NEUROERGONOMICS IN HUMAN-ROBOT INTERACTION

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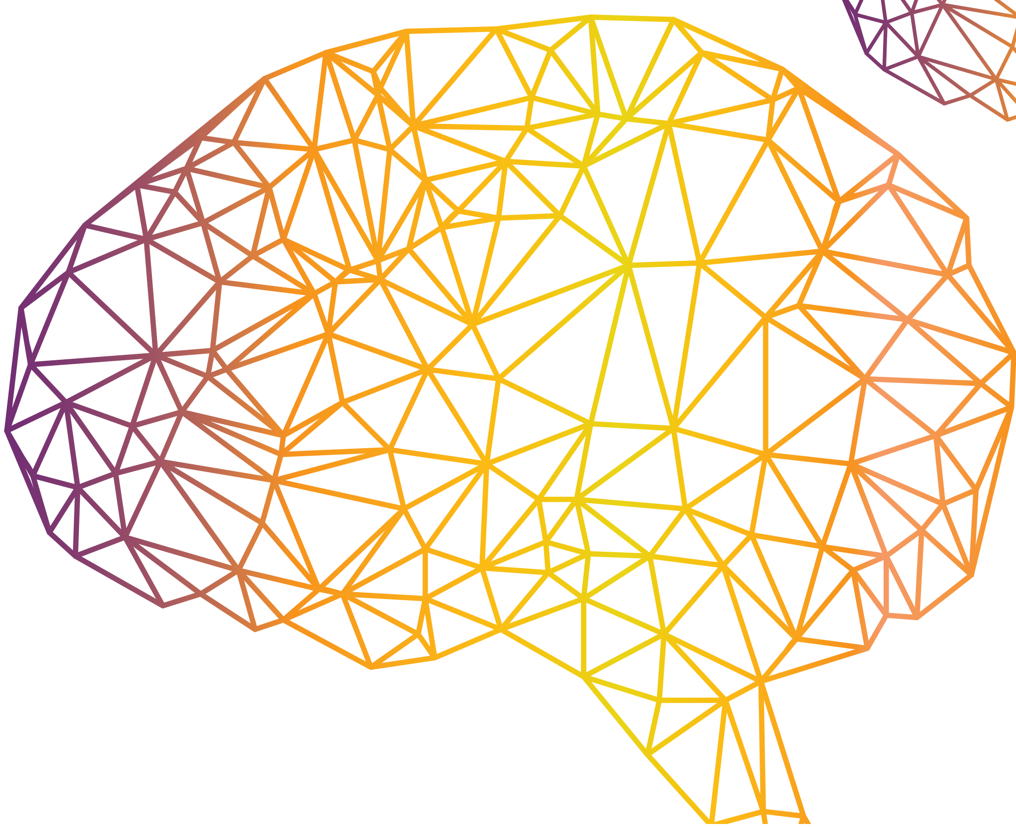

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NEUROERGONOMICS IN HUMAN-ROBOT INTERACTION

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Editorial: Neuroergonomics in Human-Robot Interaction

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KEYWORDS

neuroergonomics, Human-Robot Interaction, human factors, robotics, human-centered technology

Editorial on the Research Topic
Neuroergonomics in Human-Robot Interaction

Neuroergonomics (Parasuraman, 2003; Ayaz and Dehais, 2021; Gramann et al., 2021) can be quite impactful to investigate and improve Human-Robot Interactions (HRIs) (Scotto di Luzio et al., 2018; Roy et al., 2020; Rosén, 2021), analyzing and affecting the neural processes of any individual interacting with a smart machine that can work as collaborator, tool, or even extension of its user in ecologically valid contexts. Accordingly, we can achieve a "neuroergonomic robot": usable, acceptable, safe, and minimally demanding in terms of mental workload according to indices of neural activity, considered as the antecedents of any experience and behavior. A robotic system may exploit these indices to recognize the individual conditions for adjusting its activity to ameliorate the human-machine system performance alongside the safety and the wellbeing of the user. The collection of papers presented in this Research Topic propose examples of investigations and concepts on neuroergonomics in HRI, suggesting further breakthroughs in user-centered robotics.

For instance, a manuscript introduces relevant topics in neuroergonomics that highlight how the roots of this discipline also reach the ground between the discoveries in neuroscience and the innovations in neuroengineering. *Direct Communication Between Brains: A Systematic PRISMA Review of Brain-To-Brain Interface*, Nam et al. discussed the current state of brain-to-brain interface (B2BI) technologies and its potential in transmitting information between two individuals through a brain-computer interface (BCI) and a computer-brain interface (CBI). Such a revolutionary concept can lead to novel neuroergonomic paradigms of collaboration across robotic devices and multiple users. This review definitely remarks the importance of the neurocognitive and neurobiological concepts in this field, as presented about framework for teaching and training in *The Complexity of Remote Learning: A Neuroergonomical Discussion* by

Cassioli and Balconi. However, pondering the individual and contextual requirements in this path also needs techniques of other branches of human factors. Accordingly, Bevilacqua et al. presented their *Design and development of a scale for evaluating the acceptance of social robotics for older people: The Robot-Era Inventory*: in this manuscript, the authors introduce a set of scales for assessing social assistive robots cooperating with older adults. This inventory can certainly work in synergy with psychophysiological measures of elderly reactions during the interaction with a device.

This would be especially advantageous in the domain of social HRI, which encompasses neuroscientific studies like the one of Marchesi et al.: *I Am Looking for Your Mind: Pupil Dilation Predicts Individual Differences in Sensitivity to Hints of Human-Likeness in Robot Behavior*. Through an experimental investigation involving the humanoid robot iCub, the authors demonstrate how patterns of pupil dilation and response time can unveil individual biases in interpreting the behavior of a human-like artifact, perceived as an intentional agent. These results may lead to innovations in the design of socially attuned humanoids. This neuroscientific approach could surely be extended through the adoption of portable neurotechnologies, as argumented by Cassioli et al. in *Human–Co-Bot Interaction and Neuroergonomics: Co-Botic vs. Robotic Systems*. The approach proposed by these authors is especially peculiar for demonstrating the advantages of organizational neuroergonomics on collaborative robotics. Such a perspective remarks how neuroergonomics in HRI can express its own contribution across multiple branches of human factors. Another example of this versatility, considering both physical and cognitive ergonomics, is constituted by a study authored by D'Antonio et al. and titled *Robotic Assessment of Wrist Proprioception During Kinaesthetic Perturbations: A Neuroergonomic Approach*. In this research, the authors present a refined methodology, based on a haptic neuroergonomic wrist device, for investigating the effects of systematic perturbations on the user's proprioceptive and kinaesthetic acuity. Their results are particularly valuable for the clinical evaluation of neurological damages: such a delicate field requires levels of performance, reliability, and robustness of robotic devices that just the approaches of human factors—including neuroergonomics— can guarantee. This study also dedicate special attention to its methodological appropriateness, a critical point in any interdisciplinary domain.

Indeed, we surely need to design and implement novel solutions for research, as discussed by Savković et al. in *Development of Modular and Adaptive Laboratory Set-Up for Neuroergonomic and Human-Robot Interaction Research*. The authors describe their specialized infrastructure for assessing workers' performance, safety, wellbeing, and experience, considering anatomical, anthropometric, physiological, and biomechanical data. However, devising innovative equipment also requires to explore groundbreaking concepts to introduce novel methodologies. For instance, Del Vecchio et al. wrote *Peripheral Neuroergonomics – An Elegant Way to Improve Human-Robot Interaction?* to remark how most non-invasive human-robot interfaces based on the peripheral nervous system seems to offer an appropriate interpretability. This makes them currently advantageous over solutions (especially the invasive ones) collecting data from the central nervous system. Fostering synergistic approaches based on peripheral neural signals alongside central ones and motor data seems particularly promising, and it can become imperative for the twinning strategy presented by Barresi et al. in *Beyond Digital Twins: Phygital Twins for Neuroergonomics in Human-Robot Interaction*. This paper proposes a concept to replicate a remote human-robot system through a partially virtual and partially mechatronic solution, exploiting "phygital" features that make it more reliable and easy to be manipulated by a person assessing its potential states. Such a twinning design enables "metalaboratories" for investigating the conditions of the remote robot users in their context according to multimodal data collected by wearable sensors. The need of heterogenous information is furtherly highlighted by Corti in *The Role of Neuroergonomics in the Design of Personalized Prosthesis: Deepening the Centrality of Human Being*. The author points at the value of a quanto-qualitative approach to bridge phenomenological and the neuroscientific concepts and methods to investigate relevant topics within the domain of neuroergonomics in HRI like the prosthetic embodiment. This is a compulsory step for understanding a multifaceted system based on the interactions between humans and their robotic collaborators, tools, and extensions.

Overall, this Research Topic offered the opportunity to collect insightful contributions from experts in different domains (from psychology to engineering, from neuroscience to philosophy), foreseeing neuroergonomic (even neurosensitive) robots as a step-change in human-centered technology transfer within a greater journey for achieving practicality and sustainability in HRI.

Author contributions

All authors contributed to the manuscript, revised, and approved its final version.

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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ORIGINAL RESEARCH
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Robotic Assessment of Wrist Proprioception During Kinaesthetic Perturbations: A Neuroergonomic Approach

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Position sense refers to an aspect of proprioception crucial for motor control and learning. The onset of neurological diseases can damage such sensory afference, with consequent motor disorders dramatically reducing the associated recovery process. In regular clinical practice, assessment of proprioceptive deficits is run by means of clinical scales which do not provide quantitative measurements. However, existing robotic solutions usually do not involve multi-joint movements but are mostly applied to a single proximal or distal joint. The present work provides a testing paradigm for assessing proprioception during coordinated multi-joint distal movements and in presence of kinaesthetic perturbations: we evaluated healthy subjects' ability to match proprioceptive targets along two of the three wrist's degrees of freedom, flexion/extension and abduction/adduction. By introducing rotations along the pronation/supination axis not involved in the matching task, we tested two experimental conditions, which differed in terms of the temporal imposition of the external perturbation: in the first one, the disturbance was provided after the presentation of the proprioceptive target, while in the second one, the rotation of the pronation/ supination axis was imposed during the proprioceptive target presentation. We investigated if (i) the amplitude of the perturbation along the pronation/supination would lead to proprioceptive miscalibration; (ii) the encoding of proprioceptive target, would be influenced by the presentation sequence between the target itself and the rotational disturbance. Eighteen participants were tested by means of a haptic neuroergonomic wrist device: our findings provided evidence that the order of disturbance presentation does not alter proprioceptive acuity. Yet, a further effect has been noticed: proprioception is highly anisotropic and dependent on perturbation amplitude. Unexpectedly, the configuration of the forearm highly influences sensory feedbacks, and significantly alters subjects' performance in matching the proprioceptive targets, defining portions of the wrist workspace where kinaesthetic and proprioceptive acuity are more sensitive. This finding may suggest solutions and applications in

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multiple fields: from general haptics where, knowing how wrist configuration influences proprioception, might suggest new neuroergonomic solutions in device design, to clinical evaluation after neurological damage, where accurately assessing proprioceptive deficits can dramatically complement regular therapy for a better prediction of the recovery path.

Keywords: proprioception, robotic assessment, multi-joint, static perturbation, motor control, biomechanics

INTRODUCTION

The term "proprioception," introduced in the early twentieth century, refers to the self-perception of position, motion and orientation of the body or body segments (Goldscheider, 1898; Sherrington, 1907; Evarts, 1981). Proprioceptive signals arise from mechanoreceptors embedded in our joints, muscles, and tendons such as muscle spindles or Golgi tendon organs (Proske and Gandevia, 2012). In general, two submodalities of proprioception are distinguished: (i) *kinaesthesia*, the sense of limb movement; (ii) *joint position sense,* the sense of limb position (Proske, 2006). These two senses constitute the sensory stream colloquially referred to as conscious proprioception.

Neurological pathologies, such as stroke (Carey, 1995) or Parkinson's disease (Konczak et al., 2012), can permanently deprive the brain of its main sources of dynamogenic information from skin and muscles (Debert et al., 2012), leading to a compromised coding of the proprioceptive information, with negative consequences in motor control and the associated recovery progress (Marchal-Crespo and Reinkensmeyer, 2009; Schabrun and Hillier, 2009). Accurate assessment and quantification of proprioceptive function becomes a leading factor in the diagnosis and treatment of neurological diseases.

Despite the paramount importance of proprioceptive feedback in motor coordination and recovery (Raspopovic et al., 2014), actually, there are no established methods capable of assessing multi-joint proprioceptive acuity in a reliable, objective fashion. Recent advancements in robotic and haptic technology (Yeong et al., 2009; Oblak et al., 2010) represent the starting point for the development of automated, repeatable robot-aided methodology for studying proprioception and potentially provide standardized, quantitative methodology to evaluate kinaesthetic and proprioceptive performance characterized by a continuous ratio scale (Simo et al., 2014; Deblock-Bellamy et al., 2018; Klein et al., 2018; Mochizuki et al., 2019). In addition, the use of robotic devices to study sensory motor control should be designed considering anthropometric and biomechanical features, not only for what concerns the mechanical design but also for the implementation of the related control strategies (Chiri et al., 2012). These complementary characteristics (design & control) are paramount to exploit the real potential of robotic technology in both neuroergonomics, addressing general motor behavioral aspects, and clinical environment where robustness and reliability of such devices can be only reached starting their conception from human factors.

Although it has been demonstrated that proprioception of distal joints is particularly involved in fine manipulation of daily living activities (Hoseini et al., 2015; Ponassi et al., 2018), scientific literature primarily reports contributions focused on proprioception at the level of proximal upper limb (shoulder and elbow). Previous research focused on distal joints, with particular emphasis on wrist's proprioceptive functions (Aman et al., 2015; Rose et al., 2018). In particular, concerning our group, we extensively tested proprioceptive acuity using a device named WristBot (Masia et al., 2009), which allows for the implementation of a widely used test for the assessment of position sense (Cappello et al., 2015), the *Joint Position Matching* (JPM) paradigm (Goble, 2010): the test is run in absence of visual feedback and evaluates the proprioception by quantifying the accuracy in replicating a joint posture (proprioceptive target), previously imposed as angular displacement. Previous works investigated the wrist proprioception along a single degree of freedom (DoF) evaluating (Marini et al., 2016a) its anisotropy across wrist abduction/adduction (AA) and flexion/extension (FE) DoFs, as well as a gradual change of proprioceptive acuity during the developmental phase for individuals (Marini et al., 2017). However, proprioception for distal multi-joint movements, involving more than a single DoF, still remains an open question, and there is limited evidence in literature on the mechanism underlying the integration of proprioceptive sensory stream from multiple concurring anatomical joints (Sketch et al., 2018).

In daily manipulation tasks, the use of the wrist and hand requires a complex motion strategy between the fingers and the two distal DoFs corresponding to wrist FE and AA. Moreover, the forearm can rotate along its longitudinal axis by engaging a third wrist DoF, the pronation/supination (PS), which allows the hand to cover a wider workspace and exploit the arm's kinematic redundancy. The wrist biomechanics, almost unique among all human anatomical districts, allows an extremely efficient manipulation dexterity, as highlighted by the study of Kane et al. (2014), which showed how the combination of FE and AA ROMs results in a workspace which is independent from the rotations around the PS axis, being its motion completely disconnected from the previous wrist joints. Within the framework of the current study, we hypothesize that providing perturbations along the PS axis, consisting in rotational offset of variable amplitude along the forearm, will not lead to physical limitations on the remaining wrist DoFs and sensory conflicts in terms of proprioception acuity during joint position matching tasks. The multi-joint biomechanics of the wrist joint are known, yet the processing of proprioceptive information across its DoFs is less well understood. Proprioceptive efferent signals are encoded in reference frames localized at the level of joints (Flanders and Soechting, 1995): in order to compute motor commands, the central nervous system must process such sensory information and project it into a spatial representation of motion (Colby, 1998). Yet, movement generation relies on information redundancy by merging both visual and proprioceptive feedback, continuously streamed during a general task execution, and consequently integrating both absolute spatial and local sensory streams, respectively (Snyder et al., 1998). What happens if visual information is excluded from the integrative process and motion computation must rely on one sensory feedback? How, in such condition, an external disturbance, altering the encoding of proprioceptive information, influences the task performance? With this in mind, we designed an experiment to investigate if the sole proprioceptive information, can be robustly retained by the brain even in presence of a kinesthetic disturbance altering the geometric conditions between the presentation of the task and its execution.

How proprioceptive information is interpreted when complex wrist motions are performed, and whether multi-joint kinaesthetic sensory streams are encoded throughout the wrist workspace, are examples of unanswered questions crossing the domains of neurophysiology and clinical rehabilitation. Most studies involving multi-joint tasks, have primarily investigated distal arm goal directed movements toward visual targets: results suggest that the relative contributions of vision and proprioception to motor planning can change, depending on the modality in which task relevant information is represented (Sarlegna and Sainburg, 2007). Yet, all this extensive production of results has covered experimental paradigms deeply involving visual-feedback (Goble and Brown, 2009), while encoding of proprioceptive targets in coordinated tasks is still an open debate, especially for what concerns integration of proprioceptive information among the DoFs of a multi-joint articulation.

The goal of the present research is to investigate, using a neuroergonomic approach, the influence of wrist posture on proprioceptive acuity during multi-joint JPM tasks and under different perturbations. By imposing angular offset rotations in different fashions of amplitude and sequence on the DoF which is not involved in the matching task (PS), we tested proprioceptive acuity on the remaining wrist joints, with the purpose of providing insights on how (i) proprioception is encoded in a complex biomechanical structure, (ii) sensory information are integrated, and (iii) external disturbances are rejected.

METHODS

Participants and Experimental Setup

Eighteen young healthy subjects (age 27.4 ± 2.8 years (Mean ± STD), 9 females) were recruited for the study: participants self-reported no evidence or known history of neurological disease and exhibited normal joints range of motion and muscular strength. To be included in the study subjects had to be right-handed, according to the Edinburgh Handedness Inventory (Oldfield, 1971) [EHI score > 60; EHI score = 81.89 ± 13.07 (Mean ± STD)]. The research was in accordance with the ethical principles of the 1964 Declaration of Helsinki, which protects research participants. Each subject signed a consent form conformed to these guidelines to participate in the study and to publish pseudonymized individual data. All the study procedures and documents were approved by the Heidelberg University Institutional Review Board (S-287/2020). Experiments were carried out at the Aries Lab (Assistive Robotics and Interactive Ergonomic Systems) of the Institute of Computer Engineering of Heidelberg University (Germany).

The experimental design involved a task, where subjects were sitting in front of a screen, holding the handle of a haptic device (WristBot) with their right hand (**Figure 1A**). Subjects were blindfolded during the whole experiment, but during a phase of familiarization the visual feedback was provided to explain the task sequence and how to perform it correctly.

The employed device has three DoFs: FE (± 62°); AA (+45/−40°); PS (± 60°) and it allows almost the full range of motion of the human wrist. It is driven by 4 brushless motors dimensioned in order to compensate for weight and inertia and to provide sufficient haptic rendering at the level of wrist. Angular rotations on the three axes are acquired by means of incremental encoders, resulting in a resolution of 0.17°. The continuous torque ranges at the different wrist joints are 1.57 Nm on FE, 3.81 Nm on AA, and 2.87 Nm on PS, **Figure 1A**. During the experiment, participants sat beside the robotic device with the frontal plane of their body aligned perpendicularly to the PS axis of the robotic device, **Figure 1B**. The position of each participant was carefully adjusted to ensure a 90° elbow angle and the correct alignment between the wrist and the robotic system axes, **Figure 1B**. Participants' trunk was not constrained, yet the forearm was secured in such a way that backrest ensures a 90° elbow angle, while hand position on the device's handle was kept constant over the course of the experiment and registered for each participant on her/his anthropometrics. Subjects forearm was strapped to a mechanical support using anatomical references (i) to ensure repeatability of wrist positioning, thus trying to limit inter-trial variability, (ii) to avoid joints misalignment, and (iii) involuntary relative movements between the device and the wrist during task execution. Moreover, the device's handle was carefully designed to be opportunely adaptable to the different subjects' anthropometrics, by means of a sliding system that allows to secure the forearm on the device.

Task and Procedure

The protocol implemented explored how angular perturbations can affect sensory acuity and consequently altering proprioceptive thresholds. A similar experimental design has been described in Masia et al. (2009), where, in a point-to-point reaching task, rotational misalignments were applied between the visual (spatial) and the proprioceptive (local) frames, creating a visuo-proprioceptive miscalibration. We wanted to use a comparable paradigm applied to a single sensory feedback by using local rotations among the wrist degrees of freedom by changing the configurations between the presentation of the proprioceptive stimuli (target) and the matching task. In particular, we used the wrist rotation along the PS axis to provide the perturbation in the context of a passive JPM test, which was exploited using the remaining DoFs of the wrist (Goble, 2010; Marini et al., 2016b). The proprioceptive task consisted in an ipsilateral JPM along two DoFs of the wrist (FE and AA):

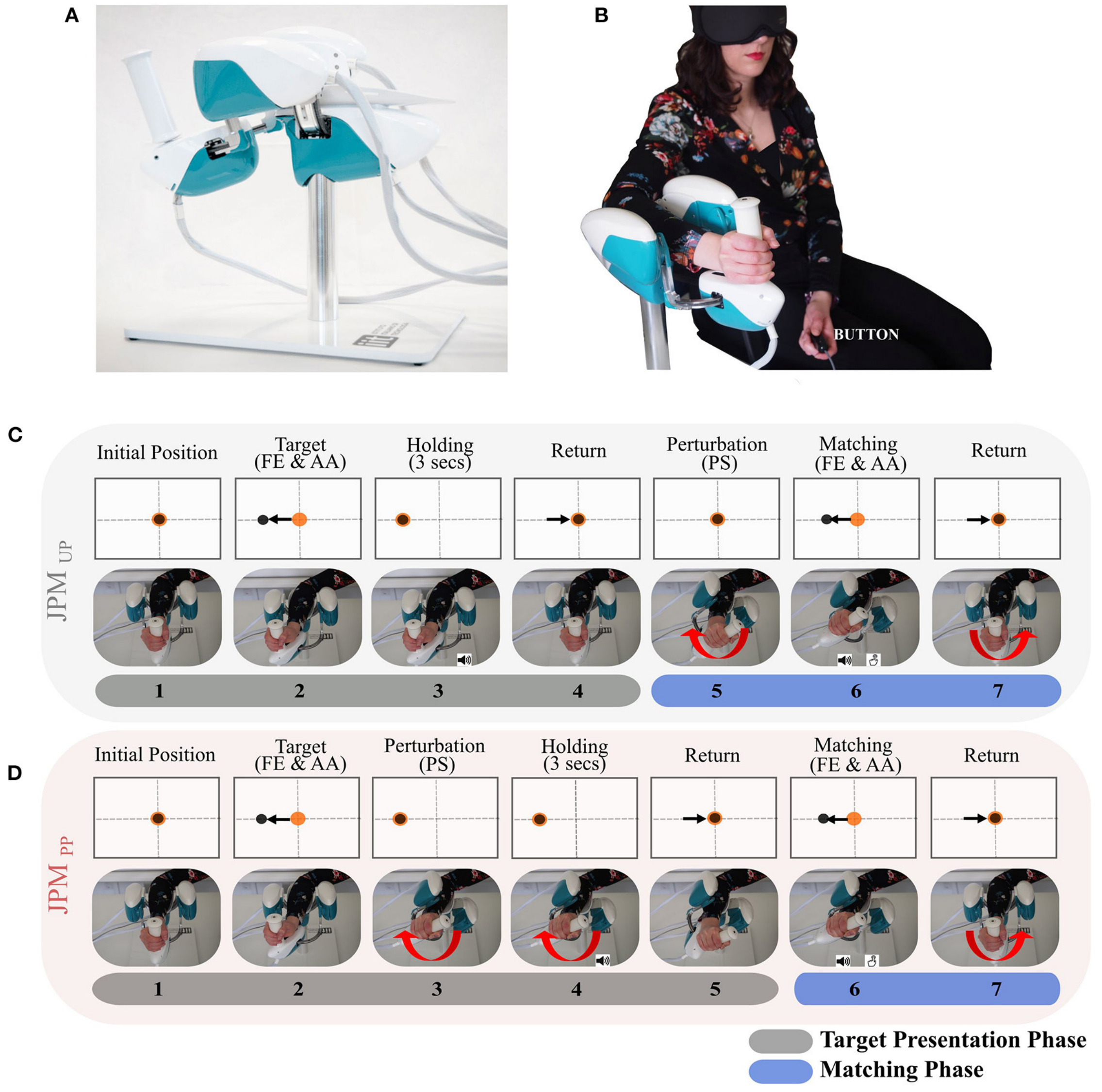

FIGURE 1 | (A) The WristBot device. **(B)** Experimental setup. The subject is comfortably seated on a chair with the right forearm fixed on the WristBot robotic device while holding its handle. In the contralateral hand the subject holds the button to press during the proprioceptive "Matching Phase." The subject wears a mask over his eyes to perform the experiment based only on his proprioceptive feedback. **(C,D)** are represented the temporal sequences for the two JPM conditions: JPMUPJPM$_{UP}$ and JPM$_{PP}$PM. From the initial position, the wrist joint is passively moved towards the proprioceptive target (passive reaching) and then maintained for 3 s. An auditory cue marks that the proprioceptive target is reached. After returning to the resting position participants are asked to match the target, as accurate as possible (Matching Phase) by pressing the button with the contralateral hand. Another auditory cue signals to the subject the start of the Passive Matching Phase in which it is required to stop the robot once the same movement amplitude has been perceived. In different temporal moments, depending on the condition experienced, a perturbation is given (angular rotation along the PS axis of a certain random amplitude). This is evidenced by the red arrow in the figure. Orange dot represents the device end-effector position, while the black dot represents the proprioceptive target position.

from an initial rest position (0° of FE, 0° of AA and 0° of PS) a preset wrist stimulus or proprioceptive target, corresponding to about 50% of the total functional wrist ROM (Kim et al., 2014), was passively presented to a blindfolded participant, who was then asked to match it, as accurately as possible in a subsequent movement. In particular, these angles were: 32° for FE; 16° for AA (Marini et al., 2016a).

The perturbation delivered to participants during the JPM task consisted in seven pseudo randomized rotations along the PS axis (−45°, −20°, −5°, 0°, +5°, +20°, +45°), at speed equal to 12°/s and in two separate temporal fashions: depending on the time in which the perturbation was given, we distinguished two task conditions named JPM_{UP} (Unperceived Perturbation) and the JPM_{PP} (Perceived Perturbation), which will be explained in detail in the next paragraphs.

Each target set consisted of 48 repetitions (trials) for each of the two DoFs separately (FE and AA), for a total of 96 provided

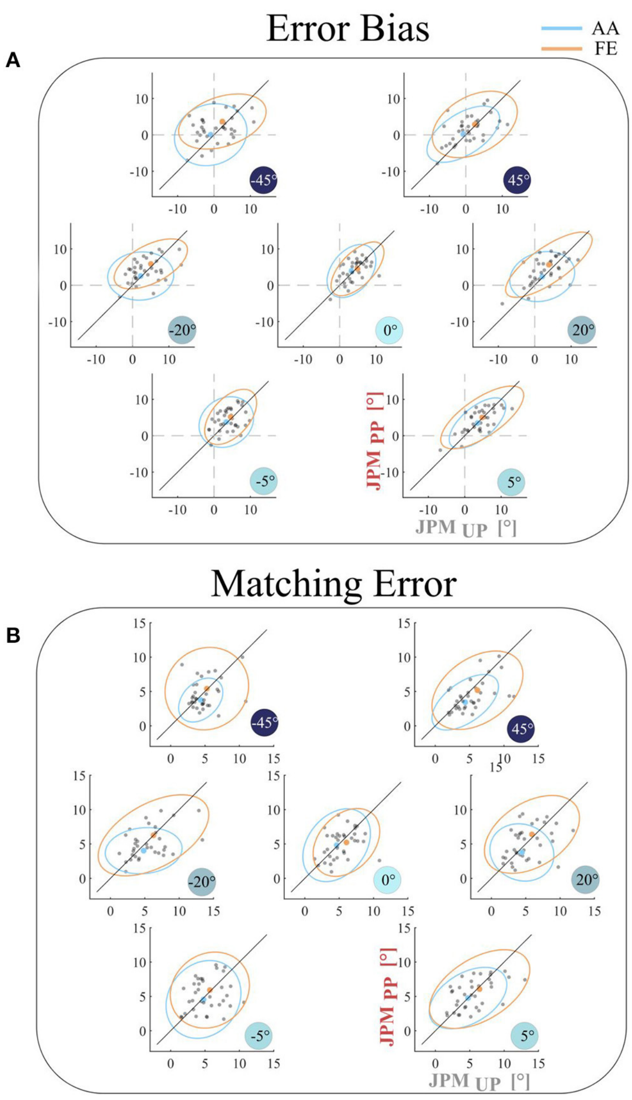

FIGURE 2 | Comparison between the two experimental conditions (JPM_{UP} vs. JPM_{PP}) for the **(A)** *Error Bias* and for the **(B)** *Matching Error* outcomes for AA (light blue) and FE (orange) DoFs. Each gray point represents the average result for a single subject. The mean result across the population is reported as light blue point for AA and orange point for FE joint. The line through the origin (equality line) is represented by a black line; if the subject performance stays above this line the error is higher for the JPM_{PP} task, vice versa if it stays under the line.

proprioceptive targets. It was divided into 2 sub-sets (20 min each), with a break of about 10 min, to avoid fatigue and loss of concentration.

Each single trial consisted in two separate phases indicated as "*Target Presentation Phase*" and "*Matching Phase*": seven blocks composed the aforementioned phases and are depicted as a breakdown in **Figures 1C,D** (in the figure, only test on the FE is illustrated for sake of simplicity). From the initial wrist position (Block 1), the robot moved one DoF to the preset angular position corresponding to the proprioceptive target or stimulus (Block 2). An *auditory cue* (high-frequency beep) was provided when the robot reached the proprioceptive target: from this block onward, the trial can follow a different order of presentation depending on the two disturbance conditions, as explained as follows:

1. Condition JPM_{UP}(**Figure 1C**): the current experimental condition is separated in three main events during each trial: *presentation of the proprioceptive target PS perturbation matching phase.*
   In details, each single trial in such condition started with the wrist of the participant in the physiological neutral configuration (Block 1), then the robot moved the wrist to a *proprioceptive target* (Block 2) along FE (or AA) and maintains such configuration for 3 s (Block 3) (Fuentes and Bastian, 2010). Successively, the subject's wrist is moved back to the initial *rest* configuration (Block 4); At this point a pseudo random *perturbation* around the PS axis (Block 5) was provided. An *auditory cue* indicated the initiation of the *Matching Phase*, where the rotated subject's wrist was passively moved by the robot toward the same direction of the previously presented target (Block 6) on FE (or AA). During this block subjects were instructed to stop the robot motion by pushing a *button* with the contralateral hand, as soon as they perceived to have reached a joint amplitude matching the one of the previously presented target. The robot speed was changed respect to the one experienced during the *proprioceptive target* presentation (Block 2), to prevent subjects from relying on the memory time factor during execution of the *matching phase*. At last, the robot drove back the subject's wrist to the initial position prior next trial initiation (Block 7).
2. Condition JPM_{PP} (**Figure 1D**): contrarily to the previous condition, we had 2 (and not 3) events: *presentation of the proprioceptive target including PS perturbation matching phase.*
   The presentation of the target along FE (or AA) was passively imposed by the robot starting from a rest position (Block 1–2). At this point, contrarily to the previous condition, the pseudo random PS perturbation (Block 3) was presented while maintaining the target presentation on FE (or AA), held for 3 s (Block 4) and successively repositioning FE (or AA) to the rest configuration (Block 5): this was the end of the *Target Presentation Phase*. The *Matching Phase* started with the *passive matching* (Block 6): after an *auditory cue,* subjects were required to stop the robot motion, by pressing the button in the contralateral hand, once the same movement amplitude has been perceived. Immediately after pressing the button, the robot brought the subjects wrist back again to the initial position for the next trial (Block 7).

Subjects were instructed to focus only on the location of the proprioceptive target and try to reject the effect of the perturbation along the PS axis during the *Matching Phase*. They did not receive any feedback about their performance, to eliminate a possible recalibration of the responses during the test. Across 2 days of testing (day 1 and day 2), participants were required to perform the task in a randomized order for the two conditions JPM_{UP} (day 1 or day 2) and JPM_{PP} (day 1 or day 2).

