and (3) coordinate and adapt its behavior based on the shared goals and the feedback from the ongoing collaboration.

Interdependence is another foundational aspect of current theories of the evolution of human cooperation Tomasello et al. (2012). It refers to the reliance of individuals on one another to achieve shared goals or complete tasks, and its key role in vital tasks for early humans such as obligate collaborative foraging Tomasello (2009), O'Madagain and Tomasello (2022). Applied to the context of HRC, interdependence implies that both human workers and robots depend on each other's actions, skills, and knowledge to execute tasks effectively. The Interdependence Hypothesis Tomasello et al. (2012) suggests that interdependence fosters cooperation, as it encourages individuals to align their goals, share information, and coordinate their actions.

In HRC, task interdependence between humans and robots can motivate the design of systems that (1) recognize the skills and capabilities of human workers and adapt their behavior accordingly, (2) share task-related information with human workers, facilitating mutual understanding and efficient task execution (3) respond to changes in the task or environment, adjusting their actions to maintain effective collaboration.

To illustrate, consider a collaborative robot in an automotive assembly line. The cobot could be designed to recognize the specific skills of the human worker, such as their proficiency in installing certain parts. Based on this recognition, the cobot could adapt its behavior to complement the worker's skills, perhaps by preparing the necessary parts or tools for the worker's next task. Moreover, the cobot could share task-related information with the worker, such as the sequence of assembly steps or the status of the parts supply, facilitating mutual understanding and efficient task execution. Finally, the cobot should be able to respond to changes in the task or environment. For instance, if a part is missing or defective, the cobot could adjust its actions, perhaps by fetching a replacement part or alerting the worker to the issue.

In understanding and implementing these core principles of joint intentionality and interdependence, it becomes apparent that a sophisticated cognitive architecture is required: one that not only comprehends human social behaviors but also adapts and responds to the dynamic nuances of industrial settings. This necessity brings us to the Distributed Adaptive Control (DAC) approach, which provides a validated and biologically-inspired framework. The DAC approach, with its layered control system and emphasis on adaptability, is ideally suited to embed these principles into the fabric of human-robot collaboration. As we transition to exploring the DAC-HRC architecture, we will see how each of its specialized modules is designed to operationalize the principles of joint intentionality and interdependence, thereby creating a harmonious and effective collaborative environment between humans and robots in industrial settings.

1.2 The distributed adaptive control approach to human-robot collaboration

A cognitive architecture is a modular control system that governs a robot's decision-making, information processing, and environmental interaction Vernon (2022), Moulin-Frier et al. (2017). It is from the interaction and interdependence of its constituent modules that a cognitive architecture displays cognitive capabilities such as perception, decision-making, memory, or social learning. The Distributed Adaptive Control (DAC) theory of mind and brain Verschure, (2012) offers a robust theoretical foundation for such architectures, as it has been previously shown in various HRI scenarios Lallée et al. (2015), Moulin-Frier et al. (2017), Fischer et al. (2018). DAC views the brain as a hierarchical system with multiple control layers, each crucial for adaptive behavior in diverse physical and social contexts Verschure, (2012), Verschure et al. (2014). This biologically grounded modular modeling approach is especially suitable for addressing the HR-Recycler environment's challenges, which demand adaptive and goal-oriented actions.

Informed by the DAC framework, the DAC-HRC architecture we introduce in this paper integrates four specialized modules that reflect key principles for effective HRC. Each module is tailored to specific principles, forming a cohesive and operational control system:

- Task Planner: Coordinates the proper disassembly steps for each device, organizes the disassembly procedure and the turn-taking between human and robot actions, centralizes task-related information among the DAC-HRC modules, and implements safe and robust error-handling protocols. The Task Planner reflects the principles of shared intentionality and interdependence, as it involves a mutual understanding between the human and robot about the sequence of tasks and reliance on each other's capabilities to complete these tasks. Moreover, by orchestrating robot control and human-robot interaction, it also embodies the principles of 'implicit switch modes' and 'direct world manipulation'.
- Interaction Manager: Serves as a multimodal, non-verbal communication interface, facilitating efficient communication and interaction between humans and robots. To achieve this, the module integrates multimodal channels of communication, ranging from audiovisual interfaces such as tablets to embodied gesture-based, communication. By handling natural embodied human-robot interaction based on gestures and adapting to the context of the information visualized on tablet devices, this module implements the principles of 'natural cues', 'attention management', 'information manipulation', and 'situational awareness'. By jointly visualizing in the tablet device the progress and information about the status of the human worker and the robot, this module also creates a sense of shared intentionality.
- Socially Adaptive Safety Engine: Acts as a context-aware adaptive safety mechanism, controlling the safety distances between humans and robots as well as the speed of the interactions, adapting them to the context and the preference of the human co-worker. It deals with the integration of the relevant environmental, social, and material information that comes from other modules to adapt the safety mechanisms of the human-robot collaboration, directly addressing the principles of 'safety' and 'situational awareness'. It dynamically adjusts robot behavior to align the safety measures with human preferences and the task context, also emphasizing the principle of interdependence.
- Worker Model: Creates an internal model of human workers, focusing on the principles of 'information manipulation', 'implicit switch modes', 'situational awareness', and 'interdependence'. This module handles information about the human worker, using it to adapt the robot's behavior in alignment with the worker's preferences. This module is instrumental in adaption the overall collaboration schemes to the human worker, enabling the robot to adjust its actions and fostering a collaborative relationship where both parties rely on and benefit from each other's strengths.

By integrating these modules within a single cognitive architecture, DAC-HRC, we create a robust control system for HRC in industrial settings. This system is inherently socially adaptive, as it is capable of dynamically adjusting in real-time to accommodate the varied preferences of human workers and the nuances of different scenarios. Moreover, it facilitates mutual understanding and fosters effective collaboration between human workers and robots, a critical requirement for addressing the complex tasks encountered in the HR-Recycler's recycling plant use case. Comprising various specialized modules, the DAC-HRC cognitive architecture implements distinct functions, each grounded in contemporary, state-of-the-art solutions derived from the literature.

1.2.1 Task planner as a hierarchical finite state machine

Task planners play a pivotal role in robotics, especially in enabling robots to adeptly navigate complex and unpredictable environments. In domains like electronic waste recycling operations, the ability of robots to perform a range of tasks, from sorting to processing diverse types of devices and components, hinges on sophisticated task planning mechanisms Alami et al. (2005). The cornerstone of contemporary task planning in robotics is the use of finite-state machines (FSMs), revered for their simplicity and intuitiveness in modeling robot behavior amidst uncertainty Foukarakis et al. (2014).

Finite-state machines are essentially mathematical constructs encompassing a finite set of states, transitions between these states, and corresponding input/output events. This structure empowers robots with the ability to efficiently adapt their behavior in response to varying conditions, a feature crucial in the fluctuating environment of a recycling plant. The inherent simplicity of FSMs, however, can be a limitation when dealing with more complex behaviors.

To address this complexity, hierarchical finite-state machines (HFSMs) have emerged as a potent solution to orchestrate complex robot behaviors. HFSMs represent behaviors in a layered structure of FSMs, where each level corresponds to a specific subtask or behavior component Johannsmeier and Haddadin (2016). This hierarchical arrangement facilitates a modular and scalable approach to task planTask Planner, the Socially Adaptive Safety Engine, the Worker

Model and the Interaction Managerning. By breaking down overall robot behavior into manageable subtasks, HFSMs offer a tailored solution to the multifaceted tasks encountered in electronic waste recycling. This approach not only enhances the robot's efficiency and adaptability but also allows for easier integration and updates to the task planning system as recycling requirements evolve.

Moreover, the incorporation of human-in-the-loop methodologies in task planning signifies a significant evolution in robotic systems. This approach involves integrating human feedback and inputs directly into the robot's control mechanism, enabling a more dynamic and adaptable interaction between humans and robots Raessa et al. (2020). In the context of electronic waste recycling, this means that robots can be more responsive to human operator's preferences and needs, thereby enhancing collaboration efficiency and safety.

In implementing HFSMs, the Task Planner module within the DAC-HRC cognitive architecture embodies these principles, leveraging the hierarchical structure to manage complex tasks while remaining adaptable to the diverse challenges presented in electronic waste recycling. The module's design allows for seamless incorporation of human inputs, ensuring that the robotic system is not only responsive but also attuned to the needs and preferences of different human workers. This integration of advanced HFSMs within the DAC-HRC architecture illustrates a commitment to developing robotic systems that are both technically proficient and collaboratively effective in complex industrial settings.

1.2.2 Interaction manager as a multimodal non-verbal communication protocol

The DAC-HRC architecture's Interaction Manager advances the paradigm of multi-modal non-verbal communication, pivotal for intuitive and effective human-robot collaboration in industrial settings. In the human-centered HRI paradigm, an essential aspect of implementing a successful and effective HRI is building a natural and intuitive interaction Wang et al. (2022). In recognition of the importance of non-verbal communication modalities, particularly in noisy industrial settings, the Interaction Manager eschews auditory channels in favor of gesture-based and tablet-based interfaces.

Gestures serve as a fundamental form of human communication, making them ideal for conveying rapid commands in human-robot interaction (HRI) Vouloutsi et al. (2020), Pezzulo et al. (2019). Gesture-based communication harnesses the natural propensity for humans to use physical gestures, thereby facilitating a more immediate and universal form of interaction Liu and Wang (2018), Wang et al. (2022), Peral et al. (2022). The Interaction Manager incorporates a repertoire of shape-constrained gestures Alonso-Mora et al. (2015) tailored to the communication needs specific to the HR-Recycler's project, which facilitates natural and intuitive interactions without extensive training Vouloutsi et al. (2020) while also ensuring accurate recognition and interpretation by the robotic agents Peral et al. (2022).

To complement gesture-based interactions and cater to scenarios necessitating more detailed information exchange, the architecture also integrates tablet-based communication. This method leverages interactive applications, which, while commonly used for teleoperation Yepes et al. (2013), Best and Moghadam (2014), Luz et al. (2019), are repurposed in the DAC-HRC to enhance the human-robot bond and situational awareness Goodrich and Olsen (2003). The tablet application provides a direct interface for the human worker to receive updates on the robot's internal state and environmental interpretations, aligning with key HRI principles Goodrich and Olsen (2003), Adams (2005).

The combined use of gesture and tablet-based interactions by the Interaction Manager represents a state-of-the-art approach to non-verbal HRI. It successfully navigates the challenges of noisy industrial settings, where traditional verbal communication is untenable, and establishes a robust, adaptive, and user-friendly communication system conducive to the dynamic requirements of the HR-Recycler's operations.

1.2.3 Socially adaptive safety engine as an allostatic control system

A robot must not endanger a human under any circumstances. This premise, already formulated by Isaac Asimov in his famous "Three Laws of Robotics," is crucial for any robotic installation but especially for those promoting interaction and collaboration between humans and synthetic agents Asimov, (2004). Importantly, in industrial settings interactions must be designed bearing in mind that robots occasionally will represent a source of danger to humans because of the tools they employ to perform hazardous tasks such as cutting, hammering, or moving heavy objects. Safety measures need to be implemented both according to the work to be performed and the human demands Van Wynsberghe (2020).

In the context of the WEEE recycling factory, humans and robots have to interact with a variety of different objects and tools and realize many changing sequences of actions in order to successfully complete their tasks Axenopoulos et al. (2019). Although each of the robotic components has its own built-in safety mechanisms and corresponding certified ISO safety measures, the interaction of all these elements together will require an additional layer of control that can adapt their behavior to the requirements of the hybrid recycling plant while following human-centered design principles. This layer of control is the Socially Adaptive Safety Engine (SASE).

The Socially Adaptive Safety Engine within the DAC-HRC architecture goes beyond mere harm avoidance to actively promote cooperation Freire et al. (2020a). The SASE not only adheres to basic safety principles but also engages in more flexible adaptation of the robot's behavior to the preferences of the human worker, thus fostering a more cooperative and harmonious human-robot interaction. It also reflects the principles of shared intentionality and interdependence, as it involves a mutual understanding between the human and robot about the safety measures and reliance on each other's capabilities to maintain safety during the disassembly process.

The goal of the SASE is to promote human-robot cooperation by building safer, more trustworthy, and personalized interactions with human users Kok and Soh (2020), Christoforakos et al. (2021). It does so by regulating and adapting the robot's behavior to the particular human preferences of every user Senft et al. (2019), Edmonds et al. (2019). In this way, it also serves as an extra layer of security for the system by integrating contextual information from the environment and using it to prevent potentially harmful situations Yang et al. (2018). At the heart of this approach is the implementation of an allostatic control system Sanchez-Fibla et al. (2010), Guerrero Rosado et al., 2022. This system aims to ensure harm avoidance and promote cooperative behaviors, which are two fundamental aspects of ethical machine behavior Freire et al. (2020a).

In essence, the Socially Adaptive Safety Engine encapsulates the ethos of the DAC-HRC architecture—prioritizing human safety and introducing dynamic adaptability, thereby exemplifying a model of responsible and responsive artificial intelligence in industrial settings.

1.2.4 Worker model based on human-centered design principles

User modeling systems rely on data gathering to create user models, either explicitly or implicitly Luna-Reyes and Andersen (2003). The integration of novel machine learning techniques has significantly enhanced the capabilities of these systems, steering them towards more data-driven strategies Kontogianni et al. (2018). One emerging technique being implemented in these data-driven user modeling practices is the Digital Twin concept, which generates or collects digital data representing a physical entity, emphasizing the connection between the physical and virtual counterpart through real-time information flow Bruynseels et al. (2018), Negri et al. (2017).

Digital Twin technologies have been applied in various contexts, such as healthcare Croatti et al. (2020) and human-robot interaction Wilhelm et al. (2021), Malik and Brem (2021), Wang et al. (2020). In industrial settings, Digital Twins have been utilized for tasks like interactive welding, bridging human users and robots through bidirectional information flow, and benefiting novice welder training Wang et al. (2020), Jokinen and Wilcock (2015). However, these data-driven approaches raise concerns regarding big data management, privacy, and trustworthiness, especially when applied to sensitive fields Kumar et al. (2020). The Human-Centered AI paradigm aims to address these concerns by prioritizing methodologies that meet user needs while operating transparently, delivering equitable outcomes, and respecting privacy Xu (2019), Riedl (2019). This approach also aligns with legislation such as the European General Data Protection Regulation (GDPR) Kloza et al. (2019).

The Worker Model module of the DAC-HRC cognitive architecture follows such human-centered design principles by maximizing functionality while minimizing the amount of data gathered from the user Xu (2019), Riedl (2019). This design strategy ensures that the Worker Model respects user privacy while still providing effective support for human-robot collaboration in the disassembly of WEEE devices. The main goal of the Worker Model is to collect, process, and store all the relevant information regarding each user of the system and integrate it into one single, coherent data structure. This information is used by the DAC-HRC architecture to flexibly adapt the human-robot collaboration paradigm to the human partner. In other words, the Worker Model creates a virtualization of the human worker that allows the collaborative architecture to dynamically adjust its parameters to ensure a personalized interaction.

In essence, the Worker Model's integration into the DAC-HRC architecture not only enhances the adaptability of the human-robot collaboration paradigm but also embodies a human-centric focus into the design of these new technologies Xu (2019), Riedl (2019).

The rest of the chapter is organized as follows: In the following section section, we first describe the aCell, a specific experimental setup designed for the collaborative disassembly of WEEE devices. We then continue describing in detail each of the components of the DAC-HRC architecture along with its interactions. We proceed with a report of the main results showcasing the functionalities of the architecture across the different tested use cases, and conclude with a discussion of the main outcomes of the study, its limitations, implications, and future work.