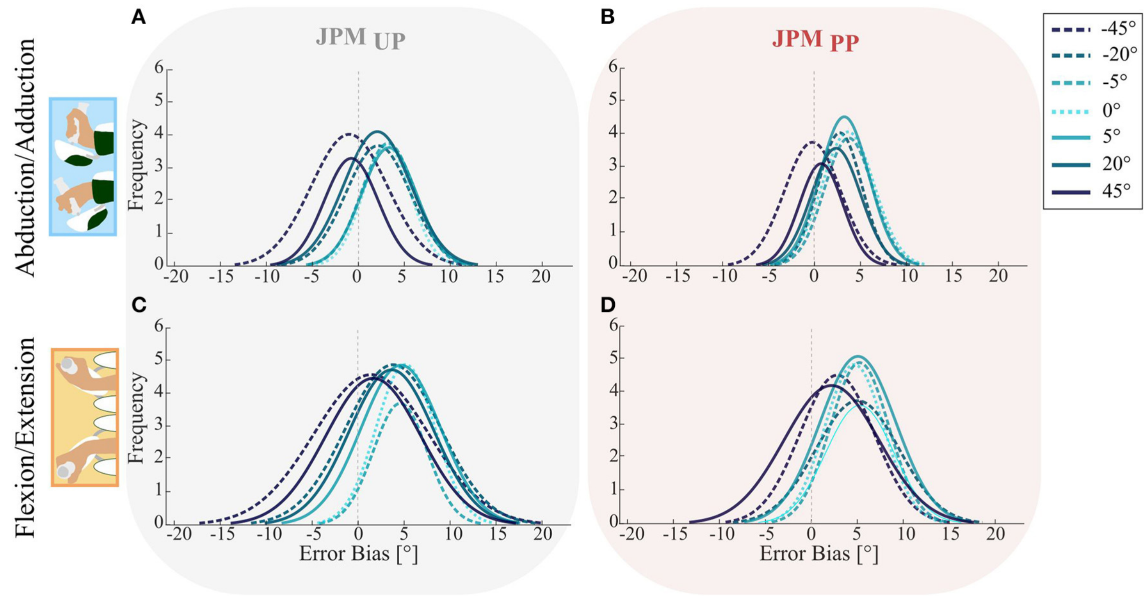

FIGURE 3 | Probability density distributions for the Error Bias of the two DoFs AA **(A,B)** and FE **(C,D)** in both the JPM_{UP} (first column) and JPM_{PP} (second column) conditions. Colored lines show the mean distribution for the specific perturbation denoted in the legend. The vertical dotted line highlights the error equal to zero, a distribution shifted to the left indicates error undershooting, while a distribution shifted to the right represents a tendency of target overshooting.

Data Analysis

Wrist joint rotations were recorded by means of the digital encoders of the WristBot (data collection frequency set at 100 Hz). Data were filtered offline using a 3rd order Savitzky–Golay low-pass filter (cut-off frequency of 10 Hz). For each condition, as a measure of the overall accuracy, we computed two indicators: the *error bias* and the *matching error* (Schmidt et al., 2018).

- The *error bias* ([°]), is the mean, over N repetitions for the same proprioceptive target (same DoF and disturbance condition), of the signed difference between the presented proprioceptive target location (ϑ_{target}) and the wrist position at the end of the matching task movement (ϑ_i). It indicates the subject's tendency to overshoot (positive *error bias*) or undershoot (negative *error bias*) the target after the *Matching Phase*. For a consistent interpretation, we transformed the signed *error bias* to a measure of a signed overshoot, *error bias* $_{OS}$ (Galofaro et al., 2019):

$$error\ bias_{\ OS} = sign(\vartheta_{target}) * \frac{\sum_{i=1}^{N} (\vartheta_i - \vartheta_{target})}{N} \quad (1)$$

where ϑ_i is the measured value at the end of the *i-th* trial, ϑ_{target} is the target position. In this metrics, negative values represent an undershoot, while positive values represent an overshoot independently of the sign of the target.

- The *matching error* ([°]), evaluates the accuracy during the *Matching Phase* and it is defined as the absolute value of the difference between the ϑ_i and the ϑ_{target} averaged over N repetitions of the same target in the same disturbance condition:

$$matching\ error = \frac{\sum_{i=1}^{N} |\vartheta_i - \vartheta_{target}|}{N} \quad (2)$$

Statistical Analysis

Data normality distribution was assessed using Shapiro-Wilk test, and sphericity condition for repeated measures analyses of variance (rANOVA) was assessed using the Mauchly test. The first test was always verified: when the second was violated, we applied the Greenhouse-Geisser correction. The three-way repeated measures ANOVA test was used to examine the effects, on the dependent variables (*error bias*, *matching error*) of the robot rotation around the PS axis, the DoF and the tasks condition, using three within-subject factors: (i) 'condition' (2 levels: JPM_{PP} and JPM_{UP}), (ii) 'PS perturbation' (7 levels: $-45°, -20°, -5°, 0°, 5°, 20°, 45°$), (iii) 'DoF' (2 levels: AA and FE) and their interaction. A *post-hoc* analysis was performed using Paired *t*-tests to evaluate the significant pairwise differences between each perturbation, DoF and condition. For all the tests, the level of statistical significance was set at 0.05, except for *post-hoc* analysis, where the significance level was chosen according to the Bonferroni correction for multiple comparisons. Statistical analysis was conducted by using IBM SPSS Statistics 23 (IBM, Armonk, New York, USA).

RESULTS

Comparison Between JPM_{UP} and JPM_{PP}

Figure 2 shows the comparison between the two disturbance conditions (JPM_{UP} vs. JPM_{PP}) in terms of the *error bias* (A) and the *matching error* (B). As evidenced also by the rANOVA results, for both outcomes, we did not find any significant difference between the two conditions (JPM_{UP} vs. JPM_{PP}; *error*

TABLE 1 | Statistical *p*-values for the error bias between the seven perturbations.

PS [°]		JPM_{UP}		JPM_{PP}	
		P (AA)	P (FE)	P (AA)	P (FE)
45					
	20	<0.001*	0.007*	<0.001*	<0.001*
	5	<0.001*	<0.001*	<0.001*	0.003*
	0	<0.001*	<0.001*	<0.001*	0.008*
	−45	0.558	0.877	0.389	0.532
	−20	<0.001*	0.012*	0.002*	0.002*
	−5	<0.001*	0.001*	<0.001*	0.001*
20					
	5	0.007*	0.026*	0.015*	0.636
	0	0.011*	0.015*	<0.001*	0.200
	−45	<0.001*	0.013*	<0.001*	0.001*
	−20	0.721	0.614	0.884	0.355
	−5	0.011*	0.169	0.001*	0.838
5					
	0	0.569	0.430	0.245	0.171
	−45	<0.001*	<0.001*	<0.001*	0.01*
	−20	0.043*	0.284	0.186	0.734
	−5	0.796	0.909	0.213	0.855
0					
	−45	<0.001*	<0.001*	<0.001*	0.017*
	−20	0.05	0.155	0.020*	0.270
	−5	0.705	0.426	0.863	0.136
−45					
	−20	<0.001*	<0.001*	0.001*	0.002*
	−5	<0.001*	0.001*	<0.001*	0.006*
−20					
	−5	0.016*	0.620	0.005*	0.891

**represents significant differences between the two perturbations compared.*

bias: $F = 0.986$, $p = 0.329$; *matching error*: $F = 1.424$, $p = 0.211$ F). *Error bias* and *Matching Error* indicated that the performance, averaged across all subjects and independently on the investigated DoF (FE and AA), it's closely distributed along the *equality line*, demonstrating that the process underlying encoding of proprioceptive target is not influenced by the order of rotation of the reference frames between *target presentation* and *matching movement*. Moreover, the same behavior persists across all the spanned values of the PS perturbation.

Effects of Pronation/Supination Disturbance on Over- and Under-Shooting the Proprioceptive Targets

The trend of the subjects to overshoot or undershoot the angular position of the proprioceptive target during the *Matching Phase* was examined by analyzing the probability density distribution of the *error bias* for across the two investigated DoFs FE and AA (**Figure 3**). We evaluated the distribution for the 7 amplitude pseudo-random perturbations along PS and for both the JPM_{UP} and the JPM_{PP} conditions. The tendency to overshoot the proprioceptive target during the matching task was higher for low amplitude PS perturbations, rather than for the largest ones (−45° and +45°) in both tested DoFs (FE and AA). As previously reported in section Comparison between JPM_{UP} and JPM_{PP}, also in this metric the two conditions (JPM_{UP} and JPM_{PP}) did not influence the *error bias*. Task execution along the AA axis (**Figures 3A,B**) shows a tall narrow distribution mainly shifted to the right side for the perturbations which are closer to the physiological neutral posture of the wrist ($0, \mp 5°$, $\mp 20°$). For large PS perturbations ($\mp 45°$), the distributions were mainly centered around zero *error bias*, indicating a better matching performance of the proprioceptive target. As for the FE task, the results were similar, although characterized by a less distinct, behavior: for both the target presentation conditions (**Figures 3C,D**) subjects tended to overshoot the proprioceptive targets, but with a more accurate matching for those perturbations at the boundaries of the workspace ($\mp 45°$), rather than in configurations ($0, \mp 5°, \mp 20°$) close to the neutral position of wrist.

The aforementioned differences related to *Error Bias* were confirmed by the rANOVA highlighting a significant effect of the PS perturbation ($F = 22.939$, $p < 0.001$), and DoF ($F = 37.199$, $p < 0.001$), but not their interaction effect ('PS perturbation* DoF' effect $F = 1.198$, $p = 0.312$).

We statistically inferred the role of PS perturbation amplitude by a paired *t*-test *post-hoc* analysis for the *Error Bias,* and it revealed multiple significant differences (see **Table 1**). In particular, for all perturbations' amplitudes with the exception of the case related to the DoF FE and the condition JPM_{PP}, we found an overshoot inversely proportional to the PS amplitude as visible by a bell shape graph (**Figure 4A**).

At last, a *post-hoc* analysis between the two tested DoFs, is reported in **Table 2** for the *Error Bias* outcome: we found a significant difference between FE and AA for all the perturbations except for the condition JPM_{PP} at 0° of PS. In particular, subjects presented a larger overshoot along the FE DoF, for all the perturbations and conditions.

Proprioceptive Anisotropy Related to the Perturbation Amplitude

In order to explore the distribution of proprioceptive acuity over the different PS perturbation amplitudes and across the two DoFs, we analyzed the *Matching Error* trend (**Figure 4B**).

The rANOVA showed on *Matching Error* showed a significant main effect of the DoF (FE vs. AA) ($F = 44.695$, $p < 0.001$) as well as of the PS perturbation amplitude ($F = 3.025$, $p = 0.008$). Detailed numerical outcomes of the *post-hoc* analysis across the two DoFs are reported in **Table 3**: again on the *Matching Error*, a significant difference between FE and AA was found for almost all the perturbations with the exception of 0° for the JPM_{PP} and −45° for the JPM_{UP}. In particular, for both the conditions JPM_{UP} and JPM_{PP} and for all the PS amplitudes, subjects showed a larger *Matching Error* along the FE than the AA (**Table 3**), indicating an anisotropy of proprioceptive acuity across two DoFs which persists independently on the provided perturbations.

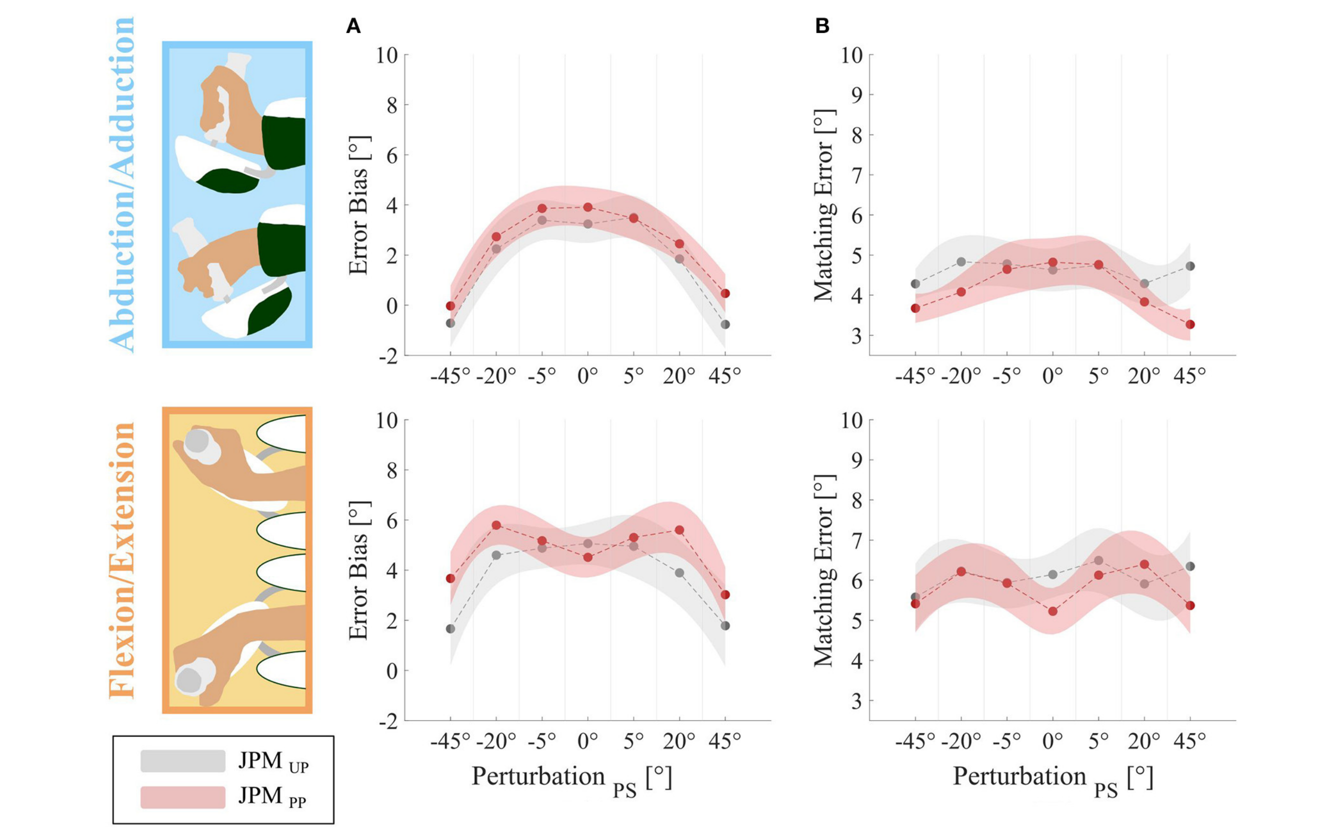

FIGURE 4 | Outcome measures relative to the two DoFs: AA on the top and FE on the bottom for JPM_{UP} (gray) and JPM_{PP} (magenta) conditions. First column represents the *Error Bias* **(A)**. Second column is relative to the *Matching Error* **(B)**. On the x-axis is evidenced the amount of angular perturbation provided along the PS axis (−45°, −20°, −5°, 0°, 5°, 20°, 45°) during the experiment.

The *post-hoc* analysis between PS amplitudes for the *Matching Error* are reported in **Table 4** and highlighted significant differences for the JPM_{PP} and the AA DoF. For all perturbations' amplitudes, we found a proprioceptive error inversely proportional to the PS amplitude as visible by a bell shape graph, **Figure 4B**. For large PS perturbations (∓45°), results show a better matching performance of the proprioceptive target.

DISCUSSION

Understanding how proprioceptive information is encoded at distal joints, has multiple intersections across different fields involving physiology, motor learning, sensorimotor recovery as well as those applications in haptics where proprioception is predominantly involved in a robot mediated manipulation. In rehabilitation practice, it is a common opinion among clinicians that current proprioceptive assessment fails in providing a reliable and quantitative information which would allow to compare motor and sensory deficits, known to be complementary information to a comprehensive diagnosis of the recovery process. However, authors usually focus on motor recovery (Soekadar et al., 2019) while limited evidence can be found in literature on the physiology of proprioception involving distal joints at the level of hand and wrist, despite they are anatomical districts covering an essential role in manual handling, and being the joints mostly involved in fine manipulation and exploitation of human dexterity, which is still unmatched in nature among species (Hoseini et al., 2015; Moser et al., 2020). With this in mind, we wanted to provide further evidences that using haptics, proprioceptive acuity can be accurately and geometrically characterized across the wrist's DoFs, synergistically involved during motor coordinated activities.

Hence, we decided to investigate if perturbations along one wrist joint (PS), can significantly alter the mechanism underlying perception of proprioceptive information on the adjacent DoFs (FE and AA). Outcomes revealed multiple aspects, which, to our knowledge have never been reported in previously published contributions, for the reason that most of the literature on proprioception primarily focused on proximal joints—shoulder and elbow—and privileged research on influence and role of multisensory integration in goal directed movements. Another reason for such lack of results, is the affordability of complex haptic devices, which not only assume operators able to skillfully program and run specific tailored physiological tests, but also they must be designed in such a way to provide robust and

TABLE 2 | Statistical *p*-values for the error bias between the two DoFs (AA/FE).

	UP		PP	
PS [°]	**Mean ± SD [°]**	***p***	**Mean ± SD [°]**	***p***
−45	**−0.72 ± 4.09**	0.016*	**0.39 ± 3.06**	<0.001*
	1.66 ± 6.21		3.76 ± 4.55	
−20	**2.24 ± 4.40**	0.002*	**3.31 ± 3.06**	0.002*
	4.59 ± 4.92		5.84 ± 3.19	
−5	**3.39 ± 3.42**	0.004*	**3.51 ± 3.18**	0.035*
	4.88 ± 3.45		5.05 ± 3.65	
0	**3.24 ± 3.22**	<0.001*	**3.65 ± 3.32**	0.197
	5.06 ± 3.54		4.51 ± 3.42	
5	**3.50 ± 3.67**	0.034*	**3.26 ± 3.55**	0.010*
	4.95 ± 5.23		5.30 ± 3.85	
20	**1.84 ± 4.05**	0.013*	**2.36 ± 3.17**	<0.001*
	3.89 ± 5.56		5.33 ± 4.28	
45	**−0.77 ± 4.10**	0.018*	**0.76 ± 3.03**	0.007*
	1.78 ± 6.90		3.02 ± 4.74	

**represents significant differences between the two compared DoFs. Bold values represent AA axis.*

TABLE 3 | Statistical *p*-values for the matching error between the two DoFs (AA/FE).

	UP		PP	
PS [°]	**Mean ± SD [°]**	***p***	**Mean ± SD [°]**	***p***
−45	**4.81 ± 2.65**	0.053	**3.67 ± 1.55**	0.001*
	5.95 ± 4.00		5.68 ± 3.10	
−20	**4.83 ± 2.72**	0.012*	**4.18 ± 1.97**	<0.001*
	6.45 ± 3.55		6.73 ± 3.05	
−5	**4.78 ± 2.42**	0.014*	**4.64 ± 2.79**	0.008*
	5.94 ± 2.73		6.14 ± 3.11	
0	**4.63 ± 2.80**	<0.001*	**4.82 ± 2.56**	0.128
	6.50 ± 3.54		5.59 ± 2.83	
5	**4.75 ± 2.59**	0.005*	**4.76 ± 2.63**	0.002*
	6.49 ± 3.44		6.62 ± 3.47	
20	**4.53 ± 2.64**	0.022*	**3.75 ± 1.86**	<0.001*
	5.91 ± 3.52		6.15 ± 3.03	
45	**4.13 ± 2.04**	0.005*	**3.36 ± 1.74**	<0.001*
	6.22 ± 3.73		5.84 ± 3.31	

**represents significant differences between the two compared DoFs. Bold values represent AA axis.*

TABLE 4 | Statistical *p*-values for the matching error between the seven perturbations.

		JPM_{UP}		JPM_{PP}	
	PS [°]	**P (AA)**	**P (FE)**	**P (AA)**	**P (FE)**
45					
	20	0.377	0.473	0.145	0.114
	5	0.296	0.813	0.023*	0.152
	0	0.351	0.987	0.008*	0.860
	−45	0.409	0.323	0.478	0.810
	−20	0.312	0.863	0.061	0.160
	−5	0.318	0.522	0.019*	0.246
20					
	5	0.666	0.198	0.020*	0.963
	0	0.724	0.300	0.002*	0.120
	−45	0.828	0.770	0.766	0.099
	−20	0.526	0.513	0.456	0.711
	−5	0.527	0.946	0.027	0.741
5					
	0	0.754	0.802	0.854	0.09
	−45	0.458	0.245	0.031	0.058
	−20	0.866	0.635	0.182	0.975
	−5	0.926	0.194	0.947	0.793
0					
	−45	0.483	0.577	0.028	0.805
	−20	0.620	0.977	0.067	0.104
	−5	0.613	0.332	0.804	0.083
−45					
	−20	0.328	0.245	0.200	0.074
	−5	0.350	0.692	0.069	0.131
−20					
	−5	0.883	0.483	0.157	0.861

**represents significant differences between the two perturbations compared.*

accurate position/force rendering and at the same time perform as reliable measurement systems.

By introducing a different order of presentation of the proprioceptive targets and disturbance input, we tried to understand if proprioceptive information is stored by the central nervous system in an absolute or relative coordinates frame. In our hypothesis the rotation of the reference system during or after the presentation of a target could have affected the final performance. Results clearly highlighted that mechanisms underlying the encoding of a proprioceptive target does not depend on the temporal order of the superimposed geometrical conditions; subjects are, in fact, able to store sequence of joints' configurations and to replicate, with the same accuracy, a previously experienced proprioceptive target independently on the initial conditions in which the target is presented and encoded.

We also found that proprioceptive acuity varies across DoFs: previously published works (Cappello et al., 2015; Marini et al., 2016a) experimentally demonstrated the existence of wrist proprioceptive anisotropy among its DoFs. Marini et al. (2016a) provided a map of the wrist position sense across each DoF, by means of the same robotic device used in our study, observing that wrist AA has a higher proprioceptive acuity respect to the remaining DoFs. Our results are in accordance, but also provide a wider perspective, reporting evidences that proprioception at the distal and multi-joint level, might be highly influenced by the mutual configuration between the DoFs composing the wrist anatomical joint, when the provided proprioceptive targets differ in amplitude across each DoF.

In details, the quantification of wrist anisotropy across its workspace and the dependence on initial posture, demonstrate that our peripheral sensory system tunes its sensitivity depending on geometric conditions and independently from the order of their presentation. Results clearly show a higher proprioceptive acuity for large perturbation amplitude, when the pronation supination (PS) was rotated $\mp 45^{\circ}$. We found the lowest value of the *Matching Error* for both AA and FE when the maximum wrist PS perturbation of $\mp 45^{\circ}$ was applied, unexpectedly meaning that the neutral physiological posture of the forearm (zero rotation of the PS) is not a configuration which enables the best proprioceptive sensitivity. This effect finds its explanation when considering the mutual relationship between the activation of the mechanoreceptors, the anatomical structures of the muscular and connective tissues that are instrumental in proprioceptive coding (van der Wal, 2009). The aforementioned parts cannot be divided into either joint receptors or muscle receptors when muscular and connective tissues work in series to maintain joint integrity and stability: this happens at the boundary of their workspace.

It is known that joint receptors are highly reactive at the extremes of joint workspace (Ferrell et al., 1987), when the joint capsule is significantly stressed (McCloskey, 1978), for example (in our experiment) when the wrist is rotated at $\mp 45^{\circ}$ along PS axis. The activation of the joint receptors, induced by the connective tissues after the changes in muscle tension, occurs at the limits of wrist' range of motion (van der Wal, 2009), and it might be responsible for the high proprioceptive acuity.

In our study there are anyway limitations: the first concerns the small sample of subjects included in our experimental sessions. Another limitation mostly refers to the number of trials provided for each DoF, which has been limited in order to avoid longer sessions with consequent loss of attention from the subjects. In order to deeply correlate joint- and mechano-receptor activation, proprioceptive acuity and perturbations, other measurements, such as surface electromyography (Mugnosso et al., 2018), could have been included in order to highlight the physiological aspects in terms of bio signals and not merely relying on kinematic data extracted by the haptic device. At last, since the current study investigates the influence of static wrist posture variation on proprioceptive acuity, future research could explore how sensory information is coded when time-variable dynamic conditions are provided.

We also mentioned in the introduction the possible application of the proposed paradigm for clinical settings: we believe that using a neuroergonomic haptic technology for quantification of sensory impairment is a viable option. Our approach was meant to analyze the proprioceptive anisotropy across the different DoFs of the wrist workspace, in particular for healthy subjects. Yet the methodological approach must be tailored in such a way to design a more compact test which can be dispensed on patients where physiological conditions are unpredictably variable and heterogeneous.

CONCLUSION

This study aims at providing a wider and more comprehensive view on the physiological aspects influencing proprioception in the complex multi-joint articulation of the human wrist by means of a neuroergonomic robotic technology.

The outcomes are of interest for multiple disciplines: in neuroergonomics and medicine, for instance, the tests assessing sensory system's integrity, must be performed considering that different postural conditions may alter proprioceptive acuity. Testing patients' proprioception in a configuration which is close to the joints' physiological workspace limits, may increase mechanoreceptors excitation and provide a fine measurement of sensory acuity.

In haptics, especially for those applications where telemanipulation of real or virtual objects are mediated by robotic devices (robot aided surgical intervention), small movement of the master can be better perceived and controlled by the operator if her/his proprioception is set to a high sensitivity level and therefore in a posture with is proximal to the physiological boundaries of the joints' workspace.

DATA AVAILABILITY STATEMENT

The datasets generated and/or analyzed for this study are available from the corresponding author on reasonable request.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Heidelberg University Institutional Review Board (S-287/2020). The patients/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

ED'A and EG helped to conceive the idea and concept, they designed and implemented the experiment, acquired the data, analyzed and interpreted the data, and drafted the manuscript. JZ technically supported the development of the robotic application. FP, JK, and MC critically revised the manuscript content. LM conceived the idea and concept, critically revised the manuscript content, and supervised the study. All authors read and approved the final manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnbot.2021.640551/full#supplementary-material

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Human–Co-Bot Interaction and Neuroergonomics: Co-Botic vs. Robotic Systems

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HUMAN–ROBOT INTERACTION: A TECHNICAL AND MANAGERIAL MATTER

The fourth industrial revolution comprehends smart manufacturing, where sensors, computing platform, and data modeling are employed (Kusiak, 2018). Di Nardo et al. (2020), in the frame of Industry 4.0, developed a model where the role of management is key in this new highly networked environment. It is suggested that cyber-physical systems, along with massive data acquisition and mining, might support the decision making and planning execution phases.

In this framework, technological advancements are a necessary, but not sufficient condition. In fact, a functional and targeted human–machine interaction, defined as a communication/interaction between the human user and machines via different interface in a dynamic context, is also essential.

Management has to oversee the rising demand for tech-innovation, which is essential because of the renewed complexity, the stricter time-to-market process, and a higher competition generated by globalization (De Carolis et al., 2016), and to ensure that innovation fits well within the work environment. In this sense, the automation of part of the process adds value only if substantial changes are implemented among all the organization, which happens when the efficiency of the machine is strengthened by human cognitive skills and adequate flexibility. Under this light, neuromanagement, a new branch of management, was recently developed, where decision-making processes (Balconi and Fronda, 2019, 2020a) and social behavior and interaction (Balconi and Vanutelli, 2017; Venturella et al., 2017; Balconi and Fronda, 2020b) are studied in real-world situations by using a neuroscientific approach.

The conjunction and the outcome of this multidisciplinary approach might boost smart manufacturing, in particular for co-bot technology, where operational fluency between agents has a significant weight for safety and productivity reasons. In this work, with the term “co-bot,” we intend to underline its collaborative dimension, being it the main feature that differentiates from other technological systems (Ajoudani et al., 2018).

CO-BOTS FOR THE INDUSTRY: ROLE AND APPLICATIONS

Co-bots can be defined as novel technological manufacturing systems, which are able to work with a certain degree of dexterity and in conjunction with humans in the same physical workspace (Bauer et al., 2016), with no barriers, mainly aiming at improving efficiency, flexibility, and quality in the overall industrial process. Other possible appreciable dimensions are related to ergonomics and safety (Kildal et al., 2018), being the co-bot mostly responsible and employable for monotonous

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and unergonomic tasks. Regarding the safety, it must be pointed out that Industry 4.0 brings also emerging risks and challenges, which are related to the human performance (Brocal et al., 2019).

More generally, according to the International Federation of Robotics (IFR), co-bot technology might help in two different contexts. In the small- to medium-sized companies, it could be introduced to automate some parts of the production line, without altering the rest and offering higher productivity and quality improvements. Second, in companies with already automated process (e.g., automotive sector), it could support workers in completing assemblage tasks, often causing physical injuries. Regarding the market data, in 2019, the professional service robots sector grew by 32% (from US $8.5 billion to $11.2 billion) (Executive Summary World Robotics, 2020), and the sales volume for collaborative robots grew more compared to the traditional ones (IFR Press Conference, 2020). Also, the pandemic seems to have boosted the market for robotic components in warehouses, factories, and home delivery and also because the technology supports social distancing.

However, some important differences should be considered and elucidated when comparing "robotic" and "co-botic" systems, focusing on the level of interaction with the workers, higher for the co-botic compared to the robotic one, which is physically separated and has a fixated position.

The recent developments in sensors and data processing led to systems that better assist and interact with humans (e.g., Fryman and Matthias, 2012). Although, fully collaborative co-bot applications are not completely developed and used yet, and there is a significantly high variance in the technical applications of co-bot. In fact, depicting a hypothetical continuum for human–robot collaboration, from no direct human–robot contact to a real-time system that adjusts in response to the human behavior, it is most common to have just shared workspace and/or sequential collaboration conditions.

A successful industrial adoption of co-bots is derived from proper training programs and an open communication that address the company objectives. In the literature, three categories of factors are highlighted: internal (management support, company structure, research, physical conditions, and receptiveness), external (regulatory environment, business partner), and technological (technology context, degree of innovation, and workspace) (Correia Simões et al., 2020). Besides the delicate coexistence of operational efficiency and safety requirements, another possible issue, as suggested by Bauer et al. (2016), because of the novelty of co-bot technology, is that old models assessing efficiency and profitability fail to give a proper cost–benefit analysis, and these are not usually carried out by companies. Furthermore, some dimensions, such as ergonomics, stress, flexibility, and relationship data, are difficult to be measured and quantified.

DISCUSSION: NEUROERGONOMICS IN THE ORGANIZATION

The new paradigm advocates for an optimized human–robot interaction (HRI), where robots carry out a fully collaborative behavior, and both the strengths of the involved agents are maximized. As already mentioned, previous approaches to HRI showed difficulties in the measurement and quantification of some dimensions such as ergonomics and interaction. Other previous theoretical frameworks were proposed (e.g., Goodrich and Schultz, 2007). In particular, a more novel approach (Gervasi et al., 2020) postulates that collaborative systems can be evaluated by combining both technical aspects with human social factors and highlights eight latent dimensions, such as information exchange, autonomy, adaptivity and training, human factors, ethics, team organization, task, and cyber-security. In light of these contributions, we believe that, with such set goal, the adoption of neuroergonomics, for its study of neural networks involving cognitive, perceptual, and emotional processing and, in general, applied neuroscience, is mandatory to be considered.

As a result of the increased and renewed portability of brain–computer interface (BCI), at reasonable cost, neurophysiological and behavioral sensors can be useful for the development of fully collaborative co-bots into the industrial context. In fact, some of the weighting factors that should be considered in the developed of co-bots are human fatigue, as a function of time and workload, and executive functions (in particular working memory, inhibition, and cognitive flexibility), which are responsible for dynamic attentional coordination and are impaired by stress (e.g., Shields et al., 2016), selective attention, and cognitive states.

Indeed, each of these factors may better explain the usefulness, applicability, and quantitative impact of co-botic systems in real workplaces. Specifically, regarding fatigue, the optimization process and the management of adjusting robots' trajectories could facilitate the human operator's work. In this regard, to reduce worker's fatigue, elements such as the condition of stability, the possible constraints of the activities, and the presence of shared workspaces should be considered (Kim et al., 2018; Hashemi-Petroodi et al., 2020). The presence of co-bots in the industrial context could also be effective in terms of performance, allowing better use of resource skills and executive functions (Tsarouchi et al., 2016). Indeed, the advantages introduced by the inclusion of robots with characteristics such as strength, speed, precision, tirelessness, and repeatability will allow reduced cognitive load and effort for the workers performing their duties and allowing better use of intelligence, creativity, and learning (Hashemi-Petroodi et al., 2020).

To assess mentioned dimensions in the co-bot, we highlighted and propose some of the neurometrics that respond to the purpose. A major distinction that should be taken into consideration is the parameter domain, meaning if it refers to the central electroencephalography (EEG) and event-related potentials (ERPs), peripheral [electrodermal activity (EDA), electrocardiogram data, respiratory system], or behavioral (mostly derived from visual eye and gaze tracking systems) system. The consideration of these parameters, consisting in the detection and processing of sensory data, could allow co-bots to more easily understand the objectives and intentions of human partners and assist them in carrying out specific tasks.

Regarding the mental load, many studies used slow-wave and fast-wave increases/decreases and $(\alpha/\theta)/\beta$ or $(\alpha/\theta)/(\alpha + \beta)$

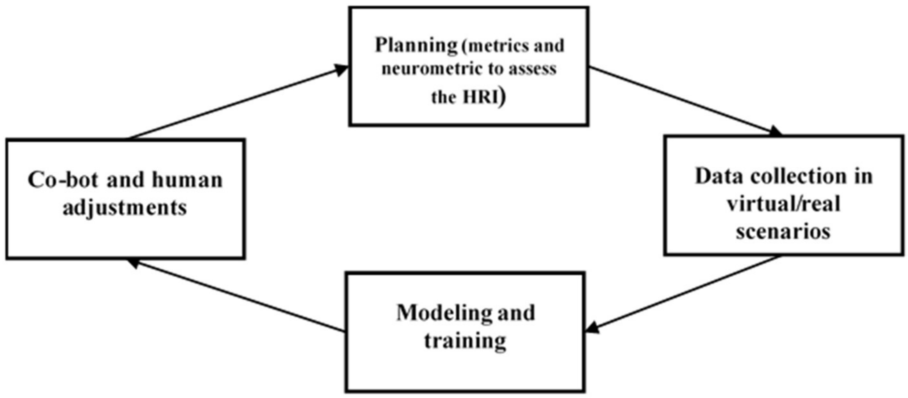

FIGURE 1 | A hypothetical model applied to HRI for the industrial adoption of co-bots, based on the Deming cycle.

ratios in the frontal and central brain areas (e.g., Wang et al., 2020) to explore the brain networks contribution in cognitive and emotional planning. In parallel, information about emotion recognition has been collected via frontal asymmetry (Balconi and Mazza, 2010; Balconi et al., 2014), normalized frontal asymmetry (Balconi et al., 2009, 2015), theta-beta ratio (Angelidis et al., 2018), and Hjorth parameters for affective state estimation (e.g., Rakibul Mowla et al., 2020).