2 Methods

2.1 The aCell experimental setup

The experimental setup consists of a specific spatial and technical configuration of an adaptive Collaborative Cell (aCell) designed for the collaborative disassembly of Waste Electrical and Electronic Equipment (WEEE) devices. The concept of an aCell represents an evolution in the way we approach task allocation in HRC Axenopoulos et al. (2019). Traditional industrial HRI methodologies often focus on individual tasks within a single work cell, with the human and robot working in isolation on specific tasks. However, the aCell concept promotes a more holistic view of HRC that takes into account the interdependence between humans and robots. It envisions a dynamic, integrated system where the human and robot work together across multiple tasks, adapting to changes in the work environment and each other's capabilities. This approach aims to enhance the overall efficiency and effectiveness of the collaboration, rather than optimizing individual tasks in isolation.

An aCell is a dynamic and adaptive component of a hybrid factory, responsible for a specific task and for a given time period. The responsibilities, resource allocation, and overall positioning of its elements within the factory are dynamically assigned and adapted in real time with respect to the overall factory workflow demands, available skills, and available resources. In the context of our study, the cell consists of a human worker collaborating with a cobot, with each of them possessing specific, known skills. They operate as part of a joint intentional team with shared goals: to disassemble a series of Waste Electrical and Electronic Equipment (WEEE) devices.

The design of the aCell is grounded in the interdependence and joint intentionality between the human worker and the cobot. The components of the aCell are interdependent since effective task completion requires the combination of both human and robot capacities while sharing the same goals for disassembly. By taking into account the complementary skills and shared goals of the human-cobot dyad, the aCell can be seen as a single collaborative unit whose control is distributed. The DAC-HRC architecture we present in this chapter is designed as a control system to deal with such hybrid collaborative entities, by orchestrating the disassembly process while also taking into account human workers' safety, and promoting context and real-time adaptation in the dynamic and complex environment of the WEEE recycling plant.

In this work, the aCell is composed of two primary regions (Figure 1): the open space, where the human worker performs tasks without hindrance, and the workbench, where the DAC-HRC synthetic actuators are strategically located.

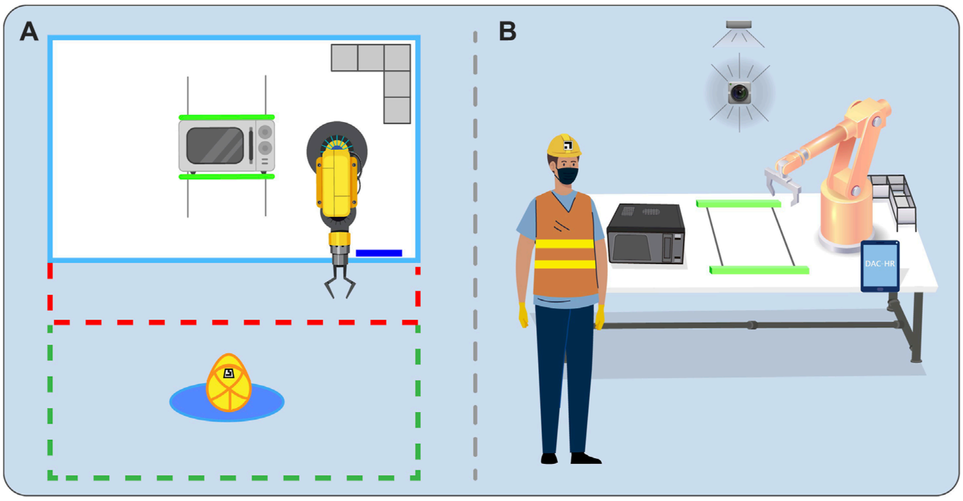

FIGURE 1
Experimental Set-up. **(A)** Cenital view of the aCell. Green dashed lines illustrate the human working area, being limited by a safety threshold (red dashed lines). **(B)** Complete configuration of the aCell including the human worker, the cobot, the WEEE device to be disassembled, the clamping tool, the tablet device where the Interaction Manager app is displayed, the cobot tool rack, and the cameras monitoring the behavior of both the human worker and robot.

WEEE materials are positioned on the workbench for collaborative disassembly by the human worker and a COMAU Racer-5 collaborative robot (cobot). To further augment the functionality of the cobot, a tool rack is in place to house and arrange Racer-5 tools that are not currently in use. These tools include a screwdriver, a vacuum gripper, a finger gripper, and a cutting device.

Two vision modules allowed DAC-HRC to be informed by the aCell regarding the status of the disassembly task and the human worker. These vision modules were designed following state-of-the-art computer vision techniques Tran et al. (2018), Ghadiyaram et al. (2019), Cao et al. (2017), Kalitsios et al. (2022), Gabler and Wollherr (2022) and provided by other HR-Recycler partners. A vision system oriented towards the open space captures and processes information related to the human worker, such as their identity, position, and behaviors like gestures. To enable the cobot to gather information on the WEEE device, such as the status of its components, an additional vision system is directed toward the disassembly area, informing about the device's state. A mechanical clamping tool is also integrated with the workbench to stabilize the WEEE device while either the human worker or cobot performs actions on it.

Lastly, the workbench, and by extension, the aCell, are supplemented by a tablet display that enables a bilateral communication channel between DAC-HRC and the human worker, displaying relevant information (e.g., current task status), and serving as a medium for human feedback.

2.2 The DAC-HRC cognitive architecture

The aim of the DAC-HRC architecture is to develop a robust human-robot collaboration control system for industrial settings that adapts to different workers through strategies learned from data obtained during the interaction. This process reflects the principles of shared intentionality, as it involves a mutual understanding between the human and the robot about the worker's skills and preferences. It also illustrates the principle of interdependence, as the architecture relies on both the human and robot's capabilities to ensure safe and efficient human-robot collaboration.

More concretely, DAC-HRC enables robotic components to tailor their interactions to the needs of their collaborative human partner, taking into account their unique skills, capabilities, and preferences. In order to achieve such a level of personalized adaptation to each human partner, each of its core four functionalities, control, safety, adaptation, and interaction are all distributed across the whole architecture, while having their specialized cognitive modules: the Task Planner, the Socially Adaptive Safety Engine, the Worker Model and the Interaction Manager, respectively.

DAC-HRC follows the design principles of the Distributed Adaptive Control theory, which states that the goal of cognition in embodied agents is to control action, and as such, any cognitive system can be described as a modular, hierarchical control system operating at different spatiotemporal timescales Verschure et al. (2012). The DAC theory can be expressed as a robot-based cognitive architecture organized in two complementary structures: layers and columns. The columnar organization defines the processing of states of the world, the self, and the generation of action. The organizational layers define the different levels of control, starting from the Soma Layer integrating all sensors and effectors of the system, the real-time reactive sensorimotor control in the Reactive Layer, the adaptive associative learning and allostatic control in the Adaptive Layer, up to abstract and symbolic manipulation and context-based control in the Contextual Layer.

DAC-HRC is organized following DAC's layered structure, where each of its specialized HRC cognitive modules is located at different levels of the layered architecture based on their spatiotemporal timescales of control and their informational and

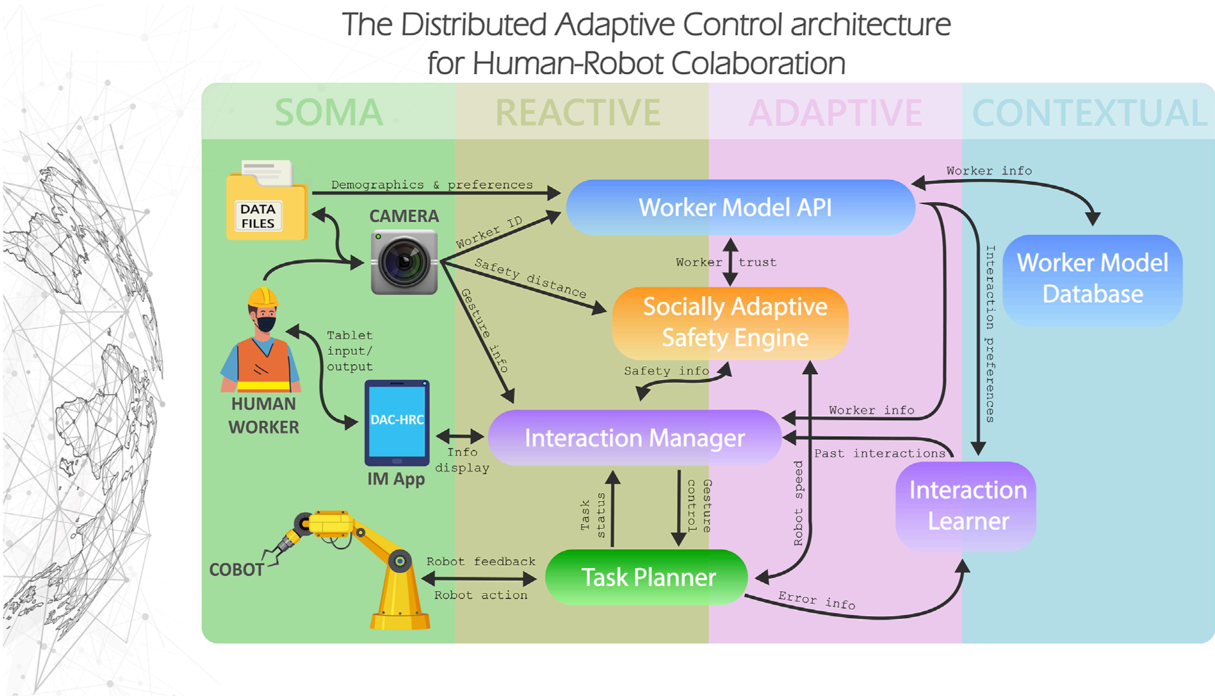

FIGURE 2
The DAC-HRC architecture for human-robot collaboration in industrial settings. DAC-HRC is structured in four layers of control (from left to right): Soma, Reactive, Adaptive, and Contextual; and composed of four specialized cognitive modules: the Task Planner, the Interaction Manager, the Socially Adaptive Safety Engine, and the Worker Model. The cognitive modules are distributed across various levels of the layered architecture, aligning with their control timescales and levels of information and sensory abstraction. The Soma Layer represents the physical components of the aCell, including the cameras, tablet, cobot, and human worker. The Reactive Layer houses the Interaction Manager and Task Planner modules, responsible for orchestrating human-machine communication and managing task allocation, respectively. The Socially Adaptive Safety Engine and the API component of the Worker Model, which adapts safety measures and processes real-time worker information, span both the Reactive and Adaptive Layers. The Contextual Layer is hThe effectiveness of DAC-HRCome to the Worker Model Database, storing long-term memory of past interactions and user preferences, and the Interaction Learner, which uses this information to adapt tablet display options based on past interactions.

sensory abstraction, as we can see in Figure 2. In other words, the cognitive modules are strategically distributed throughout the architecture based on the specific temporal and spatial requirements for control, as well as the degree to which they process and abstract sensory information and relevant data.

Its Soma Layer is defined by the hybrid combination of synthetic and biological sensors and actuators that comprise the aCell, that is, the cameras, the tablet, the cobot, and the human worker. In its reactive layer, DAC-HRC incorporates the Interaction Manager and the Task Planner modules. The Interaction Manager is devoted to the human-machine interaction protocols necessary to orchestrate communication between the human and the cobot. The Task Planner is in charge of the adequate task allocation among the members of the collaborative entity. It sequentially organizes the disassembly tasks and controls the correct turn-taking behavior between the human and the cobot. The Socially Adaptive Safety Engine, which is in charge of providing an additional layer of safety that adapts the security distances and robot speed to the particular preferences of the human partner and the current task context, spans both the reactive and adaptive layers. The same applies to the API component of the Worker Model, which deals with the real-time information related to the worker, as well as with the update of the Database. In the contextual layer, the Worker Model Database provides the system with an internal model of the human workers, storing in its long-term memory the past interactions between each user and the system, as well as relevant information for adapting the overall collaboration to the preferences of the human partner. The Interaction Learner, spanning both the contextual and adaptive layers, uses the contextual information to learn from past interactions with the system to adapt the options displayed by the Interaction Manager through the tablet device. In the following sections, we describe in detail the technical implementation of the cognitive modules of the DAC-HRC architecture.

2.2.1 Task planner

The DAC-HRC's Task Planner module is conceived as a human-in-the-loop hierarchical finite state machine that encompasses all disassembly steps of all devices, as well as the error-handling protocols. The Task Planner (TP) has been developed to ensure robust orchestration of various components contributing to the disassembly of WEEE devices within the aCell system. The objectives of the TP are to coordinate the proper disassembly steps for each device, organize the disassembly procedure and robot-worker interleaving, centralize task-related information among the DAC-HRC modules, and implement safe and robust error-handling protocols. The TP reflects the principles of shared intentionality and interdependence, as it involves a mutual understanding between the human and robot about the sequence of tasks and reliance on each other's capabilities to complete these tasks. The TP integrates and coordinates low-level sensorimotor information (coming from the computer vision and robotic components of the aCell) with high-level information about the task and the interaction (coming from the upper control layers of the architecture). Therefore, within the TP's HFSM, we find states with different levels of abstraction and description. The Task Planner operates at five levels:

- Task Planner. This level corresponds to the highest level of abstraction, which contains the state machines (SM) of all 4 Devices. It also contains the functionalities that deal with continuous status reports, as well as direct human interactions (through the Interaction Manager, or IM) that allow the TP to be suddenly interrupted by the worker.
- Device. This level contains the state machine (SM) that links the steps (i.e., Tasks) needed for the proper disassembly of a particular device, in a sequential manner (i.e., without internal loops). Thus, it comprises a straightforward sequential SM with all the necessary steps or Tasks to be executed in the right order, steps which have been pre-defined based on domain-specific knowledge of the proper disassembly of the devices (see Figure 3A).
- Task. In this level, a particular Task–involving one or more Actions (see below)— is executed, with the end result of removing a particular component of the device (e.g., "top lid removal of the e-light"). Here, errors during the execution of an Action are handled in a dedicated SM so that the worker is engaged whenever needed (see Figure 3B). Feedback and responses from the worker redirect the state of the TP accordingly (e.g., if an error with the robot occurs and the worker decides to complete that Task themselves).
- Action. This is the atomic level of description, where specific modules are uniquely engaged via ROS communication (e.g., ROS-actions or ROS services). During an Action, either a ROS action is sent to a robot to perform a specific action (e.g., "change tool to vacuum gripper," or "dispose lid"), or a ROS service is issued to the vision module to acquire the necessary information that the robot will need to perform a subsequent action (e.g., "identify the grasping pose of the lid").
- Sub-action. In some cases where Actions need to be repeated several times and imply feedback loops with vision and the robot, an additional level is introduced so that the SM design becomes more modular and robust (e.g., "Unscrew the six screws of the microwave's cover" is designed so that a dedicated SM to unscrew coordinating the robot and vision feedback can be called in loop until all screws have been removed).

The Task Planner is implemented with the Smach-ROS python library, which allows seamless integration of HFSMs with ROS-based communication protocols Bohren and Cousins (2010), Pradalier, (2017). Crucially, internal data structures allow the conveying of information received from vision (response of a ROS service) to the robot (goal of a ROS action). In an SM, the transitions between states depend on the outcome of each State after having been executed. An example of a Task can be seen in Figure 3. In general, an outcome "succeeded" will make the SM transition to the next Task or Action (depending on the level). The outcome "aborted" will engage the error-handling loop (see section Error Handling below), which asks the worker for feedback, and transitions to different states according to the worker's decision (e.g., the robot tries again, or the worker finishes the Task and then the TP moves to the next Task). The hierarchical structure of the FMS can be achieved because all SMs are treated as States too, inheriting their properties.