Regarding selective attention, instead, ERP approach can be widely used to study the degree of attention, employing P1 and N1 and later components such as P300, reflecting, among the others, the identification of a target. In addition to cerebral outputs, also behavioral measures can be collected, as the identification of stimulus-driven saccades, time-to-first fixations, and pupil dimension, which might be very informative about visual attentional behavior and the overall representation of the workers of their body position, movement, and acceleration in the workplace.

On the other side, always more novel and varied techniques are applied to biosignal and behavioral research (Cassioli and Balconi, 2020), aiming at classifying, reducing the dimensionality (Zhang et al., 2019), and predicting workers' behavior. The most notable is that the recent application of machine learning to neurophysiological signal seems encouraging. Some of the methods are artificial neural networks (Baldwin and Penaranda, 2012), k-nearest neighbors, support vector machine (Son et al., 2013), and decision trees techniques (Solovey et al., 2014; Wang et al., 2020), via deep learning brain decoding techniques, showing that EEG signal might be used not only to obtain data but also as a support in the designing process through the use of brain activities, although it is important to note that actual data and models refer to limited dataset and set of categories. Also, intergroup differences might heavily limit the applications of these approaches.

We then propose a quality cycle, structurally based, for the most part, on Deming cycle (Deming, 1986) and in line with the concept of neuroindustrial engineering coined by Ma et al. (2012) adjusted to the conjectured context for the development of an optimal HRI drawn in this work (**Figure 1**).

In the first phase (planning), a screening and a compartmentalization of the required processes are carried out. In this phase, it is important to establish objectives and the consequent BCI specifics (methods, chosen metrics) based on the procedural flow and set goals. In the second phase (doing), selected virtual and real scenarios are executed while data are collected. As in co-bot systems the fluidity of interaction and safety are primary requirements, we advocate for the application of a holistic approach and the joint consideration of central, peripheral, and behavioral parameters for the HRI evaluation. The following dimensions, among others, should be considered: the worker emotional discomfort, the executive functions (with a focus on irrelevant stimuli inhibition), the fatigue, and cognitive and emotional states in order to assist in decision-making processes. Also, an easy-to-use interface on which a feedback system is inserted should be provided in order to make the workers aware of their performance and status. Collected data is then (modeling/learning) used to create bottom-up models, which will be tested again in the next quality cycle. Finally, in the fourth phase, adjustments (change) are implemented in the workspace for both workers and the co-bots systems.

Furthermore, hyperscanning paradigms are now able to obtain data on actions and social adaptation during human-to-human interaction (Balconi et al., 2019a,b; Balconi and Fronda, 2020b). If portability will be increased, co-bots could receive precious information about multiple and complex work–environment settings with multiple agents.

Collaborative technology is still in its embryonic stage. We expect that further technological, neuroscientific, and behavioral developments will enrich and make this technology more intuitive, intelligent, and suitable for the human, leading to an optimized and safe human–co-robot interaction.

Because of the augmented portability of sensors and neuropshysiological systems, we believe that in the future smart manufacturing could adopt neuroscientific protocols to support workers on the field, aiming at increasing efficiency, ergonomics, and safety. In this work, we proposed a neuroindustrial quality process for the development of an optimized HRI for co-bot technology, based on the Deming cycle. We expect that further technological and neuroscientific developments will enrich and make co-bots more intuitive and suitable for the human.

AUTHOR CONTRIBUTIONS

FC, GF, and MB wrote the first draft and each section of the manuscript and contributed to the manuscript final writing and revision, read, and approved the submitted version. All authors contributed to the article and approved the submitted version.

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SYSTEMATIC REVIEW
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Direct Communication Between Brains: A Systematic PRISMA Review of Brain-To-Brain Interface

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This paper aims to review the current state of brain-to-brain interface (B2BI) technology and its potential. B2BIs function via a brain-computer interface (BCI) to read a sender's brain activity and a computer-brain interface (CBI) to write a pattern to a receiving brain, transmitting information. We used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to systematically review current literature related to B2BI, resulting in 15 relevant publications. Experimental papers primarily used transcranial magnetic stimulation (tMS) for the CBI portion of their B2BI. Most targeted the visual cortex to produce phosphenes. In terms of study design, 73.3% (11) are unidirectional and 86.7% (13) use only a 1:1 collaboration model (subject to subject). Limitations are apparent, as the CBI method varied greatly between studies indicating no agreed upon neurostimulatory method for transmitting information. Furthermore, only 12.4% (2) studies are more complicated than a 1:1 model and few researchers studied direct bidirectional B2BI. These studies show B2BI can offer advances in human communication and collaboration, but more design and experiments are needed to prove potential. B2BIs may allow rehabilitation therapists to pass information mentally, activating a patient's brain to aid in stroke recovery and adding more complex bidirectionality may allow for increased behavioral synchronization between users. The field is very young, but applications of B2BI technology to neuroergonomics and human factors engineering clearly warrant more research.

Keywords: brain-to-brain interface, brain-computer interface, computer-brain interface, brain communication, neuroergonomics

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INTRODUCTION

In the past decade or so, a new neural interface technology, also known as a brain-to-brain interface (B2BI), has entered literature as an extension of the usual applications of neuroimaging technology, measuring one's brain activity such as brain-computer interface (BCI, Nam et al., 2018), and brain stimulation technology, activating the brain directly with electricity (hereinafter computer-brain interface or CBI), to a multi-subject (sender-receiver) approach. B2BI allows two brains to mutually exchange decoded neural information with each other through a BCI that reads a sender's brain activity and a CBI that writes the delivered brain activity to a receiving brain.

Since its proof of concept by Pais-Vieira et al. (2013), B2BI has found several interesting applications, ranging from simply transmitting binary information (Grau et al., 2014) to creating biological neural networks (Pais-Vieira et al., 2015). Perhaps more excitingly, B2BIs have been used to issue instructions to users (Jiang et al., 2019) and respond to questions (Stocco et al., 2015). While these applications still only apply binary information transfer, they show more complex applications of such communication. Mashat et al. (2017) created a B2BI system more focused on rehabilitation for patients. By combining a B2BI with functional electrical stimulation (FES), they argued that systems like this could allow more advanced physical therapy. Lee et al. (2017) argued that brain-to-brain systems could eventually be applied to create thought-based communication between people and even closed-loop feedback of one's own brain activity.

Figure 1 shows a timeline of major events in B2BI research. Though the first direct B2BI study involving transmitting sensorimotor information between rodents was conducted in 2013, there existed very simple proof of concept studies and exploratory literature on the subject as early as 2011. Early studies used rodent models to test their devices, with Yoo et al. (2013) controlling a rodent via a human connected to EEG, but the first human-to-human study arrived from Grau et al. (2014). Stocco et al. (2015) were the first to employ a bidirectional design, transmitting information via magnetic stimulation in one direction and visual feedback in the other. The same year, Pais-Vieira expanded on their earlier system to create a biological neural network through multiple ICM rats connected bidirectionally. Stocco's system was expanded on by Jiang et al. (2019) with a different task, expanding the indirect bidirectional B2BI literature.

Research Motivation

Despite the potential of its applications, B2BI is still in its infancy and has a long way to go before mainstream adoption. In particular, the contemporary B2BI research calls for additional investigations in order to progress to maturity. First, no systematic review study has been conducted in the field; to the best of our knowledge, no comprehensive review study of any kind has been conducted. This has the effect of isolating studies from each other rather than forming a complete body of research. Alongside the advances made in the field, B2BI research also identifies many gaps in the literature that warrant further investigation. Though small in number, the currently published B2BI studies pose various problems, including (i) how to highlight methodological concerns in research studies (Eagly and Wood, 1994) critical in improving future work and (ii) how to identify questions and areas where further research is or is not necessary (Mahood et al., 2014). A systematic review, defined as a "review of the evidence on a clearly formulated question that uses systematic and explicit methods to identify" (Jahan et al., 2016, p. 1), address both of these issues. A systematic review selects and analyzes relevant research to extract and analyze the data present. To our knowledge, existing literature on B2BI has not been reviewed in depth, and we present the first systematic review of the field. In this study, we seek to provide a systematic review of B2BI literature allowing researchers, both current and future, the ability to understand the state-of-the-art of B2BI as well as determine future directions, topics, and terminology of the field.

In regards to that final point, the exact definition of a B2BI varies between publications, and no set definition is agreed upon or standardized. From the literature, B2BI can be defined as a system, composed of a BCI and CBI portion, which records

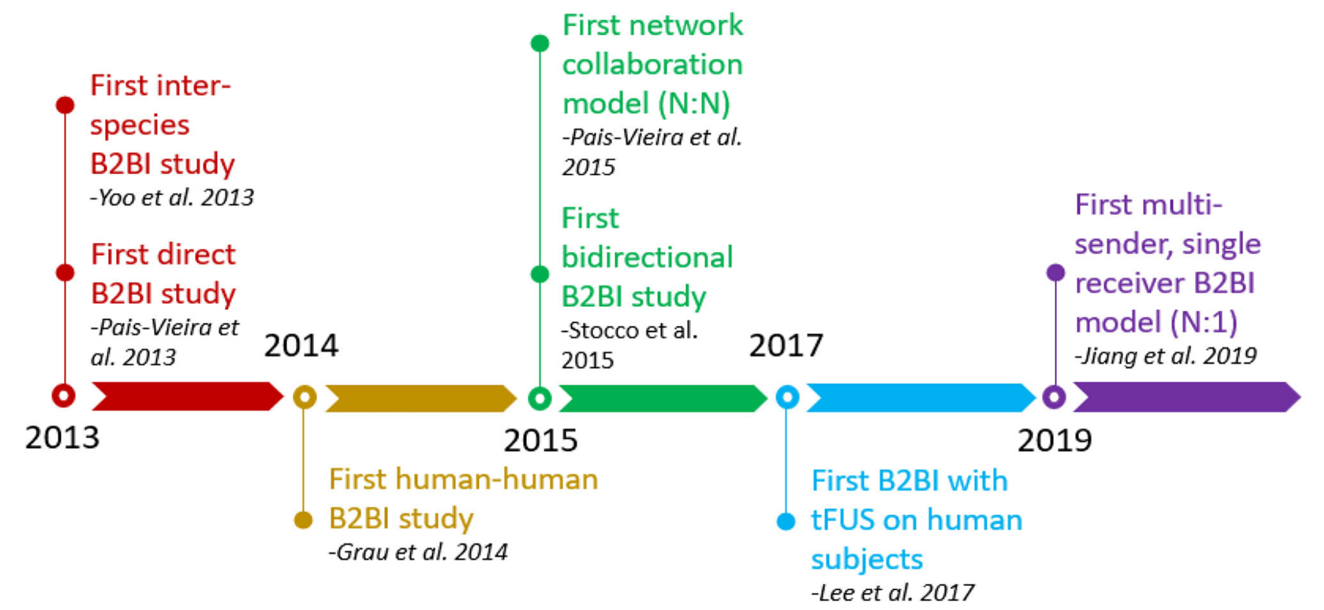

FIGURE 1 | Timelines of advancement in brain-to-brain interface (B2BI) research.

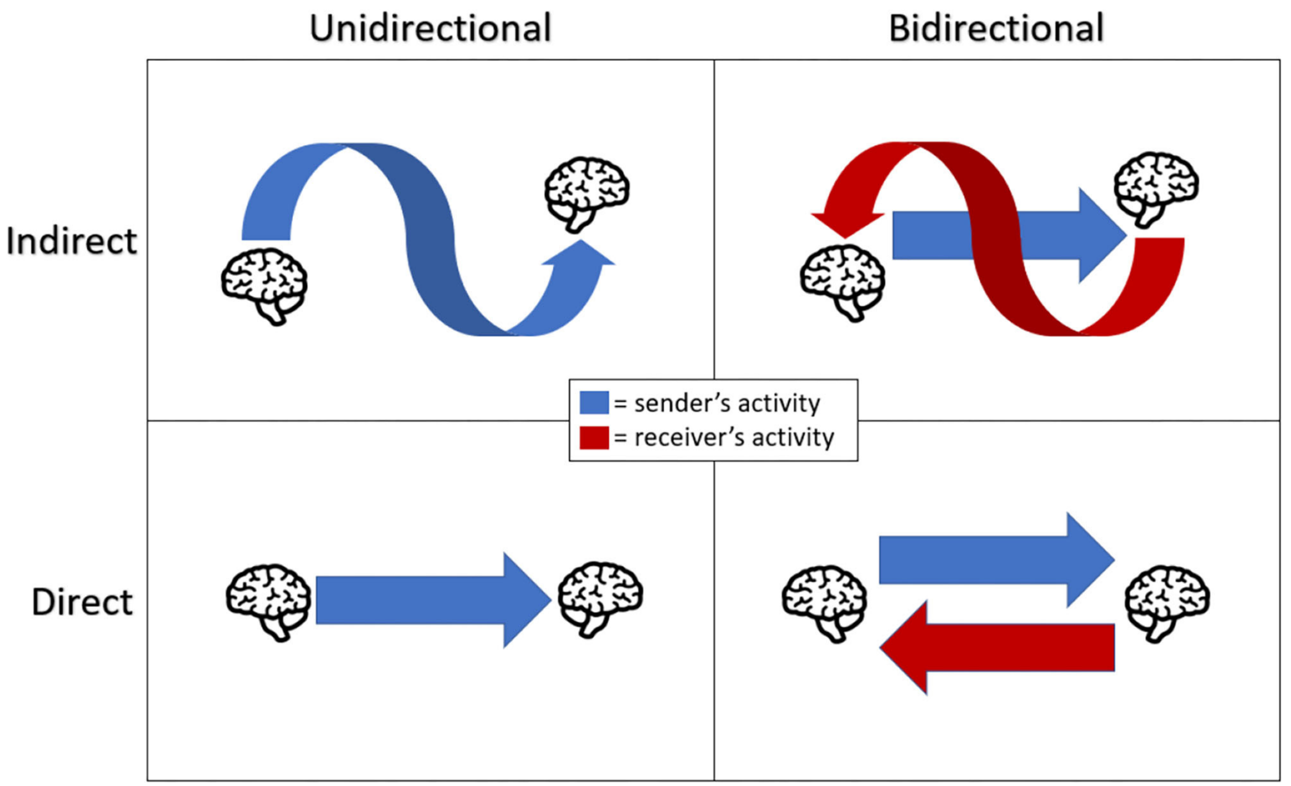

FIGURE 2 | A graphical scheme of collaboration type. Directionality refers to the flow of information, either just from sender to receiver or in both directions. Directness refers to the use of brain stimulation to send information (a straight arrow) or other means (a curved arrow). It is important to note that indirect unidirectional systems do not qualify as B2Bs by our definition and that indirect bidirectional systems could involve indirect (curved arrow) information transmission from the sender or the receiver, not just as depicted.

a user's brain activity and uses it to modulate another user's brain activity allowing information transfer between the two brains. However, this definition does not accurately reflect the rich diversity of B2BI systems. Through this systematic review, we will define current B2Bs in terms of directionality (the flow of information) and directness (the use of brain stimulation to send information) (see **Figure 2**); in this study a true B2BI is defined as a direct bidirectional B2BI. Unidirectional systems only transmit information from one subject to another, while bidirectional systems allow for the transmission of information back in a call-and-response design. Each of these directions can also be labeled as direct or indirect, indicating the means through which information is sent. Direct transmission involves activation of the receiving brain via the B2BI, through some means such as magnetic, ultrasonic, or electrical stimulation. Direct B2BIs employ only neuromodulation to impart information to the receiver. Indirect transmission refers to any system that uses any method other than neuromodulation at any point of the communication. Direct and indirect uni and bidirectional B2BIs, though fundamentally different in their design, often have similar applications. B2BIs show potential in allowing communication with locked-in patients, advanced user state monitoring, and even potential military applications (Hildt, 2019). Some literature that discusses B2BI does not meet these criteria; research by Maksimenko et al. (2018) is fascinating and adjacent to the field, but we believe closer relates to the subject of hyperscanning and is outside the scope of this review. James (2011) has a similar issue, discussing and theorizing about brain-to-brain communication however failing to present a device that we think qualifies as a true B2BI. These definitions allow us, as well as other researchers, to continue to analyze and produce research in this new field. Finally, we seek to identify research issues that have not been fully addressed by the literature to date. Establishing research directions and questions can help guide researchers looking for new avenues and investigations to pursue in the budding field of B2BI. In particular, this study focused on four main research questions (RQs) regarding (1) BCI methodology, (2) CBI methodology, (3) Collaboration type, and (4) Collaboration model by subject type.

Chronologically, B2BI research has advanced from indirect unidirectional systems to direct unidirectional systems to indirect bidirectional systems. Early devices presented by James in 2011, as well as other indirect unidirectional systems, bear most resemblance to traditional BCI systems with visual feedback rather than actual B2BIs. It was not until 2013–2015 that direct B2BI systems became commonplace in research. From there, researchers began to improve the systems and develop new paradigms to test their applications. Such improvements include use of transcranial focused ultrasonic stimulation (tFUS) for increased spatial accuracy of neuromodulation (Lee et al., 2017) in non-invasive B2BI. Rodent studies are often capable of invasive methods of neurostimulation, and thus research in the animal model began with technology like implanted electrodes (Pais-Vieira et al., 2013; Yu et al., 2014) and have equally advanced into technology such as optogenetic recording and stimulation of rat brains (Lu et al., 2020). Beyond just the individual BCI and CBI devices or methods employed, task design has evolved as well. Referred to in this paper as the collaboration model, most studies in this review employ a 1:1 model, however N:N models involving transmission of information between a network of rodent brains have been tested (Pais-Vieira et al., 2015). In 2019, Jiang et al. added to the body of literature supporting the collaborative potential of B2BI with a N:1 collaboration model.

Review Objectives

The overarching objective of this study was to conduct a comprehensive review on B2BI research, with the goal of systematically identifying, critically appraising, and synthesizing all relevant studies on neural communication between two or more brains. An explicit systematic method, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) was used to address four specific research questions (RQs) regarding BCI methodology (RQ1), CBI methodology (RQ2), collaboration type (RQ3), and collaboration model by subject type (RQ4) which together articulate the current-state-of research being conducted in B2BI. PRISMA is known to minimize bias and thus provide reliable findings from which conclusions can be drawn (Liberati et al., 2009). To the best of our knowledge, this is the first systematic review study that used PRISMA to compile all relevant and cutting-edge B2BI research to address the current state-of-the-art brain-to-brain interface research since its first publication in 2011.

RQ1. What is the BCI system employed and what region of the brain is neural activity recorded? To answer this BCI methodology-related question, we analyze the usage frequency of different BCI methods in the 15 selected research papers on B2BI. Due to the small body of literature, all 15 studies can be divided into using either electroencephalogram (EEG) recording, intracortical microelectrodes (ICM), or optogenetics. For increased clarity, these categories were further subdivided into the region of the brain that the methods targeted: the motor cortex, somatosensory cortex, visual cortex, or the nucleus incertus. The BCI method used is important, as it relates to not only the task performed by the "sender" in a B2BI system, but also the type of information being encoded and sent (i.e., motor movements).

RQ2. What is the CBI system employed and what method does that system use to elicit neural activity? To address the CBI methodology of B2BI systems in literature, this paper analyzes the usage frequency of different CBI technology and the regions of the brain that they target. B2BI studies utilize either intracortical microelectrodes (ICM), transcranial magnetic stimulation (tMS), transcranial focused ultrasonic stimulation (tFUS), or optogenetics. These devices were used to stimulate either somatosensory cortex, motor cortex, or visual cortex (phosphenes) in humans. In animal models, either the somatosensory cortex, nigrostriatal pathway, nucleus incertus, or antenna are targeted. The CBI methodology indicates what the "receiver" is intended to do in a given B2BI task (i.e., move left or right).

RQ3. Which of the four categories (indirect/direct unidirectional or indirect/direct bidirectional) does the collaboration between subjects fall under? To address the question of collaboration type, we categorize all of these selected literature based on directionality. As mentioned previously, these terms refer to the overall design of the B2BI system, indicating how the participants were able to communicate with each other (i.e., using peripheral nervous system pathways or direct neuromodulation).

RQ4. Through what model (1:1, N:1, 1:N, N:N) do the subjects collaborate? To answer this collaboration model-related question, we also further divide papers by species of subject, as several studies employ cross-species B2BI. The 15 experimental research papers selected only utilize humans, rodents, and cockroaches as subjects. Inter-species pairs exist on several occasions, and answering this question allows us to determine the application of B2BI systems (e.g., communication, team collaboration, decision making).

REVIEW METHOD

We applied the systematic approach PRISMA (Liberati et al., 2009) in this review. Research articles were gathered from four different databases: (a) IEEE Xplore for a technology perspective; (b) PubMed, for a medical perspective, (c) Engineering Village, for an engineering perspective; and (d) Web of Science for a cross-disciplinary perspective (Powers et al., 2015).

Inclusion and Prescreening Criteria

Inclusion criteria were English articles written between 2013 and August 18th 2020. The first experiment conducted using direct B2BI was published in 2013, so that year functioned as our starting point. Unpublished or working papers, dissertations, news articles, book chapters, conference papers, and ethical reviews were excluded. Experimental research will be the focus of this analysis, but mention will be given to those papers that do not conduct an experiment but still contribute information to the budding field of brain-to-brain communication.

The search term used in all four search engines was "brain to brain." Typically, a systematic review might include a more complex search term, however there are very few publications on this subject and even fewer domains that the technology has been applied to. **Figure 3** shows the flow diagram of PRISMA with the number of studies from each online database. After the keyword search, duplicates were removed and 193 articles remained. Those articles were screened again based on titles and abstracts, and 43 studies remained. Lastly, 15 experiment-conducting articles were selected.

Eligibility Criteria

This review pertains specifically to experiments conducted with B2BI devices. Experiment studies where subjects' brain

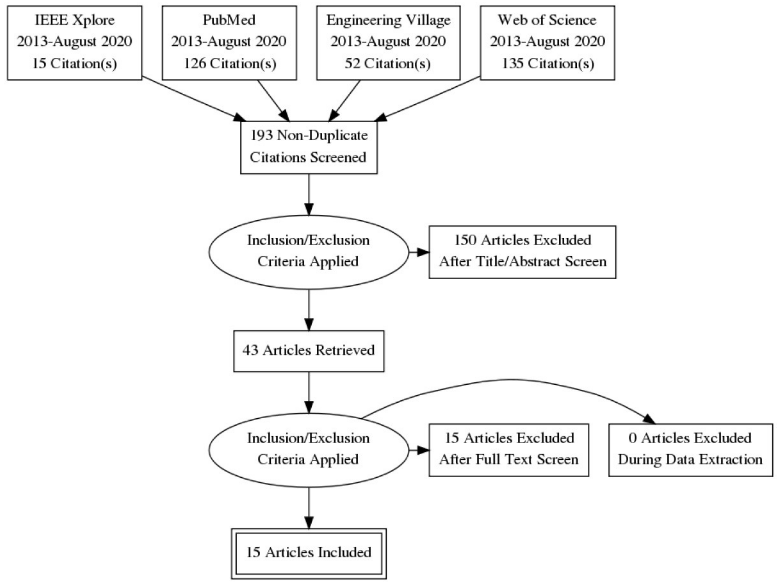

FIGURE 3 | PRISMA flow diagram of brain-to-brain interface research paper review.

activities were measured simultaneously but no data was actively "sent" from one brain to the other were excluded. Due to the small pool of literature, further screening based on subject or experimental design (control group, measured variables, etc.) proved infeasible. The main question when screening full text articles for eligibility was whether or not the study recorded activation from one brain that was used to selectively modulate activation in a different brain. Screening based on this question resulted in the 15 selected experimental studies.

RESULTS

The current status of B2BI research, based on the 15 selected papers, is shown in **Figure 4** and **Table 1**. The most commonly used device for BCI is EEG (12 papers, 80% of the literature), specifically the method of targeting the motor cortex in a motor imagery (MI) task (7, 46.7%). ICM was the most common CBI technology employed (6, 40%), and most frequently stimulated the somatosensory cortex (5, 33.3%). The majority of papers utilized a direct unidirectional collaboration (11, 73.3%) and the large majority of papers utilized a 1:1 collaboration model (13, 86.7%).

BCI Methodology

In the 15 B2BI studies analyzed, a total of 3 different neuroimaging technologies were applied to record neural signals. EEG was used by 80% (12) of the studies, ICM was used by 13.3% (2), and optogenetics was used by 6.7% (1) of the studies. Every study that involved human subjects employed EEG for the BCI portion of their experiment while ICM was used as a BCI exclusively for rodent-to-rodent studies. Optogenetics was

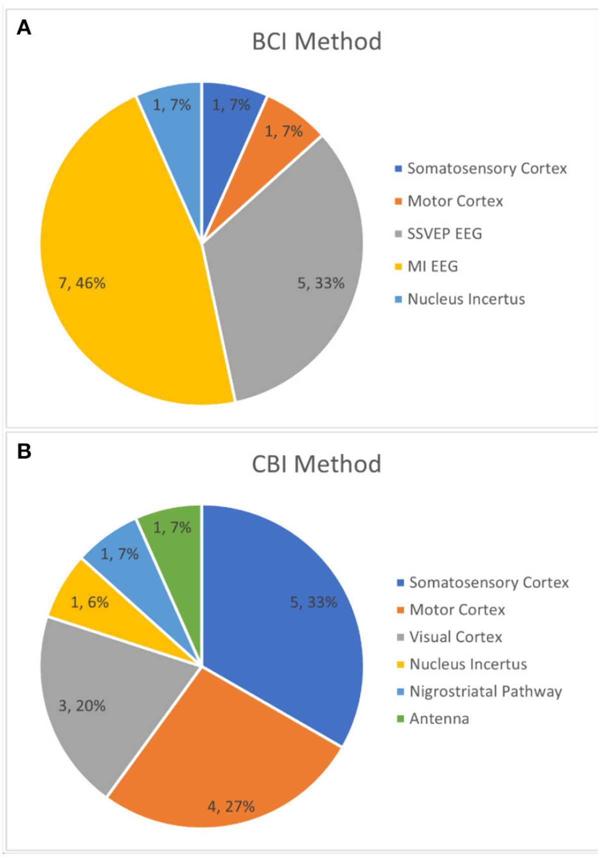

FIGURE 4 | (A) The percentage of papers that target each region with their BCI. **(B)** The percentage of papers that target each region with their CBI.

TABLE 1 | Summary of 15 brain-to-brain interfacing studies.

BCI Device	BCI Method	CBI Device	CBI Method	Collaboration Type	Collaboration Model	References
(Neuroimaging)		(Stimulation)				
EEG	MI	tMS	Visual Cortex	Direct Unidirectional	1:1 (Human:Human)	Grau et al., 2014
			Motor Cortex	Direct Unidirectional	1:1 (Human:Human)	Rao et al., 2014, Rajesh et al., 2020
				Indirect Bidirectional	1:1 (Human:Human)	Mashat et al., 2017
		ICM	Somatosensory Cortex	Direct Unidirectional	1:1 (Human:Rodent)	Yu et al., 2014, Zhang et al., 2019
		tFUS	Somatosensory Cortex	Direct Unidirectional	1:1 (Human:Human)	Lee et al., 2017
	SSVEP	tMS	Visual Cortex	Indirect Bidirectional	1:1 (Human:Human)	Stocco et al., 2015
					N:1 (Human:Human)	Jiang et al., 2019
		ICM	Antenna	Direct Unidirectional	1:1 (Human:Cockroach)	Li and Zhang, 2016
			Nigrostriatal Pathway	Direct Unidirectional	1:1 (Human:Rodent)	Koo et al., 2017
		tFUS	Motor Cortex	Direct Unidirectional	1:1 (Human:Rodent)	Yoo et al., 2013
ICM	Motor Cortex	ICM	Somatosensory Cortex	Direct Unidirectional	1:1 (Rodent:Rodent)	Pais-Vieira et al., 2013
	Somatosensory Cortex	ICM	Somatosensory Cortex	Indirect Bidirectional	N:N (Rodent:Rodent)	Pais-Vieira et al., 2015
Optogenetics	Nucleus Incertus	Optogenetics	Nucleus Incertus	Direct Unidirectional	1:1 (Rodent:Rodent)	Lu et al., 2020

only used once (Lu et al., 2020), and that study was also a rodent-to-rodent experiment. This discrepancy can be ascribed to the high accuracy of invasive methods such as ICM and optogenetics, assuming that the subject is willing to undergo the operation. In human studies, non-invasive methods take precedence despite their lower accuracy most likely because of ease of access, application, and data analysis.

Of the studies that employed EEG, either motor imagery (MI) or steady state visually evoked potentials (SSVEP) were measured by the BCI. MI EEG was used as a simple method of generating a binary signal, based on event related desynchronization (ERD) between the left and right hemispheres during right and left hand/feet movements, in Grau et al. (2014), Rao et al. (2014), and Rajesh et al. (2020). MI EEG also functioned as a direct translation, where the imagined movement of a hand corresponded to a similar action on the receiving end (right hand movement begets right turn, etc.) in Yu et al. (2014), Mashat et al. (2017), Lee et al. (2017), and Zhang et al. (2019). SSVEP EEG was applied in similar ways, with Stocco et al. (2015) using the visually evoked potentials to create a simple binary signal (subject focusing on one flashing LED or another) while Li and Zhang (2016) and Koo et al. (2017) used flashing LEDs on the left and right of a screen that corresponded to left and right movement of the receiver.

As mentioned, invasive methods were used for all the studies involving rodent-to-rodent transmission of information. The higher accuracy of these methods allowed for more unique applications. Pais-Vieira et al. (2013), the first study to employ a direct brain-to-brain paradigm, measured motor cortex activation in rats via ICM. Pais-Vieira et al. (2015) later went on to measure somatosensory cortex activation in rats in their network of rodent brains also using ICM. Lu et al. (2020) used optogenetically modified rats to measure activation of the nucleus incertus; this activation was used as a gauge of locomotion speed.

CBI Methodology

In total, four different CBI technologies were used in the selected B2BI literature. Used equally most frequent were ICM and tMS, each used by 40% (6) of the studies analyzed. Beyond those two, 13.3% (2) of studies used tFUS and 6.7% (1) used optogenetics. As with the BCI methodology, CBI methodology is heavily dependent on the task. In terms of ICM applications, Yu et al. (2014) and Zhang et al. directly stimulated the somatosensory cortex to steer the movement of trained rats. At the same time, the somatosensory cortex has been stimulated by ICM for far more complicated tasks, such as rodent behavioral synchronization on a series of tasks (Pais-Vieira et al., 2013) and the creation of a biological neural network of rodent brains to classify stimulus and even forecast weather (Pais-Vieira et al., 2015). ICM was also used to steer a cockroach through a maze via antenna stimulation (Li and Zhang, 2016) and manipulate rat movement through a maze via nigrostriatal pathway stimulation (Koo et al., 2017).

TMS forms the bulk of CBI methodology with human subjects. Phosphenes, or tMS stimulation of the visual cortex to produce artifacts in a person's field of view, were used as a visual indicator of a binary choice (1 or 0, yes or no, left or right) in Grau et al. (2014), Stocco et al. (2015), and Jiang et al. (2019). The remainder of applications of tMS were for stimulating the human motor cortex either to press a button (Rao et al., 2014; Rajesh et al., 2020) or directly move a subject's limb (Mashat et al., 2017). Though less common, tFUS is also capable of non-invasively modulating neural activity. In B2BI literature, it has been used in humans targeting the somatosensory cortex to produce tactile sensations in the hands (Lee et al., 2017) and in rodents targeting the motor cortex to produce tail movements (Yoo et al., 2013). Lastly, as with their BCI, Lu et al. (2020) used optogenetically modified rodents in the CBI portion of their study. The rodent's nucleus incertus was hit with light to produce activation, allowing control of locomotive speed in the rat.

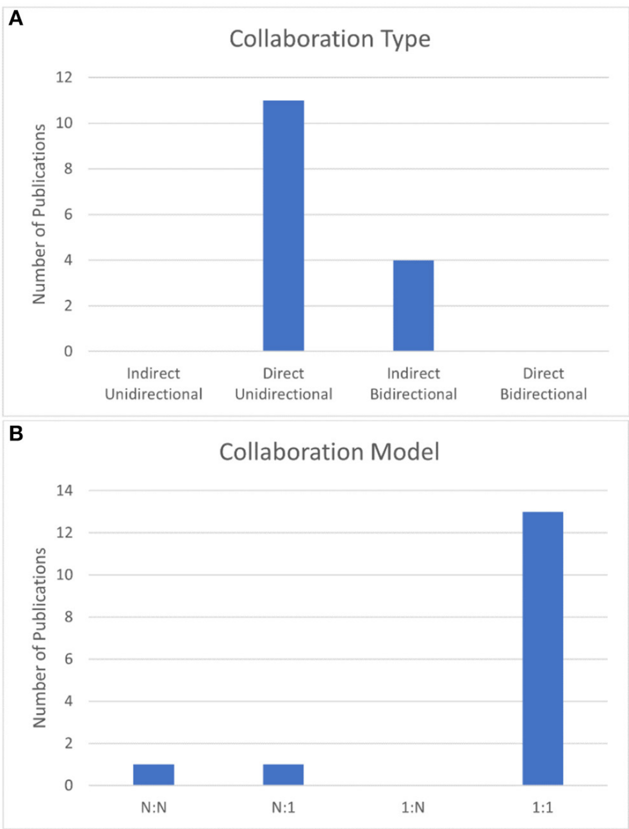

FIGURE 5 | (A) Number of papers that employ each collaboration type. **(B)** Number of papers that employ each collaboration model.