2.2.2 Interaction manager and interaction learner

The Interaction Manager module plays a vital role in facilitating efficient communication and interaction between humans and robots. To achieve this, the module integrates multimodal channels of communication, ranging from audiovisual interfaces to embodied non-verbal communication. To account for high levels of noise and equipment worn by workers, verbal communication was excluded from the communication repertoire. The two main modes of interaction, gesture-based communication, and tablet-based communication, have been chosen to address the noisy industrial environment and safety concerns during collaboration between human workers and robots.

Gesture-based communication provides a fast and direct means for the human worker to convey simple and fast control commands and responses to the robotic companion, making it a useful and naturalistic way of communicating in the collaborative environment of the aCell. The Interaction Manager integrates eight different communication signals, providing a rich set of gestures for effective communication between the worker and the robotic system.

aCell-to-human communication is enabled through a tablet-based application, representing the main communication channel through which the system can provide detailed information about the current task's state. Additionally, through this Interaction Manager application (IM app), the system can request human intervention during the disassembly or request human input for problem-solving or decision-making when unforeseen problematic situations are faced.

These two main modes of interaction have been chosen to cover the speed-accuracy trade-off, with gestures for simpler but time-sensitive interactions, and tablets for slower but more fine-grained information exchange. This dual communication paradigm accommodates individual human preferences and ensures efficient collaboration in various human-robot collaboration scenarios, as we will see in the Results section.

The Interaction Learner adds a level of personalization on top of the Interaction Manager functionalities by providing it with an adaptive mechanism to support human-robot decision-making based on the prior history of interactions between the human and the cobot. Its main function is to keep track of human-robot interactions and human feedback during error-handling scenarios. It computes useful statistics based on the history of human-robot interactions, and when a similar situation is encountered, it adapts the options displayed in the tablet by the Interaction Manager in a way that enhances collaborative decision-making by highlighting on the menu the most frequently selected options by that worker in a given situation. This level of adaptation takes into account the human-robot interactions at each specific step during the disassembly and for each worker in particular.

2.2.3 Socially adaptive safety engine

The design of the Socially Adaptive Safety Engine (SASE) incorporates a set of reactive control systems inspired by Pavlovian appetitive and aversive drives Freire et al. (2020a). This approach

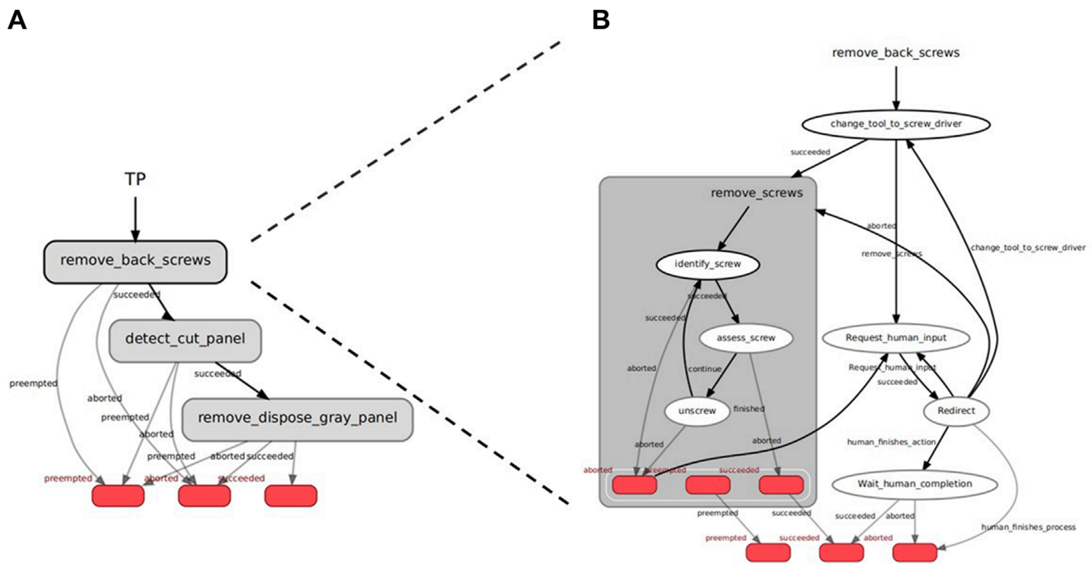

FIGURE 3
Task Planner. Visualization of the Device **(A)** and Task **(B)** levels of the Task Planner's hierarchical finite-state-machine (HFSM) for the flat-panel display use case. **(A)** Device level of the Task Planner's HFSM. This level showcases the finite-state machines responsible for sequentially connecting the disassembly steps (i.e., Tasks) required for the correct disassembly of the flat-panel display. **(B)** Task level of the Task Planner's HFSM. At this level, dedicated error-handling mechanisms within the Task Planner engage the worker when errors occur during the execution of an action (in this case, 'remove screws'). This ensures that the worker is actively involved in resolving any issues that may arise. Feedback and responses from the worker serve to redirect the state of the Task Planner, enabling effective error resolution and maintaining the overall flow of the task execution.

shapes the SASE's functionality, guiding its interactions in the DAC-HRC architecture to align with principles of both harm avoidance and proactive cooperation. This incorporation allows the Socially Adaptive Safety Engine to adapt its behavior dynamically, not only avoiding harm but also optimizing operation parameters such as speed, distance, and task allocation based on the unique context of each human worker. The Worker Model, integral to the contextual layer of the DAC-HRC architecture, helps personalize the interaction, treating each worker as a distinct individual with specific preferences and needs.

The Socially Adaptive Safety Engine module, in charge of providing a context-aware and personalized safety control system, spans across three layers of the DAC-HRC architecture. The SASE's reactive layer integrates several homeostatic modules whose purpose is to monitor key aspects of the human-robot interaction. The goal of each homeostatic module is twofold: to keep its desired variable within the optimal range of operation, and to exert control when that variable trespasses the safe range. The current implementation comprises the homeostatic control of key proxemics variables in HRI, such as the human-robot interaction security distance, the robot movement speed, and the robot action execution speed. When any of those variables reach or trespass their threshold, the control response can be either a direct modification of the exceeded value -in the case of speed modulation-, or a command directed to stop the robot's current action -in case the HRI distances are trespassed. For instance, if the actual detected distance between the human and the robot is below the desired safety value, the homeostatic control system will generate a stop signal and the robot will not move until the actual distance goes back to the desired range.

The Socially Adaptive Safety Engine's adaptive layer is composed of the allostatic control module. This is the key mechanism by which the SASE can adapt the interaction of the robot to its changing environment. This module is in charge of the transformation of the environmental information provided by the contextual layer and modifying the desired parameters of the subsequent homeostatic regulatory mechanisms of the reactive layer. For instance, when the robot is handling a dangerous tool, the allostatic control module gets this information and adapts the desired safety HRI distance, as well as the speed at which the robot will operate when being close to a human.

The Socially Adaptive Safety Engine's contextual layer deals with the integration of the relevant environmental, social, and material information that comes from other modules of the DAC-HRC architecture. It endows the SASE with context awareness. The constant integration of these different sources of information defines the specific context at every point in time, thus allowing the SASE to monitor and adapt the behavior of the robot to the changing conditions of its surroundings. For instance, the contextual layer can obtain information in real-time about the HRI preferences of the currently detected human worker, the risk level of the current robot action, and the information about the current tool being used by the robot (if any).

The incorporation of the reactive control systems inspired by the Pavlovian appetitive and aversive drives allows the Socially Adaptive Safety Engine to adapt its behavior dynamically, not only avoiding harm but also optimizing operation parameters such as speed, distance, and task allocation based on the unique context of each human worker. The worker model, integral to the contextual layer of the DAC-HRC architecture, helps personalize the interaction, treating each worker as a distinct individual with specific preferences and needs.

2.2.4 Worker model

The Worker Model is composed of short-term and long-term memory buffers along with its reactive and adaptive input processing layers. The Worker Model's reactive layer serves as a first data integration step, gathering information from several input sources, whereas its adaptive layer processes the raw data in order to produce new parameters that will be used by other modules of the Worker Model and the DAC-HRC architecture. The online information gathered by the Worker Model's reactive layer is transiently stored in the short-term memory buffer before it is further processed by the adaptive Layer to generate new relevant information about the worker and their interaction with the system. For instance, the short-term memory can store the timings of past interactions during a disassembly step, while the adaptive layer generates estimates of current task duration based on this input. The type of input information gathered by the Worker Model can be divided into offline and online variables:

- Offline variables - This type of data is mostly static, as it will not vary throughout the session (e.g., age, gender, language, and interaction preferences). This information is acquired through preliminary questionnaires before engaging with the system and defines the profile of each user based on demographic information and her opinion towards robots.
- Online variables - Comprises all the relevant user data that is dynamically updated in real-time over the course of the interaction with the system. Integrates information about the position of the worker and their performance (e.g., current disassembly task, or estimated duration), as well as about the context in which the worker is embedded (e.g., current disassembly process, a Cell number, or location).

The technical implementation of the Worker Model is based on two main components: the Worker Model's API and the Worker Model Database. The database implements the long-term memory component of the Worker Model. Its function is to store all the information related to each worker and to keep it up to date. It is deployed as a document-oriented database using MongoDB[1], where each worker profile is stored as a unique document. Each worker model entry is initialized with the offline variables acquired from the worker profile and questionnaires. Additionally, it also stores the main statistics of each interaction between the worker and the DAC-HRC collaborative architecture that has been extracted by the Worker Model API, such as the expected task duration or the history of interactions with the tablet.

All the communications with the database are centrally controlled by the Worker Model's API, which integrates the reactive and adaptive input processing layers along with the short-term memory component of the Worker Model. The API's function is twofold: it performs the basic CRUD (create, read, update, and delete) operations that keep the database up to date, and it is in charge of filtering the online and state variables to produce the task- and interaction-relevant outputs of the Worker Model. The API is written in Python and communicates with the database using BSON as the data interchange format.

1 https://www.mongodb.com

3 Results

In this section, we showcase the application of the DAC-HRC within the industrial context of the HR-Recycler hybrid recycling plant, highlighting the various functionalities of DAC-HRC that enhance human-robot collaboration in the recycling plant, specifically: (1) turn-taking human-robot collaborative interaction during the disassembly of a WEEE device, (2) error handling mechanisms personalized by past collaborative interactions, (3) adaptive and personalized safety measures for human-robot collaboration, and (4) gesture-based communication for goal-oriented collaboration. Each scenario was assessed during the disassembly of different WEEE devices, specifically: emergency lamps, computer towers, microwaves, and LCD displays. Importantly, trials to assess the robot's autonomous disassembly capabilities were conducted prior to these tests; in all cases, the robot failed to successfully disassemble any device without human intervention or the application of the DAC-HRC. This failure serves as the reference process against which we benchmark our architecture's performance. Furthermore, the experiments included various human participants to evaluate the architecture's adaptability to different human actors and preferences. Given the nature of the experiments and the robot's inability to complete tasks autonomously, we chose not to report these autonomous trials in the results section, focusing instead on the functionalities enabled by the DAC-HRC architecture.

3.1 Turn-taking human-robot collaborative interaction in the disassembly of a WEEE device

This use case describes the involvement of the DAC-HRC architecture during the collaborative disassembly of WEEE devices between a cobot and a human worker. Such a collaborative process begins when a human worker approaches the aCell. Once the worker enters the working area, they are recognized by the vision module that perceives their identity by decoding the unique fiducial code allocated in the workers' helmets (Figure 4A). Then, using the identity of the worker, the Worker Model anonymously accesses their corresponding personal information and makes it available to the entire DAC-HRC architecture, so other cognitive modules can socially adapt to the current worker. This process reflects the principle of shared intentionality, as it involves a mutual understanding between the human and the cobot about the identity and role of the current worker. It also illustrates the principle of interdependence, as the overall disassembly performance depends on both the cobot and worker (Figure 4B).

The Interaction Manager receives and processes the worker's personal information and provides them with immediate feedback about their detection by displaying such information through the IM app (Figure 4C). It is noteworthy that this information, and further notifications, are displayed meeting the worker language's preferences. Importantly, the rapid communication between the vision modules and the Worker Model ensures that the social information considered by the cognitive architecture has real-time correspondence with the current human worker at the aCell.

FIGURE 4
Human-Robot Collaborative Disassembly of a WEEE Device. **(A)** Vision module identifies a worker using their unique code. **(B)** DAC-HRC architecture adjusts to worker preferences, modulating robot behavior. **(C)** The IM app shows worker details and disassembly status and sends notifications if human input is required. **(D)** Task Planner updates after full disassembly of the WEEE device.

In parallel, the cobot continues operating primarily guided by the goals imposed by the Task Planner. The succession of steps, as well as their status and the progress during the disassembling process, is also communicated to the human worker through the IM app (Figure 4C). However, as mentioned in the description of the Task Planner, the scheduling of disassembly steps is determined as a succession of states that ensures the task allocation (human or cobot) matches the worker's skills and preferences. Thus, the optimal distribution of disassembly tasks leads to stable collaborative turn-taking dynamics, fostering predictability and facilitating the rapid acquisition of social conventions Hawkins and Goldstone (2016), Freire et al. (2020b).

Once the Task Planner has successfully overcome the robot's assignments and reached an action that requires human intervention, this module interplays with the Interaction Manager to proactively interact with the human worker. As a result, the IM app sends a notification to the human worker describing the action to be performed (Figure 4C). Moreover, this notification

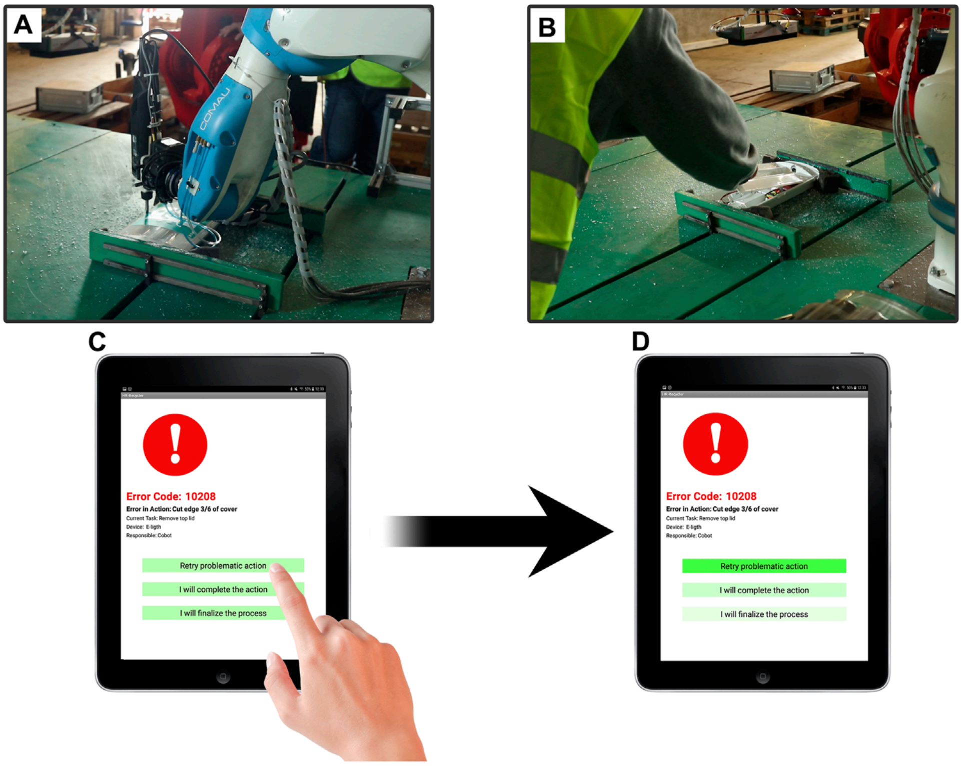

FIGURE 5
Personalized error-handling mechanisms during Human-Robot collaborative disassembly. **(A)** The complex coupling of both the aCel and the DAC-HRC architecture becomes a potential source of failure that needs to be addressed at the systems level. **(B)** Either when the cobot cannot complete a given disassembly action, or when is the worker's turn to execute a step of the disassembly, the human worker can intervene safely. **(C)** IM app notification of an error during the disassembly providing the three different actions to overcome the error. **(D)** The IM app in liaison with the Interaction Learner provides an attentional bias towards the preferred error-handling options by modulating their visual saliency.

enables the worker to control the clamping tool (see Figure 1) through the IM app when the device's translation or reorientation is needed. Once the human intervention has been completed, a completion button must be pressed to allow the DAC-HRC architecture to carry on with the next step. Additionally, an abort option is available in cases where the human worker needs to stop the collaborative disassembly and finish on their own.

Finally, when both the robot and human's disassembling actions have been completed, the Interaction Manager, in liaison with the Task Planner, informs the human worker about the completion of the disassembling process through the IM app (Figure 4D).

3.2 Error handling mechanisms personalized by past collaborative interactions

Beyond the complex interaction that DAC-HRC cognitive architecture maintains within its components, it is also in contact communication with other HR-Recycler sensory and control modules. This architecture's complexity aims to both cope with the challenge of autonomously disassembling WEEE devices, but also ask for collaboration when unexpected issues prevent the optimal performance of the cobot's assignments (Figure 5A).

To overcome these errors, the Task Planner, through the IM app, informs the human worker of any problematic action (i.e., any action that leads to errors) and provides three possible solutions. These options give the worker the possibility to (1) force the cobot to retry the problematic action, (2) inform the cobot that the worker will take care of the action (Figure 5B), or (3) to inform the cobot that the worker will take care of the remaining steps of the disassembly (Figure 5C).

Importantly, due to the involvement of the Interaction Learner module, this error-handling functionality becomes adaptive to the worker's preferences by learning from previous interactions. Thus, if a worker exhibits consistent biases toward one of the options when handling Task Planner errors, the module memorizes these preferences and facilitates future decision-making by increasing the visual saliency of the previously preferred options (Figure 5D). This reflects the principles of shared intentionality and interdependence, as it involves a mutual understanding between the human and robot about handling errors and reliance on each other's capabilities to resolve these errors and complete the disassembly process.

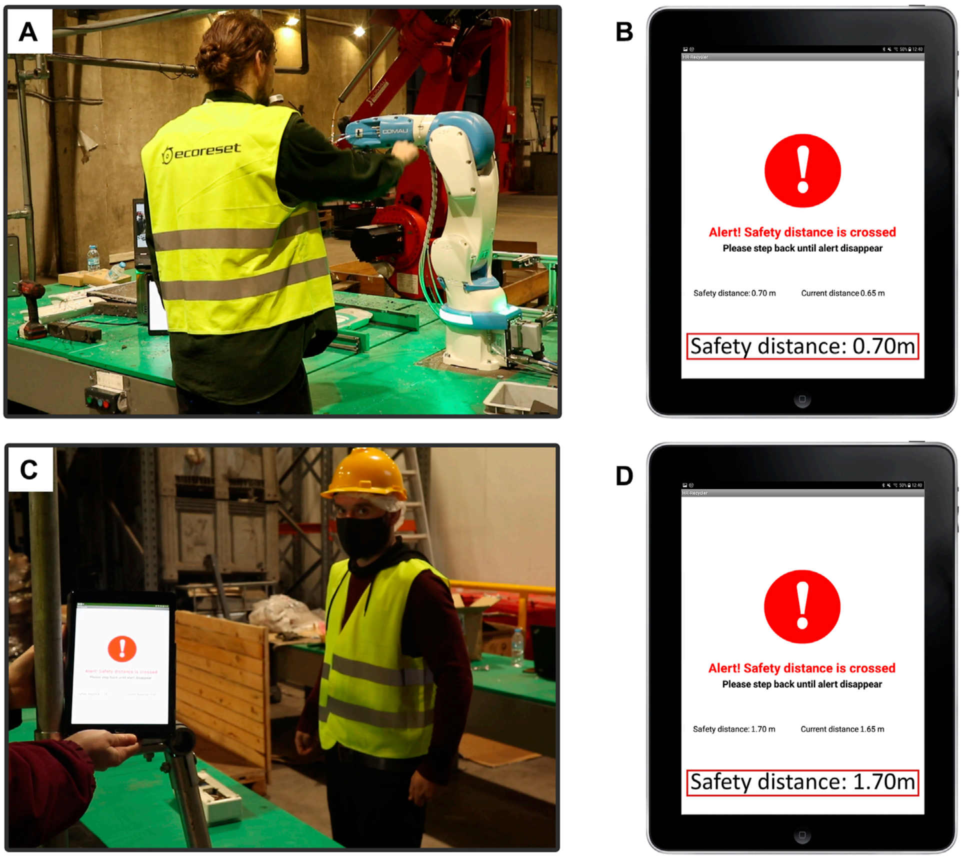

FIGURE 6
Adaptation of safety distance to human workers with different trust measures. **(A)** A worker with high trust in their robotic counterpart engages in the collaborative process of disassembling the WEEE device. Their high trust is considered by the Socially Adaptive Safety Engine which, accordingly, sets a short safety distance. Nonetheless, once this personalized safety distance is surpassed the robot comes back to its initial position and stops. **(B)** Surpass of the safety distance triggers an IM app alert notification. According to the worker's high measure of trust, the personalized safety distance is set at 0.70 m **(C)** When a different worker reporting a lower measure of trust in their robotic counterpart enters the aCell, the Socially Adaptive Safety Engine recalculates the safety distance. As a result, the safety distance is enlarged and the human worker is not allowed to get so close to the cobot without triggering the safety alert. **(D)** IM app alert notification when the worker with lower trust surpasses the safety distance. Notice that it was enlarged to 1.70 m.

3.3 Adaptive and personalized safety measures for human-robot collaboration

In parallel to the Human-Robot collaborative disassembling of WEEE devices, safety-related information is constantly monitored and processed to provide adaptive and personalized robot behavior. With this aim, once the computer vision module has detected and recognized a human worker at the aCell, the Socially Adaptive Safety Engine (SASE) draws its measure of trust from the Worker Model. In addition, the SASE updates the safety distance and robot's speed according to the worker's preferences (Figure 6). This process reflects the principles of shared intentionality and interdependence, as it involves a mutual understanding between the human and robot about the worker's trust level and reliance on each other's capabilities to maintain safety during the disassembly process.

Since the adaptation of the robot's speed to the worker's trust does not interfere with the worker's performance, it has been designed to occur covertly and automatically. Thus, the robot's speed is set at high levels when the current worker has reported high levels of trust in their robotic counterpart and decreases when a more distrusting worker enters the aCell.

However, aiming to ensure the integrity of the human workers, the normal turn-taking collaborative Human-Robot interaction can be interrupted when they surpass the safety distance (Figures 6A, B). This safety distance, as well as the robot's speed, is initially personalized by the Socially Adaptive Safety Engine based on the trust information provided by the Worker Model. Thus, human workers with higher trust are allowed to get closer to the workbench while the cobot is carrying out its tasks. Nonetheless, when a more distrusting worker enters the aCell, this safety distance is extended ensuring both their physical integrity and physiological wellbeing (Figures 6C, D and Supplementary Videos S1 and S2). Importantly, even when workers report a maximum level of trust in robots, a minimum safety distance is set, following the international safety requirements for industrial robots ISO (2011, 2016). The real-time monitoring of the workers' position relative to their personalized safety distance is accomplished by the DAC-HRC architecture due to the continuous communication between the SASE and the vision module, which provides the current worker's location.

In cases where the worker has surpassed their personalized safety distance, the Socially Adaptive Safety Engine ensures their integrity by immediately stopping the cobot's action. The trespassing of the safety distance is also reported to the Interaction Manager, which in turn notifies the human worker about their current location and the minimum distance they should keep to the cobot (Figures 6B, C). This alert remains displayed on the IM app until the worker gets back to respect their safety distance. Once the safety distance is reached again, the SASE's alert disappears from the IM app and the cobot resumes its previous task.

3.4 Gesture-based communication for goal-oriented collaboration

Besides the direct input that human workers could provide to the DAC-HRC architecture through the IM app, vision modules recognize a set of gestures that enables multimodal communication and enhance human-robot interaction during collaborative disassembly.

Unlike direct input through the IM app, which is dependent on specific events such as the requirement of human intervention or error-handling situations, gesture-based communication is available at any time during disassembly. That is, the workers can exert control over the collaborative process by performing predefined gestures that inform the DAC-HRC architecture to stop or resume the disassembling process, as well as informing that the disposal tray is full (Figure 7 and Supplementary Videos S3 and S4). Consequently, the worker also gets feedback about the detection of the recognized gesture through the IM app (Figures 7B, D, E). This reflects the principles of shared intentionality and interdependence, as it involves a mutual understanding between the human and robot about the meaning of different gestures, and a reliance on each other's capabilities to interpret these gestures and respond appropriately (Figures 7F, G).

4 Discussion

This paper introduces the Distributed Adaptive Control-based Human-Robot Collaboration (DAC-HRC) architecture, a novel cognitive framework tailored for enhancing human-robot interactions within the dynamic and evolving landscape of Industry 4.0. Unlike traditional paradigms that promoted more static and rigid interactions, DAC-HRC represents a significant leap forward, integrating socially adaptive, flexible, and intuitive interaction schemes that cater specifically to the nuanced demands of industrial contexts. By leveraging novel Human-Robot Collaboration (HRC) strategies, such as gesture-based communication and user-context adaptation, DAC-HRC facilitates a more natural and efficient partnership between humans and non-humanoid robots, particularly within the challenging environment of electronic waste recycling.

At the heart of DAC-HRC are four main cognitive modules: the Task Planner, Socially Adaptive Safety Engine, Interaction Manager, and Worker Model. Each module is meticulously designed to operate across various timescales and abstraction levels, ensuring that the architecture can provide personalized adaptive collaboration that is sensitive to the unique needs of each human user. This modular design not only underscores the architecture's flexibility but also its potential to enable seamless and organic human-robot interaction in complex and dynamic industrial scenarios.

Applied within the HR-Recycler environment, a hybrid recycling plant focused on the disassembly and recycling of Waste Electrical and Electronic Equipment (WEEE) devices, DAC-HRC's capabilities were demonstrated through several pilot studies. These studies showcased the architecture's ability to enhance human-robot collaboration through (1) adaptive turn-taking interactions, (2) personalized error-handling mechanisms, (3) dynamic safety measures, and (4) intuitive gesture-based communication. By addressing key collaboration aspects such as adaptation, safety, personalization, transparency, and real-time interaction, DAC-HRC proposes a new paradigm for human-robot collaboration in industrial settings.

In each of the outlined use cases, the DAC-HRC architecture demonstrates its capacity for real-time adaptive decision-making, informed directly by data gathered during human-robot interactions. For instance, in the collaborative disassembly of WEEE devices, the cobot's operational speed and safety distances are dynamically adjusted based on the trust levels reported by the human workers. This socially adaptive mechanism ensures that interactions are tailored to individual comfort levels, thereby enhancing the safety and efficiency of the collaborative process. Similarly, the system's ability to adapt to the language preferences of each worker, as identified through their unique fiducial codes, exemplifies how DAC-HRC leverages personal information to customize the interaction experience, ensuring clear and effective communication through the Interaction Manager. These adaptations, underpinned by principles of shared intentionality and interdependence, enable DAC-HRC to foster a cooperative environment that is responsive to the nuanced needs and preferences of human workers, significantly impacting the collaborative dynamics within the industrial setting of the HR-Recycler plant.

Despite the promising potential of DAC-HRC, current limitations such as the need for further validation and refinement, as well as the integration of additional cognitive modules for predictive task allocation and human behavior understanding, must be addressed.

The primary aim of this paper was to explore and demonstrate the feasibility and adaptability of the DAC-HRC cognitive architecture as a novel systems-level control paradigm for HRC, particularly within industrial settings. The focus of our pilot studies was to validate the cognitive architecture's conceptual and functional capabilities, such as facilitating adaptive collaboration, enhancing safety measures, and implementing intuitive communication protocols.

Given the innovative and exploratory nature of this work, the emphasis was placed on qualitative assessments of the architecture's integration and interaction dynamics within the HR-Recycler environment, rather than on quantitative performance metrics. This approach aligns with the initial stages of deploying such complex systems, where understanding the system's behavior, adaptability,

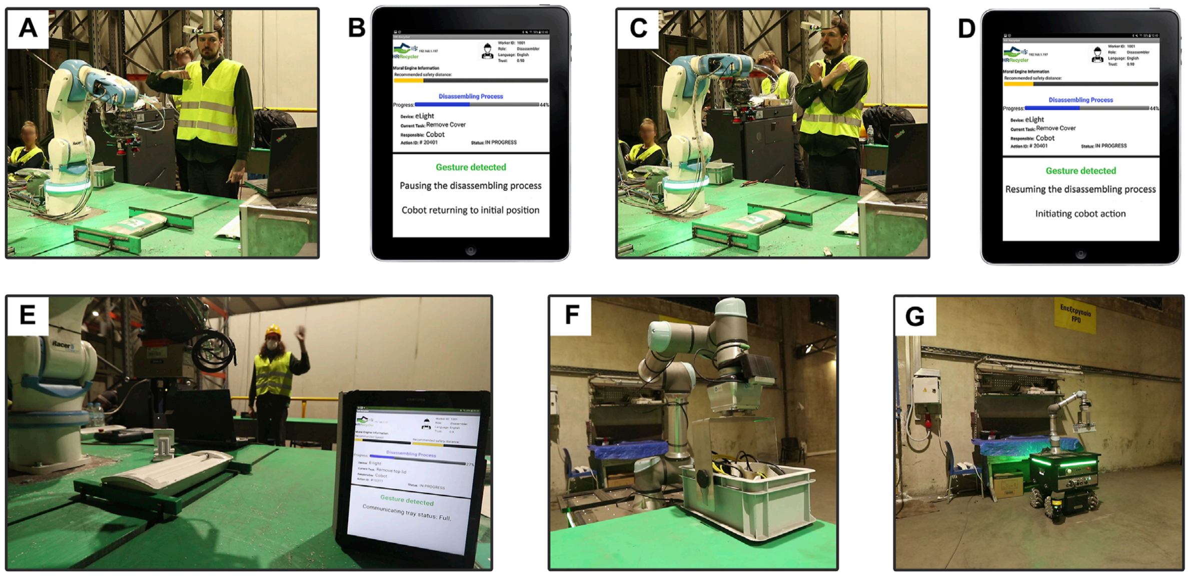

FIGURE 7
Human-Robot interaction based on gesture recognition. **(A)** Human worker performing the 'stop' gesture. **(B)** IM app notification for the recognition of the 'stop' gesture and showing information about the corresponding robot action: adopting its initial, default pose. **(C)** Human worker performing the 'resuming' gesture. **(D)** IM app notification for recognition of the 'resuming' gesture and showing information about the corresponding robot action, resuming the interrupted action. **(E)** Human worker performing the 'wave' gesture and IM app notifying about the recognition and meaning of the gesture: disposal tray is full. **(F)** Automated guided vehicle (AVG) robot picking up the full disposal tray from the aCell. **(G)** AVG robot leaving the full disposal tray in the removal area.

and potential for enhancing human-robot collaboration takes precedence. Therefore, while the inclusion of performance metrics is undoubtedly valuable for evaluating HRC systems, the current phase of this research was focused on establishing a foundational understanding and proof of concept of the DAC-HRC architecture. Future work should focus on incorporating quantitative performance metrics to rigorously evaluate the architecture's effectiveness and efficiency in enhancing human-robot collaboration.