Collaboration Type

As stated previously in this paper, B2BI designs can be broken down into four categories. These categories, and the percentage of selected B2BI papers that fall into each of them, are shown in **Figure 5**. Indirect unidirectional involves the transfer of information in only one direction between two brains, however the information transfer is not done through a neuromodulatory device. While the classification of indirect unidirectional exists, these studies are more akin to hyperscanning literature and are not classified as true B2BI. The large majority of B2BI literature, 73.3% (11) of it, uses a direct unidirectional collaboration type; direct unidirectional designs transmit information in one direction between subjects using some form of direct neuromodulation (tMS, ICM, etc.). These papers can be seen in every category of BCI and CBI systems, as shown in **Table 1**.

Less common are the indirect bidirectional studies which transmit information in both directions between subjects. These are labeled as indirect as they transmit information in one direction via neuromodulation, however the return of information to the sender is done through indirect methods such as visual feedback (e.g., messages on a computer screen). This collaboration type was employed by 26.7% (4) of the selected articles (Pais-Vieira et al., 2015; Stocco et al., 2015; Mashat et al., 2017; Jiang et al., 2019). Stocco et al. (2015) and Jiang et al. (2019) used a computer screen to close the loop and make the system bidirectional, however this is not the only approach. Mashat et al. (2017) utilized functional electrical stimulation (FES) of the original sender's arm to close the loop and signal that information has been sent *back* from the receiver. Pais-Vieira et al. (2015) directly transmitted information between a network of rodent brains using ICM. We chose to classify this as indirect bidirectional as the network was not fully connected (not every rodent connected bidirectionally to every other), though we acknowledge that the networked structure of their experiment does stretch the bounds of our definition.

Collaboration Model by Subject Type

The collaboration model employed by each study is an important descriptor of how information was sent in the system and who the information was sent to. 46.7% (7) studies transmitted information from human subject to human subject, shown again in **Table 1**. There were several studies that employed cross-species B2BIs, with 26.7% (4) of the studies transmitting information from human to rodent (Yoo et al., 2013; Yu et al., 2014; Koo et al., 2017; Zhang et al., 2019). Pais-Vieira et al. (2013, 2015) specifically worked with only rodent to rodent transmission, as did Lu et al. (2020), forming 20% (3) of the literature. One study, Li and Zhang (2016) transmitted information from a human to a cockroach as well.

Collaboration model is not diverse in the selected literature. All but two studies, or 86.7% (13) of B2BI papers, use a 1:1 model. This means that information, regardless of directionality (unidirectional or bidirectional) is only transmitted between 2 subjects. This trend is broken only by Pais-Vieira et al. (2015) who employed a networked N:N model and Jiang et al. (2019) who employed a N:1 collaboration model.

B2BI Definitions

The exact attributes of a B2BI system are not well-discussed. One third of the studies conducted in the field do not include a definition of brain-to-brain interfacing. Jiang et al. (2019) provides a comprehensive definition, stating that "brain-to-brain interfaces (BBIs) in humans are interfaces which combine neuroimaging and neurostimulation methods to extract and deliver information between brains, allowing direct brain-to-brain communication. A BBI extracts specific content from the neural signals of a 'Sender' brain, digitizes it, and delivers it to a 'Receiver' brain." Alongside this paper, the large majority of studies, 8 out of the 10 that provide a definition, specify the existence of a BCI and CBI component. This aligns with the concept of neuromodulation being key in B2BI, and the requirement of a CBI in the information transfer (i.e., a direct rather than indirect).

In order to form as inclusive a definition as possible while still maintaining the critical attributes that make a B2BI system, we created a more standardized definition and provide with it a classification of B2BI devices into further categories. A B2BI is a system, composed of a BCI and CBI portion, that records one (or several) user's brain activity and uses it to directly modulate another (or several other) user's brain activity allowing information transfer between the two brains, with the CBI activation as a function of activity recorded by the BCI allowing the receiver to infer the sender's cognitive state.

Reusing the terminology presented earlier, this definition further classifies B2BI systems as either direct unidirectional, indirect bidirectional, or direct bidirectional systems so long as they include a CBI that directly modulates a receiving brain at some point in the information transfer loop. Importantly, systems that employ only BCI devices or only neurostimulation (such as indirect unidirectional systems) are clearly excluded. Studies such as James (2011) and Maksimenko et al. (2018), mentioned previously, discuss and contribute to the realm of B2BI research, however they fail to demonstrate a system that meets the definition. In terms of further classification into categories relating to collaboration model, this definition includes systems involving more than just two subjects. Though very few studies include complex collaboration models at this time, we aim to include B2BI devices that exist now and that may exist in the future.

DISCUSSION

B2BI Systems

Pertaining to the frequency with which each BCI device was used and how it was used, we found that 80% of studies selected used EEG. No other non-invasive BCI devices were reported, with the remainder of studies using either ICM or optogenetics in exclusively rodent models. These EEG based BCI systems employed either MI (46.7%) or SSVEP (33.3%). The invasive BCI methods on the other hand were able to target more specific locations (nucleus incertus, motor and somatosensory cortex itself). The application of non-invasive BCI methods for human subjects makes sense, as implanting electrodes in humans is not currently a commonplace procedure. EEG is the chosen option, most likely due to an abundance of literature in the field of BCI utilizing the technology, however EEG lacks the spatial resolution to identify complex brain activity due to the source localization problem. Of the most common EEG methods in the selected literature, MI has been limited to mostly binary information transfer potentially due to the difficulty of classifying more than two or three options at once. SSVEP, while being capable of more than two or three classes, is more akin to eye tracking than a true measure of user-generated brain activity.

Future research should explore other BCI hardware. Though far less practical in terms of size and ease of use, functional magnetic resonance imaging (fMRI) has shown potential for recognizing more abstract cognitive states and even emotions (Ruffini, 2016). A BCI method such as functional near-infrared spectroscopy (fNIRS) could potentially serve as a middle ground in terms of the spatial resolution of fMRI and the portability of EEG. With these new devices, the software portion of a B2BI will need to change as well. Current systems transmit mostly binary information and future applications of this technology, especially those applying more advanced neuroimaging methods, will require much greater throughput and more complicated handling of brain activity before the receiver is stimulated by the CBI.

In regards to analyzing the CBI devices used and where they targeted (RQ2), there is far less consensus. The majority of studies used either ICM (40%) or tMS (40%). These systems targeted mostly the somatosensory cortex (33.3%), with slightly fewer targeting the motor cortex (26.7%) and visual cortex (20%). Invasive CBI devices were exclusively used with rodent models while non-invasive CBI devices were used with both rodents and humans. Invasive CBI techniques are usually not preferred due to invasiveness-associated complications. Non-invasive CBI systems including transcranial direct/alternating current stimulation (tDCS/tACS), tMS, and tFUS have been actively investigated because of the clinical-friendly, non-invasive approach. Compared to other non-invasive neuromodulation methods, such as tDCS and tMS, tFUS is promising due to its excellent spatial selectivity and superior penetration depth (Lee et al., 2016). The mechanism of tFUS neuromodulation remains to be explored; low-intensity tFUS is theorized to exert acoustic radiation forces via the acoustic pressure waves which can interact with neuronal membrane to induce plasma membrane deformation, and affect mechano-sensitive ion channels, to modulate the activity of neurons (Tyler, 2012; Tyler et al., 2018). Other underlying mechanisms may involve the intramembrane cavitation induced sonophoresis (Krasovitski et al., 2011) and the thermal effect of ultrasound (Darrow et al., 2019). These unclear underlying mechanisms hinder scholars from choosing optimal ultrasound parameters to modulate the neural activity of the brain. In other words, different sonication settings of ultrasound frequency, pressure, intensity, waveform, could result in excitation or inhibition of neural activity, and cause various degrees of neurofeedback. Such a challenge may increase the difficulty of controlling CBI systems from the software perspective.

Besides the interaction between ultrasound and brain, another challenge for tFUS based CBI systems has to do with the interaction between ultrasound and skull. The acoustic attenuation and distortion caused by the skull has been treated as a barrier for transcranial ultrasound application for more than half a century (Hynynen and Clement, 2007). Over the past 20 years, scholars found that low-frequency ultrasound has less acoustic attenuation and distortion for transcranial ultrasound propagation. Also, the development of phased-array transducers makes it possible for transcranial ultrasound therapy by applying aberration correction (Clement and Hynynen, 2002). The low-intensity tFUS single-element transducer, rather than multi-element (phased-array) transducer, is the most common device for transmitting acoustic energy to the desired region through the skull due to its low cost and easy manipulation. However, in this case, it is hard to adjust the directivity and focal depth of ultrasound beam, which is a limitation of tFUS CBI systems to target specific areas inside the brain from the hardware perspective. To overcome such limitations, some promising methods have been proposed recently, which includes applying acoustic lens (Maimbourg et al., 2020) or holographic plates (Jiménez-Gambín et al., 2019) in front of the tFUS transducer to achieve adjustable acoustic beam steering and focusing. Furthermore, new applications of tFUS based CBI systems may be explored more. As an example, a sonogenetics approach can be used to stimulate specific neurons in the desired area of the brain (Ibsen et al., 2015).

Improvements and standardizations in the realm of defining these systems is also an important step, as the definitions provided in the literature are inconsistent. Studies focus too much on their application for transmitting motor information, as in Mashat et al. (2017), overly specify attributes such as wireless transmission, as in Rajesh et al. (2020), or only specify the inclusion of a BCI and CBI portion and very little else, as in Rao et al. (2014) and Li and Zhang (2016). More cohesion in the field as to what type of B2BI is being presented would allow for quicker communication of applications for these devices. Ideally, a more robust definition like the one provided here will aid and expedite discussion about this budding technology.

Experiment Design

We found the design of B2BI systems in the collected literature to be lacking in diversity. As collaboration and communication are some of the core applications of B2BI, results in this area are key in demonstrating the potential of the technology. The bulk of literature followed a direct unidirectional design (73.3%) while no studies implemented a direct bidirectional design (neuromodulation on both the sender and receiver). In a similar fashion, almost every study employed a 1:1 collaboration model (86.7%). More complex models were very rare. The majority of 1:1 studies employed either a human:human model (46.7%) or a human:rodent model (26.7%). The frequency of these methods is understandable; the field is very young and unidirectional models must logically predate bidirectional models. Beyond that, the use of human-to-rodent and rodent-to-rodent models is also indicative of the precaution being taken in the realm of CBI safety with human subjects. High confidence in neuromodulation within human subjects is needed to expand into more complex designs, such as networked human brains in an N:N model resemblant of Pais-Vieira et al. (2015). Unidirectional models are also likely far more common as bidirectional models would double the cost of the device, making indirect bidirectional systems (utilizing peripheral nervous pathways for the response) more reasonable.

Future research needs to expand into more complex collaboration designs and test the capabilities of B2BI. Jiang et al. (2019) is the only study to employ a 2:1 collaboration model, where the receiver had to identify which sender was more reliable (due to the introduction of noise to a random receiver's signal). Multiple sender systems such as this more closely resemble the diversity of some real world applications, and investigation into 1:N collaboration models (with one sender broadcasting to a group of receivers) should follow suit. To see the true potential of collaboration in these devices, systems such as Pais-Vieira et al.'s (2015) N:N model warrant further exploration as well. Though uses in the domain of human subjects may not be employed as biological neural networks, a network of collaborating brains exchanging information to and fro could hold useful applications in cases requiring complex teamwork. All of these future directions require investigation into direct bidirectional systems, something we have not seen yet in B2BI literature. Transmission of information directly between brains, both to and from each subject, is necessary to explore complex applications of B2BI technology.

Unfortunately, and similar to the procedure used with existing CBI systems such as tMS, tFUS neuromodulation usually requires patients to get CT or MR scans first to provide researchers the skull morphology. Then, based on such information and through the assistance of a neuronavigation system, an appropriate ultrasound beam with designed acoustic parameters can be generated and transmitted into the desired region of the brain for a given period of time. Given the two limitations of tFUS-based CBI systems mentioned in B2BI Systems, how to monitor and evaluate the ultrasound beam inside the desired region of the brain would be a key to increase the success rate, and decrease the risk of CBI experiments. Future work should include mention of imaging guidance, temperature and neural response monitoring for the sake of safety and effectiveness, information that is lacking in some tMS and tFUS B2BI studies. Since acoustic radiation force plays a crucial role for ultrasound neuromodulation, magnetic resonance-acoustic radiation force imaging (MR-ARFI) method can be used to specify the location, and quantify the magnitude of ultrasound beam inside the brain (Phipps et al., 2019). Furthermore, MR-thermometry is a useful tool to show the temperature rise in the sonication area of the brain (Ozenne et al., 2020). With these methods, it is expected to ensure the operational safety of ultrasound neuromodulation for clinical applications. Meanwhile, functional magnetic resonance imaging (fMRI) has shown its effectiveness for measuring neural activity of the brain (Beisteiner et al., 2020), and could help researchers choose optimal sonication parameters for future CBI and B2BI studies.

Applications

Applications of B2BI range from rehabilitation and treatment to communication, collaboration and synchronization. After an injury that is potentially treatable by brain stimulation, such as a stroke, activation motor regions of the brain can help the patient recover faster. Activation of motor cortex via brain stimulation such as tMS can help promote neuroplasticity and a relearning of lost motor ability (Neren et al., 2016). A physical therapist could, through a B2BI, issue motor commands to a patient during rehabilitation to assist in recreating lost pathways in their brain. Something similar to this was done by Mashat et al. (2017) using functional electrical stimulation (FES) of the arm; the next logical step up from FES would be direct neural stimulation rather than muscular. This application of B2BI could potentially expedite rehabilitation of post-stroke patients through neuroplasticity. Beyond the professional-patient relationship, B2BI has significant future applications in communication and collaboration. In the first B2BI study, Pais-Vieira et al. (2013) demonstrated that rodents connected to a B2BI could learn to synchronize their behavior without any peripheral nervous system cues (such as sight of the other rat). Behavioral synchronization such as this could be very advantageous in a workplace where it is important for workers to move with each other during a complex task. Adding to this a networked, or at least >1:1, collaboration model could result in a team of workers moving as a collective unit while completing a potentially hazardous task. Stocco et al. (2015) posits that B2BI could find application in communication between users when traditional verbal communication falls short, such as in users with Broca's aphasia or even different native languages. These applications are supported by the relatively small body of literature we have to date, but as research and technology progresses futuristic applications become less futuristic.

As BCI technology becomes more capable of recording nuanced brain activity and CBI technology more precise at stimulating the brain, it becomes more possible to transmit complex information between B2BI users. Future B2BI devices could transmit abstract thoughts, memories, or emotions from user to user, things that are often quite difficult to convey to other humans through conventional means. As the body of research continues to grow, so do the possibilities and applications of this technology.

CONCLUSIONS

We systematically identified, critically appraised, and synthesized 15 relevant studies on brain-to-brain interfaces for information transmission between brains. These studies, all published after 2013, fit the pre-specified inclusion and eligibility criteria. We used an explicit systematic method, the preferred reporting items for systematic reviews and meta-analyses (PRISMA) to address 4 specific questions regarding BCI methodology (RQ1), CBI methodology (RQ2), collaboration type (RQ3), and collaboration model by subject type (RQ4). We also present a wide-encompassing definition of a brain-to-brain interface to simplify later reviews and classification.

Future challenges and directions for B2BI research demonstrated in this review include:

- The lack of consensus on CBI methodology, indicating the existence of benefits and drawbacks to each region of the brain that may have been chosen.
- Very little diversity in CBI technology used. The large majority of studies used either tMS or ICM. In terms of non-invasive neuromodulation, other devices such as tFUS and transcranial direct/alternating current stimulation (tDCS/tACS) could allow novel applications of the technology in future studies (Rao et al., 2014).
- Only a few studies that employ complicated collaboration designs showed that few researchers have looked to stretch the limits of what B2BI may be capable of.
- No direct bidirectional collaboration types, only studies using peripheral nervous pathways (visual feedback). Future research into direct bidirectional systems could allow B2BI communication while performing more complicated tasks.

This systematic review is unfortunately limited in several ways due specifically to the limited number of publications. The PRISMA system could not be employed in its entirety as certain measures, like the PICOS statement, were too limiting for the small number of papers. Rather than filter the papers analyzed by metrics such as participants and interventions, specific research questions were listed in detail for analyses and as many experimental papers were selected as possible. The small number of papers targeted also poses possible problems regarding bias within and across studies. In order to most thoroughly present the state of B2BI research though, all 15 studies were included and analyzed. All limitations considered, this systematic review, based on the findings of documented, transparent, and reproducible searches, should help build cumulative knowledge and guide future research regarding direct communication between brains via B2BIs. The summarized findings herein will hopefully help facilitate new discoveries and experimentation to push the boundaries of brain-to-brain interfacing.

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 author/s.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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I Am Looking for Your Mind: Pupil Dilation Predicts Individual Differences in Sensitivity to Hints of Human-Likeness in Robot Behavior

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The presence of artificial agents in our everyday lives is continuously increasing. Hence, the question of how human social cognition mechanisms are activated in interactions with artificial agents, such as humanoid robots, is frequently being asked. One interesting question is whether humans perceive humanoid robots as mere artifacts (interpreting their behavior with reference to their function, thereby adopting the design stance) or as intentional agents (interpreting their behavior with reference to mental states, thereby adopting the intentional stance). Due to their humanlike appearance, humanoid robots might be capable of evoking the intentional stance. On the other hand, the knowledge that humanoid robots are only artifacts should call for adopting the design stance. Thus, observing a humanoid robot might evoke a cognitive conflict between the natural tendency of adopting the intentional stance and the knowledge about the actual nature of robots, which should elicit the design stance. In the present study, we investigated the cognitive conflict hypothesis by measuring participants' pupil dilation during the completion of the InStance Test. Prior to each pupillary recording, participants were instructed to observe the humanoid robot iCub behaving in two different ways (either machine-like or humanlike behavior). Results showed that pupil dilation and response time patterns were predictive of individual biases in the adoption of the intentional or design stance in the IST. These results may suggest individual differences in mental effort and cognitive flexibility in reading and interpreting the behavior of an artificial agent.

Keywords: intentional stance, human–robot interaction, pupil dilation, individual differences, human-likeness

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INTRODUCTION

Artificial agents are becoming increasingly present in our daily environment. From vocal assistants to humanoid robots, we are observing a change in the role played by these new entities in our lives (Samani et al., 2013). However, it is still a matter of debate as to whether humans perceive embodied artificial agents, such as humanoid robots, as social and intentional agents or simple artifacts (Hortensius and Cross, 2018; Wykowska et al., 2016). Several researchers have investigated whether humans would deploy similar sociocognitive mechanisms when presented with a novel type of (artificial) interaction partner (i.e., humanoid robots) as they would activate in an interaction with another human (Saygin et al., 2012; Cross et al., 2019; Wykowska, 2020).

In this article, we report a study in which we investigated whether robot behavior—by being humanlike or mechanistic—can modulate the likelihood of people adopting the intentional stance (Dennett, 1971). The study also addressed the question of whether pupil dilation—a marker of cognitive effort—can predict the type of stance people would adopt toward the robots, and how all these factors are related to individual "mentalistically inclined" or "mechanistically inclined" biases.

According to Dennett (1971), the *intentional stance* is a strategy that humans spontaneously adopt to interpret and predict the behavior of other humans, referring to the underpinning mental states (i.e., desires, intentions, and beliefs). The intentional stance is an efficient and flexible strategy, as it allows individuals to promptly interpret and predict others' behavior. However, when interacting with nonbiological systems, humans might adopt a different strategy, which Dennett describes as the *design stance*. According to the author, we deploy this strategy when explaining a system's behavior based on the way it is designed to function. The intuition behind Dennett's definition is that humans would adopt the stance that allows them to predict and interpret the behavior of a system in the most efficient way. Thus, the adoption of either stance is not predefined; on the contrary, if the adopted stance is revealed as inefficient, one can switch to the other stance.

Several authors have demonstrated that people tend to spontaneously adopt the intentional stance toward other human and nonhuman agents (Abu-Akel et al., 2020; Happé and Frith, 1995; Heider and Simmel, 1944; Zwickel, 2009; see also Perez-Osorio and Wykowska, 2019a and Schellen & Wykowska (2019) for a review). However, it is not yet entirely clear which of the two aforementioned stances humans would adopt when interacting with humanoid robots. On the one hand, humanoid robots present humanlike characteristics, such as physical appearance (Fink, 2012). Hence, it is possible that these characteristics elicit representations and heuristics similar to those that we rely on when interacting with humans (Airenti, 2018; Dacey, 2017; Waytz et al., 2010; Złotowski et al., 2015). This might trigger the neural representations related to the adoption of the intentional stance (Chaminade et al., 2012; Gallagher at al., 2002; Ozdem et al., 2017; Spunt et al., 2015). Indeed, the presence of humanlike characteristics is one of the key factors that, according to Epley et al., 2007, contribute to anthropomorphism toward artificial agents, facilitating the adoption of the intentional stance. On the other hand, humanoid robots are man-made artifacts, and therefore, they might evoke the adoption of the design stance, as they can be perceived simply as machines (Wiese et al., 2017).

Recent literature has addressed the issue of adopting the intentional stance toward robots. For example, Thellman et al., 2017 presented a series of images and explicitly asked their participants to rate the perceived intentionality of the depicted agent (either a human or a humanoid robotic agent). The authors reported that participants perceived similar levels of intentionality behind the behavior of the human and the robot agents. Marchesi et al. (2019) investigated the attribution of intentionality to humanoid robots, developing a novel tool, the InStance Test (IST). The IST consists of a series of pictorial "scenarios" that depict the humanoid robot iCub (Metta et al., 2010) involved in several activities. In Marchesi et al. (2019), participants were asked to choose between mentalistic and mechanistic descriptions of the scenarios. Interestingly, individuals differed with respect to the likelihood of choosing one or the other explanation. Such individual bias in adopting one or the other stance toward humanoid robots called for examining whether it is possible to identify its physiological correlates. In fact, Bossi et al. (2020) examined whether it is possible to relate individual participants' EEG activity in the resting state with the individual likelihood of adopting the intentional or design stance in the IST. The authors found that resting-state beta activity differentiated people with respect to the likelihood of adopting either the intentional or the design stance toward the humanoid robot iCub. Recently, Marchesi et al. (2021) have identified a dissociation between participants' response time and the stance adopted toward either a human or a humanoid robot. Moreover, the individual bias emerged as being linked to participants' individual tendency to anthropomorphize nonhuman agents.

Since the literature presents evidence for various individual tendencies to adopt either the design or the intentional stance, in the present study, we aimed at using pupil dilation as a marker of individual bias and cognitive effort invested in the task of describing a robot's behavior, by adopting either stance. In addition, we were interested in finding out whether observing different types of robot behavior (humanlike or mechanistic) would have an impact on adopting the two different stances, taking into account individual biases.

Pupillometry as an Index of Cognitive Activity

We focused on pupil dilation, as pupillary response is a reliable psychophysiological measure of changes in cognitive activity (for a review, see Larsen and Waters, 2018; Mathôt, 2018). Literature reports show that the pupils dilate in response to various cognitive activities. Previous studies have investigated the mechanisms underpinning pupil dilation, such as emotional and cognitive arousal (how much activation a stimulus can elicit) and cognitive load (the mental effort put into a task) (Larsen and Waters, 2018; Mathôt, 2018). de Gee et al., 2014 reported that, in a visual detection task, pupil dilation was greater for participants with a tendency to stick to their decisional strategy (defined as "conservative participants") who made a decision not in line with their individual bias in the task. This result shows that pupil dilation can be considered as a marker of conflict between participants' individual bias and the decision they take. Moreover, it has been shown that the variation in pupil size is linked to the activity in the locus coeruleus (Jackson et al., 2009) and to the noradrenergic modulation (Larsen and Waters, 2018), and thus, greater pupil size can be considered as an indicator of general arousal and allocation of attentional resources. Other studies have used pupil dilation as an indicator of cognitive load and mental effort. For example, Hess and Polt (1964) reported that pupil dilation is closely correlated with problem-solving processes: the more difficult the problem, the greater the pupil size. Moreover, the recent literature (Pasquali et al., 2021; Pasquali et al., 2020) assessed the use of pupillometry in real and ecological scenarios where participants interacted with the iCub robot. The authors show that pupillometry can be a reliable measure to investigate cognitive load in the context of human–robot interaction. Overall, these studies provide evidence that pupillometry is an adequate method to study individual tendencies and how they are related to resources allocated to a cognitively demanding task (for a comprehensive review, see also Mathôt, 2018). Here, we consider pupil dilation as a measure of cognitive effort related to the activation of one or the other stance in the context of one's individual biases.

Aims of the Study

The aims of the present study were to 1) examine whether observing an embodied humanoid robot exhibiting two different behaviors (a humanlike behavior and a machine-like behavior) would modulate participants' individual bias in adopting the intentional or the design stance (assessed with the IST) and 2) explore whether this modulation would be reflected in participants' pupil dilation, which is considered as a measure of cognitive effort. More specifically, we explored whether observing a humanoid robot behaving either congruently or incongruently with respect to participants' individual tendency to adopt the intentional stance would lead them to experience different levels of cognitive effort in the InStance Test. That is because we expected participants to experience an increase in cognitive effort due to the dissonance between their individual tendency in interpreting the behavior of a humanoid robot and the need for integrating the representation of the observed behavior manifested by the embodied robot.

MATERIALS AND METHODS

Participants

Forty-two participants were recruited from a mailing list for this experiment (mean age: 24.05, SD: 3.73, females: 24) in return for a payment of 15€. All participants self-reported normal or corrected-to-normal vision. The study was approved by the local Ethical Committee (Comitato Etico Regione Liguria) and was conducted in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki). Each participant provided written informed consent before taking part in the experiment. All participants were naïve to the purpose of this experiment and were debriefed upon completion. Five participants were excluded from data analysis, due to technical problems occurring during the recording phase. Three participants were excluded due to insufficient amount of valid pupil data (<60%). A total of 34 participants were included in the data analysis.

Pupil-Recording Apparatus, Materials, and Procedure

In a within-subject design, participants first attended, in a dimly lit room, the robot observation session, where they were positioned in front of the embodied iCub and observed it exhibiting a humanlike or a machine-like behavior. Right after this session, the participants were led to a different room (dimly lit) where they were instructed to sit down and position their head on a chinrest. They were then presented with the IST. The procedure would then be repeated for the second behavior of the robot. Choosing a within-participants design, and exposing participants to both behaviors of the robot, allows for a higher control of their previous knowledge and experience related to the iCub robot.

Items from the IST were presented on a 22-″ LCD screen (resolution: 1,680 × 1,050). A chinrest was mounted at the edge of the table, at a horizontal distance of 62 cm from the screen. The monocular (left eye) pupil signal was recorded using a screen-mounted SMI RED500 eyetracker (sampling rate of 500 Hz). The dim illumination of the room was kept constant through the whole duration of the experimental sessions. The IST items were displayed through Opensesame 3.2.8 (Mathôt et al., 2012).

Robot Behavior

Before taking part in the IST, the participants were asked to observe the embodied iCub robot, which was programmed to behave as if it was playing a solitaire card game on a laptop positioned in front of it. From time to time, the robot was turning its head toward a second monitor, located on its left side, in the periphery. On this lateral monitor, a sequence of videos was played for the entire duration of this session. The behaviors displayed by the robot, in terms of eye and head movements, were manipulated between two experimental conditions. One condition involved the robot displaying a humanlike behavior, which was a replica of the behavior recorded in a previous attentional capture experiment from a human participant (detailed description of the robot behaviors is beyond the scope of this article; for details, see Ghiglino et al., 2018). It is important to point out that the behavior displayed by the robot in this condition fully embodied the variability and the unpredictability of the behavior displayed by the human when the recording was first made. As a contrast condition, we programmed the robot to display another behavior, which was extremely stereotypical and predictable, defined as "machine-like" behavior. While the "humanlike" behavior consisted of several patterns of neck and eye movements, the "machine-like" behavior consisted of just one pattern of neck and eye movements. In other words, the "machine-like" behavior was generated in order to display no variability at all. The order of presentation of these two behaviors was counterbalanced across participants.

InStance Test Stimuli and Task

After the observation session, the participants performed a 9-point calibration, and they were then presented with the IST (Bossi et al., 2020; Marchesi et al., 2019; **Figure 1**). The

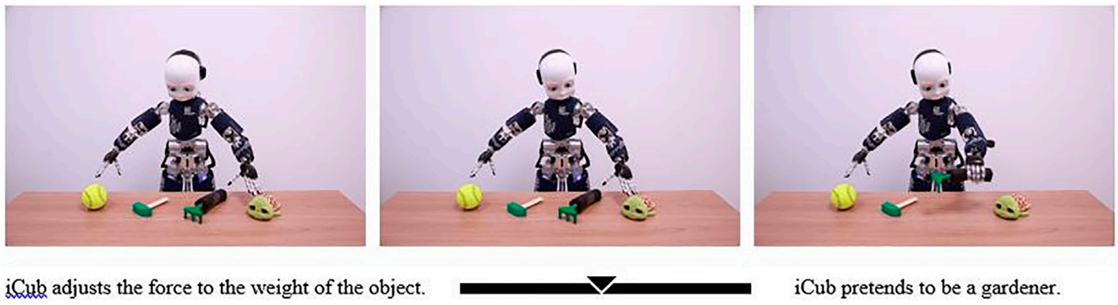

FIGURE 1 | Exemplification of the IST items with exemplification of Sentence A and Sentence B (Marchesi et al., 2019).

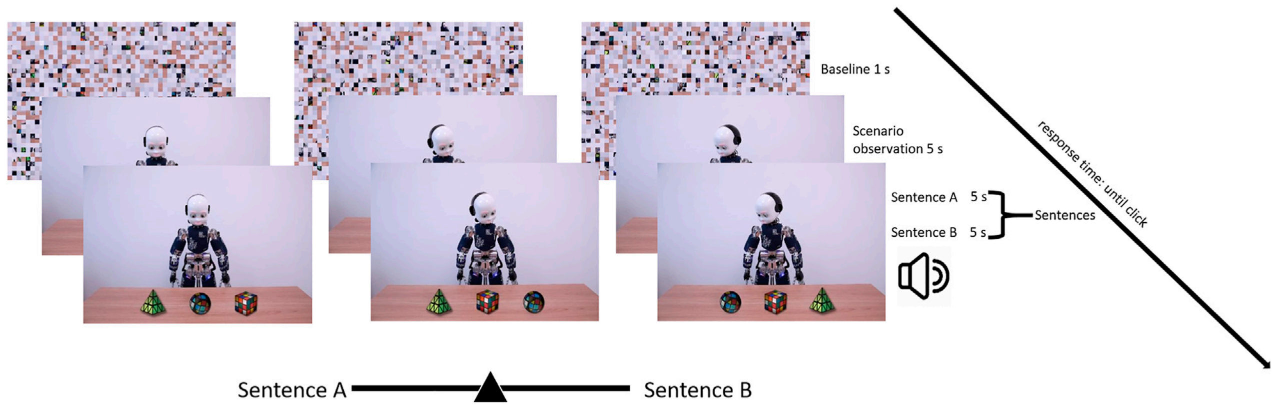

FIGURE 2 | Experimental time line.

instructions in each trial were as follows: (i) first, look freely at the baseline image (1,000 ms), (ii) freely explore the presented item (5,000 ms), (iii) listen to the two sentences (5,000 ms Sentence A and 5,000 ms Sentence B), and finally, (iv) choose the description that you think better explains the presented scenario by moving a cursor on a slider (until click) (**Figure 2**). The presentation order of mechanistic and mentalistic sentences was counterbalanced. Presentation of items was randomized. The IST was split into two subsets[1] of items, with half (one subset, 17 items) presented after one observation session and the other half (17 items) after the second observation session (the order of presentation of the subsets was counterbalanced). An example of the mentalistic sentences is "iCub pretends to be gardener"; an example of a mechanistic sentence is "iCub adjusts the force to the weight of the object" (**Figure 2**). The complete list of mechanistic and mentalistic sentences, associated with the corresponding scenarios, is reported in Marchesi et al. (2019) Supplementary Materials.

[1]The two groups of items of the IST were created based on the results of Marchesi et. al (2019), in such a way that the mean score and SD for both groups were comparable (Group 1: M = 40.60, SD = 15.31; Group 2: M = 40.85, SD= 16.55, t(34) = .82, p = .415).

To avoid eye movements related to the reading process, for each scenario, the two descriptions were presented auditorily through headphones (similarly to the procedure adapted for EEG, Bossi et al., 2020). Moreover, to allow a reliable baseline correction, we created a luminance-related baseline version of each scenario using MATLAB function Randblock (https://it.mathworks.com/matlabcentral/fileexchange/17981-randblock). This function allowed us to create a scrambled version of each item scenario with randomized blocks of pixel positions. The scrambled items were used as specific baselines for each corresponding scenario. This process was necessary to control the different luminance levels of each item.