Recognizing the importance of these human-centric factors, future research should also incorporate more formal evaluations of the human aspects of collaboration. This includes assessing the user experience, perceived usefulness, and mental load using standardized tools like the NASA-TLX, alongside additional metrics that can provide a more comprehensive understanding of the human-robot interaction dynamics. These future studies aim to balance the focus between technical innovation and human factors, ensuring that advancements in HRC systems like DAC-HRC not only meet technical and safety requirements but also align with human workers' needs and preferences for a truly collaborative and supportive work environment.

The interdisciplinary nature of DAC-HRC's development, drawing from cognitive science, robotics, and human-robot interaction research, is a testament to its innovative approach to solving complex HRC challenges. This cross-disciplinary collaboration has enabled the creation of an architecture that not only meets the technical requirements of industrial applications but also aligns with the cognitive and social dynamics of human-robot interaction.

The collaborative entity of DAC-HRC termed the aCell, symbolizes a distributed cognitive organism akin to an ant colony, where cognitive processes are shared among agents to achieve collective goals. This analogy is rooted in the notions of extended cognition Clark and Chalmers (1998) and liquid brains Solé et al. (2019), which describe how cognitive processes can be distributed across multiple agents in a system, rather than being confined to a single individual. It highlights the importance of designing distributed hybrid collaborative systems that leverage the complementary strengths of humans and robots. By fostering shared control and distributed agency, DAC-HRC paves the way for innovative approaches to human-robot collaboration that can significantly impact Industry 4.0 and beyond.

In an ant colony, for example, no single ant possesses the entire knowledge of the colony's activities. Instead, each ant contributes to the collective intelligence of the colony through its individual actions and interactions with other ants. Similarly, in an aCell, the human and cobot work together as a cohesive unit, with each contributing their unique skills and capabilities to the collective performance of the task at hand.

This perspective offers valuable insights for designing distributed hybrid collaborative systems. For instance, it suggests that we should focus not only on the individual capabilities of humans and robots but also on how they can best interact and coordinate their actions to achieve shared goals. This could involve developing natural language understanding methods that enable humans and robots to share information more effectively Dong et al. (2019), Thomason et al. (2019), or designing control algorithms that allow robots to adapt their behavior based on the expected actions and intentions of their human partners Shum et al. (2019), Lake et al. (2017), Freire et al. (2023).

Moreover, by integrating principles of shared intentionality and interdependence, the DAC-HRC architecture provides a robust foundation for future endeavors in human-robot collaboration across industrial settings and beyond, aiming to enhance the cognitive and communicative dynamics of collaborative tasks. This principled framework encourages the creation of more socially-aware, adaptable hybrid systems capable of supporting nuanced human-robot interactions in diverse environments. For example, in manufacturing, such insights could guide the development of cobots engineered to proactively respond to human workers' needs, facilitating real-time adjustments to workflow tasks or machine pacing to alleviate worker fatigue or optimize productivity. Similarly, in healthcare, DAC-HRC's approach could lead to assistive robots that offer tailored support to patients or healthcare providers, learning from each interaction to improve responsiveness and adapt behavior based on individual preferences or emotional cues. Looking ahead, DAC-HRC's expansion into other sectors such as logistics and warehouse management promises to leverage these insights further, driving the creation of more efficient, empathetic, and adaptable collaborative systems that elevate the efficacy of human-robot partnerships in any context. By capitalizing on the complementary strengths of humans and robots in this way, we can create hybrid collaborative systems that enable them to work together more effectively and efficiently.

In sum, DAC-HRC's commitment to enhancing the collaborative bond between humans and robots through adaptation, safety, personalization, and transparency sets a new blueprint for future hybrid industrial collaborative efforts. The architecture's modular and flexible framework aims to advance the efficiency and efficacy of human-robot partnerships, providing valuable insights for both industrial applications and the broader human-robot interaction research community. As we continue to explore and expand the capabilities of DAC-HRC, it stands as a testament to the potential of cognitive architectures to revolutionize the way humans and robots work together, paving the way for more responsive, understanding, and cooperative collaborative systems.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

Ethics statement

Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

IF, OG-R and AA implemented the cognitive architecture, concieved and conducted the experiments and the real-site demonstrations. IF and OG-R wrote the manuscript AA and PV revised and edited the manuscript PV initiated and supervised the research. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frobt.2024.1248646/full#supplementary-material

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Integrating collaborative robots in manufacturing, logistics, and agriculture: Expert perspectives on technical, safety, and human factors

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This study investigates the implementation of collaborative robots across three distinct industrial sectors: vehicle assembly, warehouse logistics, and agricultural operations. Through the SESTOSENSO project, an EU-funded initiative, we examined expert perspectives on human-robot collaboration using a mixed-methods approach. Data were collected from 31 technical experts across nine European countries through an online questionnaire combining qualitative assessments of specific use cases and quantitative measures of attitudes, trust, and safety perceptions. Expert opinions across the use cases emphasized three primary concerns: technical impacts of cobot adoption, social and ethical considerations, and safety issues in design and deployment. In vehicle assembly, experts stressed the importance of effective collaboration between cobots and exoskeletons to predict and prevent collisions. For logistics, they highlighted the need for adaptable systems capable of handling various object sizes while maintaining worker safety. In agricultural settings, experts emphasized the importance of developing inherently safe applications that can operate effectively on uneven terrain while reducing workers' physical strain. Results reveal sector-specific challenges and opportunities: vehicle assembly operations require sophisticated sensor systems for cobot-exoskeleton integration; warehouse logistics demand advanced control systems for large object handling; and agricultural applications need robust navigation systems for uneven terrain. Quantitative findings indicate generally positive attitudes toward cobots, particularly regarding societal benefits, moderate to high levels of trust in cobot capabilities and favorable safety perceptions. The study highlights three key implications: (1) the need for comprehensive safety protocols tailored to each sector's unique requirements, (2) the importance of user-friendly interfaces and intuitive programming methods for successful cobot integration, and (3) the necessity of addressing workforce transition and skill development concerns. These findings contribute to our understanding of human-robot collaboration in industrial settings and provide practical guidance for organizations implementing collaborative robotics while considering both technological advancement and human-centered design principles.

KEYWORDS

collaborative robots, human-robot collaboration, industrial automation, safety perception, trust development, workforce transition

1 Introduction

Recent research on collaborative robots (cobots) highlights their increasing adoption across various sectors, including automotive, logistics, and agriculture, primarily aimed at enhancing efficiency, productivity, and worker safety. Cobots are designed to work alongside human operators, enhancing productivity and safety while addressing the challenges posed by traditional automation methods. The integration of cobots into these sectors is driven by advancements in technology, particularly in artificial intelligence (AI), machine learning, which facilitate more intuitive human-robot interactions and operational efficiencies (Malik and Bilberg, 2019).

In the manufacturing sector, cobots are increasingly utilized to optimize assembly lines and improve operational workflows. They assist workers with tasks that are ergonomically challenging, thereby reducing physical strain and enhancing overall workplace safety. Studies indicate that cobots can significantly improve productivity by automating repetitive tasks while allowing human workers to focus on more complex activities that require cognitive skills (Borboni et al., 2023; Kakade, 2023). Furthermore, the implementation of cobots in manufacturing environments has been shown to foster a collaborative atmosphere that enhances worker satisfaction and reduces turnover rates (Othman and Yang, 2022).

In logistics, cobots are transforming supply chain operations by automating material handling and inventory management tasks. Their ability to navigate dynamic environments and interact with human workers makes them invaluable in warehouses and distribution centers. Research indicates that cobots can streamline logistics processes, reduce errors, and enhance the speed of operations, particularly in last-mile delivery scenarios (Pessot et al., 2023). The integration of AI-driven cobots allows for predictive maintenance and real-time data analysis, which further optimizes logistics operations.

The agricultural sector is also witnessing a surge in the use of cobots, particularly for tasks such as harvesting, sorting, and planting. These robots not only increase efficiency but also address labor shortages in the agricultural workforce. Studies have shown that cobots can improve the precision of agricultural tasks, leading to better crop yields and reduced waste. The collaborative nature of these robots allows them to work closely with human farmers, enhancing productivity while ensuring safety in potentially hazardous environments (Rowan, 2022; Guruswamy et al., 2022).

Despite the numerous benefits of cobots, challenges remain regarding their widespread adoption. Issues related to safety, trust, and the potential displacement of human workers are significant concerns that need to be addressed (Adel, 2022; Raja Santhi and Muthuswamy, 2023). Research emphasizes the importance of developing robust safety standards and training programs to ensure that both workers and cobots can operate effectively and safely in shared environments (Guertler et al., 2023). Additionally, as the technology evolves, continuous vocational training will be essential to equip workers with the necessary skills to collaborate effectively with cobots.

Human factors and ergonomics serve as fundamental elements in human-robot collaboration (HRC), significantly influencing interaction effectiveness, acceptance, and overall success (Green et al., 2008; Simone et al., 2022). Contemporary research has expanded into cognitive domains, examining user experience (Gervasi et al., 2022), cognitive load (Kim, 2022), and social cognition (Henschel et al., 2020). This heightened attention to human-related aspects aligns with the emerging Industry 5.0 (I5.0) concept, which represents an evolution from Industry 4.0. This transformation emphasizes the seamless integration of advanced technologies with human-centric approaches, particularly focusing on resilience, human wellbeing, and sustainability (Trstenjak, et al., 2022). While I5.0 encompasses various sectors, its impact is particularly significant in manufacturing (Narkhede et al., 2023), logistics (Berkers et al., 2023), and agriculture (Henriksen et al., 2022). These sectors stand at the forefront of the I5.0 revolution, where HRC dynamics play a pivotal role. Nevertheless, despite HRC's growing importance in these settings, substantial gaps remain in understanding the challenges associated with workers' safety and skills development within these new collaborative environments. Additionally, there is limited comprehension of the requirements and specific standards necessary for such innovative transformation (Villani et al., 2018).

The main objective of this study is to investigate the collaborative dynamics between workers and cobots across three distinct industrial sectors: vehicle assembly operations (manufacturing), robotic handling in warehouses (logistics), and vineyard operations (agriculture). These sectors represent diverse applications of HRC, each presenting unique requirements and challenges (Shamshiri et al., 2018). Through a questionnaire-based qualitative approach targeting technical professionals in automation and robotics, this research aims to comprehensively examine experts' perceptions regarding technical, ethical, and safety aspects of cobot deployment.

The study specifically focuses on understanding three key dimensions: attitudes toward collaborative robots (Koverola et al., 2022), trust in robotic systems (Charalambous et al., 2015), and safety perceptions (Arents et al., 2021). This qualitative methodology enables the exploration of nuanced experiences and perspectives that quantitative methods might not capture, including workers' adaptation to technological changes, job security concerns, and expectations about system efficiency (Stapels and Eyssel, 2021). Furthermore, this approach allows for examining contextual factors such as cultural attitudes towards technology and task-specific considerations in cobot applications (Søraa et al., 2023), providing insights into how assembly line workers perceive their interactions with cobots, including safety considerations and job satisfaction impacts (Bhargava et al., 2021).

Conducting qualitative studies to gather perceptions of targeted technical professionals in automation and robotics is crucial for understanding the collaborative dynamics between workers and collaborative robots in specific use cases. Qualitative research allows for an in-depth exploration of how assembly line workers perceive their interactions with cobots, including their feelings of safety, job satisfaction, and the perceived impact on their roles (Bhargava et al., 2021) but also can provide insights into how workers adapt to these changes, their concerns about job security, and their expectations regarding the efficiency of robotic systems (Stapels and Eyssel, 2021).

2 Literature review

2.1 Collaborative robots in manufacturing

Recent research on collaborative robots in manufacturing and assembly lines has explored various dimensions of HRC, revealing insights into how these interactions can be improved (Ajoudani et al., 2018; Kumar et al., 2021).

One significant area of research is the impact of cobots on worker productivity and posture. Bouillet's study demonstrated that the introduction of a cobot in collaborative tasks resulted in longer collaboration times and increased production output, suggesting that the proactive coordination of cobots can enhance hybrid collaboration and improve overall productivity Bouillet (2023). This finding underscores the need to consider how cobots can be designed to facilitate smoother interactions with human workers, thereby reducing physical strain and improving ergonomic outcomes. Moreover, the relationship between human-cobot interaction fluency and job performance has been a focal point in recent studies.

Paliga's research indicated that fluent and well-coordinated cooperation between humans and cobots positively affects job performance and satisfaction, regardless of the workload (Paliga, 2023). This highlights the importance of designing cobots that can adapt to the dynamic nature of human work, ensuring that operators feel a sense of control and fulfillment in their tasks. Such insights are critical for fostering a collaborative environment that enhances both productivity and worker wellbeing. The qualitative assessment of cobot interactions with different demographics, such as senior workers, has also been explored.

Rossato et al. (2021) found that cobots can significantly enhance the efficiency of manufacturing systems while improving the quality of life for human operators. This is particularly relevant as the workforce ages and the need for ergonomic solutions becomes more pressing. Understanding how different worker profiles interact with cobots can inform the design of adaptive workstations that cater to diverse needs.

Safety remains a paramount concern in HRC. The Cobot And Robot Risk Assessment (CARRA) method developed by Stone et al. emphasizes the need for safety assessments that consider the unique dynamics of human-cobot interactions (Stone et al., 2021). This method aims to improve fluency in safe interactions, highlighting the necessity of integrating safety protocols into the design and operation of cobots. Furthermore, the psychological aspects of human-cobot interactions have gained attention, particularly regarding mental workload and emotional states. Pluchino's study utilized eye-tracking and cardiac activity indices to assess senior workers' mental workload during assembly tasks with cobots, emphasizing the need for a human-centric approach in designing collaborative systems (Pluchino et al., 2023).

Kumar and colleagues (2021) made significant contributions to the understanding of various HRC techniques, in the manufacturing processes, highlighting the potential for enhanced productivity and efficiency through effective human-robot interaction. They explored both one-way and two-way collaboration models, which are essential for understanding how humans and robots can work together effectively. This classification helps in identifying the specific needs and challenges associated with each type of collaboration, thereby providing a framework for future research and practical applications in the field (Inkulu et al., 2021). Kumar et al. also addressed the challenges faced in implementing HRC techniques, such as safety concerns, the need for effective communication between humans and robots, and the importance of designing user-friendly interfaces. The most recent research highlights the role of advanced technologies, such as artificial intelligence and machine learning, in facilitating more intuitive interactions between humans and robots, allowing for adaptive responses based on real-time feedback from the work environment. Kumar and colleagues emphasized that leveraging these technologies can lead to more efficient workflows and improved safety outcomes, as robots can learn from human actions and adjust their behavior accordingly (Othman and Yang, 2022).

2.2 Collaborative robots in logistics

Recent research on collaborative robots in logistics has highlighted their potential in enhancing operational efficiency, safety, and flexibility within supply chain processes. The integration of cobots into logistics operations is increasingly seen as a critical component of the broader trend towards Logistics 4.0, which leverages advanced technologies to optimize logistics activities.

One of the primary contributions is the exploration of safety mechanisms for cobots operating in logistics environments (Kiangala and Wang, 2022). proposed an experimental safety response mechanism that utilizes Q-learning algorithms and speech recognition to enhance the safety of autonomous moving robots in smart manufacturing settings. This research underscores the importance of developing robust safety protocols that ensure safe interactions between human workers and cobots, particularly in dynamic logistics environments where the risk of accidents can be heightened (Kiangala and Wang, 2022). Additionally, Rautiainen et al. (2022) emphasized the significance of multimodal interfaces for intuitive human-robot interaction, which is crucial for effective collaboration in logistics. Their findings suggest that enhancing communication between humans and cobots can improve operational outcomes, as workers are better equipped to interact with and manage robotic systems. This aligns with the growing recognition that successful HRC relies not only on the robots' capabilities but also on the quality of interaction and the ease of use of control systems (Saenz et al., 2022).

Wei et al. (2022) highlighted the role of automated guided vehicles (AGVs) in warehouse systems, where multi-robot collaboration is optimized through advanced path planning and obstacle avoidance techniques. This research illustrates how collaborative approaches can enhance the efficiency of logistics operations by enabling multiple robots to work together seamlessly, thereby reducing operational bottlenecks and improving throughput.

Lambrechts et al. (2021) conducted a comprehensive investigation into the human factors influencing the implementation of cobots in order picking operations, a critical component of warehouse logistics. Their research identified several key human factors that impact the successful integration of cobots, including resistance to change, organizational culture, communication regarding changes, and leadership support. They found that resistance to change is often rooted in fear of job displacement and a lack of understanding of the benefits that cobots can bring to the workforce. Effective communication and leadership are essential to mitigate these concerns and foster a culture of acceptance and collaboration between human workers and robots. This highlights the importance of addressing psychological and organizational barriers when implementing new technologies in logistics. Berkers et al. (2023) further explored the implications of human factors in the context of logistics automation, emphasizing the need for a human-centered approach to the design and deployment of cobots. Their research underscores the significance of creating intuitive interfaces that facilitate seamless interaction between humans and robots. They argue that understanding the cognitive load and physical demands placed on workers is crucial for optimizing HRC systems. Their findings align with the broader trend in logistics research that advocates for integrating human-centered design principles in the development of automated systems.

2.3 Collaborative robots in agriculture

Collaborative robots have been applied to enhance productivity, sustainability, and efficiency in farming practices. One of the significant contributions to the field is the exploration of HRC techniques that leverage the strengths of both humans and robots. Yerebakan and Hu (2024) provides a comprehensive review of current research on HRC in agriculture, emphasizing its potential to design modern agricultural systems that capitalize on the unique capabilities of both parties. This review underscores the importance of integrating human expertise with robotic precision, particularly in tasks such as planting, harvesting, and pest control, where human cognitive skills can complement robotic efficiency.

The ability of robots to communicate and coordinate their actions is crucial for tasks that require high levels of precision and adaptability. The safety and ergonomics of HRC in agriculture have also been addressed. Tagarakis et al. (2021) explored the use of wearable sensors to monitor human activity in collaborative agricultural environments, emphasizing the need for safety measures when humans and robots operate in close proximity. This research highlights the importance of creating a safe working environment that minimizes risks associated with human-robot interaction.

More recently, Adamides and Edan (2023) conducted a comprehensive review of HRC strategies and approaches in the agricultural industry and proposed that HRC systems could function as transitional solutions toward full automation, effectively combining robotic capabilities with human skills to address current technological limitations and streamline system design. The study emphasizes the importance of adopting a mixed-methods approach to examine the multifaceted nature of human social aspects, including experiential knowledge, practical implementation, and cultural considerations. The authors advocate for broad stakeholder engagement, particularly technical experts, in addressing social dimensions during the deployment of robotic systems. This comprehensive strategy ensures a balanced understanding of HRC technical and social aspects, ultimately facilitating more effective cobot integration and acceptance in agricultural settings.

2.4 Human factors in cobot integration

The integration of collaborative robots (cobots) in industrial settings represents a significant advancement in HRC, yet it brings complex challenges regarding safety, trust, and human acceptance. While the technical capabilities of cobots continue to evolve, understanding the human factors that influence their successful implementation remains crucial (Faccio et al., 2023).

This study stems from the theoretical foundations of HRC through multiple lenses. By investigating attitudes, trust development, and safety perceptions in three distinct industrial contexts - vehicle assembly, warehouse logistics, and agricultural operations - this research aims to provide comprehensive insights into the dynamics of HRC. The study combines expert opinions with quantitative assessments to understand both the technical requirements and human factors essential for successful cobot integration. This approach acknowledges that while cobots offer significant potential for enhancing workplace efficiency and safety, their effectiveness ultimately depends on the careful consideration of human perceptions, trust dynamics, and safety requirements within specific industrial contexts.

2.4.1 Foundational aspects

Understanding the foundational aspects of HRC requires examining multiple theoretical frameworks that explain how humans and robots interact and integrate in workplace settings. Mubin et al. (2013) establish three primary categories of robot roles during activities: tool, partner, and tutor. In industrial settings, particularly where cobots are equipped with AI systems, additional roles such as supervisor may emerge. These varying roles determine different types of collaboration and significantly impact trust and safety perceptions, largely due to the technical complexities of cobot operations that may not be immediately transparent to users.

The concept of "functional organs" (Benvenuti et al., 2020; Mazzoni and Benvenuti, 2023) provides a crucial framework for understanding the integration of technological artifacts and humans. This concept emphasizes how combined human-robot performance can exceed individual capabilities of either party. However, not all tools qualify as functional organs; only those deeply integrated into human practices, evolving through repeated use to become true extensions of human capability and operating without conscious control, achieve this status.

Building on this foundation, Human-robot "coefficiency" (Lagomarsino et al., 2022; 2023) offers another vital theoretical perspective. This concept suggests that during HRC, where humans and automated systems share common objectives, individuals view the interaction as a holistic unit, similar to human-human interactions. They select actions aimed at maximizing overall efficiency rather than focusing on individual components. The application of coefficiency principles proves crucial for skills development and can enhance workers' trust and safety perceptions within manufacturing ecosystems. Recent research by Vianello et al. (2023) supports these theoretical frameworks through empirical evidence, showing how humans adapt to changing roles and control strategies of collaborating robots. Their study, focused on a sawing task, revealed preferences for energy-efficient modes and collaborative interactions, emphasizing the importance of understanding human responses to cobot behavior in fostering trust and positive attitudes.

2.4.2 Attitudes and acceptance

Attitudes toward collaborative robots in organizations span a spectrum of positive and negative perceptions (Savela et al., 2022; Koverola et al., 2022). Edison et al. (2003) emphasize the distinction between personal and societal attitudes, noting that individual enthusiasm for technology doesn't necessarily correlate with positive views of its societal implications. As Koverola et al. (2022) observe, personal attitudes might involve simple enjoyment or discomfort with robot interaction, while societal concerns often center on broader issues like workforce displacement. Recent research by Kaur et al. (2023) provides valuable insights into worker perceptions, finding that robots offering as-needed assistance were viewed more favorably than fully interventional or standoff robots, particularly regarding autonomy and job security. This finding highlights the critical role of cobot deployment strategy in shaping worker attitudes.

2.4.3 Trust development and dynamics

The development of trust in HRC presents unique challenges, as workers initially experience uncertainty regardless of prior robotic system experience (Groom and Nass, 2007). Multiple studies emphasize trust's crucial role in successful human-robot engagement (Lee and See, 2004; Kopp et al., 2021; Maurtua et al., 2017), linking it to enhanced efficiency and productivity (Charalambous et al., 2015).

Hancock et al. (2021), Hancock et al. (2023) have extensively studied trust factors in human-robot interaction, identifying robot performance, anthropomorphism, and transparency as key predictors. Their recent work proposes an elaborate interpersonal trust model incorporating non-human entities. Atchley et al. (2023) introduce the "contagion effect" concept in trust, where initial system-wide trust can shift to component-specific trust based on individual robot performance. Recent innovations, such as integrating Large Language Models (Ye et al., 2023), demonstrate how enhanced communication interfaces can significantly increase trust levels in HRC, pointing toward future directions in cobot development and integration.

2.4.4 Safety perceptions

Safety perception in HRC encompasses users' risk assessment and comfort levels during interactions (Bartneck et al., 2009). This perception fulfills basic human needs (Ryan and Deci, 2000) and represents a state where individuals feel protected from physiological and psychological harm (Dyreborg et al., 2022). Arents et al. (2021) classify collaboration levels into three categories: coexistence, cooperation, and collaboration, each presenting unique safety challenges. Recent studies (Sahin and Savur, 2022) demonstrate how robot behavior changes significantly influence human safety perceptions during collaboration.

3 Methodology

3.1 The use cases

This study emerges from the SESTOSENSO project, an EU-funded initiative involving a consortium of European universities, research institutions, and private companies. The project's primary objective is to develop advanced sensing technologies for robots to enhance HRC effectiveness and safety. We investigate three distinct industrial sectors where collaborative robots and assistive systems are implemented to improve worker safety and operational efficiency: manufacturing, logistics, and agriculture. Each sector presents unique technical, safety, and ethical challenges for HRC implementation.

The research examines three specific use cases that exemplify different aspects of human-robot collaboration:

3.1.1 Manufacturing: COBOT-worker cooperative assembly

This use case focuses on vehicle assembly operations where workers perform tasks requiring diverse postures and varying workloads. Cobots assist workers by supporting heavy components (such as vehicle roofs) and managing tool logistics. The complexity of this environment is heightened by the simultaneous use of exoskeletons and cobots in confined spaces like vehicle cockpits. Key challenges include collision avoidance and optimizing worker movements. To address these challenges, the project develops AI control strategies and enhanced sensorization for both cobots and exoskeletons, ensuring safe and efficient three-way cooperation in this dynamic environment (Fournier et al., 2023; Razin and Feigh, 2023).

3.1.2 Logistics: dual arm handling of large objects

Set within an online grocery fulfillment center, this use case explores bi-manual robotic manipulation of large, bulky objects. The system features a specialized robotic setup with sensorized skin for enhanced object-handling capabilities. Human workers primarily serve supervisory and collaborative roles, intervening only when the robotic system requires assistance or guidance with complex manipulation tasks. This setup represents a shift in traditional human-robot interaction paradigms, emphasizing cognitive rather than physical collaboration.

3.1.3 Agriculture: collaborative mobile manipulators for harvesting

This use case addresses the challenges of grape harvesting in hillside vineyards, where workers traditionally face significant biomechanical stress from manual handling, awkward postures, and repetitive movements. The proposed solution integrates worker-worn exoskeletons with autonomous mobile manipulators that provide physical assistance. The system actively monitors human features and working conditions to optimize biomechanical load reduction, enhancing physical ergonomics and supporting efficient farming operations.

3.2 Selection of participants

An online questionnaire was designed to investigate the perceptions and attitudes of technical experts in the collaborative robotics domain towards HRC within three settings: manufacturing, logistics, and agriculture. The selection of participants was based on a strategic approach to ensure that the sample consisted of technical experts with relevant experience and knowledge in collaborative robotics. The participants were chosen based on their professional backgrounds, roles within their organizations, and experience working with or near cobots.

The recruitment strategy targeted individuals with technical job profiles within the manufacturing and automation sectors. This approach was chosen to ensure the participants had the technical expertise to provide valuable insights into adopting cobots in various industrial settings. Including participants with different roles within their organizations, such as Technical Field Managers, Technical Field Specialists, and experts in Human Resources (HR) or Health, Safety, and Environment (HSE), allowed us to provide a holistic overview of cobot adoption. Technical Field Managers and Specialists were selected for their hands-on experience and knowledge of the technical aspects of cobot implementation. At the same time, HR and HSE experts were included to offer insights into the social, ethical, and safety implications of cobot adoption in the workplace.

3.3 Measures

The questionnaire consisted of two main sections. The first section aimed to gather qualitative data by focusing on three specific use cases' technical, ethical, and safety aspects. This approach sought to provide a richer understanding and capture diverse viewpoints on deploying cobots in these distinct industries. Participants were presented with detailed descriptions of each use case and asked to respond to open-ended questions regarding the potential technical and safety issues and the social and ethical implications of implementing cobots in these scenarios.

The second section of the questionnaire employed established psychometric scales to quantitatively assess relevant psychological factors, including attitudes towards robots, trust in their operations, and perceptions of safety during interactions. These scales were carefully selected based on their reliability, validity, and relevance to the study's objectives. Participants were asked to rate their agreement with a series of statements using a Likert-type scale, providing a standardized measure of their perceptions and attitudes.

Three pairs of researchers analyzed the responses to the open-ended questions, ensuring a comprehensive and balanced data elaboration process. Each pair independently reviewed the responses within the context of the specific use case scenarios, identifying initial categories and themes. Through an iterative process of comparison and synthesis, the researchers refined these categories into central themes that emerged as pivotal to the study's objectives. This collaborative approach helped to minimize individual biases and enhance the reliability of the qualitative findings.

By combining open-ended questions and validated psychometric scales, this study offers a comprehensive examination of the human factors' issues surrounding human-robot collaboration, as perceived by technical experts. The mixed-methods approach allows for a deep understanding of the complex interplay between technical, social, and safety considerations, providing valuable insights into the challenges and opportunities associated with the deployment of cobots in three distinct settings. The questionnaire was distributed using the Qualtrics online platform, and data collection took place from March to June 2023.

3.3.1 Qualitative measures: cobot adoption in the three use cases

Participants were presented with detailed descriptions of three distinct use cases involving collaborative robots in various industrial settings. Each use case highlighted the specific challenges, objectives, and potential benefits of implementing cobots in that context. After reviewing each use case, participants were asked to provide their insights and opinions by answering three open-ended questions designed to capture key aspects of cobot adoption:

3.3.1.1 Technical issues

"*What are the key technical issues of cobot adoption in this particular use case?"*. This question aimed to elicit participants' views on the critical technical factors, challenges, and opportunities associated with implementing cobots in the given scenario. Participants were encouraged to consider efficiency, productivity, flexibility, and innovation potential.

3.3.1.2 Safety issues

What safety-related issues warrant careful consideration in the design and deployment of cobots in this given use case?" This question focused on identifying the critical safety aspects that should be prioritized when developing and implementing cobots in the specific use case. Participants were encouraged to consider factors such as collision avoidance, human-robot interaction protocols, fail-safe mechanisms, and the potential risks associated with the specific tasks and environments.

3.3.1.3 Social and ethical implications

"*How could cobots facilitate or impede ethical and social considerations within this context?"*. This question sought to explore participants' perspectives on the potential social implications of cobot adoption. Participants were asked to reflect on how cobots might influence factors such as job displacement, workforce diversity, skill requirements, and overall social acceptance of the technology.

The open-ended nature of these questions allowed participants to provide rich, qualitative responses based on their expertise and insights. The questions were designed to ensure a comprehensive understanding of the participants' perspectives on cobot adoption in each use case.