Pupil Data Preprocessing

All data were preprocessed (and analyzed) using R (version 3.4.0, available at http://www.rproject.org) and an open-source MATLAB (The Mathworks, Natick, MA, United States) toolbox provided by Kret and Sjak-Shie (2019). To clean and preprocess the data, we followed the pipeline proposed by Kret & Sjak-Shie: 1) first, we converted the eyetracker data to the standard format used by Kret & Sjak-Shie's MATLAB toolbox. Since we were interested in exploring how pupil dilation could predict participants' choice in the IST, we decided to take the duration of each sentence as our time window of interest. Thus, data were segmented and preprocessed separately for the selected time windows. By applying this procedure, we reduced the probability that the pupil dilation signal would be biased by the preprocessing procedure (Procházka et al., 2010; Mathôt et al., 2018). In this dataset, we included information relevant to the pupil diameter, start/end time stamps of each segment, and validity of the data point, in separate columns. 2) We filtered dilation speed outliers, trend-deviation outliers, and samples that were temporally isolated, applying the parameters described by Kret and Sjak-Shie (2019). In greater detail, in order to mitigate possible gaps due to nonuniform sampling, dilation speed data were normalized following the formula below:

$$d'^{[i]} = \max\left(\frac{|d[i] - d[i-1]|}{|t[i] - t[i-1]|}, \frac{|d[i+1] - d[i]|}{|t[i+1] - t[i]|}\right). \tag{1}$$

where $d'^{[i]}$ indicates the dilation speed at each sample, d[i] indicates the pupil size series, and t[i] indicates the corresponding time stamp. Dilation speed outliers were then identified using the median absolute deviation (MAD, Leys et al., 2013). MAD is a robust metric of dispersion, resilient to outliers. Samples within 50 ms of gaps were rejected; contiguous missing data sections larger than 75 ms were identified as gaps. The MAD metric was applied to identify absolute trend-line outliers. 3) We interpolated and smoothened the signal using a zero-phase low-pass filter with a cutoff of 4Hz (Jackson et al., 2009). After having applied the pipeline described above, data were baseline-corrected by subtracting the mean pupil size during the baseline phase from the mean pupil size in our time of interest (ToI), and dividing by the mean pupil size during the baseline (Preuschoff et al., 2011).

$$\frac{M_{pupil\ size\ in\ ToI} - M_{baseline\ pupil\ size}}{M_{baseline\ pupil\ size}}. \tag{2}$$

This process allows a clean comparison of the resulting percentage of pupillary change relative to the baseline.

Sample Split and Dichotomization of the IST Response

In line with Bossi et al. (2020), in order to investigate individual biases, participants were grouped by their average individual InStance Score (ISS, the overall score across both robot behavior conditions): mentalistically biased people (>0.5 SD over the mean score, N = 12, average ISS for this group: 62.25, SD: 7.64) and mechanistically biased people (<-0.5 SD below the mean score, N = 9, average ISS for this group: 28.23, SD: 5.66). People who were not clearly over or under the cutoff value (−0.5 < score < 0.5 SD, N = 13, average ISS for this group: 44.90, SD: 4) were considered as the "unbiased" group. Moreover, to be able to investigate participants' stance in the IST (mentalistic vs. mechanistic), we considered the type of selected sentence (by considering as mechanistic a score <50 and mentalistic a score >50) as the attributed explanation to the item (from here on, defined as "Attribution"), leading to a binomial distribution. Although this practice could lead to a considerable loss of information, it allowed for a higher control of the interindividual variability present in the raw IST scores that could bias the overall mean score.

Data Analysis: Pipeline Applied for (Generalized) Linear Mixed-Effects Models

Data analysis was conducted on the mean pupil size (baseline-corrected) for the time windows of interest (Sentence A and Sentence B time periods) using linear (or generalized linear where needed) mixed-effects models (Bates et al., 2015). When it comes to linear mixed-effects models (LMMs) or generalized linear mixed-effects models (GLMMs), it is important to specify the pipeline that was followed to create the models. (i) First, we included all the fixed effects that allowed the model to converge. (ii) We included random effects that presented a low correlation value (|r| < 0.80) with other random effects, to avoid overfitting. In all our models, Participant was included as a random effect. (iii) The significance level of the effects for the LMM was estimated using the Satterthwaite approximation for degrees of freedom, while for the GLMM, we performed a comparison with the corresponding null model (likelihood ratio tests, LRTs). Since time series analyses were not planned, autocorrelation of factors was not modeled. Detailed parameters for each model are reported in the Supplementary Materials.

RESULTS

In line with Marchesi et al. (2019), the score in the InStance Test was calculated ranging on a scale from 0 (extreme mechanistic value) to 100 (extreme mentalistic value). In order to obtain the average InStance Score (ISS) per participant, the scores across single scenarios were averaged. Before performing any preprocessing, the overall average score at the InStance Test after observing the mechanistic behavior was 43.80, with SD: 17.69, and the overall average score after observing the humanlike behavior was 43.44, with SD: 18.03 [$t(65.97) = -0.08$, $p = 0.934$]; thus, the type of robot behavior that participants observed did not modulate the ISS. The overall sample average score at the InStance Test was 43.62, SD: 17.26.

As in the study by Bossi et al. (2020), given that our focus was the individual bias at the IST, in the present section, we will report the results from the mechanistically and mentalistically biased participants, leading to an overall total sample of N = 21 participants. Results on the very same models involving unbiased participants as well are reported in the Supplementary Materials (overall N = 34 participants).

InStance Test Individual Attribution and Pupil Size

The first model (GLMM) aimed at investigating the relationship between pupil size and participants' attribution at the IST. Our fixed effects were as follows: 1) the mean pupil size, 2) robot behavior previously observed, and 3) participants' general bias at the IST, while we considered the selected attribution as the

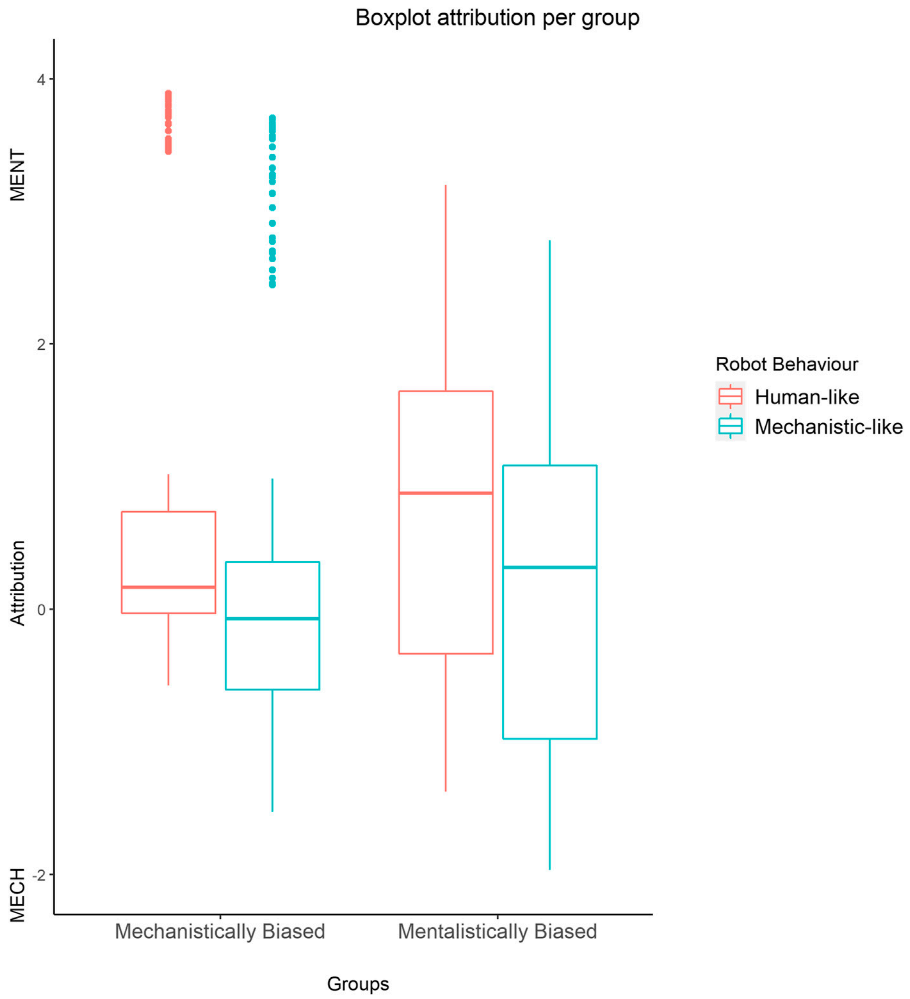

FIGURE 3 | GLMM: boxplot showing the statistically significant effect of RobotBehaviour * Bias on attribution, with extreme values as predicted by the model.

dependent variable. Because of this, the distribution of the GLMM is binomial.

The main effect of RobotBehavior emerged as statistically significant (b = −0.537, model comparison: χ^2 (1) = 24.286, p = <0.001). Results showed that participants chose more often an attribution congruent with the behavior previously observed on the robot (more mechanistic attribution after watching machine-like behavior and *vice versa*) (**Figure 3**).

The interaction effect between RobotBehaviour * mean pupil size was statistically significant as well (b = −9.291, model comparison: χ^2 (1) = 9.355, p = 0.002). Although the three-way interaction between RobotBehaviour*mean pupil size * individual bias was significant only when taking into account the Unbiased group (see Supplementary Materials), our main *a priori* hypotheses aimed at exploring differences due to participants' individual bias in the IST. Therefore, we performed a planned comparison GLMM for each bias group (Tucker, 1990; Kuehne, 1993; Ruxton and Beuchamp, 2008) to test the interaction between RobotBehaviour * mean pupil size: mechanistic group (model comparison: χ^2 (1) = 7.701 p = 0.005); mentalistic group (model comparison: χ^2 (1) = 3.001, p =0 .083). These results show that mechanistically biased participants showed a greater pupil dilation for attributions congruent with the robot behavior (b = −9.28, z = −2.757, p =0.005, **Figure 4**) when attributing a mechanistic description after the observation of the robot behaving in a machine-like way and when attributing a mentalistic score after the observation of the robot behaving in a humanlike way. On the other hand, mentalistically biased participants showed a tendency, although statistically not significant, toward greater pupil sizes for mentalistic attributions, relative to mechanistic attributions, regardless of the robot behavior (b = −4.45, z = −1.73, p = 0.083, **Figure 4**).

Behavioral Data Analysis

In order to investigate the relationship between behavioral data and participants' response times, we tested the quadratic effect of the z-transformed IST score (included as the fixed factor) on log-transformed response times (our dependent variable), as we expected them to be smaller in the extremes of the score distribution of the IST. Results showed a statistically significant

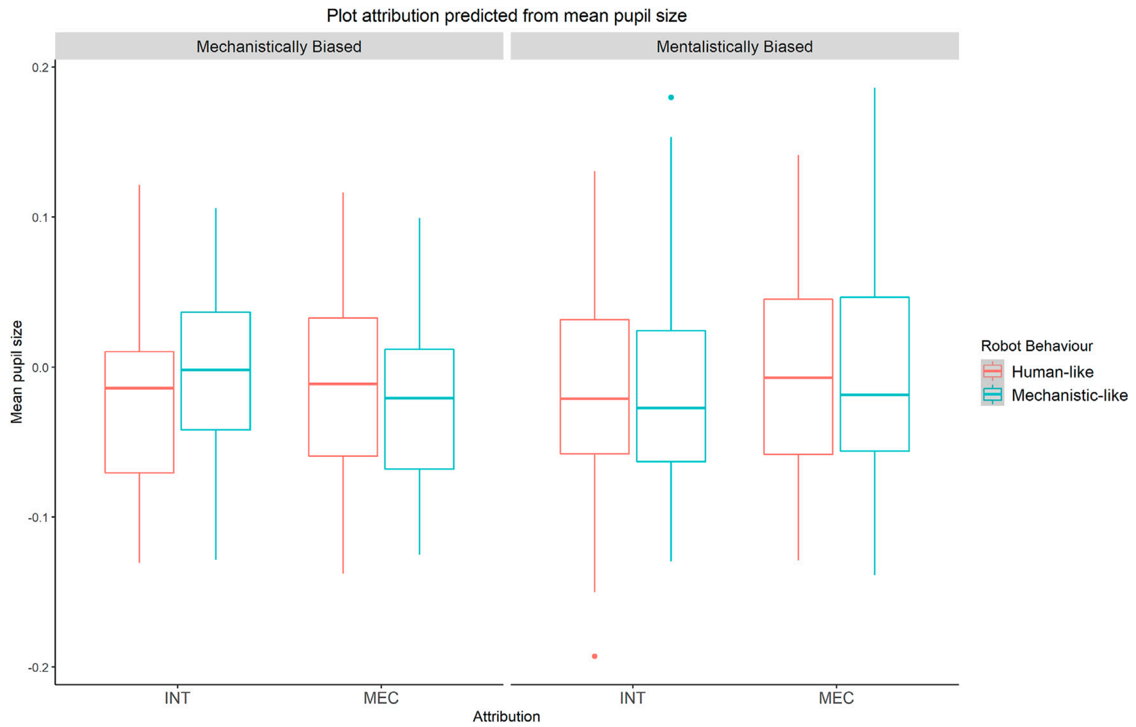

FIGURE 4 | GLMM on the mechanistic group ($N = 9$) and the mentalistic group ($N = 12$). The mechanistic bias group shows the interaction effect between attribution and mean pupil size. No statistically significant effect on attribution and pupil size in the mentalistic bias group.

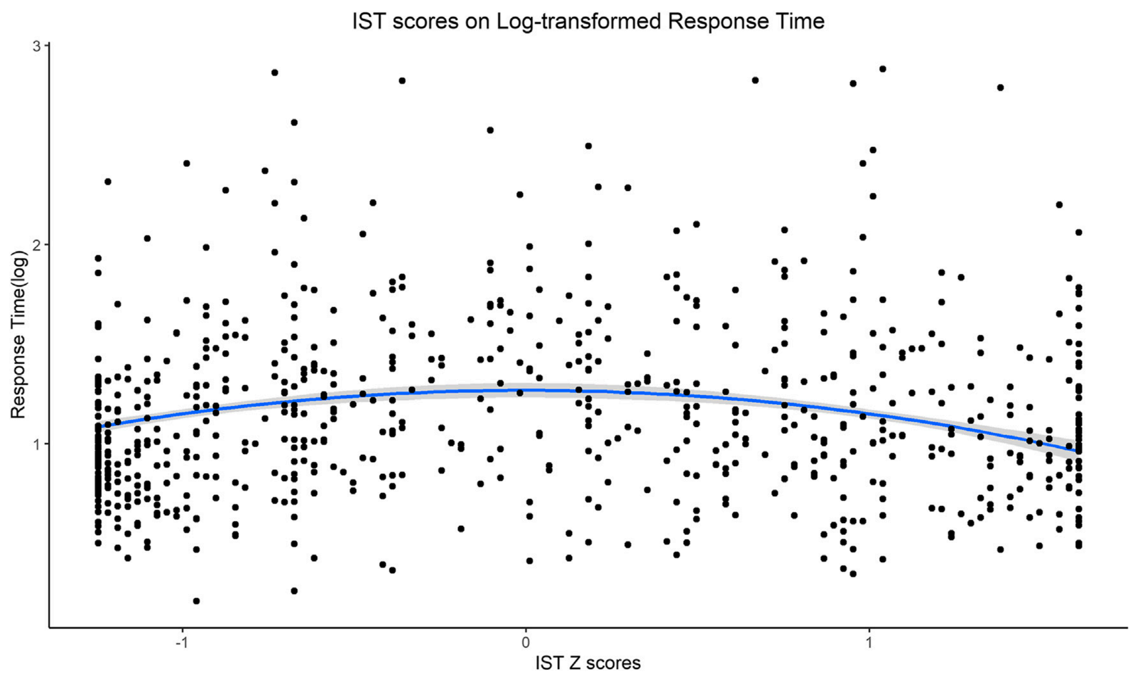

FIGURE 5 | LMM: statistically significant quadratic effect of the IST-z score on log-transformed response time showing faster RTs for extreme scores.

quadratic effect of the IST score [b = −0.146, t (1,419.99) = −9.737, p = <0.001] (**Figure 5**). These results show that participants were overall faster when scoring on the extremes of the IST scale.

DISCUSSION

In the present study, we investigated whether adopting the intentional/design stance could be predicted by changes in pupil dilation and how both effects are modulated by participants' individual bias in adopting the intentional stance and by a behavior of a robot observed prior to the test. To address these aims, we conducted an experiment in which participants first observed the embodied humanoid robot iCub, programmed to behave as if it was playing solitaire on a laptop positioned in front of it. From time to time, the robot was programmed to turn its head toward a second monitor on its left periphery, where a sequence of videos was being played. The behaviors exhibited by the robot were manipulated in a within-subjects design: in one condition, the robot exhibited a humanlike behavior, and in the second condition, the robot exhibited a machine-like behavior. After each session with the robot, participants' pupil data were recorded while they completed the InStance Test. Participants were then divided into two groups, based on the bias showed by their IST score: a mentalistically biased group and a mechanistically biased group.

We found that both mechanistically and mentalistically biased participants leaned more toward mentalistic attributions in the IST after observing the robot's humanlike behavior, as compared to the mechanistic behavior. This shows that participants had some sensitivity to the subtle differences in the robot behavior, thereby attributing more "humanness" to the humanlike behavior, independently of their initial bias (Ghiglino et al., 2020b).

We also explored the relationship between the individual bias and the changes in pupil dilation as a function of the behaviors displayed by the robot. We found that the two groups showed different patterns. On the one hand, for mechanistically biased people, pupil dilation was greater when they chose descriptions of the robot behavior in terms that were "congruent" with the previously observed robot behavior: a mentalistic attribution after the humanlike behavior and a mechanistic attribution after the machine-like behavior. We argue that this is due to the engagement of additional cognitive resources, caused by the cognitive effort in integrating the representation of the observed behavior into the judgment (Kool et al., 2010; Kool and Botvinick, 2014). In other words, these participants might have had enough sensitivity to detect the "human-likeness" or "machine-likeness" in the behavior of the robot. We argue that the integration of this piece of evidence into the judgment in the IST might have required additional cognitive resources.

On the other hand, mentalistically biased participants showed a tendency for greater pupil dilation when choosing the mentalistic description, independent of the observed robot behavior. Perhaps this group of participants showed engagement of additional cognitive resources when they were choosing descriptions that were in line with their initial bias (Christie and Schrater, 2015). Adherence to the "mentalistic" descriptions, independent of observed behavior, indicates, on the one hand, lower cognitive flexibility than the mechanistically oriented participants and, on the other hand, might be related to the general individual characteristic to structure and make the external world reasonable. This tendency to structure the external environment and engage in cognitive effortful tasks is defined as "need for cognition" (Cacioppo and Petty, 1982; Cohen et al., 1955; Epley et al., 2007). Mentalistically biased participants might have a lower need for cognition, and therefore pay less attention to all the subtle behavioral cues exhibited by the agent and stick to their original bias. Therefore, we may argue that this group is less prone to changing the stance adopted to interpret an agent's behavior.

One last (and interesting) finding of our study was that RTs were faster on the extremes of the IST score distribution. This suggests that perhaps once participants made a clear decision toward mentalistic or mechanistic description, it was easier and more straightforward for them to indicate the extreme poles of the slider. On the other hand, when they were not convinced about which alternative to choose, they indicated this through keeping the cursor close to the middle and longer (more hesitant) responses.

Overall, it seems plausible that the general mechanistic bias leads to allocating a higher amount of attentional resources toward observation of the robot (Ghiglino et al., 2020a), resulting in paying more attention to the details of the observed behavior (in line also with Ghiglino et al., 2020b; see also Marchesi et al., 2020). This, in turn, might influence the subsequent evaluation of robot behavior descriptions. On the other hand, a mentalistic bias might lead participants to stick to their spontaneous first impression (Spatola et al., 2019) and a lower need for cognition (Cacioppo and Petty, 1982; Cohen et al., 1955; Epley et al., 2007). Commonly, individual differences and expectations shape the first impression about a humanoid robot (Ray et al., 2008, Bossi et al., 2020, Horstmann and Krä mer, 2019; Marchesi et al., 2021). Perez-Osorio et al. (2019b) showed that people with higher expectations about robots tend to explain the robot behavior with reference to mental states. This might indicate that our participants with a mentalistic bias were predominantly influenced by their expectations about the abilities of the robot and, therefore, paid less attention to the mechanistic behaviors of the robot. To conclude, we interpret the results in light of the influence of individual differences in the allocation of cognitive resources that might differ between people who are prone to adopting the intentional stance toward humanoid robots and people who, by default, adopt the design stance (Bossi et al., 2020; Marchesi et al., 2021).

LIMITATIONS OF THE CURRENT STUDY AND FUTURE WORK

In the present study, we opted for a within-subjects design to reduce the influence of interindividual differences related to prior knowledge/experience with the iCub robot. Nevertheless, we cannot rule out the fact that our approach was indeed too conservative, leading to a null effect of the robot behavior manipulation on the raw IST scores due to a carry-over effect. Future research should consider adapting similar paradigms to a between-subjects design, since this option will allow for controlling possible carry-over effects.

CONCLUDING REMARKS

In conclusion, our present findings indicate that there might be individual differences with respect to people's sensitivity to subtle hints regarding human-likeness of the robot and the likelihood of integrating the representation of the observed behavior into the judgment about the robot's intentionality. Whether these individual differences are the result of personal traits, attitudes specific to robots, or a particular state at a given moment of measurement remains to be answered in future research. However, it is important to keep such biases in mind (and their interplay with engagement of cognitive resources) when evaluating the quality of human–robot interaction. The evidence for different biases in interpreting the behavior of a humanoid robot might translate into the design of socially attuned humanoid robots capable of understanding the needs of the users, targeting their biases to facilitate the integration of artificial agents into our social environment.

DATA AVAILABILITY STATEMENT

Data from this experiment can be found at the following link: https://osf.io/s7tfe.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Comitato Etico Regione Liguria. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

SM and AW designed the pupillometry task. DG and AW designed the observational task. DD programmed the behaviors of the robot. SM and DG performed data collection. SM and FB analyzed the data. SM and AW wrote the manuscript. All authors contributed to reviewing the manuscript and approved it.

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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.2021.653537/full#supplementary-material

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OPINION
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Peripheral Neuroergonomics – An Elegant Way to Improve Human-Robot Interaction?

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1. INTRODUCTION

The day seems not too far away, in which robots will be an active part of our daily life, just like electric appliances already are. Hence, there is an increasing need for paradigms, tools, and techniques to design proper human-robot interaction in a human-centered fashion (Beckerle et al., 2017). To this end, appropriate Human-Machine Interfaces (HMIs) are required, and there is a growing body of research showing how the Peripheral Nervous System (PNS) might be the ideal channel through which this interaction could proficiently happen.

During daily motor tasks such as grasping, walking, or speaking, the central nervous system (CNS) recruits a number of α-motoneurons in the ventral horn of the spinal cord and modulates the rate at which they discharge action potentials. The α-motoneurons are further modulated by supraspinal, afferent volleys and intrinsic motoneuron properties (Heckman et al., 2005; Enoka, 2008). The motoneuronal axonal action potentials are transformed into forces by a group of muscle fibers (the muscle unit) innervated by one axon. The muscle unit and the motoneuron form the final ensemble of all motor actions, the so-called *motor unit*. Translating neural commands into muscular forces, (spinal) motor units represent a promising interface to the CNS. However, there are some physiological constraints of motor control that must be taken into account by robotic applications.

In this opinion paper, we claim that better user experience would lead to more intuitive control and tighter human-robot interaction or even human-machine integration and vice-versa (see **Figure 1**).

Using PNS data for intent detection as well as for online assessment of user experience renders such interfaces technically promising and a tool to understand human behaviors and reactions (Beckerle et al., 2019). To improve on this, we discuss developments in intent detection and user feedback and user feedback emphasizing on anthropomorphic systems, which are directly controlled by humans, e.g., prostheses and teleoperation, and aiming to create novel sensorimotor paradigms.

2. PERIPHERAL-NERVOUS-SYSTEM–MACHINE INTERFACES (PNS-MIs)

Interfaces for controlling anthropomorphic robotic systems, e.g., HMIs for self-powered prostheses, cannot function like a joystick or a touch-screen for instance, since the user cannot

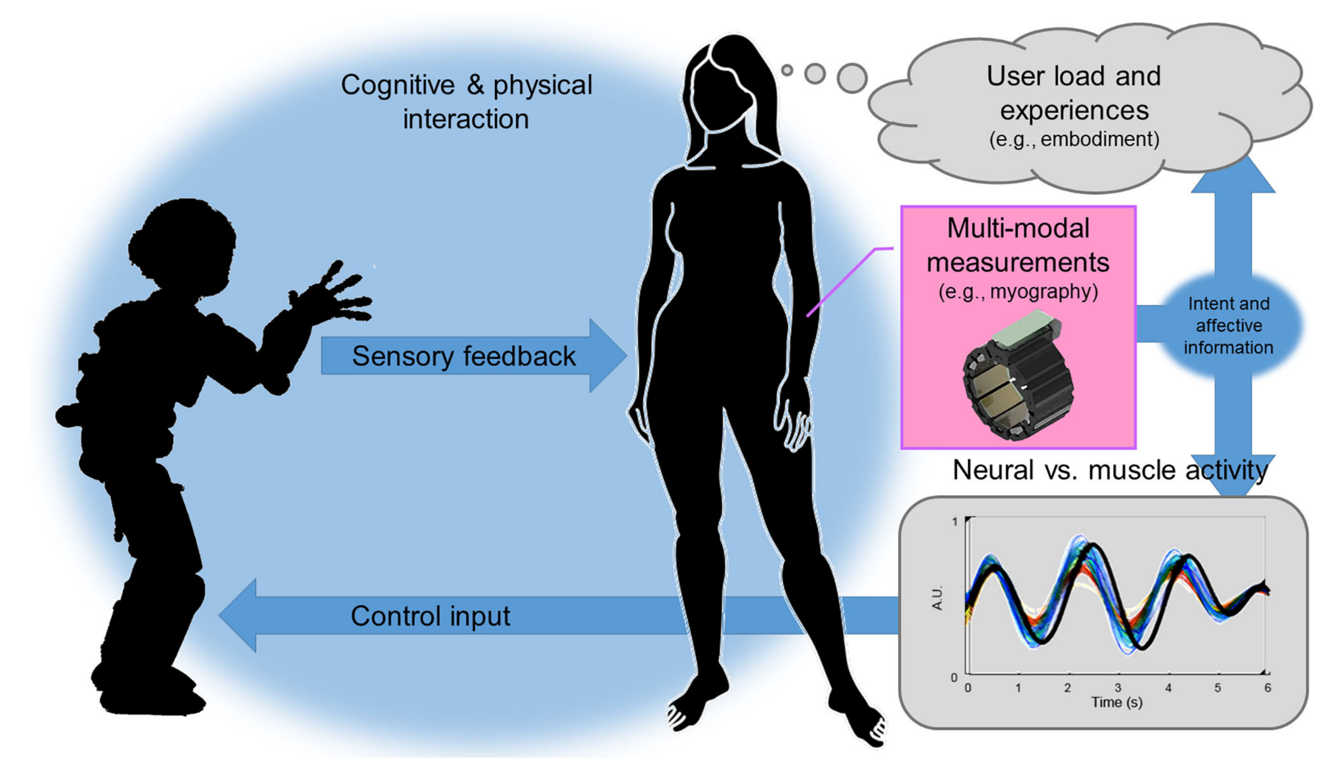

FIGURE 1 | Peripheral-Nervous-System–Machine Interfaces (PNS-MIs) in human-robot interaction: PNS data facilitates simultaneous intent recognition and online experience evaluation. This fosters novel sensorimotor interaction paradigms, sheds light on human behavior and reactions, and thereby opens up new directions for human-robot interaction.

physically operate such devices. These HMIs must rather resort to interpreting the user's intent based on signals the user is able to produce - usually, relevant biological signals related to the intended muscle activation (Beckerle et al., 2019). Surface electromyography (Merletti et al., 2011) is a primary example, although different kinds of signals are currently being explored, e.g., tactile information (Beckerle et al., 2018, 2019) and also promising for other applications such as anthropomorphic teleoperation (Nostadt et al., 2020) or teaching collaborative robots (Cansev et al., 2021).

In principle, all signals generated by the users can and should be used to interpret their intent, but clearly, the optimal choice of signals and sensors depends on a tradeoff involving several factors. This includes, e.g., how well the sensors can be worn (ergonomy), how expensive the processing is (both economically and computationally), and how invasive their setup is. Furthermore, intent detection does not necessarily coincide with classification of signal patterns; rather, it's the ability to provide the user a seamless control experience based upon such signals, e.g., using regression instead of classification.

2.1. The Pros and Cons of CNS/PNS-MIs

Broadly speaking, signals related to movement and muscle activation can be classified according to whether they are recorded from the CNS or the PNS (Castellini et al., 2014). HMIs relying on CNS signals include brain-machine interfaces using surface electroencephalography as well as electrocorticography with direct implants on the motor cortex and spinal implants (Micera et al., 2010), or by decoding spinal motoneurons from high-density EMG signals (Farina et al., 2017; Del Vecchio and Farina, 2019). PNS-based HMIs, on the contrary, are those using signals recorded from the limbs, either invasively or non-invasively, e.g., implanted electromyography and direct connections to peripheral nerves vs. surface electromyography, force- and magneto-myography (Fang et al., 2015). Although EMG interfaces are placed in the periphery (muscles) the signal carried by the electrical activity generated by muscle fibers is in a one-to-one relation with spinal motoneurons. Moreover, minimally invasive approaches like local tomography of the limbs, which entail no surgery but indeed the injection of energy into the body, exist (Sierra González and Castellini, 2013; Gibas et al., 2019).

Given the extreme density of neural cells found in the CNS, most signals useful for robotic control to be potentially found in it are physically unavailable for direct inspection, unless one resorts to very invasive methods, e.g., the Braingate (Hochberg et al., 2012). Non-invasive methods, on the other hand, strongly suffer from cross-talk: the main problem is to tell signals pertaining to the intent under examination from "all the rest." Surface electroencephalography, for instance, poses extremely complex problems to interpret and discern the neural firing patterns of interest, since each sensor can only record potentials from a large pool of neurons. Accordingly, damping and distorting effects due to skull bone tissue complicate pattern recognition (Lazarou et al., 2018). As opposed to that, an excellent signal-to-noise ratio can be obtained at the price of getting in contact with the cerebral cortex or the spinal cells (Hochberg et al., 2012).

PNS-based systems, on the other hand, can use better separated and physiologically relevant signals, naturally enforced by the anatomical branching of nerves and neurons as they depart from the brain, brainstem, and spinal cord. If one is interested in detecting the intent to move, exert forces and torques, and/or activate one's own muscles, then detecting such activity from the PNS appears to be a better choice especially if non-invasiveness is desired (Castellini et al., 2014). On top of this, if minimal invasiveness is permitted or desired, PNS approaches are probably even the best choice nowadays. Ultrasound scanning and electromyographic sensors implanted during osseointegration (Ortiz-Catalan et al., 2014) or injected into the muscles (Becerra-Fajardo and Ivorra, 2019) offer high signal-to-noise ratios while entailing rather low risk.

2.2. Improving on PNS-MIs

It has been known to physiologists for the last three decades that the neural activation that is transmitted by the motoneuron is delayed by the muscle tissue over a large range of values, from roughly 50 to more than 200 ms (Partridge, 1965; Baldissera et al., 1998). During fast motor tasks the nervous system compensates this delay by increasing the motoneuron firing frequency and the delay between the recruitment of successive motor units. Therefore, the CNS tunes this delay dynamically. Previous experiments in animal preparations demonstrated that changes in stimulation frequency alters the delay between the myoelectrical signal and the force produced by the muscle tissues in a very large range (Partridge, 1965; Baldissera et al., 1998). Recently, by decoding the activity of a large population of motoneurons during contraction at different speeds, we also found that the human nervous system modulates such delays in a very broad range (50–250 ms for hand and leg muscles Del Vecchio et al., 2018).

In virtually all prosthetic applications, however, this delay is fixed (Farina et al., 2014) yielding devices that do not follow the physiological modulation during natural processes like muscle fatigue (Zhou et al., 1998), adaptation of contraction speed (Del Vecchio et al., 2018), and muscular force output (Del Vecchio et al., 2018). Still, neuroergonomics should indeed translate these basic physiological findings into novel interface designs and, potentially, prosthetic applications for improving human robot-interactions. One potential solution to overcome this limitation is to decode surface EMG in real-time. We have previously shown that it is possible to retrieve the motoneuron discharge timings with delays smaller than 2 ms (Glaser et al., 2013; Barsakcioglu and Farina, 2018; Chen et al., 2020; Ting et al., 2021). Moreover, the potential to identify individual motor unit discharge times allows to label each motor unit to its unique motor space, e.g., encoding flexion/extension or which digit. Therefore, classification of EMG activity can be performed in a highly accurate way by associating each motor unit to its specific spatiotemporal space, as shown in a spinal cord injury case (Ting et al., 2021).

2.3. Considering User Experience Through PNS-MIs

Recent research outlines that PNS-MIs also have potential in directly assessing user experience going beyond established psychometric and physiological methods. An interesting example is the embodiment of robotic systems such as prostheses or teleoperation systems (Beckerle et al., 2019; Nostadt et al., 2020): the embodiment of artificial limbs can be assessed through surveying subjective experience with questionnaires (Longo et al., 2008), objective behavioral measures (e.g., proprioceptive drift), or (neuro)physiology (Christ and Reiner, 2014). This effect was also shown for artificial limbs with myoelectric control (Romano et al., 2015; Sato et al., 2018), but we might ask ourselves whether myoelectric measurements could also be used to analyze neuroergonomics of interaction with such devices. Recent work by Preatoni et al. for instance (Preatoni et al., 2021) indicates that proper sensory feedback makes a leg prosthesis feel lighter.

For patients suffering from stroke, the experience of device embodiment seems to have similar influence on electromyographic activity as for other physiological measures, i.e., electrodermal activity and skin temperature (Llorens et al., 2017). While, Tsuji et al. (2013) even report subjective survey results to be better represented by electromyography than by electrodermal activity, (Llorens et al., 2017) state that interactions between their subjective and neurophysiological results were inconclusive. Besides embodiment, the perception of pleasantness of affective touch can be related to electromyographic as well as to electrodermal measurements (Ree et al., 2019). This is very interesting since providing affective information through touch was shown to increase the embodiment of artificial limbs (Crucianelli et al., 2013, 2018; van Stralen et al., 2014) and, hence, appears worth considering in human-robot interaction (Beckerle et al., 2018).

Although myographic activity was measured at different sites, i.e., hand and face (Tsuji et al., 2013; Llorens et al., 2017; Ree et al., 2019), considering it in the assessment of user experience seems promising. We have ourselves recently put forward the potential connection between control based upon muscle activation and action schemes in the sense developed by Piaget (Piaget, 1950). Here, a proper PNS-MI could foster the creation of novel circular reactions, leading to embodiment as a natural consequence (Bettoni and Castellini, 2021). The factors influencing the effect remain unexplored so far. Understanding and shaping these interactions might be supported by multimodal data from an interface integrating myography with other physiological data, e.g., electrodermal activity or heart rate.

3. DISCUSSION

With this position paper, we advocate peripheral neuroergonomics as an *elegant* way to improve HRI. Non-invasively interfacing the peripheral nervous system seems to provide very good interpretability and is currently advantageous over CNS-based interfaces, which outline higher invasiveness as well. Moreover, peripheral interfaces can augment or complement other modalities such as eye-tracking and electroencephalography to improve the recognition of user intentd and cognitive status. Generally, we expect considering neuromechanical insights in novel interfaces designs to foster improved HRI characteristics of robotic systems and devices. An accurate closed-loop control of the neuromechanical delays matching the physiological pathways would likely improve sensorimotor interactions. In addition, peripheral neural information can complement psychometric and physiological methods to assess user experience, which indicates that integrating myographic assessment in multimodal PNS-MIs would bring the neuroergonomics of human-robot interaction to a new level of quality.

AUTHOR CONTRIBUTIONS

PB coordinated its development as well as the integration of individual contributions. All authors conceptualized the structure, contributed content, perspectives, and references as well as discussed and revised the manuscript.

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The Complexity of Remote Learning: A Neuroergonomical Discussion

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THE INHERENT COMPLEXITY OF LEARNING

In this work, we aimed at affirming the inherent complexity of learning processes and the consequent benefits derived from a *multi-layer cascade* approach that considers heterogeneous disciplines and furnishing actionable best practices, for the designing of a learning experience in an organization.

Since disciplines, at different scales, bring together heterogeneous knowledge, we advocate for an integration of them. The various types of learning (i.e., non-associative, associative, perceptual, and motor) can be explored to understand the development, storage, and recall of memories, using molecular, cellular, and systems data. Neurobiologically, learning corresponds to functional and structural changes in the synapses at a variety of loci, throughout the central nervous system (e.g., Kopec et al., 2007). These modifications consist in post-translational variations of proteins in the synaptic site, connected to synaptic plasticity, *via* interrelated changes in biochemistry, physiology, and subcellular redistribution. Evidence from laboratory animals strongly supports this relation (Lynch et al., 2007), even though a direct causality linked to behaviors is an open discussion (Mao et al., 2011).

At a higher scale, modern brain imaging procedures have provided information about the activation of brain regions such as the *limbic system*, the *cerebellum*, *striatum*, *amygdala*, and other motor or sensory systems, which encode and store information into long-term memory (Markowtich, 2005). These brain areas contribute to the development of competence and skills in a worker.

Parallelly, assuming a synthetic rather than reductionist perspective, learning does not necessarily consist of specific responses made to certain stimuli, conversely learning and memories should not be considered stable and definite.

Finally, a distinction between learning and performance is needed. Even if highly related, these two concepts do not perfectly match. For example, latent learning could be obscured by a performance factor (e.g., a motivation deficiency can inhibit goal-oriented behaviors), such as attention, sensory-receptor sensitivity, motivation, and arousal.

Recent human-based studies on cognition regarding training and memory added value to the research line of learning. In this light, human brain functions are thought within an environment, together with a *dynamic relation*, which is at least partially socially constructed, with work and technology. The application of techniques such as fMRI, fNIRS, electroencephalography (Balconi and Molteni, 2016; Belkhiria and Peysakhovich, 2020; Nozawa et al., 2021), together with behavior-oriented approaches, allowed the development of *neuroergonomics*. Its main advance consists of the assumed bottom-up, situational-oriented perspective. *Via* these techniques, combined with novel computational modeling (Cassioli and Balconi, 2020), strategies for effective training can be assessed (e.g., Kenny and Power, 2021), by comparing the related underlying neural processes.

For example, the impact of digital technology on learning processes in the organizational framework is a crucial key point, even if it is still mostly unexplored. Novel organizational tools may determine different behaviors and novel responses, with significant consequences on the training efficacy.

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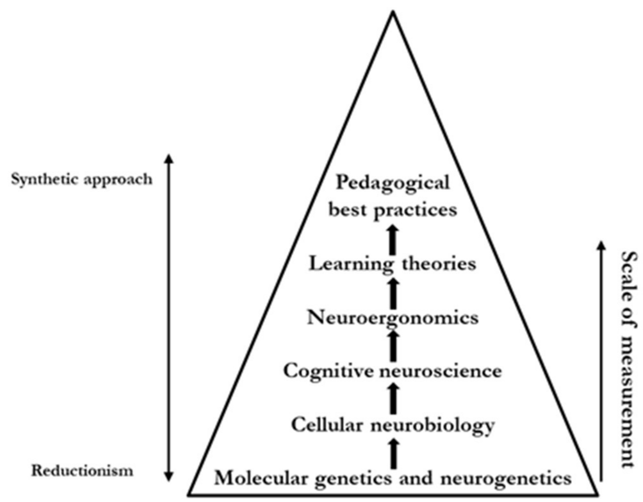

FIGURE 1 | The representation of a "*multi-layer cascade*" approach concurring in the development of applicable best practice regarding the learning process.

Since the learning process is heavily influenced by the employed medium and environmental factors, we propose neuroergonomics as that perspective that uses neurobiological evidence, by considering stressors and well-being, and focuses on the cognitive and affective dimensions.

Each of these presented paradigms composes a layer that concurs in the development of applicable knowledge for the organization, enriching learning theories. We firmly believe that the consideration of multiple sources of information could help the development of best practices. A scheme is reported in **Figure 1**. A multi-layer cascade orientation refers to that epistemological approach we advocate for that sees cross-contamination between different disciplines as valuable. Every layer is enhanced by insights derived from previous layers and leads in the direction of the development of actionable best practices.

Despite this promising opportunity, scarce evidence, which, for example, considers neurocognitive and emotional parameters, was gathered, with limited applications in the pedagogy of education for heterogeneous tasks or settings.

NEUROERGONOMICS IN THE ORGANIZATION

An Operational Definition of Neuroergonomics

Neuroergonomics investigates the neural bases of mental and physical functions, in applied settings, such as work, transportation, and health care (Parasuraman et al., 2012). It is defined as the study of human brain function in relation to work, together with technology (Parasuraman, 2003). Real-world contexts are assessed within a framework where human intentions, actions and behaviors are considered interdependent with the environment (Dehais et al., 2020).

The emergence of new digital tools, together with the ubiquity of technology, is known to play a transformative role within organizational processes. For this reason, neuroergonomics, by considering the neurocognitive and the physical dimensions, can support the investigation of the complex relationship between workers and learning mediated by technology.

From an epistemological and methodological perspective, neuroergonomics in the organization assumes that the effects of computer-mediated interaction are mirrored at psychological, neurocognitive, and physiological levels. Biomarkers, which refers to psychophysiological states, are then selected to assess the cognitive dimension, by considering attentional processes, executive functions and mental workload, and affective states, such as arousal activity, emotional categorization, cardiovascular fitness, and resiliency (Balconi et al., 2019; Crivelli et al., 2019; Getzmann et al., 2021). Neuroergonomics, merging neurobiological and neurocognitive evidence, with quantitative-based behavioral analysis, can be employed to record outcomes, and provide feedback on learning. In this sense, neuroergonomics represents an approach that supports a deeper understanding of workers and their behaviors and facilitates the reaching of their maximum potential. To design a training in an organization, the added value of neuroergonomics might be substantial. For this reason, aspects such as environmental factors and employed technologies (i.e., *learning management system*) should be considered.

Environmental Factors and Learning Experience

As mentioned above, training should be considered from a holistic perspective, as people act within a learning environment. In fact, as Kaplan and Kaplan (2003) argued, environment has a profound effect on human cognition, behavior, and well-being. Within the framework of *attention restoration theory* (Kaplan, 1995), environmental processes play a significant role in the mental fatigue levels and in how restorative settings can foster recovery. Many factors can intervene in the learning experience, such as lighting. In fact, a natural source seems to influence the limbic system, with positive impacts on mood, sleep, and cognitive performance (Samani et al., 2013). Other parameters that might interfere are room temperature, environmental noise and many more. For example, the environmental *restorativeness* should be as well considered because it elicits emotional, cognitive, and physiological responses. Furthermore, spatial arrangement helps defining the individual *place identity*, which is a good driver for performance and fosters the sense of community (Knight and Haslam, 2010) within the organization.

Technology Disruption and Learning

Technology-mediated interactions face a further challenge. The technology disruption we experienced, calls for a sophisticated analysis between different modalities (i.e., face-to-face vs. remote) which impact the learning process. Since organizations extremely often make decisions based on available resources, when administering a training course, only the most efficient solution should be considered (Waytz and Gray, 2018). Actual evidence appears troublesome. Overall, there is a small understanding of how virtual contexts work on psychological dimensions and how they impact work performance.

Online communication is sometimes linked to lower empathy (Wellman et al., 2006). Also, remote training, often explored on students or healthcare workers and is reported to present both pros and cons. In fact, remote training allows no spatial constraints, flexibility, and the possibility to easily access the available resources (Hoyer, 2006). It could be then inferred that *lifelong learning* in workers could be facilitated by distance learning. Unfortunately, past research has shown that the proliferation of open courseware (e.g., MOOCs) tends to exacerbate individual differences, which are explained by training motivation (Horrigan, 2016). Furthermore, the affordances of technologies and their effects are not neutral (Houlden and Veletsianos, 2019) and should also be contemplated. In addition, since remote settings are not always designed for learning scopes, they might present features which are not optimal for training. Conversely, face-to-face interactions might result challenging and stressful because of personal factors (i.e., anxiety trait), with significant performance penalties.

Further evidence should be gathered considering setting (e.g., face-to-face vs. remote) conditions and their effects on the learning outcome in workers. Authors think that both cognitive neuroscience and neuroergonomics contributions are expected to deliver more evidence in the coming era.

Moreover, research before SARS-CoV-2 highlighted a mild positive relationship between employees' engagement levels and time spent in remote conditions. Data showed that, when spending up-to-20% of the time from distance, employees tend to be more motivated and attached to the company (Gallup Organization, 2013). Moreover, the outspread of covid-19 limited physical proximity and imposed stay-home restriction and remote- and/or smart-working, accelerating the digital transformation. Data indicated that people worked fewer hours or even temporarily stopped working at their job (e.g., Gallup Organization, 2021), showing decreased engagement levels in the daily activities and experienced (>40%) daily worries and stress. In this light, being unengaged employees means not having psychological attachments, with a lack of energy and passion and a tendency to be resentful that your own needs are not being met and thus avoiding the acquisition of skills that strengthen the performance and boost a company's success.

Finally, we believe that remote learning on online platforms is often presented to trainees *via* reward-oriented platforms. Risks of an attentional shift from the course content to the activity completion time (often offered in percentage) are more than plausible. Indeed, workers might be wrongly rewarded not by the skills or knowledge they acquire but by other factors, such as the pace they keep. As previous scientific evidence suggests, an inherent reward tends to be a stronger psychological driver for a certain behavior compared to an external one.

In the following paragraph, we briefly present some recommendations which could be considered by practitioners when designing a learning module within an organization.

CONCLUSION: RECOMMENDATIONS AND FUTURE DIRECTIONS

As expounded, neuroergonomics can be operationalized as the study of human brain function in relation to work and technology.

To manage the inherent complexity of learning, we now propose to consider the following recommendations which should be considered when designing a learning experience in an organization.

- *Applying a multi-layer cascade approach.* Based on current scientific evidence-based knowledge from neurobiology, cognitive neuroscience and neuroergonomics, best practices should be developed and shared with trainers and learners. The underlying neurobiological principles shape the pedagogy of learning.
- *Test, implement, test.* Both reductionist and synthetic approaches have shown to provide useful insights. Therefore, we should design research that investigates how digital tools impact human wellbeing, work performance, output quality and learning. Since existing evidence is troublesome, a better comprehension of its effects on the physiological, cognitive, and affective dimensions is needed. According to the authors, small evidence has been gathered on real-world contexts so far. Neuroergonomics represents a good perspective where the evaluation of learning processes is considered interdependent with human behaviors, intentions, and the environment.
- *Simplicity is seductive but often wrong.* Learning abilities differ due to age, role, motivation, mental state, and environmental factors. Learning happens in all ages of a living organism, although not always under equal conditions. Remote and face-to-face settings both present pros and cons. Siding with a certain one, until sufficient evidence is gathered (see *ii.*), denies the inherent complexity of learning.
- *Assuming an equality between behavior and learning is wrong.* Streaming and completing a training course does not necessarily convert into the acquisition of competence. When computing the efficiency of a technology system, not pondering human factors might undermine the ultimate purpose.
- *Learning management systems should be competence-oriented.* Online platforms for learning courses (e.g., MOOC) should not be reward-based considering completion, but knowledge- and competence-oriented. Trainees should develop a focus on the abilities they are learning, understanding how those skills might be pragmatically valuable for them.
- *Knowledge and competence are also socially constructed.* Remote vs. face-to-face training activities should be considered based on trainees, course content, situational and environmental factors. Blended solutions could represent a possibility.
- *Acknowledge the existence of miscellaneous unaccountable phenomena.* Culture, digital divide, data security, and privacy are just a few of the many issues which should be further considered when designing a training course.

In this work, we highlighted how a multi-layer cascade approach represents an attempt for an overall comprehension of learning processes. Despite all, this study presents limitations. We did not consider other factors such as the learning content, individual traits, and personal predisposition. Future studies could investigate the impact of these dimensions as well.

To conclude, future lines of research should focus on the impact of technology disruption on human beings at work and consider side factors by integrating contributions from heterogeneous domains. Ultimately, beyond the chosen medium, trainers, supported by scientists, should enable learners to obtain gratification from the doing, not the results.

AUTHOR CONTRIBUTIONS

FC and MB theoretically designed the framework and together finalized the actual version of the article. All authors contributed to the article and approved the submitted version.

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OPINION
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The Role of Neuroergonomics in the Design of Personalized Prosthesis: Deepening the Centrality of Human Being

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1. FROM HRI TO HUMAN-ROBOT MERGE

In recent decades, we have witnessed the rapid development of new technologies in several fields of our life. In particular, robotics grows so fast that it is often described as the technology of the future, as in Gates (2007); this trend is also confirmed by the Executive Summary World Robotics (IFR, 2020). From a theoretical point of view, all these devices could be framed according to a paradigm, which describes technology as a "medium" that relates the human being and the world (Ihde, 1990; McLuhan, 1994; Floridi, 2014); in this way, the technological devices could be depicted by two main characteristics: a) "being-between" (Floridi, 2014), and b) "being-for" (Heidegger, 2010).

The first dimension, the "in-betweenness," describes the functional and practical role of technological mediation that takes place in the human-world relation; the preposition "between" identifies the physical mediation of the devices which play, in different ways (Ihde, 1990), the role of an intermediary of the experience. Instead, the second dimension, the "being-for," emphasizes an opposite dynamic related to the relationship between human beings and technological devices. In this case, the preposition "for" highlights the necessity to design technology for someone and, for this reason, to consider the technology according to a defined setting and a specific condition. In particular, the "being-for" implies the necessity to rethink technological devices according to a human-friendly paradigm. In this emerging framework, the importance of a relational approach to technology becomes relevant in the design of reliable, efficient, and safe systems. Recently, this focus on the user and their needs has been deepened into the human-centered approach (Boy, 2017; Auernhammer, 2020); its importance can be found in all devices requiring the development of synergies and relationships between human and machine, from industrial robots to bio-medical devices (Riener et al., 2005; Schaal, 2007; Zhou et al., 2017).

This article will address the case of active upper-limb prostheses to discuss the importance and the limits of the neuroergonomics approach and human-centered design. In the relationship exemplified by prosthesis, the technological device physically alters the human being (Verbeek, 2008). From the theoretical point of view, this intimate relation opens up a new interaction model, which is based on a "merge" between the subject and technology. In line with Carrozza (2019), it is possible to argue that this form of mediation goes toward a neurophysiological symbiosis between humans and machines. The primary consequence of this approach is a focus on neurophysiological

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aspects considered essential and irreducible. Nevertheless, this article argues that this emphasis is unable to gather the dimensions necessary to develop functional and accepted prostheses. In particular, this opinion paper argues that a neuro-based approach is a necessary but not sufficient requirement for a human-friendly device.

2. NEURO-APPROACHES: BENEFITS AND RISKS

In response to the need to design prostheses "for" human beings, which have better functionality and controllability (Carrozza et al., 2006; Zollo et al., 2007; Atzori and Müller, 2015), research and prototypes of bio-inspired artificial limbs have been developed in recent years. Compared to cosmetic prostheses, these active devices, which are able to manipulate objects, have a greater degree of usability, significantly improving users' quality of life and ADL (Activities of Daily Living) (Cordella et al., 2016). Mainly the manipulative capacity is modeled through myoelectric control (Scott and Parker, 1988), or neural interface (Schultz and Kuiken, 2011). The myoelectric control is based on identifying user intention through MES (myoelectric signals) (Geethanjali, 2016); instead, in most cases, the neural interfaces use TIME (Transversal Intrafascicular Multichannel Electrode) (Badia et al., 2015). In this regard, a recent study described the use of the PNS (peripheral nervous system) as an "elegant" strategy to improve HRI because "peripheral neural information can complement psychometric and physiological methods to assess user experience, which indicates that integrating myographic assessment in multimodal PNS-MIs would bring the neuroergonomics of human-robot interaction to a new level of quality." (Del Vecchio et al., 2021). Both these methodologies exploit the PNS (Ciancio et al., 2016) that is emerging as the "ideal channel" of human-robot interaction (Del Vecchio et al., 2021). The methods mentioned above realize this "merge" according to two opposite dynamics.

The use of myoelectric technologies has had a significant development in recent years because of some advantages that are recognized by it. The decoding of the MES takes place in a non-invasive way, as it is detected through the surface of the skin, and is a reasonably accurate way as little muscle activity is needed to control the prosthesis (Parker et al., 2006). Currently, this method of prosthesis control is the most widely used for commercial purposes. The TIME, on the contrary, is a more invasive technique that allows not only to decode the intention of the user but also to return manipulation feedback. For this reason, this methodology needs electrodes implanted in the afferent and efferent pathways (Raspopovic et al., 2014) for bidirectional control of the prosthesis. Although they are still investigational and very invasive techniques, early studies, as in Zollo et al. (2019), highlight that, compared to myoelectric technology, bidirectional prostheses have more refined control in grasping and manipulating objects. This is explicitly due to the sensory capacity of the prosthesis.

Since the literature review (Cordella et al., 2016) has revealed a better control of the prosthesis and a more remarkable ability to manipulate these devices, it is evident the strong appeal that the neuro-based approach has in the design of efficient prostheses. From this perspective, it is possible to affirm the central role of neuroergonomics for further investigation focused on the user's needs. In particular, this discipline, which studies the brain and its functions in performing tasks (Parasuraman, 2003; Parasuraman and Wilson, 2008), has a strong impact in the field of biomedical engineering and prosthesis design because neuroergonomics defines an innovation working on the deep investigation of perceptual and cognitive functions (Parasuraman, 2003). This approach, based on recognizing the brain's role in perception, highlights the quantitative measure of the stimulus and its reproduction in an artificial system. This approach is helpful in developing systems that are able to realize a synergic "merge" between human beings and technological devices; the significant benefit of neuroergonomics can be summarized in two main aspects: a) the discovery of the neural basis of perception, and b) a more careful analysis of the neural resource of the action, such as grasping. For this reason, in line with Parasuraman (2003), I recognize an "added value" for this research field that goes beyond the traditional limits of both neuroscience and the ergonomic approach. According to this statement, it is possible to conclude that there are several advantages to using a neuro-based approach in terms of prostheses functionality and performance; indeed, a neuroergonomics study could have finer decoding of the user's intention based on the brain activity and better comprehension of the manipulation and grasping tasks.

In conclusion, the "added value" of neuroergonomics concerns, in particular, the chance to design and development of more functional and personalized prostheses. In this perspective, the lack of functionality is recognized as a factor hindering the use of the prosthesis (Biddiss and Chau, 2007); for this reason, it (Cook and Polgar, 2015) is conceived as a necessary element. Scientific evidence, as Petrini et al. (2019), supports the hypothesis that an approach based on the body's neurophysiology represents a valuable solution to the problems currently plaguing commercial prostheses. Nevertheless, we may question whether a neuro-based approach is capable of guiding design through a comprehensive focus on the human being. In this perspective, functionality understood as the method that estimates the performance of the device (Chappell, 2016), turns out to be a necessary but not sufficient condition for a human-friendly device as this perspective lacks in considering the consequences and reasons that lead subjects to refuse or reject prostheses. In literature, it is possible to find alternative solutions that try to solve the problem; e.g., Biddiss proposes a human-centered approach, called Need-Directed Design, which provides a study of prostheses according to the priorities of the user able to take into account, specifically, comfort, cost, anthropomorphism, sensation, and functionality (Biddiss, 2009). Starting from this approach, it is possible to identify another useful parameter for the design of prostheses, the first-person experience[1]. It concerns a direct stakeholder's

[1] In this perspective, I argue that the inability to take into account the first-person experience of the prostheses use may afflict the phase of personalization of the prosthesis.

involvement in the design phase of the prosthesis. The analysis of the first-person prosthesis experience is not intended to replace the neuro-based approach but rather to support it by making explicit the central role of the user. This integration responds to the problem of the explanatory gap (Levine, 1983) by trying to address neuro-based and phenomenological approaches as two different perspectives on the subject. From a methodological point of view, this new approach, which can be defined as quanto-qualitative (Corti, 2021), wants to combine diverse perspectives. This new investigation relates both objective data, obtained by measuring the stimulus, and the subjective feeling, described during the prosthesis's use. This critique aims not to revoke in doubt the central role of the brain in the design phase but rather to highlight the incomplete adequacy of a neuro-based paradigm for personalized devices. Specifically, as argued before, a direct user's involvement in the design phase can significantly improve prosthesis acceptance.

3. DISCUSSION: A HUMAN-CENTRIC APPROACH, INCLUDING THE FIRST-PERSON DIMENSION IN THE DESIGN OF PROSTHESES

In the design of personalized prostheses, the phenomenological dimension that involves the first-person approach is becoming increasingly important; e.g., Biddiss explicitly states, "If a person feels that a prosthesis enhances their function and/or appearance, they will use the device. Conversely, if the prosthesis is perceived to hinder function or comfort, or spoil the appearance, they will not use the device" (Biddiss, 2009). Therefore, recognizing the importance of feeling for prosthetics implies the need to rethink an appropriate methodology, which includes a phenomenological dimension, for assessing prosthetic acceptability and embodiment. It is clear that even if a neuro-based approach allows the creation of interfaces between computer and brain, a first-person analysis also has significant benefits for prosthetic design. Specifically, this new methodology helps investigate upper limb prostheses with haptic feedback as the sensory feedback implies the first-person dimension. For this reason, in the evaluation of sensitive prostheses, direct involvement of patients' subjective reports is mandatory, as in Zollo et al. (2019). Nevertheless, from a methodological point of view, there are two potential risks:

1. consider subjective reports as secondary in that they are useful only to support neuroscientific findings;
2. not investigating the experience according to a rigorous methodology and criteria.

In literature, it is possible to find some methods that solve the above problems and integrate the two dimensions, e.g., neurophenomenology (Varela, 1996; Lutz and Thompson, 2003). Specifically, this approach aims at emphasizing how a first-person approach can provide additional and essential information (Thompson and Cosmelli, 2005) for the neuroscientific investigation[2].

The neurophenomenological approach has been empirically tested in some studies, such as Lutz et al. (2002), Lutz (2002), Lutz and Thompson (2003), and Lutz et al. (2008). In particular, Lutz et al. (2002) conducted a study on visual tasks in which, in front of continuous monitoring through Electroencephalography (EEG), the subject is asked to describe the phenomenological content of the action performed. The study showed that it is possible to establish a relationship between the subject's verbal descriptions and the measurement of neural activity. The recognition of mutual constraints between first-person experience and EEG data suggests that the same study can be applied to upper limb prostheses. This quanto-qualitative approach involves the subject in the design process in an active and participatory[3] way (Corti et al., 2020). In this perspective, it is plausible to hypothesize experimental settings to find mutual constraints between the subjective (qualitative) reports on manipulation tasks and the quantitative measure of brain activity. In particular, this strategy aims at highlighting some phenomenological elements relevant to personalized prostheses, such as naturalness of sensation, perceived ability, and embodiment.

In conclusion, I argue that the mixed paradigm proposed above can help in the development of functional devices and also in detecting prosthetics embodiment. Thus, the quanto-qualitative approach helps to connect paradigms, e.g., the phenomenological and the neuroscientific ones, shedding light on issues, such as embodiment. Adopting a methodology capable of integrating multimodal data supports the investigation of embodiment since it has 2-fold nature and cannot be completely quantified (Corti, 2021). On one side, it has a neurophysiological basis; on the other side, it is a phenomenological dimension (Murray, 2008; De Preester and Tsakiris, 2009; De Preester, 2011). Specifically, three conditions seem to emerge that simultaneously involve the neurophysiological aspect and the phenomenological dimension: (a) the physical presence of the prosthesis in continuity with the body, (b) the disposition to use the prosthesis for action, and (c) the recognition of that device as part of one's body.

AUTHOR CONTRIBUTIONS

LC conceived of the study and drafted the manuscript.

[2]In line with Gallagher and Zahavi (2020), I argue that this new research methodology can offer a direct contribution to the empirical research and, specifically, to the prostheses design developing a more accurate evaluation of Human-Robot Interaction.

[3]From a methodological point of view, the subject's involvement in the design phase contributes to the opening of the human-centered approach in a human-centric paradigm. On the one hand, the human-centered approach emphasizes the user's perspective, which, as we have seen in the case of prostheses, may imply the measurement of the stimulus; on the contrary, the emerging human-centric involves directly the stakeholders. In the case of bionic prosthesis design, the shift between human-centered and human-centric paradigm can be represented by a third-person paradigm, which evaluates as relevant only the objective measure of brain stimulus, and a phenomenological perspective that, directly involving the subject through a questionnaire or personal reports, also captures the first-person dimension of experience.

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METHODS
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Development of Modular and Adaptive Laboratory Set-Up for Neuroergonomic and Human-Robot Interaction Research

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The industry increasingly insists on academic cooperation to solve the identified problems such as workers' performance, wellbeing, job satisfaction, and injuries. It causes an unsafe and unpleasant working environment that directly impacts the quality of the product, workers' productivity, and effectiveness. This study aimed to give a specialized solution for tests and explore possible solutions to the given problem in neuroergonomics and human–robot interaction. The designed modular and adaptive laboratory model of the industrial assembly workstation represents the laboratory infrastructure for conducting advanced research in the field of ergonomics, neuroergonomics, and human–robot interaction. It meets the operator's anatomical, anthropometric, physiological, and biomechanical characteristics. Comparing standard, ergonomic, guided, and collaborative work will be possible based on workstation construction and integrated elements. These possibilities allow the industry to try, analyze, and get answers for an identified problem, the condition, habits, and behavior of operators in the workplace. The set-up includes a workstation with an industry work chair, a Poka–Yoke system, adequate lighting, an audio 5.0 system, containers with parts and tools, EEG devices (a cap and smartfones), an EMG device, touchscreen PC screen, and collaborative robot. The first phase of the neuroergonomic study was performed according to the most common industry tasks defined as manual, monotonous, and repetitive activities. Participants have a task to assemble the developed prototype model of an industrial product using prepared parts and elements, and instructed by the installed touchscreen PC. In the beginning, the participant gets all the necessary information about the experiment and gets 15 min of practice. After the introductory part, the EEG device is mounted and prepared for recording. The experiment starts with relaxing music for 5 min. The whole experiment lasts two sessions per 60 min each, with a 15 min break between the sessions. Based on the first experiments, it is possible to develop, construct, and conduct complex experiments for industrial purposes to improve the physical, cognitive, and organizational aspects and increase workers' productivity, efficiency, and effectiveness. It has highlighted the possibility of applying modular and adaptive ergonomic research laboratory experimental set-up to transform standard workplaces into the workplaces of the future.

Keywords: modular and adaptive laboratory workstation, experimental set-up, cognitive ergonomics, human-robot collaboration, Poka—Yoke system, musculoskeletal disorders, industry—4.0

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INTRODUCTION

Numerous studies and research articles show that integrating innovative advanced technologies of Industry 4.0 utilizing lean and ergonomic helps to enhance the health and safety of the workers performing monotonous, manual, repetitive, physical demanding assembly activities at the workstations in contemporary organizations (Schwab, 2016; Battini et al., 2020; Pinzone et al., 2020) and to increase the efficiency of the operators by improving performance, reducing production time, and reducing errors (Colim et al., 2021).

With the increasing customer demand for unique, customized, personalized, low-cost products in small batches in the shortest possible time, organizations are being pressurized to proactively answer and to improve the flexibility and effectiveness of the production systems to maintain a competitive advantage in the market (Battini et al., 2011; Battaïa et al., 2018). The abovementioned can be achieved through automation and manufacturing advancement (Tsarouchi et al., 2016; El Zaatari et al., 2019), introducing collaborative robots and other innovative Industry 4.0 technologies into production processes (Tobe, 2015; Salunkhe et al., 2019; Cimini et al., 2020).

The monotonous, repetitive movements at high speed at the industrial workstations are often performed in ergonomically inadequate and non-physiological body positions over a long period. It can cause occupational diseases (Shikdar and Garbie, 2011) such as mental and physical effort (Schaub et al., 2013), fatigue, discomfort, forearm muscle effort, extreme joint positions, which increases the risk of back pain and musculoskeletal disorders (Barr et al., 2004) and other health and safety problems (Petreanu and Seracin, 2017).

In the European Union member states, musculoskeletal disorders (MSD) are one of the leading health problems of workers (Maurice et al., 2017), causing absenteeism, inefficiency, and productivity loss in the manufacturing industry (Schneider et al., 2010; Bevan, 2015; El Makrini et al., 2019). MSD arises from repetitive movements of body parts, awkward postures (Ranavolo et al., 2020), high demand for work or low autonomy, and low job satisfaction (Petreanu and Seracin, 2017). The installation of EMG sensors enables monitoring of muscle activity during the assembly activities of parts and components and determines the load and tension of the neck, arm, and shoulder muscles during these activities. In this way, it is determined that when the first symptoms of MSD begin to appear, the frequency of pain in different regions of the body is examined so that appropriate preventive measures could be taken (Segning et al., 2021).

Some research suggests a link between conditions in which workers perform uncomfortable activities and decreased productivity (Liao and Drury, 2000; Dainoff, 2002; Haynes and Williams, 2008; Husemann et al., 2009). Numerous scientific research articles indicate the importance of an ergonomically acceptable designed work environment where repetitive assembly work is performed (Coury et al., 2000; Isa et al., 2011). In that case, special attention must be paid to the "golden zone" (Sanders and McCormick, 1993). This zone is the cylindrical segment-shaped area from the worker's waist to shoulder height and with forearm length as the radius. As the golden zone is different for each worker, the workstation ensures that workspace and arrangement of materials, components, and tools positions could be adapted to the individual needs. Also, human–robot collaborative interaction has been proposed as a potential solution to improve workplace conditions, eliminate risk factors, and improve wellbeing and satisfaction through physical and cognitive aspects need to be considered (Fast-Berglund et al., 2016; Kadir et al., 2018; El Zaatari et al., 2019; Prati et al., 2021).

At industrial workstations where manual, repetitive, and assembly activities are performed, human errors are almost inevitable, and numerous errors cannot be easily detected at the further stages of production or during inspection (Wallace and Vodanovich, 2003). Timely detection of falls in attention and concentration through advanced EEG research contributes to improving Occupational Safety and Health (OSH)—reducing injuries during work and reducing accidents that could be fatal in some situations (Parasuraman and Rizzo, 2006; Strasser, 2021; Botti et al., 2022.

The motivation for writing this scientific research article could be found in the fact that MSD, ergonomics, and neuroergonomics have many common points that should be identified and researched in the future within scientific research. Examining the mental and emotional reactions, monitoring operators' performance, and examining all significant factors that affect them during the cooperation between collaborative robots and workers is an open question that should be explored in the future through scientific research. Researching the behavior of operators, monitoring neuroergonomics parameters during collaborative work, and monitoring attention and fatigue contribute to a better understanding of the phenomena that occur and indicate the specifics of workers' behavior. To achieve the above, it is possible to design and develop a modular and adaptive ergonomic research laboratory experimental set-up for human–robot interaction and to test it according to the already defined scenarios.