3.3.2 Quantitative measures: attitudes, trust, and safety perception

3.3.2.1 Attitudes toward cobots

The General Attitudes Towards Robots Scale (GAToRS; Koverola et al., 2022) was used to assess participants' attitudes toward collaborative robots (cobots). This 20-item scale comprises four distinct dimensions, each containing the five items: 1) Personal Level Positive (P+): Measures the level of comfort and enjoyment during interactions with cobots (e.g., "I would feel comfortable working with a cobot."); 2) Personal Level Negative (P-): Assesses levels of unease and anxiety surrounding cobots (e.g., "I would be anxious about making mistakes while interacting with a cobot"); 3) Societal Level Positive (S+): Evaluates positive viewpoints about the societal benefits of cobots (e.g., "Cobots can enhance human capabilities and productivity."); 4) Societal Level Negative (S-): Quantifies reservations and concerns about the broader societal impacts of cobots (e.g., "Overreliance on cobots may lead to a loss of human skills").

Participants responded to each item using a 5-point Likert scale (1 = completely disagree; 5 = completely agree).

3.3.2.2 Trust toward cobots

The Trust Perception Scale - HRI (Schaefer, 2016), a 14-item scale, was used to measure the multidimensional nature of trust in cobots. This scale assesses trust based on various parameters, such as functionality, maintenance requirements, performance expectations, and safety features. Example items include "Most cobots meet the user or operator's expectations" and "I would feel comfortable assigning a cobot a critical task." Participants responded to each item using a 5-point Likert scale (1 = completely disagree; 5 = completely agree).

3.3.2.3 Perception of safety during human-cobot interactions

A four-item scale developed by Weiss et al. (2009), initially used to study novice users' experiences with humanoid robots, was adapted to evaluate participants' perceptions of safety during interactions with cobots. The scale covers four aspects of safety concerns: 1) Fear of causing harm to the cobot (e.g., "I fear to use cobots, as an error might harm the cobot"); 2) Fear of self-harm (e.g., "I hesitate to use cobots for fear of making errors that will harm me"); 3) Perception of safety in the interaction (e.g., "I feel safe when working with cobots"); 4) Overall safety perception (e.g., "I perceive cobots as safe"). These items provide a multidimensional view of perceived safety, assessing varying levels of fear, confidence, and overall safety perception. Participants responded to each item using a 5-point Likert scale (1 = completely disagree; 5 = completely agree).

3.4 Participants

The study initially involved 64 respondents who began the questionnaire. After screening and data validation, 31 participants, coming from the European Countries of the project's partners (England, France, Greece, Italy, Latvia, Netherlands, Spain, Sweden, Switzerland) were included in the final analysis. The technical experts had an average age of 40.4 years (with a range from 26 to 58) and were predominantly male, with 24 males (77.4%) and seven females (22.6%). Participants were professionals actively engaged in various sectors. Specifically, 35.5% of the participants were from robotics and automation, 29.4% were involved in manufacturing, 16.1% in packaging, 9.7% in the automotive industry, and 9.3% in the chemistry and agrifood sector. Regarding their roles within their organizations, 13 participants (41.9%) were Technical Field Managers, 11 (35.5%) were Technical Field Specialists, and 7 (22.6%) were experts in either Human Resources (HR) or Health, Safety, and Environment (HSE) fields. In terms of their experience with collaborative robots (cobots), 14 respondents (45.2%) were currently actively engaged with cobots at the time of the study, while 17 respondents (54.8%) had experience working near cobots within the last 5 years.

4 Results

4.1 Experts' opinions on the use cases

Table 1 summarizes the key insights from experts' opinions on the technical impacts, social and ethical considerations, and safety issues related to adopting collaborative robots (cobots) in three distinct use cases: vehicle assembly operations, logistics, and vineyard harvesting.

4.1.1 Experts' opinions on the use case about vehicle assembly operation

Experts reported on the technical impacts of cobot adoption in vehicle assembly operations, where workers perform tasks with diverse postures, workloads, and complexity, often requiring exoskeletons to reduce biomechanical load. They emphasized the importance of developing accurate kinematic models and control systems for specific tasks, determining the range of movement, and utilizing sensors, cameras, and machine learning to enhance recognition of the work environment. Cobots can assist by supporting heavy parts, such as the vehicle roof, picking components and tools for workers, and reducing human injuries due to repetitive loads. Enabling effective collaboration between exoskeletons and cobots is crucial to predicting and preventing collisions and improving workload management. One engineer in the automotive sector stated: "*Cobots can improve workload management by assisting workers in handling heavy vehicle components, such as the roof, or by efficiently selecting and delivering the necessary tools and parts to the workers, streamlining the assembly process*". Other issues are related to developing user-friendly interfaces and intuitive programming methods to enable easy deployment and adaptation of cobots for different assembly tasks.

Regarding social and ethical considerations, experts highlighted that cobots could assist with lifting parts while humans/exoskeletons

TABLE 1 Experts' opinions on the three use cases.

Technical impacts of cobot adoption	Social and ethical considerations	Enhancing safety in cobot Design and deployment
Use case "vehicle assembly operations"		
• Enabling effective collaboration between cobots to predict and prevent collisions • Improving workload management by enabling cobots to support heavy parts or handle component and tool selection for workers • Determining the range of movement based on the specific task • Utilizing sensors, cameras, and machine learning to enhance recognition of the work environment	• Facilitating tasks for operators, reducing the need for particular skills or physical conditions • Addressing limitations in the use of exoskeletons for workers with limited motor functions • Assessing socio-economic impacts of potential worker substitution by cobots • Ensuring cobots support rather than replace jobs, enhancing working conditions • Making cobots adaptable and user-friendly for all workers	• Designing cobot tools to ensure safety (e.g., avoiding sharp or non-reversible tools) • Real-time analysis of human movement to predict potential collision points • Adjusting cobot velocity to mitigate risk to humans • Considering ergonomics and testing forces exerted on the operator's body • Minimizing risk through careful design, using minimal weights and speeds
Use Case "Logistics"		
• Facilitating the management of large loads, reducing accidents from incorrect weight assessments • Eliminating errors in picking products through electronic identification (e.g., barcode or RFID) • Redesigning physical work environments for safe cobot operation alongside humans • Flexibility, versatility, and sensitivity in handling food products, minimizing space requirements • Ensuring safety for human workers and preventing food contamination	• Assisting workers with physically demanding tasks, potentially affecting job numbers • Enabling humans to undertake more complex activities while cobots handle simpler tasks • Reducing physical labor and reshaping workforce dynamics • Potentially replacing low-paid jobs, impacting social dynamics • Helping people with disabilities but raising concerns over job losses due to automation	• Ensuring operators cannot enter the cobot's work area during hazardous operations (e.g., using proximity sensors) • Addressing the absence of mature safety standards for close operator-cobot interactions • Considering nearby operator interference and implementing instant motor stop measures • Providing special safety equipment and intrinsically safe systems that activate in anomalies • Ensuring cobot reactivity to human touch and robust handling of objects to prevent accidents
Use Case "Vineyard"		
• Autonomous mobile manipulators can enhance precision and reduce harmful movements, allowing workers to carry more grapes with less effort and in less time • Implement visual technology like cameras to compensate for environmental irregularities (ground conditions, fruit shape, etc.) • Integration of soil conservation techniques, including precision seeding and minimal chemical impact, to prevent soil fatigue	• Improvement of worker's quality of life, leading to higher productivity and a reduced risk of musculoskeletal diseases • Enhancing job access for individuals with physical disabilities • Importance of reliability and ease of use in wearable devices • Addressing cultural readiness among agrifood operators to adopt new technologies • Addressing exploitation issues often associated with manual, labor-intensive tasks like harvesting	• Developing inherently safe applications, prioritizing the ability of cobots to halt operations immediately in both typical and atypical risks • Considering worker mobility on uneven ground surfaces to ensure safety and efficiency (e.g., balancing, weight distribution, and movement considerations in steep slopes) • Emphasizing the redundancy of sensors and robust mechanical designs as critical safety measures

perform precision operations, facilitating tasks for operators and reducing the need for particular skills or physical conditions. They also noted the importance of addressing limitations in using exoskeletons for workers with limited motor functions and assessing the socio-economic impacts of potential worker substitution by cobots. Adopting cobots may lead to job displacement for some workers, particularly those involved in repetitive and physically demanding tasks. Nevertheless, it can also create new job opportunities in areas such as cobot programming, maintenance, and supervision. Cobots can help reduce workers' physical strain and risk of injuries, improving their overall wellbeing and job satisfaction. One expert stated: "*In my opinion, the integration of cobots in the assembly process can greatly assist operators by reducing the physical demands and skill requirements for certain tasks, thereby creating a more inclusive and accessible work environment for employees with diverse abilities and backgrounds*". However, there may be concerns about the long-term effects of working closely with machines and the potential for over-reliance on technology. Implementing cobots may require workers to acquire new skills and adapt to working alongside machines, which could be challenging for some individuals and require significant training and support.

Safety issues in cobot design and deployment were a major concern for experts. They stressed the need for real-time analysis of human movement to predict potential collision points, adjusting cobot velocity to mitigate risk to humans, and incorporating data from external equipment like exoskeletons to prevent collisions. Considering ergonomics and testing forces exerted on the operator's body, minimizing risk through careful design using minimal weights and speeds and designing cobot tools to ensure safety (e.g., avoiding sharp or non-reversible tools) were also deemed essential. They also highlighted the need for comprehensive safety training and education for workers to ensure they understand and adhere to the safety protocols when working with cobots and exoskeletons.

4.1.2 Experts' opinions on the use case "robotic handling in the warehouse"

Experts highlighted various technical impacts of cobot adoption in the logistics use case. They emphasized the importance of adaptability to the working environment, efficient pick and pack activities, and flexibility in handling food products while minimizing space requirements. Cobots can assist with physically demanding tasks, increase operational safety, and eliminate errors in picking products through electronic identification. Redesigning physical work environments is necessary for safe cobot operation alongside humans. Cobots can also facilitate the management of large loads, reduce accidents from incorrect weight assessments, ensure safety for human workers, prevent food contamination, and reduce movement speed and costs associated with technical safety solutions.

One robotics engineer in the logistics sector stated: "*The sensing skin and control algorithms need to be robust enough to adapt to the varying shapes, sizes, and weights of the objects being handled, ensuring a secure grip and smooth manipulation. Other issues include optimizing the robotic system's performance to maximize throughput and efficiency in the warehouse setting and developing intuitive interfaces for human workers to monitor and intervene when necessary*".

Concerning social and ethical implications, adopting bi-manual robotic manipulation systems in warehouse settings can lead to significant job role changes for human workers. Cobots can reduce physical labor and reshape workforce dynamics, but there are concerns about potential job displacement due to automation. Introducing cobots may replace low-paid jobs often held by immigrant workers, impacting social dynamics. However, cobots can also enable humans to undertake more complex activities while they handle simpler tasks. While some jobs involving manual handling of large objects may be displaced, new roles may emerge in areas such as robot supervision, maintenance, and exception handling. One industry expert noted: "*The introduction of these robotic systems will shift the focus of human jobs towards more high-level decision-making and problem-solving tasks, requiring workers to develop new skills and adapt to working alongside advanced automation technologies*". However, there may be concerns about the potential impact on employment levels and job security, particularly for lower-skilled workers. Implementing these robotic systems may require significant retraining and upskilling efforts to ensure workers can effectively transition to new roles and responsibilities.

Experts extensively discussed safety issues in cobot design and deployment. They emphasized the importance of ensuring operators cannot enter the cobot's work area during hazardous operations and using proximity sensors to manage the space between cobots and operators. Redesigning workspaces with inputs from engineers, architects, and health professionals is crucial. Experts also highlighted the need to address the absence of mature safety standards for close operator-cobot interactions, consider nearby operator interference, and implement instant motor stop measures. Proper training and clear communication are essential to prevent safety incidents. Providing special safety equipment and intrinsically safe systems that activate anomalies, evaluating potential impact speeds and trajectories to prevent crushing and shearing incidents, and ensuring cobot reactivity to human touch and robust handling of objects is critical for avoiding accidents.

One expert said: "*Regarding this use case, The use of cobots for this application will facilitate the management of large loads. It will reduce the possible accidents this handling could cause if incorrect assessments were made regarding the object's weight*." Another expert states: "*From the point of view of safety, it must be ensured that in certain operations, the operator cannot enter the work area of the cobot. For example, when a large and heavy load is at a certain height. The presence of proximity sensors capable of detecting the distance of the cobot from the operator can, for example, be useful for decreasing the movement speed of the cobot*".

4.1.3 Experts' opinions on the use case "cobots in the vineyard operations"

In the vineyard use case, experts discussed the technical impacts of cobot adoption. Autonomous mobile manipulators can enhance precision and reduce harmful movements, allowing workers to carry more grapes with less effort and in less time. The availability of management infrastructures, such as WIFI connections, is crucial to support cobot operations. Cobots can improve workers' quality of life, leading to higher productivity and a reduced risk of musculoskeletal diseases. The assistance of cobots can significantly reduce workers' physical effort. Participants reported that the collaborative system may increase efficiency and improve the quality of life for vineyard workers through reduced physical effort and enhanced carrying capacity. Factors such as reliability, ease of use, and consistent proximity of the cobot were emphasized to maximize benefits.

Experts also emphasized the importance of reliability and ease of use in wearable devices. The integration of soil conservation techniques, including precision seeding and minimal chemical impact, can help prevent soil fatigue. The implementation of visual technology like cameras can compensate for environmental irregularities, such as ground conditions and fruit shape. As one agricultural robotics expert pointed out, "*The autonomous mobile manipulator needs to be able to navigate through narrow, uneven terrains and adapt to changing weather conditions while precisely locating and assisting the human worker*".

Regarding social and ethical considerations, experts noted that while cobots may initially be perceived as awkward, they can potentially transform industry practices, especially in harsh environments. Cobots can enhance job access for individuals with physical disabilities, elevating work from a social perspective to be more technical. They can also attract a younger workforce, but managing the impact on current workers is essential. Addressing cultural readiness among agrifood operators to adopt new technologies is crucial, focusing on balancing cost reduction with investments in life quality. Cobots can eliminate physical ability disparities among workers, thus democratizing the field. They can also help address exploitation issues often associated with manual, labor-intensive tasks like harvesting. An expert noted, "*The introduction of assistive technologies like exoskeletons and mobile manipulators could greatly improve the working conditions and overall wellbeing of agricultural workers, who often face significant physical demands and health risks*". On the other hand, there may be concerns about the potential displacement of jobs, particularly for low-skilled workers who may not have the necessary training or skills to adapt to working with advanced technologies. Additionally, these collaborative systems may raise questions about the equitable distribution of benefits and the potential widening of the skill gap between workers who can effectively use these technologies and those who cannot.

Safety issues in cobot design and deployment were a significant concern for experts. They emphasized the importance of ensuring cobots comply with safety standards, such as UNI EN ISO 10218, to guarantee worker protection in all operational scenarios. Developing applications that are inherently safe and prioritizing the ability of cobots to halt operations immediately in both typical and atypical risks is crucial. Experts also stressed the need to consider worker balance and mobility on uneven ground surfaces to ensure safety and efficiency. Special attention should be given to balancing, weight distribution, and movement considerations, especially in areas with steep slopes, to prevent accidents. The redundancy of sensors and robust mechanical designs were highlighted as critical safety measures.

Regarding safety issues, participants stressed the importance of implementing reliable stability control and collision avoidance mechanisms to ensure the safe interaction between the human worker and the mobile manipulator, particularly on steep and uneven terrains. One safety engineer commented, "*The collaborative system should be designed to detect and respond to the human worker's movements and potential loss of balance, adjusting its actions accordingly to minimize the risk of injury. We need to consider the steep surface of the ground. Moreover, the robotic system should not limit mobility*".