LITERATURE REVIEW

Konz (1995) and Das (2007) pointed out that job creation with non-respect for the ergonomic principles is common in the industry. Concerning this, performing complex operations of assembling parts and components in non-ergonomic postures on the workstations is an essential field of research for many researchers (Loch et al., 2016). Performing activities in an ergonomically inadequate workplace can cause MSDs, physical and emotional stress on the workers, low efficiency and productivity, and unsatisfactory product quality (Ulin and Keyserling, 2004). Chiasson and Major (2015) surveyed 473 workers in 1 year. The examination results showed that a large percentage of workers had MSDs and that a large number of workers reported feeling pain. Bernal et al. (2015) consider that MSD is more conditioned by psychological and social risk factors than physical factors.

Numerous studies and research articles have shown that long-term work in a sitting position results in increased feelings of discomfort for the workers (McLean et al., 2001; Fenety and

Walker, 2002; Callaghan et al., 2010). Some authors believe that the most significant discomfort in the lower extremities occurs when workers perform activities only in a standing position (Roelofs and Straker, 2002). Frequently, changes in the body position and performing activities combined with sitting and standing positions and increasing breaks reduce discomfort (McLean et al., 2001).

Scientific literature showed that ergonomic intervention is the best strategy to improve workers' health and safety by preventing MSD and reducing injuries during the work, discomfort, absenteeism (Burdorf, 2010; Takala et al., 2010; Botti et al., 2014), and enhancing operator performance, productivity, efficiency, product quality, and reliability (Hendrick, 2003; Dul et al., 2004; Roper and Yeh, 2007; Vayvay and Erdinc, 2008; Neumann and Dul, 2010). Furthermore, law regulations in this area remind organizations of the importance of including an ergonomic aspect when designing a prefabricated workstation (Otto and Scholl, 2011). The authors have proved that the application of ergonomic principles in the workplace directly impacts reducing errors and increasing product quality (Jorgen and Eklund, 1995; Hamrol et al., 2011; Thun et al., 2011; Falck and Rosenqvist, 2012). Yeow and Sen (2006) believe that even the cheapest ergonomic solutions can significantly have a positive effect on the quality of activities. González et al. (2003) showed in their study that product quality increased by 2% and additional processing of the finished product was significantly reduced after the improvement of physical ergonomics. Previous studies on improving assembly performance have focused mainly on conducting a batch experiment of different products, optimal distribution of the activities, including assembly activities (Arnold et al., 2004; Ullah et al., 2009).

In particular, some authors pointed out the importance of developing fully adjustable and ergonomically designed innovative workstations compared with the non-ergonomically designed fixed traditional workstations (Eswaramoorthi et al., 2010) to perform repetitive assembly tasks (Temple and Adams, 2000; Shikdar and Hadhrami, 2007). Other authors pointed out the advantages of performing workstation activities in an adequate ergonomic position, minimizing worker movements during the working activities (Roelofs and Straker, 2002; Lin and Chan, 2007; Davis et al., 2009). According to Muhundhan (2013), placing materials, parts, and tools at operators' fingertips reduces unnecessary stretching reach and, in that way, worker's fatigue is also reduced.

The design of the workstation can be facilitated by the innovative technologies of Industry 4.0 (Burggräf et al., 2019). Some studies showed the digital transformation of the manual workstation into a collaborative one (Pini et al., 2016; Gualtieri et al., 2020; Colim et al., 2021; Palomba et al., 2021) and indicated the benefits of collaborative cooperation between operators and robots (Consiglio et al., 2007; Sadrfaridpour and Wang, 2017; Heydaryan et al., 2018; Castro et al., 2019; Liau and Ryu, 2020; Parra et al., 2020; Pérez et al., 2020). Gualtieri et al. (2021), through the literature review of the research challenges on ergonomics and safety in industrial human–robot collaboration, pointed out the lack of studies on ergonomics compared to safety-related topics. Few studies were concerned with occupational health and indicated the benefits of human–robot collaboration (Cherubini et al., 2016; Brun and Wioland, 2021).

Numerous authors believed that collaborative robots contributed to the improvement of working conditions, productivity, MSD reduction (Sadrfaridpour et al., 2016; Awad et al., 2017; Pearce et al., 2018; El Makrini et al., 2019; Zanchettin et al., 2019; Gualtieri et al., 2020; Liau and Ryu, 2020; Palomba et al., 2021), improve the overall mental wellbeing of human operators (Parra et al., 2020), and minimize the time of execution the working activities (Hawkins et al., 2013). Ender et al. (2019) pointed out the relationship between human–robot collaboration and ergonomics (physical, cognitive, and organizational).

A review and detailed analysis of scientific research articles showed that the research on workers' effectiveness and manual and repetitive assembly work performance was mainly based on the determination of the correct body position (Fish et al., 1997; Leider et al., 2015). In scientific research, much less attention was paid to cognitive and perceptual factors that cause errors during the implementation of the work tasks (Fish et al., 1997). Falck and Rosenqvist (2012) showed that cognitive requirements are related to the operator's workload and errors made during the performance of the activities. Earlier research on mental and cognitive aspects relies on theoretical assumptions characterized by subjectivity (Parasuraman, 2003). The results obtained from the application of these methods are unreliable and biased (Parasuraman and Rizzo, 2006; Lehto and Landry, 2012).

Some authors pointed out the advantages of using EEG (Gevins and Smith, 2006) in measuring continuous and objective brain activity and the cognitive state of the operator (Luck et al., 2000; Murata et al., 2005; Jagannath and Balasubramanian, 2014) at the workplaces that require a high concentration of workers (such as assembly activities). The benefits of using an EEG device are based on the timely and objective detection in case of a drop in the attention and concentration levels, number of errors made, and so on. EEG systems provide the possibility of continual and objective measurement of workers' attention (Mijović et al., 2015, 2016a, 2017).

The literature review determined that a few scientific research articles have been written about physical and cognitive ergonomics within the human–robot collaboration, and there is room for further research in this area. Specific authors were engaged in the research of cognitive ergonomy in human–robot interaction (Maurice et al., 2013; Kim et al., 2018, 2019; Pearce et al., 2018; Lorenzini et al., 2019; Zanchettin et al., 2019; Gualtieri et al., 2020; Hopko et al., 2021) and some authors focused on the relationship between physical ergonomics and human–robot collaboration (Charalambous et al., 2016; Sadrfaridpour et al., 2016; Rossato et al., 2021).

Our study points out a wide range of experimental possibilities in human–robotic interaction. A modular and adaptive experimental set-up presented in an article will allow the researchers and practitioners to conduct neuroergonomic research seeking answers about workers' physical, mental, and emotional overload, fatigue, and decreased concentration. These aspects have become key indicators of product quality, including the constant problems with workers' absenteeism in the industry.

METHODS AND MATERIALS

This article presents a new, modular, and adaptive laboratory model of industrial assembly workstation (hereinafter referred to as workstation). This workstation model enables the realistic replication of assembly work activities in the industry, from simple ones to the complex interaction of workers and collaborative robots. During the design and construction of the laboratory model of the industrial assembly workstation, special attention was paid to the workspace for handling materials, parts, and components, considering that the operators should predominantly perform tasks within the golden zone. This zone is an ideal working area, where movements, reaching materials, stretching, and bending are minimized, and workers achieve the highest efficiency and productivity. The golden zone rules improve workplace organization and reduce muscle efforts and the occurrence of occupational diseases (MSDs). The workstations' construction is made of aluminum profiles (frames 40 × 40 mm and 40 × 80 mm), primarily used in the industry. The aluminum profiles are tightened with associated tensioning elements to stiffen the whole structure to give stability. The working surface is made of gray particleboard core covered with a silicone tablecloth protecting the piece from slipping during assembly.

Prolonged work in the same position causes strain on the operator's muscles, developing in the long-term occurrence of MSDs. Therefore, whenever working activities allow, operators should move from a sitting position to a standing position. Numerous studies have shown that back pain occurs in the workers who perform activities in a standing position (Andersen et al., 2007; Roelen et al., 2008; Nelson-Wong and Callaghan, 2010) over a long time, and therefore, operators must be allowed to perform activities by a combination of sitting and standing positions. The developed workstation is electrically height-adjustable using dual-lifting telescope system columns controlled by a 2-key hand switch and adapted to the anthropological characteristics of the participants. After a review of scientific research articles, it could be concluded that the best option would be for workers to perform activities on flexible workstations that are adjustable in height (Wilks et al., 2006). Also, the industrial work chair is height-adjustable, made of robust material, and characterized by stability when changing the participants' weight.

The workstation is upgraded with additional systems to fully simulate complex conditions characteristic of a natural work environment and enable advanced testing of participants' behavior during manual assembly tasks. An industrial computer is integrated into this workstation to monitor and control the performance of various work tasks, process visualization, and communication with the operator *via* HMI devices. A touchscreen PC is connected to the system for task definition and stimulus application.

Furthermore, special attention is paid to lighting. Lighting is an indispensable factor in the ergonomic design of the assembly workstation. It is essential to provide even illumination of the work surface to avoid straining their eyes when performing work activities. Individual reflectors that create superimposed solid shadows can cause eye strain, and, as the result, there is fatigue and a drop in concentration. Homogeneous LED lighting has been installed on the new industrial workstation since it produces only soft shadows, putting less strain on the eyes. Additionally, we set up an audio 5.0 system to emulate the sounds of the industrial environment. Different industries could record different sounds and show a realistic work environment for different workplaces.

The workstation (**Figure 1A**) is additionally equipped with blue plastic containers for storing assembly parts and tools, and the Poka–Yoke system for automatic control of assembly activities and prevention of errors. Systems that help workers to perform assembly activities make it easier to perform these activities and enable the worker to reduce errors (Fast-Berglund et al., 2013) and increase productivity (Hinrichsen and Bendzioch, 2018). The installed Poka–Yoke system (**Figure 1B**) has 6 independent lines to supply 6 different key components of the product, which are equipped with modules for access to the control at the entrance as well as the exit of the line. Vessels with mounting components move in a line *via* a wheeled conveyor. Poka–Yoke modules are equipped with indicator elements that indicate the next operation in the sequence and sensor elements to identify the fulfillment of individual orders. Removing the components for the current operation activates a sensor that automatically confirms the end of the current operation and gives a signal to activate the next operation.

Additional module for workstation represents a collaborative robot (cobot) station that enables the design of the work tasks where the operator and the robot will perform activities together. Unlike classic robots, cobots have built-in sensors that allow them to recognize and analyze workers' intentions and adapt their activities to the abilities of workers (Bonini et al., 2015) by monitoring the physical and cognitive workload of workers. The collaborative robot performs assembly activities that are monotonous, tiring, and repetitive or involve workers straining and bending. In this way, cobots improve working environment conditions by reducing worker workload as well as the risk of injuries at the workplace. Collaborative robots also perform those activities that require maximum precision and that operators cannot perform as reliably as robots. The operator performs activities that require a high level of knowledge and skills and decision-making skills (**Figure 1**).

The innovative EEG system is used to design and conduct neuroergonomical experiments. Depending on the requirements of the experiments, EEG data could be acquired using the wireless EEG system in two possible configurations. The first one is using a 24-channel gel-based EEG cap (EASYCAP GmbH, Wörthsee, Germany) with 10–20 electrode placements (the Ag/AgCl electrodes) (**Figure 2A**). The EEG data are acquired using the lightweight EEG amplifier attached to the back of the cap. The Bluetooth connection is used as a communication protocol between the EEG amplifier and the computer (mBrainTrain, 2019). The second configuration uses the Smartfones (**Figure 2B**), the modified headphones to collect EEG data (mBrainTrain, 2019). The Smartfones use 4 gel-free electrodes placed around the ears and three in the central scalp zone (Kartali et al., 2019). The EEG data were acquired using a 500 Hz sampling frequency in both configurations. In the first configuration (the gel-based system is used), the

FIGURE 1 | (A,B) A laboratory model of industrial assembly workstation.

FIGURE 2 | (A) EEG Cap, **(B)** EEG Smartfones, **(C)** EMG muscleBAN.

electrode impedances were kept below 10 kΩ, whereas in the second configuration (the gel-free system), they were kept below 20 kΩ because of the different electrode properties. For EMG measurements during the neuroergonomical experiments, muscleBAN (PLUX Wireless Biosignals, Portugal) was used. This wearable, wireless (Bluetooth or Bluetooth Low Energy data transmission) device combines a single-channel EMG sensor, triaxial accelerometer, and magnetometer and, in that way, enables real-time acquisition with up to 16-bit resolution at up to 1,000 Hz sampling rate (**Figure 2C**). Small dimensions of the device and an internal battery that ensure the autonomy of 8 h make it suitable for workplace arm muscle activity and motion data monitoring when placed in pairs on both forearms.

One of the most demanding challenges in all experiments is the proper synchronization of all elements in the measurement set-up, which needs to ensure that the timing of all events and recorded data are defined and known with sufficient precision. If the timing of these events cannot be well-measured, this will cause the loss, reduction, or blurring of any measured data and their relations to trigger events. The function of synchronization is to eliminate timing errors, which cannot be eliminated on hardware and measurement

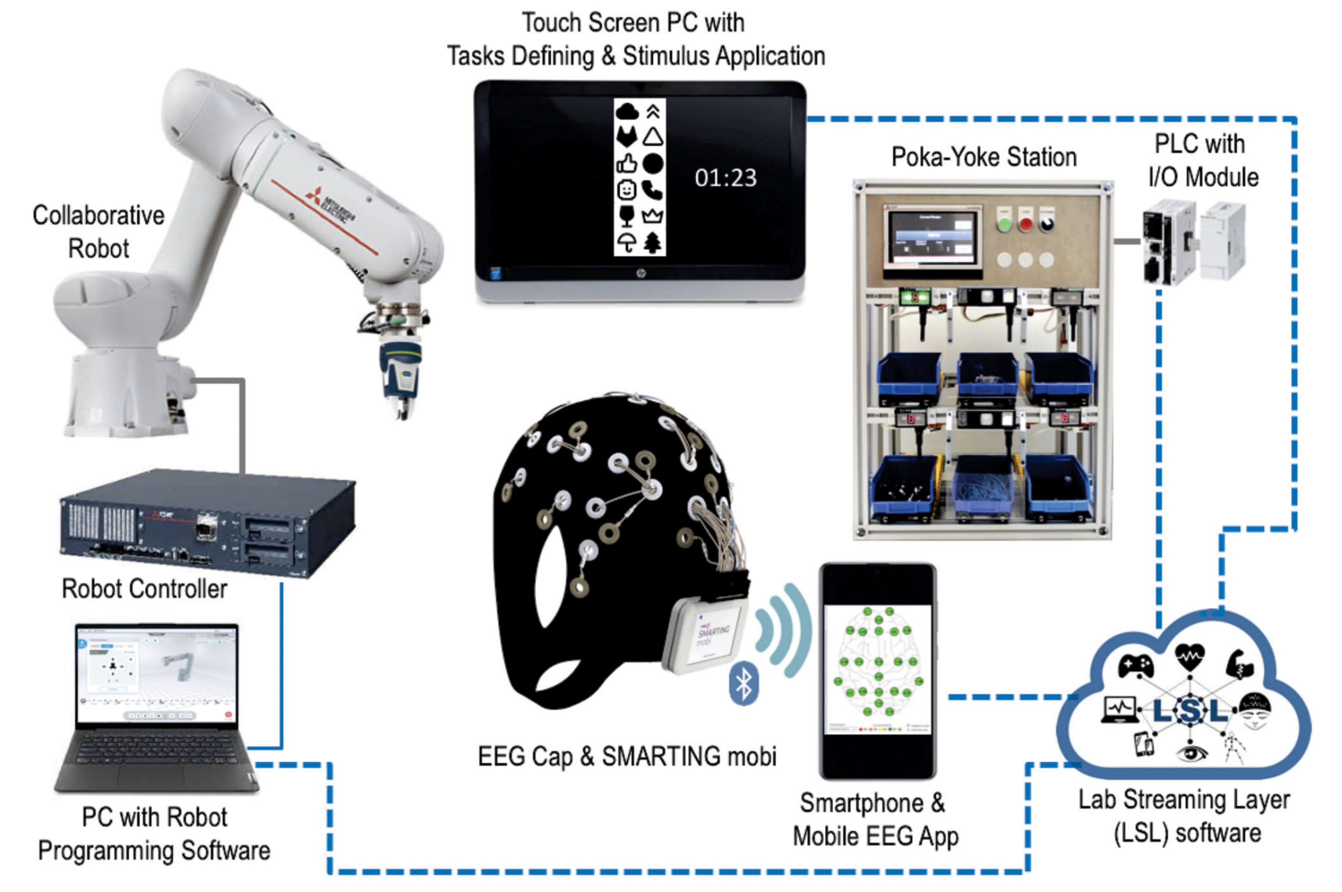

FIGURE 3 | LSL integration of key measurement set-up elements.

set-up levels or to be corrected after analysis, so they must be solved before the measurement starts. For synchronization, a specific software/API package was used, called the Lab Streaming Layer (LSL), as a powerful tool that allows multiple continuous data streams and discrete marker timestamps to be acquired in an eXtensible Data Format (.XDF). The inputs from multiple devices, connected to one measurement set-up, are collected and synchronized *via* LAN network using LSL (**Figure 3**).

Description of the Research Scenarios

The study of behavior and reactions during collaborative interaction between workers and cobot represents a particular challenge, where positive characteristics of the workers (adaptability, creativity, ability to make quick decisions, dexterity, perception, agility, cognitive abilities, ability to think critically, and intellectual abilities) are combined with technical characteristics of cobots (strength, endurance, precision, speed, repeatability, and consistency) (Helms et al., 2002; Kruger et al., 2009; Murashov et al., 2016) to perform work activities more efficiently and safely. On the other hand, in traditional work environments, work activities are strictly divided into those performed by robots and activities performed by workers (Wongphati et al., 2015; Maeda et al., 2016).

The designed workstation represents the laboratory infrastructure used for conducting neuroergonomic experiments and studying the behavior of operators at the workplace. Based on workstation construction and integrated elements, four basic scenarios could be performed to make workers' behavior comparative analyses (**Figure 4**):

1. **Standard work**—performing manual assembly work tasks for a complex product without any specific intervention or improvement at the workplace. Work is performed on workstation "as is" without personal adjustments according to ergonomic or "golden zone" standards.
2. **Ergonomic work**—work is performed on an ergonomically optimized workstation with a workplace organized in conformity with the ergonomic and "golden zone" principles and standards.
3. **Guided work**—participants perform the same work tasks as in the first scenario but with the additional involvement of the Poka–Yoke station. The Poka–Yoke system has a role in guiding operators through the repetitive process of assembling parts and components, from operation to operation, generating the start of each subsequent step

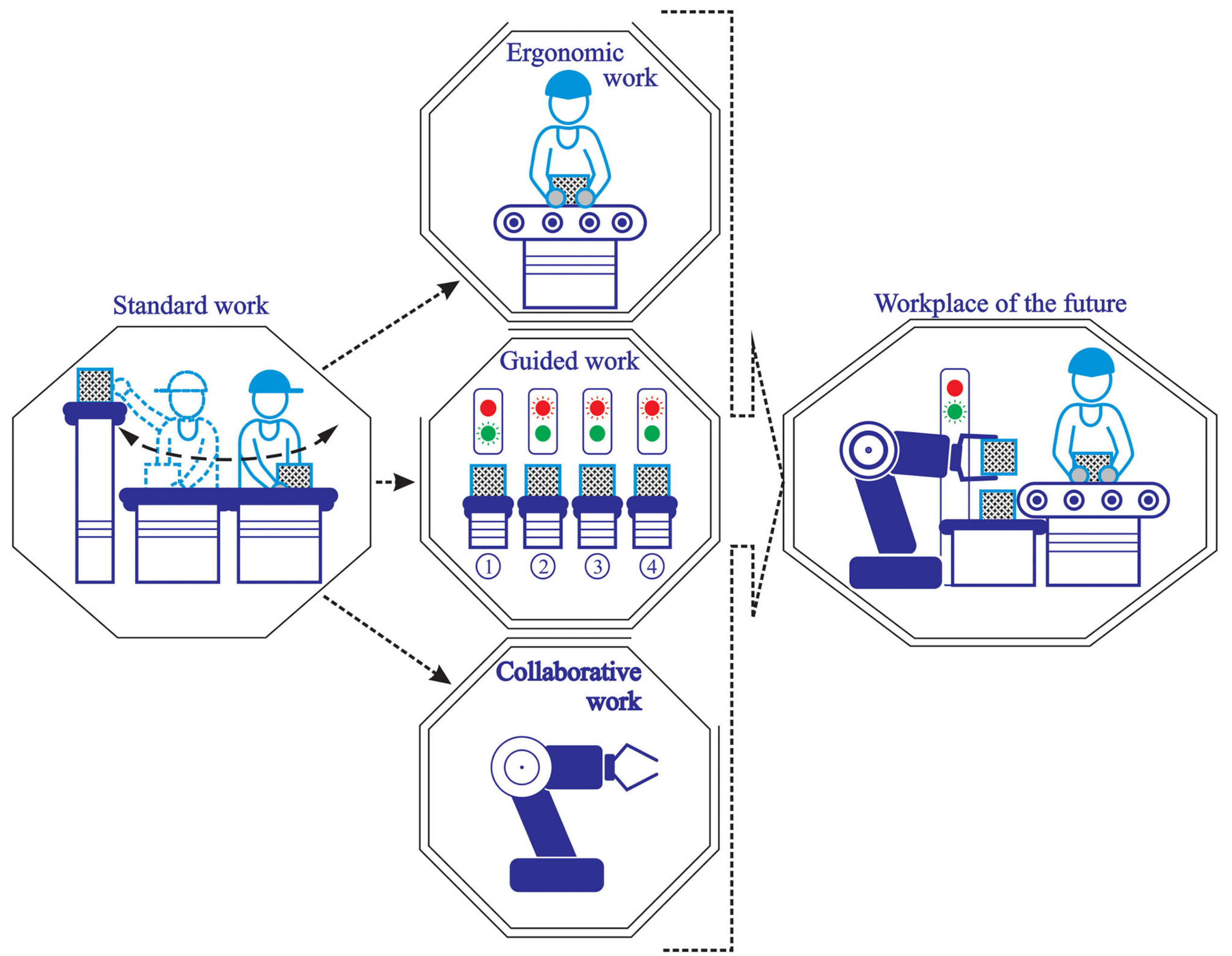

FIGURE 4 | The research scenarios.

in a predefined sequence of steps and thus preventing human errors.

4. **Collaborative work**—participants perform work tasks with the support of a collaborative robot, where the collaborative robot performs repetitive, simple activities that do not require thinking and decision making.

Previously defined scenarios represent identified tools, methods, and techniques that could ensure the transformation and improvement of the standard industrial workplace, for manual assembly tasks, into the workplace of the future (**Figure 5**). All mentioned directions will be used in the nearest future, in some forms and combinations, and that is why continuous work and investigation of human behavior and reaction, to each of them, have significant importance.

Description of the Experimental Session

The authors conducted a neuroergonomic study according to the first scenario (standard work) during the initial research phase. The participants' working tasks were manual, monotonous, and repetitive. Operator assembled parts and components into the final product following the order of assembly and pre-defined provisions concerning positioning the parts and components, and so on. The experiment was conducted in conditions that were, generally, in conformity with the natural industrial environment. The selected work activities met several prerequisites similar to actual industrial tasks, repeatable, and feasible in laboratory conditions. Activities and tasks that were identified as characteristic during the visits to the companies and interviews with persons responsible for production and safety were selected. This approach is called participatory ergonomics intervention (De Guimarães et al., 2015). In this way, the simulation of actual production is provided without changing the structure of components and assembled parts.

To perform the experiment, the authors developed and constructed a prototype model of an industrial product, which is an abstraction of the connection plate and consists of a metal base made of steel sheet with built-in threaded elements and

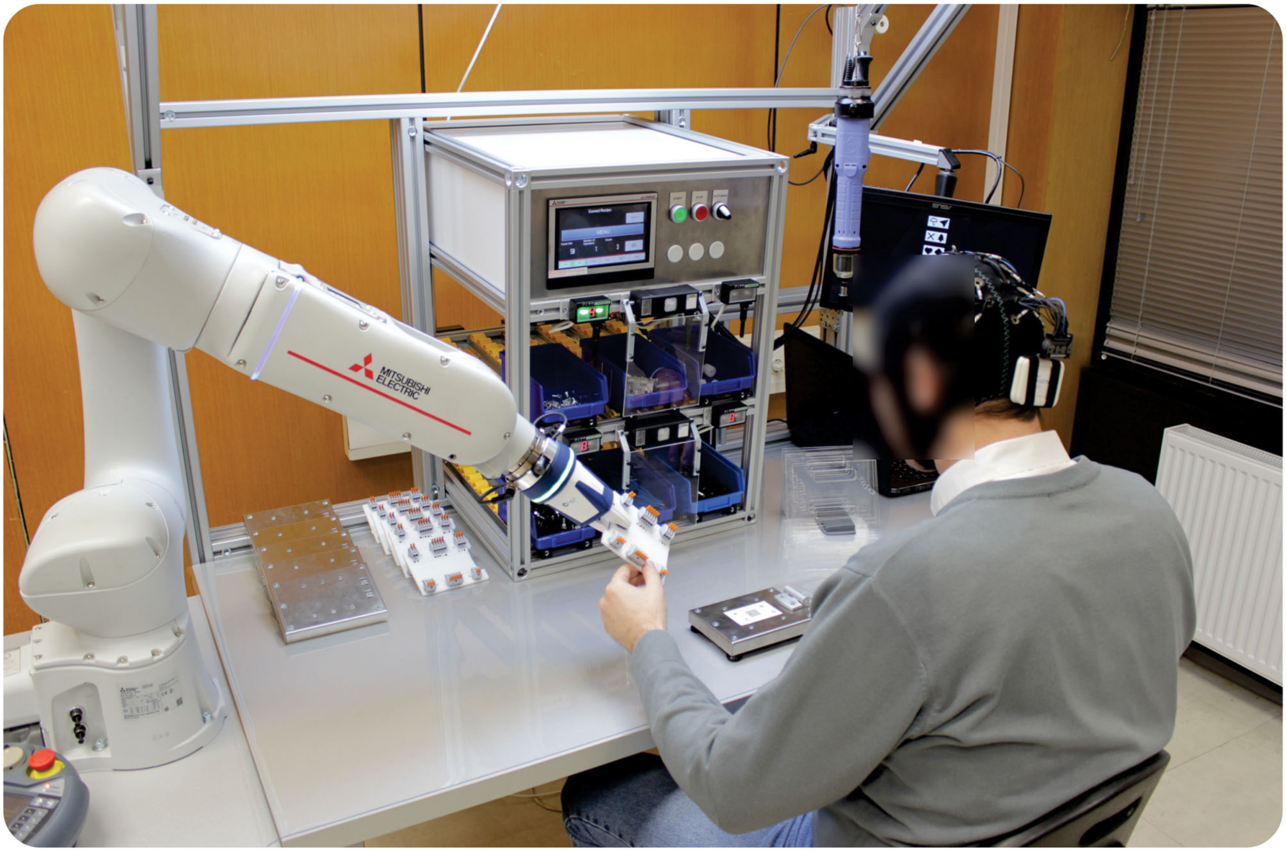

FIGURE 5 | The workplace of the future.

a transparent acrylic cover connected with an aluminum hinge (combination of three materials). Adjustable legs and electrical connectors of various sizes are placed on the stand. Wiring and connection of electrical connectors can be reported in several ways (different job variation options). The product can be completely disassembled, an essential factor for performing multiple experiments. The very fact that such research can be conducted in replicated work environments, where the work process is simulated, is an excellent progress, and it can bring necessary knowledge about worker cognition, which can later be used in designing specific jobs (Mijović et al., 2016b).

Before starting, the entire experiment and its purpose are explained to the participant. EEG cap is mounted on the participant's head, and the EEG device and associated computer are configured and set according to the internal protocol. After the final check is done, the technician starts the EEG device and plays relaxing music for 5 min. After 5 min, the participant starts the assembly process. The whole experiment consists of two rounds per 60 min, each, with a 15 min break between the sessions. The product assembly takes approximately 4 min. The assembly tasks and the components and tools used (①–⑪) are shown in **Figure 6**.

Task no. 1: Take the steel plate base from the lot ① and place it in the appropriate place, in an upside-down position.
Task no. 2: Take supports (four pieces) from the container ② and tighten them to the end, manually, in their positions.
Task no. 3: Turn the object to the upper side. Take the white acrylic with prepared glued connection elements from the lot ③. Take four round hex screws (M4x16) from container ④ and tighten them with an adequate hex key wrench.
Task no. 4: Take seven, one-by-one, wires from a container ⑤ (wires are 150 mm in length and prepared for connection) and connect them. The connections (number and task definition) are carried out according to the information showed on the installed touchscreen PC ⑥. There were two types of prepared wiring schemes. The first type was schemes assumed to be easy to connect. The second type was assumed to be challenging to connect. The participant did not know which order scheme would appear on the monitor. The participant randomly gets a picture or pair of the symbols that have to be connected (**Figure 7**).
Task no. 5: Take one hinge from container ⑦, two countersunk screws (M6x12), and tighten them with the adjustable torque screwdriver ⑧ hung on the balancer.

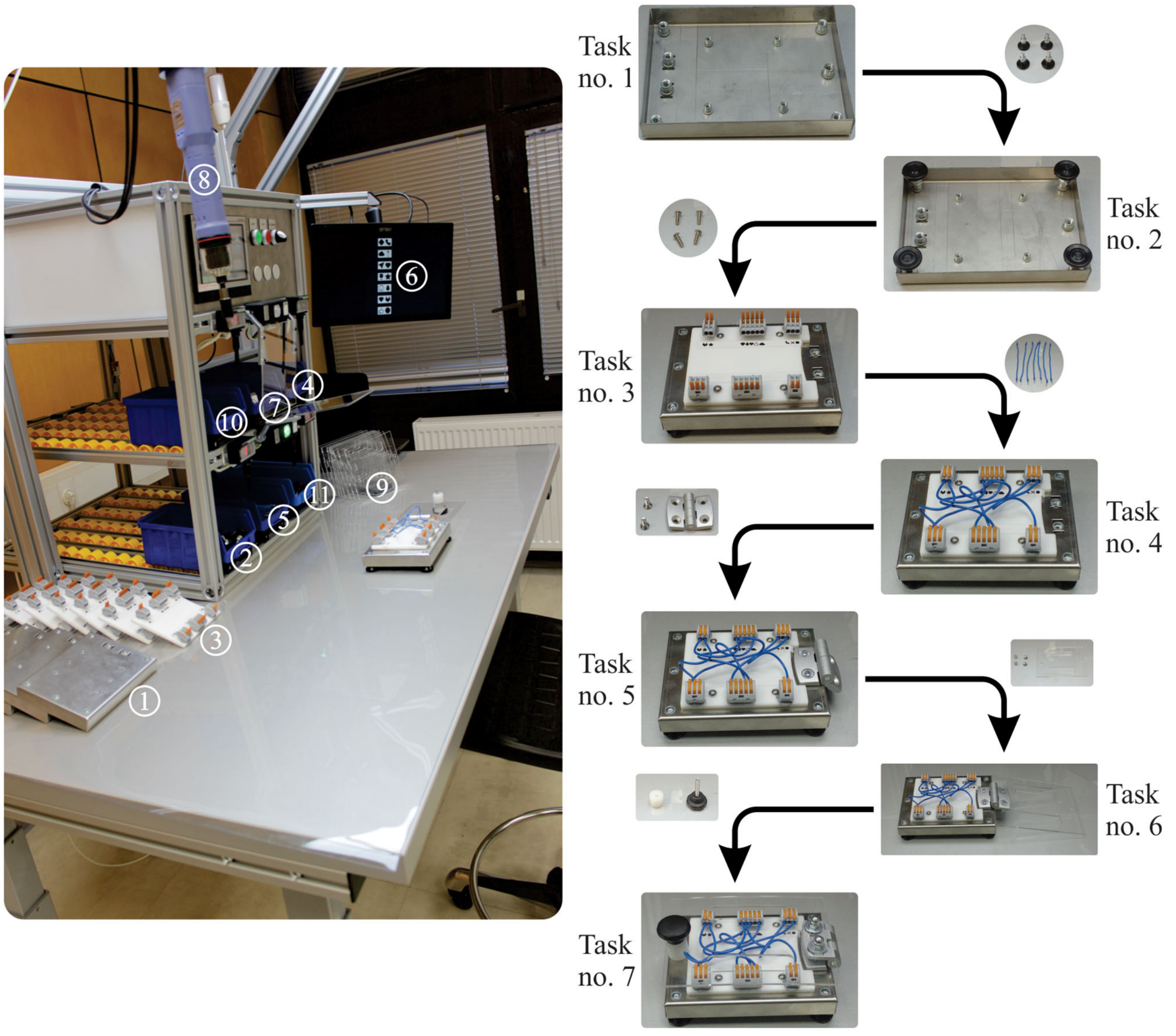

FIGURE 6 | Description of the experimental session.

Task no. 6: Take one transparent acrylic from plot ⑨, two countersunk screws (M6x12), and two cap nuts to fasten a hinge and the acrylic.

Task no. 7: Take one cylindrical plastic roller from container ⑩ and one threaded spindle rod from container ⑪ to tighten the transparent acrylic to the steel plate base.

Finished prototype model of an industrial product is stored in the predefined place while the participant starts with task no. 1 again.

Initial Results and Discussion

The study's main idea was to propose, develop, and test a modular and adaptive laboratory workstation model that could be used for various types of experiments requested by the industry. The initial results are related only to examining the possibility of conducting experiments on a developed workstation and whether it is possible to obtain satisfactory initial results by imitating the working environment. Collected EEG data were processed using MATLAB (MathWorks, Massachusetts, United States) and EEGLAB (https://sccn.ucsd.edu/eeglab/index.php). The EEG signals were first band-pass filtered in the range 1–40 Hz, using an FIR filter generated by the EEGLAB. The amplitude of the signal is in the range from 1 to 100 μV (**Figure 8**).