In vineyard operations, unique challenges are posed by the uneven terrain and slope gradients characteristic of vineyards. Participants stressed that the design of cobots for vineyard operations should prioritize the stability and balance of both the cobot and the human worker. They suggested that cobots should be equipped with features that enable them to navigate rough terrain without compromising the safety or mobility of their human collaborators. Participants underscored the need for cobots to have high situational awareness and adaptability, by dynamically adjusting their movements and behavior based on real-time data, cobots can maintain a safe working distance from human workers and minimize the risk of accidents or injuries.

4.2 Attitudes towards collaborative robots

The General Attitudes Towards Robots Scale (GAToRS) was used to assess participants' attitudes toward collaborative robots (cobots) across four dimensions: Personal Level Positive (P+), Personal Level Negative (P−), Societal Level Positive (S+), and Societal Level Negative (S−).

The mean scores for the P+ dimension ranged from 2.42 to 4.15, indicating a moderate to high level of positive attitudes towards cobots on a personal level. Participants expressed trust in the development of cobots (M = 4.15) and believed that the needs and feelings of users would be considered (M = 4.15). However, the lowest mean score in this dimension was for the item "If cobots had emotions, I would be able to befriend them" (M = 2.42), suggesting some hesitation in forming emotional connections with cobots.

The mean scores for the P- dimension were relatively low, ranging from 1.39 to 2.27, indicating that participants generally had low levels of negative attitudes towards cobots on a personal level. Participants expressed minimal fear (M = 1.39) and nervousness (M = 1.39) around cobots. The highest mean score in this dimension was for the item "I don't want a cobot to touch me" (M = 1.97), suggesting some discomfort with physical contact with cobots.

The mean scores for the S+ dimension were high, ranging from 3.91 to 4.38, indicating strong positive attitudes towards the societal benefits of cobots. Participants believed that cobots could make life easier (M = 4.38), allow people to do more meaningful tasks (M = 4.34), and help society by assisting people (M = 4.06).

The mean scores for the S- dimension were moderate, ranging from 2.13 to 3.72. Participants expressed some concerns about the societal impact of cobots, such as the need for close monitoring of robotics (M = 3.72) and the potential for societal upheavals due to unregulated use (M = 3.37). However, they were less concerned about cobots taking away jobs (M = 2.13) or encouraging less interaction between humans (M = 2.16).

Overall, the results suggest that participants held generally positive attitudes towards cobots, particularly regarding their societal benefits, as shown in Figure 1. While there were some concerns about the societal implications of cobot adoption, personal-level attitudes were mostly positive, with low levels of fear and unease.

4.3 Trust in human-cobot interactions

The Trust Perception Scale-HRI was used to assess participants' trust in collaborative robots (cobots) across 14 items. The means for these items ranged from 2.23 to 4.10, indicating a moderate to a high level of trust in cobots. The items with the highest means (above 3.70) suggest a strong belief in cobots' ability to perform tasks successfully, follow instructions, and even outperform novice human users. Participants expressed high trust in cobots' capability to do exactly as instructed (M = 4.10), succeed when performing tasks (M = 3.81), and be qualified for specific tasks (M = 3.81). Additionally, the reversed Item 13 (M = 3.77) indicates that participants believe cobots can perform tasks better than novice human users.

Items with moderately high means (between 3.30 and 3.70) indicate a reasonable level of trust in cobots' ability to function in team environments, provide appropriate information, meet user expectations, and warn of potential risks. However, items with lower means (below 3.30) suggest relatively lower trust in cobots' ability to be good teammates, work well in teams, and their maintenance requirements (see Figure 2).

4.4 Safety perception in human-cobot interaction

The evaluation of perceived safety in human-cobot interactions encompassed four specific items to evaluate the extent of apprehensions and participant confidence level. The results reveal a generally favorable perception of safety (Figure 3). Participants indicated high perceived safety (M = 3.9; SD = 1.0) and felt secure while working with cobots (M = 3.7; SD = 1.0). Conversely, concerns about potential errors that could harm the participants (M = 1.7; SD = .09) or the cobots (M = 1.6; SD = 0.8) were notably low.

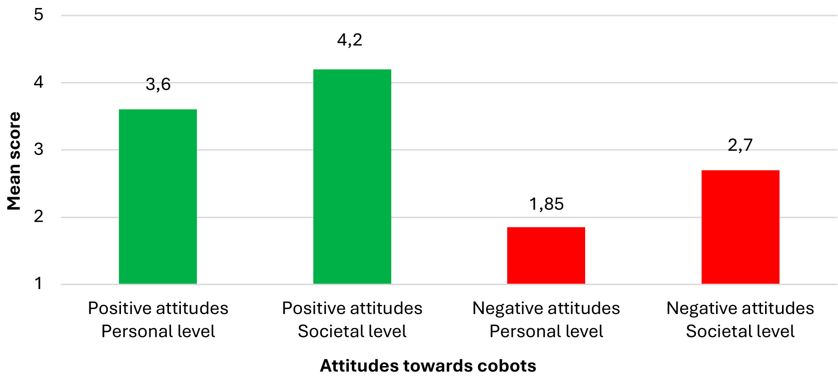

FIGURE 1
Attitudes towards cobots on personal and societal levels.

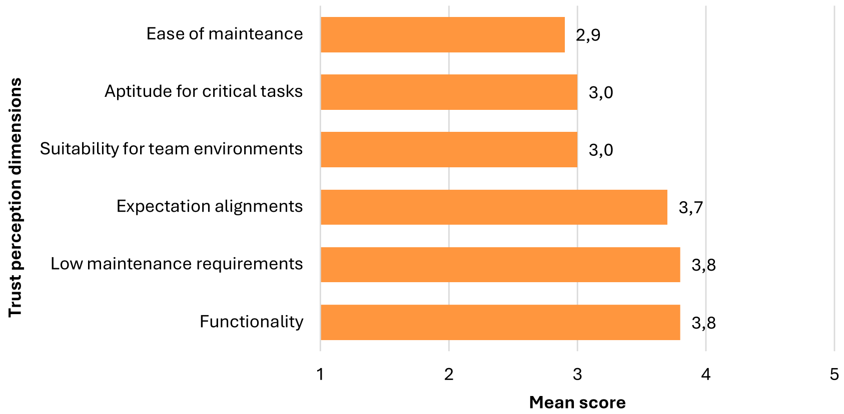

FIGURE 2
Trust towards cobots.

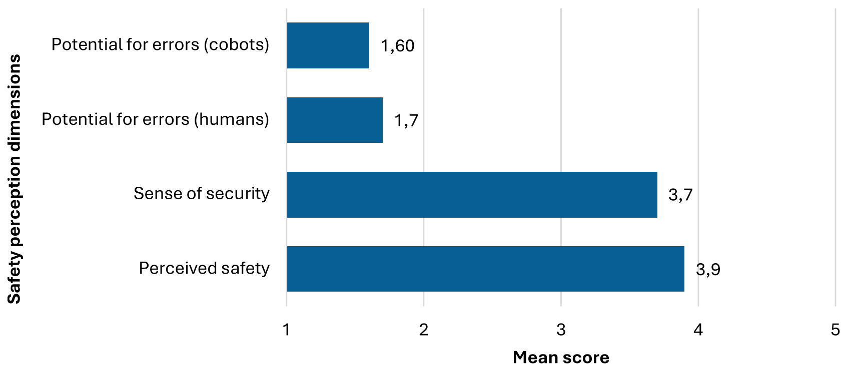

FIGURE 3
Safety perceptions of collaborative robots.

5 Discussion

The present study aimed to investigate the perceptions and attitudes of technical experts towards adopting collaborative robots in three distinct use settings: vehicle assembly operations, robotic handling in warehouses, and agricultural harvesting. The findings provide insights into the technical, safety, and social implications of implementing cobots in these industrial settings.

Regarding the vehicle assembly use case, experts highlighted the importance of developing accurate and reliable sensor systems for seamless and safe interaction between workers, cobots, and exoskeletons. These findings align with previous research that underscores the significance of sensor technology and motion planning in human-robot collaboration (Robla-Gómez et al., 2017; Villani et al., 2018). Experts also stressed the need for user-friendly interfaces and intuitive programming methods to facilitate the easy deployment and adaptation of cobots for various assembly tasks, echoing the importance of usability in implementing industrial robots (Weiss and Spiel, 2022). Usability is also one of the most relevant factors in transforming a tool into the technological part of a functional organ, allowing humans to feel comfortable and trusted when using a specific tool (Mazzoni, 2017).

In the robotic handling in warehouses use case, experts emphasized the development of advanced sensing and control systems to ensure precise and reliable handling of large, bulky objects. Optimizing the robotic system's performance to maximize throughout and efficiency was also highlighted, consistent with the goals of warehouse automation (Azadeh et al., 2019). Developing intuitive interfaces for human workers to monitor and intervene when necessary was also stressed, reinforcing the need for effective human-robot interaction in logistics settings (Rojas and Rauch, 2019). This aspect is also critical for the coefficiency of human-robot interaction, particularly in selecting actions aimed at maximizing the overall efficiency of the joint effort, achieving the best efficiency, and minimizing the probability of errors.

For the agricultural harvesting use case, experts identified developing robust navigation and localization systems as a key challenge for mobile manipulators operating in unstructured and dynamic vineyard environments (Kostavelis et al., 2017). This finding resonates with the current research focus on developing autonomous navigation systems for agricultural robots (Shamshiri et al., 2018). The importance of implementing reliable stability control and collision avoidance mechanisms to ensure safe interaction between human workers and mobile manipulators was also emphasized, particularly in steep and uneven terrains characteristic of vineyards. These are both critical for the evolution of a functional organ, allowing humans to overcome their limits and achieve better results and for the best effectiveness of the human-robot coefficiency.

Across all use cases, safety emerged as a paramount concern. Experts consistently highlighted the importance of implementing robust collision avoidance systems, fail-safe mechanisms, and emergency stop protocols to ensure the safety of human workers interacting with cobots. The emphasis on developing comprehensive safety protocols and the need for broad safety training and education for workers was also emphasized, underlining the crucial role of human factors in the successful adoption of cobots.

The social and ethical implications of cobot adoption were also explored. Experts recognized the potential for cobots to facilitate the inclusion of workers with diverse physical capabilities and limitations, promoting a more inclusive and accessible work environment. This finding aligns with the growing interest in using assistive technologies to support workers with disabilities in industrial settings (Bianchini et al., 2022). However, concerns about job displacement, particularly for workers involved in repetitive and physically demanding tasks, were also raised. This highlights the need for proactive measures to support workforce transitions and reskilling efforts (Li, 2022). Experts also noted the potential for cobots to reduce physical strain and risk of injuries for workers, improving overall wellbeing and job satisfaction. This finding is consistent with research demonstrating the ergonomic benefits of human-robot collaboration (Schmidtler et al., 2015). Addressing these concerns is urgent for formulating policies and creating organizational practices that guarantee the equitable allocation of benefits derived from the adoption of cobots. Scholars, organizational stakeholders, and policymakers are encouraged to leverage these insights to construct agendas that harmonize technological progress with social equity, ensuring that automation's dividends are equitably distributed throughout society (Weidemann et al., 2023; Mazzoni and Benvenuti, 2015).

The quantitative measures employed in this study provide further insights into technical experts' attitudes, trust, and perceptions of safety towards cobots. Participants exhibited generally positive attitudes towards cobots at both personal and societal levels, with higher positive attitudes at the societal level. This finding suggests that experts recognize the potential benefits of cobots for society, such as increased productivity (Gombolay et al., 2017). However, negative attitudes, particularly at the societal level, indicate that concerns about the broader impacts of cobot adoption, such as job displacement and skill gaps, persist and need to be addressed.

Trust perception in human-cobot interactions was found to be moderately high, with participants expressing confidence in the functionality, low maintenance requirements, and expectation alignment of cobots. This finding aligns with previous research highlighting the importance of trust in successfully implementing industrial robots (Charalambous et al., 2015). However, lower scores were observed for cobots' suitability for team environments, aptitude for handling critical tasks, and ease of maintenance, suggesting areas for improvement in cobot design and integration.

Perceived safety in human-cobot interactions was generally favorable, with participants indicating high levels of perceived safety and security while working with cobots. The findings of this study contribute to the growing body of literature on human-robot collaboration in industrial settings. By providing insights into the perspectives of technical experts on cobot adoption in three distinct use cases, this research highlights the critical technical, safety, and social considerations that need to be addressed to ensure the successful implementation of collaborative robots. The results also underscore the importance of considering human factors, such as attitudes, trust, and safety perceptions, in the design and deployment of cobots.

This study has some limitations that should be acknowledged. The sample size may not represent the broader population of technical experts in the field. Additionally, our focus on the industrial, logistics, and agricultural sectors limited our ability to explore the unique challenges and requirements of other domains (Medical, HoReCa) where human-robot collaboration is equally important. Therefore, future research should aim to address these limitations by conducting larger-scale studies across various industries and contexts. Future research could also benefit from larger and more diverse samples to enhance the generalizability of the findings. Additionally, the study relied on self-reported data, which may be subject to response biases. Future studies could employ observational or experimental methods to triangulate the findings and provide a more comprehensive understanding of human-robot collaboration in industrial settings. Furthermore, ongoing research efforts should consider longitudinal studies that track changes in attitudes, trust, and safety perceptions as collaborative robots become smaller, more advanced, and widely adopted across different sectors. Continuously surveying the same areas of cobot deployment while expanding into new industries and application contexts will help assess how technological advancements and broader use cases influence the evolving dynamics of human-robot collaboration.

6 Conclusion

This study provides comprehensive insights into the implementation of collaborative robots across three distinct industrial sectors: vehicle assembly, warehouse logistics, and agricultural operations. Through the analysis of expert opinions and quantitative assessments of attitudes, trust, and safety perceptions, key findings emerge that have important implications for both theory and practice. The study's examination of specific use cases reveals distinct challenges and opportunities. In vehicle assembly operations, the integration of cobots with exoskeletons presents unique challenges requiring sophisticated sensor systems and motion planning. For warehouse logistics, the emphasis lies in developing advanced control systems for handling large objects while maintaining human supervisor safety. In agricultural settings, the need for robust navigation systems and stability control on uneven terrain emerges as a critical consideration.

These findings have significant practical implications. Organizations implementing cobots should prioritize comprehensive safety training and user-friendly interfaces. System designers should focus on enhancing cobot capabilities in teamwork scenarios and maintenance accessibility, while industries need to develop proactive strategies to address workforce transitions and skill development. From a policy perspective, the findings underscore the need for standardized safety protocols across different industrial applications. They emphasize the importance of balancing technological advancement with workforce protection and highlight the requirement for guidelines that ensure equitable distribution of cobot-derived benefits.

In conclusion, while the implementation of cobots across different industrial sectors shows promise, success depends on carefully balancing technical capabilities with human factors. This study's findings emphasize that effective cobot integration requires not only advanced technological solutions but also careful consideration of human perceptions, safety requirements, and societal implications. The insights gained from this research contribute to our understanding of how to effectively implement cobots in various industrial settings while maintaining focus on both technological advancement and human-centered considerations.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by University of Bologna Ethics Committee. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

LP: Conceptualization, Funding acquisition, Investigation, Methodology, Resources, Supervision, Writing–review and editing. MF: Conceptualization, Data curation, Formal Analysis, Writing–original draft. FF: Conceptualization, Investigation, Methodology, Writing–original draft, Writing–review and editing. EM: Methodology, Supervision, Writing–review and editing. SM: Data curation, Methodology, Writing–review and editing. MB: Conceptualization, Methodology, Supervision, Writing–review and editing. MD: Investigation, Writing–review and editing, Methodology, Supervision.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Publisher's note

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