Research has shown that, in response to the mental demands of the task being performed, EEG signals tend to change predictably, more specifically that EEG spectral power correlates with task complexity (Brookings et al., 1996; Gevins et al.,

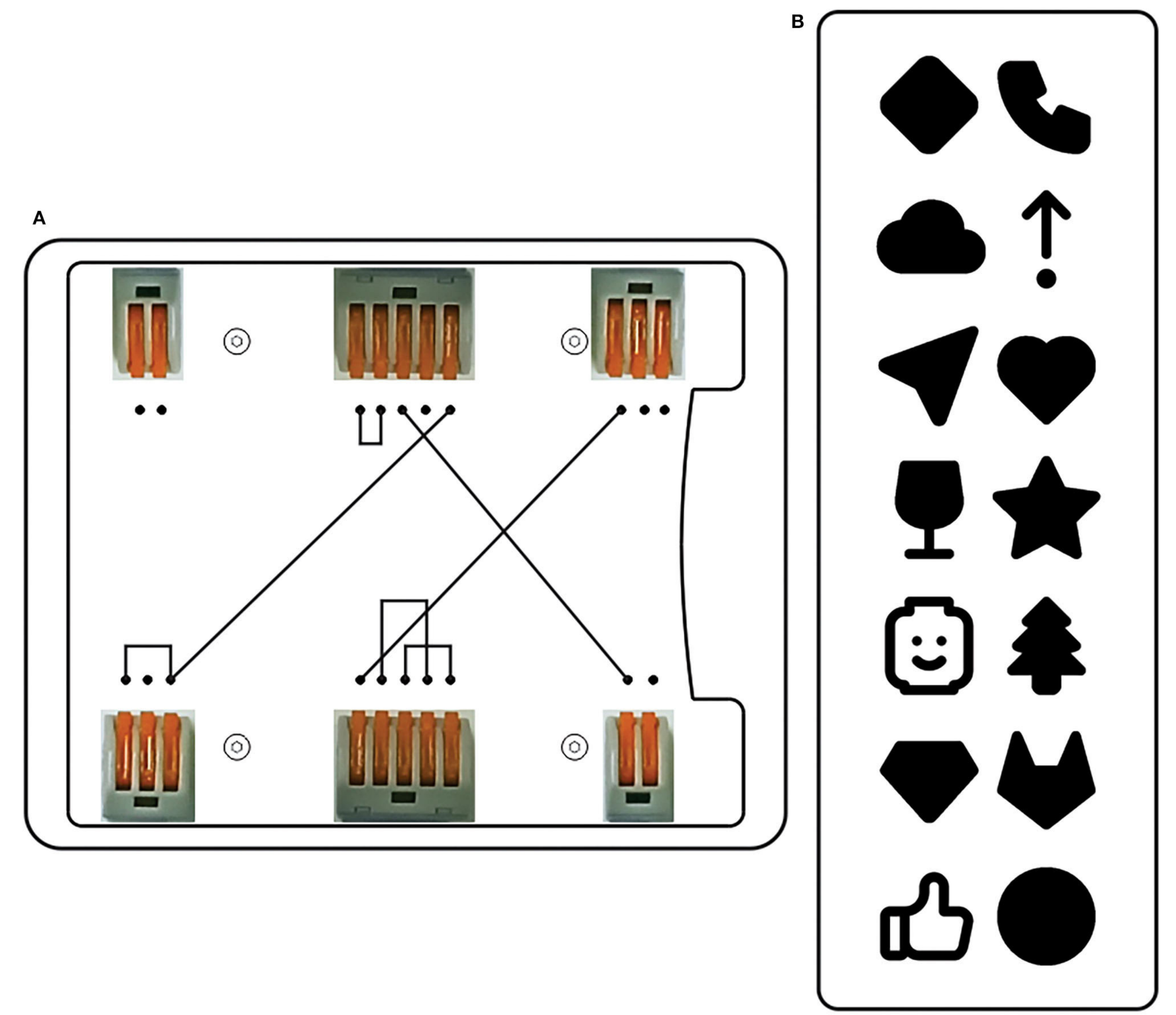

FIGURE 7 | Types of schemes **(A)** easy to connect, **(B)** harder to connect.

1997; Stipacek et al., 2003; Missonnier et al., 2006). Namely, due to observable changes in frontal midline theta band (4–7 Hz) and parietal midline alpha band (8–12 Hz), their ratio can be employed to estimate MWL (Holm et al., 2009; Zhang et al., 2018; Andreessen et al., 2021). The so-called MWL index is obtained by computing the ratio between signal power in the theta band (4–7 Hz) from the frontal midline electrode (Fz) and signal power in the alpha band (8–12 Hz) from the parietal midline electrode (Pz). We windowed the raw signal to compute the MWL index (using 5 s windows with 4.9 s overlapping). The metric can be seen in **Figure 9**. During the first 5 min, a subject was idle (listening to some relaxing music) while he was involved in the assembly work for the rest of the time. As we can see, this is evident from **Figure 8**, as the respective MWL index was low for the first 5 min.

Two participants took part in the initial experiment on the developed modular and adaptive laboratory set-up. We can extract comparative statistics for the first session to prove that the MWL index is lower for lower-engagement activity (the first 5 min of resting time). The statistical data are shown in **Table 1**.

The statistics prove that MWL is lower during the first 5 min of the session while subjects are taking rest. In addition to that, note that EEG signal has different strengths (amplitudes) for different participants, as the result of significantly different MWL indexes for participant no. 1 and participant no. 2 under the same task difficulty level. This is why EEG is usually

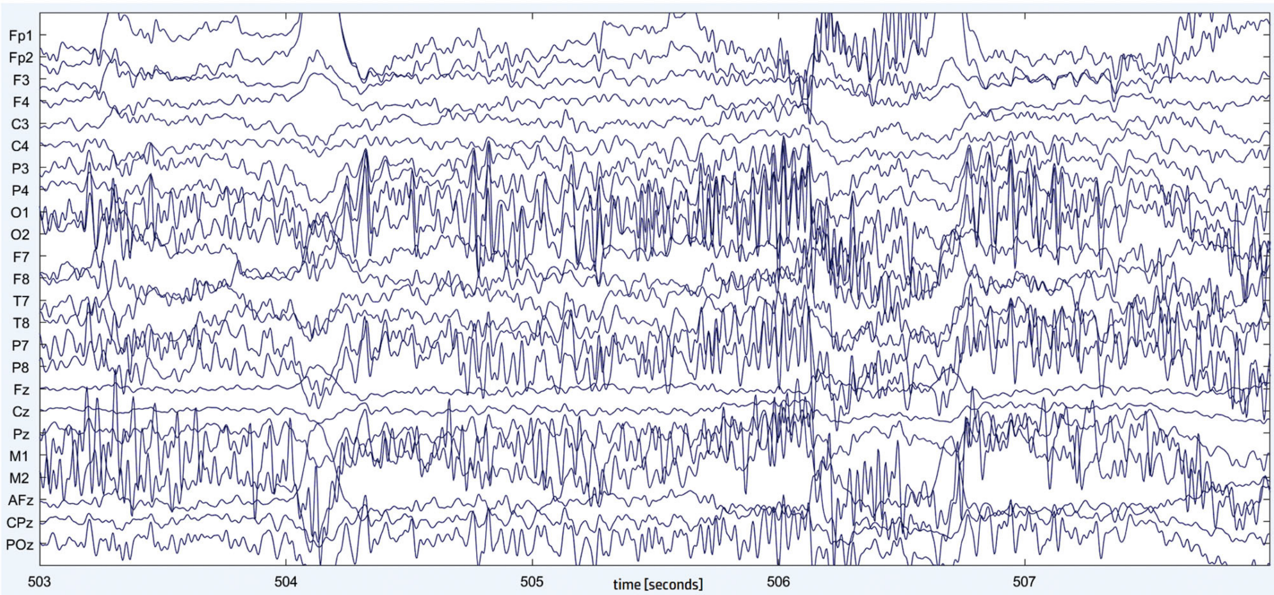

FIGURE 8 | Band-pass filtered 24-channel EEG signal (5 s) recorded during the assembly task. On the *y*-axis we have signals from 24 electrodes by their name.

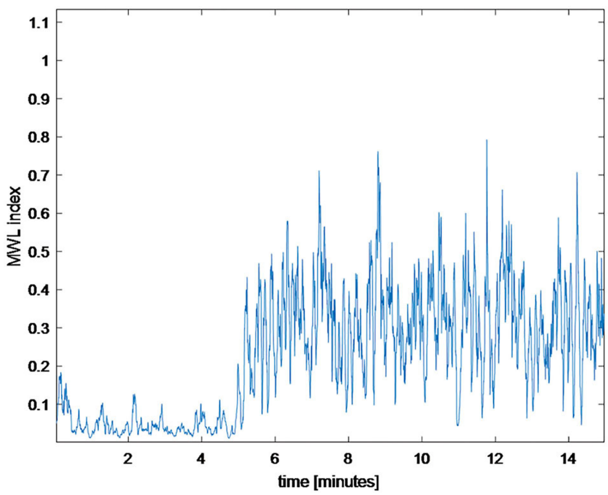

FIGURE 9 | MWL index of the first 15 min of the experiment (window size is 5 s).

normalized when processing signals of different participants together. One of the purposes of this experiment was to distinguish periods of low and high complexity schemes and estimate task difficulty with regard to time by looking at the MWL index in real time. However, we would need to test and record more subjects to conduct that analysis. That way, we could make an average over their normalized MWL index vs. time graphs and resolve the problem of individual differences between subjects. The result would be an objective (not participant-dependent) task difficulty with regard to time. We plan to carry out this research soon and on a larger sample. This research explains that it is possible to conduct neuroergonomic research on a new, modular, and adaptive laboratory workstation model.

We also noted some technical difficulties during the experiment. One of the issues was switches stiffness. Participants experienced problems if they made a wrong connection with a wire and had to unlock the switch and lock it again. We plan to solve the same making more ergonomic schemes. Another problem was that the chair was inappropriate for the experiment this long, as both subjects confirmed that they felt mild pain in their backs after some time of being in that position. Furthermore, the main participants' remark was losing focus during the 3-h experiment. They concluded that it is possible to lose focus very easily, which could be the new research hypothesis for future research work.

In the future, during our research activities, we will continue to collect data corresponding to the remaining three different scenarios (ergonomic work, guided work, and collaborative work). This should enable a comparative analysis of participants' behavior and monitor the operators' psychological reactions during the implementation of the same or similar work tasks under different scenarios. The most important part of the planned research activities is related to assessing the neuroergonomics parameters and examining operators' reactions during the performance of the working activities in cooperation with the collaborative robot.

CONCLUSIONS

Workplaces with high repetitiveness of tasks, high noise levels, and poor ergonomics can cause both mental and physical stress and reduce the operator's attention. Over time, products with many or similar components can cause an increase in the number of errors. The increasing variety

TABLE 1 | Average MWL indexes for both subjects in the cases of resting and active time.

	Participant no. 1	Participant no. 2
Resting MWL index	0.0472	0.1737
Active MWL index	0.3013	0.9187

of products was also identified as the leading cause of the complexity perceived by an operator in carrying out his tasks (Olwal et al., 2008). Taking into consideration that the workforce is getting older, it is necessary to pay attention to, so far, not so attractive parameters for monitoring and improvement such as wellbeing, operators' satisfaction, attention, concentration, and fatigue. To enable monitoring of these parameters, a new, modular, and adaptive laboratory model of industrial assembly workstation for conducting advanced research in the field of ergonomics, neuroergonomics, and human–robot interaction is designed and built. This recently designed workstation eliminates all limitations that characterize a traditional workstation.

This newly developed workstation is designed to be operator-centered and thoroughly adapted to the operator's needs, abilities, and limitations. The anthropometric characteristics of the workers were taken into account so that the workstation is suitable for both males and females and so that the workers can carry out assembly activities within the golden zone. This workstation includes the assembly area and it has a built-in Poka–Yoke system. It can guide the actions carried out by the worker and aims to improve the quality of the product being assembled. Furthermore, it minimizes errors accidentally made by the operators due to a drop in the concentration and intentional errors.

The main elements from the industry were replicated in the laboratory, taking into consideration spatial dimensions of the workplace and ambient conditions. This article describes an innovative neuroergonomic experimental set-up studying operators' comparative habits and behavior at the workplace for four different scenarios—standard work, ergonomic work, guided work, and collaborative work. This ensures the transformation and improvement of the standard industrial workplace into the workplace of the future. The assembly task proposed by the authors consists of the developed and constructed prototype model of an industrial product that can be disassembled and thus used in numerous experiments. Participants in the laboratory examination carry out characteristic and standardized assembly activities. Initial neuroergonomic tests using an EEG device were conducted to show various research possibilities on the workstation. In a replicated workplace, the whole process of producing the final product was simulated. Operators' reactions, behavior, and responses to sophisticated conditions in the work environment are monitored. The preliminary experiments showed that it is possible to conduct neuroergonomic research on a new, modular, and adaptive laboratory model of industrial assembly workstation. Moreover, the industry could request various scenarios to improve the operators' ergonomics. The requested scenario will be adapted in the advanced laboratory set-up, then tested and analyzed with specific outputs proposed to solve the identified problem.

The experimental set-up presented in this article is the basis for conducting advanced research in the future. We will collect data regarding ergonomic, guided, and collaborative work that will show participants' behavior and psychological reactions during the implementation of the same or similar work tasks. These results will be analyzed through a comparative analysis to define which parameters are most important to be monitored. The main focus will be on examining operators' reactions during working activities in cooperation with the collaborative robot.

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 author/s.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Ethics Committee of the Faculty of Medical Sciences, University of Kragujevac Decision number: 01-6471, date: June 3rd, 2021, based on submitted study protocol no. 01-5578 from May 18th 2021. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

MS and IM conceive the idea and concept. MD and IM designed and built a workstation. MP, MD, and CC designed the experiment. CC and AV collected data. MP and AV analyzed data. MS, MD, and IM wrote the manuscript. All authors read and approved the final manuscript.

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Beyond Digital Twins: Phygital Twins for Neuroergonomics in Human-Robot Interaction

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INTRODUCTION

Among the most recent enabling technologies, Digital Twins (DTs) emerge as data-intensive network-based computing solutions in multiple domains—from Industry 4.0 to Connected Health (Pires et al., 2019; Bagaria et al., 2020; Juarez et al., 2021; Phanden et al., 2021). A DT works as a virtual system for replicating, monitoring, predicting, and improving the processes and the features of a physical system—the Physical Twin (PT), connected in real-time with its DT (Grieves and Vickers, 2017; Kaur et al., 2020; Mourtzis et al., 2021; Volkov et al., 2021). Such a technology, based on advances in fields like the Internet of Things (IoT) and machine learning (Kaur et al., 2020), proposes novel ways to face the issues of complex systems as in Human-Robot Interaction (HRI) (Pairet et al., 2019) domains.

This position paper aims at proposing a physical-digital twinning approach to improve the understanding and the management of the PT in contexts of HRI according to the interdisciplinary perspective of neuroergonomics (Parasuraman, 2003; Frederic et al., 2020).

APPROACHING AND ADOPTING DIGITAL TWINS

The DT definition is still an object of debate, and reaching one could be a necessary step for efficiently managing its technical requirements in terms of computing and connectivity (Shafto et al., 2012; Haag and Anderl, 2018; Jones et al., 2020; Kuehner et al., 2021; Singh et al., 2021; Botín-Sanabria et al., 2022; Wang D. et al., 2022). However, we can ignite our discussion by considering how Fuller et al. (2020) highlighted that a DT is not just a digital model or an offline simulation of a physical object. Nor does a DT correspond to a digital shadow, depicting the real-time states and changes of a PT that can just be manually modified. The changes in a DT automatically mirror and affect the status of its PT: the data flows bi-directionally (Van der Valk et al., 2020) and in real time between twins in digital and physical worlds, possibly without any human intervention (Liu et al., 2022) through the DT-driven control of an actuated PT. However, a DT is typically "played" by experts like managers, engineers, and designers as a complex interactive simulation to predict future issues in the PT according to its past and current behavior (Semeraro et al., 2021). This leads to new policies as feedback to the real system, even with the assistance of artificial intelligence layers (Umeda et al., 2019; Gichane et al., 2020). Considering their functions (Khan et al., 2022) each DT can focus on (i) monitoring a PT, (ii) simulating the future states of a PT, (iii) directly interacting—as an "operational DT"—with a cyber-physical system as PT.

Among the fields of DT application, robotics certainly offers several examples (Girletti et al., 2020; Matulis and Harvey, 2021) of twinning solutions, especially in conditions of HRI like human-robot collaboration (Malik and Bilberg, 2018; Maruyama et al., 2021; Tuli et al., 2021).

In particular, literature in robotics offers interesting solutions of intuitive extended reality interfaces (Alfrink and Rossmann, 2019; Burghardt et al., 2020) to ease the interaction of an expert with a DT. In the next section, we propose that such an approach can be further enhanced by emulating certain PT components through a DT and others through a physical replica of the robotic system.

PHYGITAL TWINS IN HUMAN-ROBOT INTERACTION

Performing holistic, physical, and reality-based interaction with a robotic system is more intuitive for the user than contactless gestures to program or command the device and change its state to accomplish a task (Jacob et al., 2008; Heun et al., 2013; Blackler et al., 2019; Ravichandar et al., 2020). Following this reasoning, we decided to highlight the opportunity of emulating a PT through what we labeled as a "Phygital Twin." This term has already been used by Sarangi et al. (2018) to describe an IoT setup designed to collect data and represent an environment (even through portable devices) to assist a farmer in precision agriculture paradigms. However, we envisioned the usage of this label for a wider class of solutions by pondering the meaning of the "phygital" attribute outside the domain of twinning processes.

As a neologism (merging two words: physical and digital), this attribute has been typically adopted across various domains like design and marketing, blending real and virtual dimensions as in its etymology (Gaggioli, 2017; Mikheev et al., 2021). This term was used, for instance, to define Tactile User Interfaces (TUIs) like the "phygital map" in Nakazawa and Tokuda (2007), the paradigms of "phygital play" (Lupetti et al., 2015) in mixed reality-based robotic games (MRRGs) (Prattico and Lamberti, 2020), and interactive solutions for work and education proposed during the COVID-19 pandemic (Chaturvedi et al., 2021; Burova et al., 2022).

Overall, these are just examples in a general virtual-real convergence trend (Tao and Zhang, 2017), like cyber-physical twins (Czwick and Anderl, 2020). This trend occurs in healthcare too (Gregory, 2022) about managing chronic conditions and predicting their progress or the therapeutic outcome (Voigt et al., 2021; Barresi et al., 2022). Furthermore, we must highlight how intrinsically phygital are the recent definitions of the metaverse, a digital world embracing cyber-physical systems and also DTs in its connection with the real world (Yoon et al., 2021).

Exploiting the phygital approach we foresee a Phygital Twin (PDT, highlighting both its physical and digital elements) as in the example in **Figure 1**. Within a PDT, certain components of the PT are replicated by digital objects and others by physical objects within an integrated extended reality model. These physical objects would be secondary instances of the same products (not necessarily a robot) in the PT. In **Figure 1**, an example of the human-exoskeleton system in a real context is the PT emulated by a DT (in green, on the left), based on a fully virtual model of the HRI system. On the other hand, the same PT can be represented (on the right) by a PDT, based on a virtual human "wearing" a real exoskeleton (identical to the one in the real-world context and, possibly, sustained by a mannequin) into a laboratory. Both settings, visualized by an expert through a mixed reality headset, enable the live visualization of anomalies in the right shoulder of the worker in this example.

Different from the case of the fully virtual model on the left, the expert on the right can decide to alter the phygital model through intuitive physical interactions with the lab exoskeleton (working as a TUI), performing tests according to past and current data from the PT. Indeed, the expert receives visual feedback from the DT and more intuitive visuotactile feedback from the PDT. After obtaining the informed consent of the worker in the PT system, the experts can also update the remote wearable robot software according to their predictions.

Thus, the PDTs enable intuitive phygital interactions with experts to assess and improve the PT. Furthermore, its physical components can emulate the ones of the PT more reliably than a virtual simulacrum because they are based on the same products. The PDT computer-generated elements may also be visualized through a virtual reality headset instead of a mixed reality one, according to the need of depicting the PT context as a whole. However, focusing further on the virtual human component can also be greatly advantageous to deepen our knowledge of the user's conditions, especially in terms of neuromotor and neurocognitive processes, as the next section will propose.

NEUROERGONOMIC TWINNING OF HRI SYSTEMS

Through digital human modeling (Paul et al., 2021), DTs can contribute to monitoring, assessing, and designing different human-system interactions (Caputo et al., 2019; Greco et al., 2020; Sharotry et al., 2022; Wang B. et al., 2022) according to the perspective of human factors. In particular, neuroergonomics (Mehta and Parasuraman, 2013)—especially computational neuroergonomics (Farahani et al., 2019)—can advantageously exploit twinning for understanding how the human nervous system works in real contexts (Cheng et al., 2022), and improving the design of any item interacting with it. This is certainly true about neuroergonomics in HRI contexts (Cassioli et al., 2021) for applications like monitoring motor control difficulties (Memar and Esfahani, 2018), providing robots with adaptive features (Lim et al., 2021), and improving brain-robot interfaces (Mao et al., 2019). Overall, the exploitation of DTs in this field can inherit the corpus of knowledge in neuroscience, especially when human-machine interactions are investigated (Gaggioli, 2018; Ramos et al., 2021). Interestingly, literature in this area already shows several approaches presenting analogies with PDTs, which can contribute to neuroergonomics in HRI by offering intuitive interactions with a phygital emulation of the human-robot system.

For instance, the field of bionic prosthetics (Frossard and Lloyd, 2021) offers this kind of solution, with emphasis on twinning the residual limb more than the device. Interestingly, Chen et al. (2022) labeled as "mechatronics-twin" a framework integrating a 6-DoF manipulator with biomechanical models to explore, through simulations, the operational behaviors of prosthetic sockets with amputees. Such an example sounds quite

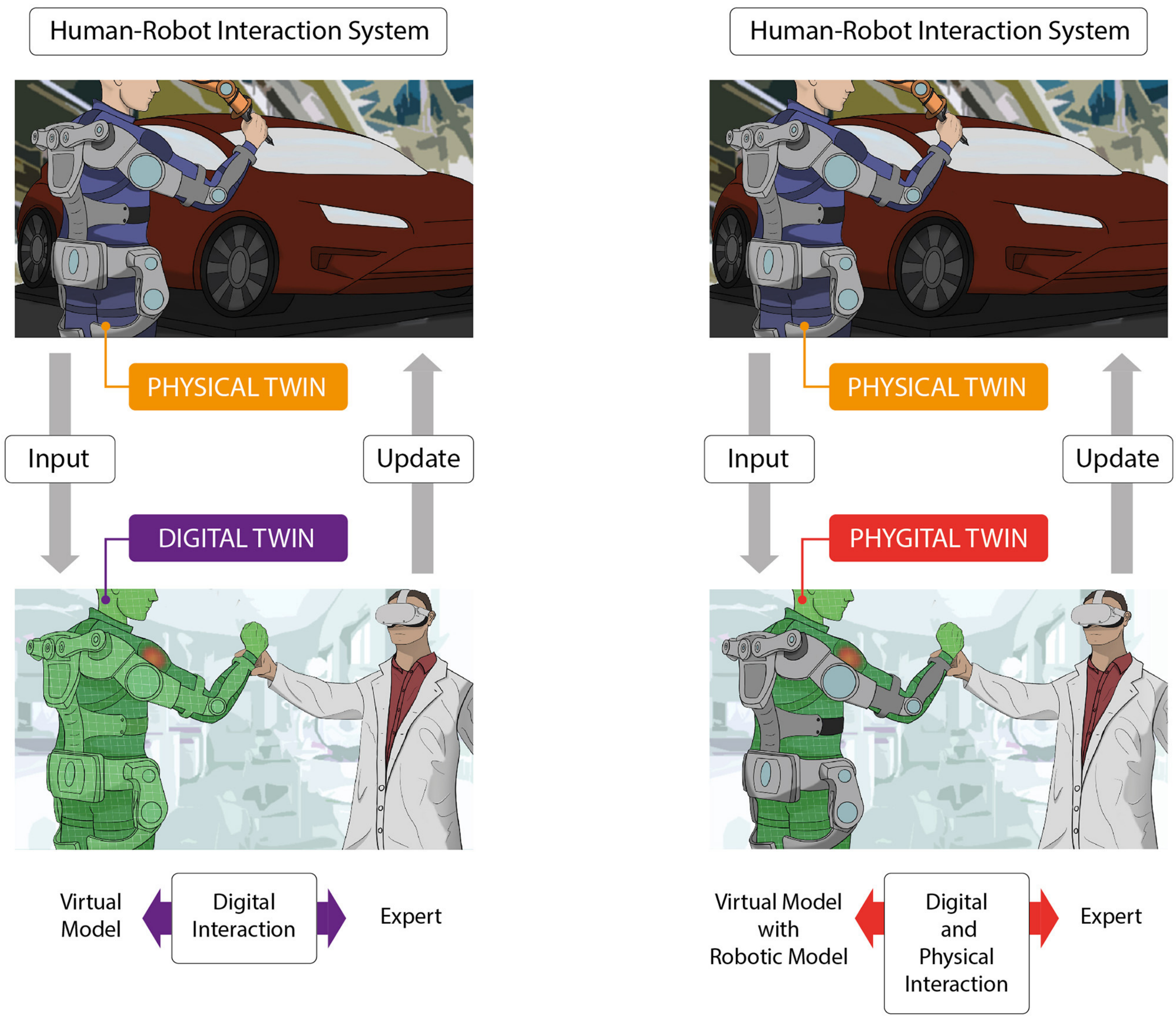

FIGURE 1 | A Physical Twin (PT), based on a human-exoskeleton system in a context of usage, connected (on the left) to its Digital Twin (DT) in green, based on a virtual model of the human-robot interaction (HRI) system, or (on the right) to its Phygital Twin (PDT), based on a holographic human "wearing" a real exoskeleton in a laboratory.

close to the concept of PDT, which can have additional features of real-time bidirectionality, intuitive physical interaction, and ecological validity (resemblance with real contexts).

Furthermore, Pizzolato et al. (2019) proposed human neuromusculoskeletal (NMS) system models for DTs to improve the outcome of the interactions between users and assistive or rehabilitative machines. NMS models implemented in robot control solutions can offer phygital features. For instance, the output of the interaction between a user and a mechatronic device (possibly enriched by extended reality solutions) can become a quantifiable index of healthy and pathological conditions and responses to treatments. This would make such an output a peculiar type of digital biomarker (Wright et al., 2017): a "phygital biomarker" or possibly, a "neurophygital biomarker" (a promising step in this direction is based on neuromechanical biomarkers for rehabilomics) (Garro et al., 2021). In line with this reasoning, we could think about "neurophygital twins" to extract biomarkers from the activity of their PTs: mechatronic devices like rehabilitative exoskeletons (Buccelli et al., 2022) or, possibly, any other robot (including humanoids) designed to interact with humans wearing sensors.

Through intuitive phygital interactions between the researcher or the clinician and the lab replica of the same machine in the real world, neuroergonomic hypotheses on psychophysiological and motor processes underlying HRIs can be tested in simulated experiments based on a PDT. We could also envision the development of neurorobotic systems (Li et al., 2019) mimicking neurocognitive and neuromotor processes to physically replace a virtual human model in a PDT: in this case, the neurorobotic model would be validated through its interaction with another machine within the same PDT. However, before addressing such challenges, the current constraints in our knowledge and know-how must be pondered. Besides the technical limitations in twinning (first of all, the computational burden of emulating neural processes in ecologically valid settings, without considering the connectivity issues to approach the real-time standards), we must also highlight how both DTs and PDTs raise ethical issues on privacy and consent in data representation and storage, and on concepts like "normality" and enhancement (Bruynseels et al., 2018; Braun, 2021; Nyholm, 2021). These issues should be discussed within the frame of the enablers and the barriers to twinning adoption (Perno et al., 2020), even pondering the opportunities offered by novel technological frameworks (Yi et al., 2022).

CONCLUSION

This position paper presented a novel "twinning design" concept: PDT, based on physical replicas of PT components enriched with virtual models and computational features to establish intuitive and reliable phygital interactions with experts. Thus, a PDT would facilitate the experts' task of assessing and improving the PT conditions. Furthermore, PDTs provide neuroergonomics with tools for iterative human-centered design and evaluation of robotic systems into a "metalaboratory" before and after their deployment.

AUTHOR CONTRIBUTIONS

GB devised the conceptual contents and structure of the paper and wrote the initial draft. CP, ML, and LDM improved the document and considering further potential applications of the proposed approach. All authors revised and approved the manuscript.

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Design and Development of a Scale for Evaluating the Acceptance of Social Robotics for Older People: The Robot Era Inventory

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Introduction: Nowadays, several robots have been developed to provide not only companionship to older adults, but also to cooperate with them during health and lifestyle activities. Despite the undeniable wealth of socially assistive robots (SARs), there is an increasing need to customize the tools used for measuring their acceptance in real-life applications.

Methods: Within the Robot-Era project, a scale was developed to understand the degree of acceptance of the robotic platform. A preliminary test with 21 participants was performed to assess the statistical validity of the Robot-Era Inventory (REI) scales.

Results: Based on the criteria observed in the literature, 41 items were developed and grouped in different scales (perceived robot personality, human–robot interaction, perceived benefit, ease of use, and perceived usefulness). The reliability of the Robot-Era Inventory scale was analyzed with Cronbach's alpha, with a mean value of 0.79 (range = 0.61–0.91). Furthermore, the preliminary validity of this scale has been tested by using the correlation analysis with a gold standard, the Unified Theory of Acceptance and Use of Technology (UTAUT) model.

Discussion: The Robot-Era Inventory represents a useful tool that can be easily personalized and included in the assessment of any SARs that cooperate with older people in real environment applications.

Keywords: technology acceptance, older people, social assistive robotics, usability, social presence, embodiment, scale validity

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INTRODUCTION

As stated by the World Population Prospects 2019 (United Nations, 2019), because of the considerable increase in life expectancy, the population of persons aged 80 years or over is thought to triple by 2050. Similarly, the number of people aged over 65 years is rapidly increasing; in 2019, they were 1 in 11, but they will be 1 in 6 by 2050 (UN Department of Economic Social Affairs., 2019).

Due to the aging population across the world, a lot of research is being carried out to improve older adults' quality of life and ensure their independence for as long as possible. In this scenario, one of the most explored technological solutions is the use of socially assistive robots (SARs). A social robot is defined as a humanoid or zoomorphic artificial agent. It has been identified as an approach to meeting the mental health needs of older adults through interaction or information exchange (Oh et al., 2018). Despite the increasing interest in the field of assistive robotics and technologies in general, one-third of all the experimented solutions are abandoned during the first year of use (Gurley and Norcio, 2009). For this reason, the design and acceptability of service robots, their ability to positively interact with individuals and coexist in domestic environments, are crucial aspects to overcoming the resistance toward service robotics (Salvini et al., 2010). This topic is frequently explored in literature, confirming that acceptance is often measured qualitatively (Krick et al., 2019). Nevertheless, several scales have been used to evaluate SARs acceptability. The most used is the Technology Acceptance Model (TAM), grounded on the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB). According to the TAM model, acceptance mainly depends on perceived usefulness and perceived ease of use. These two discussed factors determine the attitude toward use, which, in turn, influences the behavioral intention to use the technology (Ammenwerth, 2019). From the TAM, the Unified Theory of Acceptance and Use of Technology (UTAUT) was derived. The UTAUT model argues that behavioral intention and facilitating conditions influence user behavior. Behavioral intention is, in turn, determined by three constructs: performance, effort expectancy, and social factors. Furthermore, gender, age, experience, and voluntariness of use modulate every factor (Venkatesh et al., 2003). The UTAUT results have been applied to several fields of research, even if neither the TAM nor the UTAUT is specifically validated for the healthcare context (Jewer, 2018) or with older adults (Heerink, 2010). Moreover, some researchers extended the generalization of the original model to the application to patients interacting with SARs (Jewer, 2018). The Almere model is an interesting case of this attempt. This model is founded on the hypothesis that functionality and technological features may not be exhaustive in describing acceptance, but also social dimensions play a crucial role in the acceptance path. Indeed, the Almere model found that trust is moderated by attitude, which, in turn, is moderated by social influence, perceived adaptivity, and anxiety (Heerink, 2010). This model has an enhanced explanatory power, if compared to the original UTAUT (Heerink, 2010), but it was not validated with older users nor did it result theoretically strong, resulting in a limit for the generalizability (de Graaf et al., 2019).

In this article, we report an attempt to provide a comprehensive model and inventory for the evaluation of the Robot-Era platform, developed inside the Robot-Era project (GA 288899). Robot-Era was aimed at developing, implementing, and demonstrating the general feasibility, scientific/technical effectiveness, and social/legal plausibility and acceptability of an advanced social robotic platform, integrated with intelligent environments. The experimental phase of the project was divided into two phases, the first one in a realistic setting and the second one at home. A complete description of the project and publications of the results are available here (https://cordis.europa.eu/project/id/288899/it). After the first experimental phase, the results suggest the need for a more customized tool to assess the acceptability of the Robot-Era platform (Cavallo et al., 2018), as already underlined by relevant authors in this field (Heerink et al., 2009). The preliminary study conducted highlighted the need for a deeper investigation of the social presence dimension, and the abilities relevant to fostering the human–robot interaction (HRI) (Bevilacqua et al., 2015; Cavallo et al., 2018). The Robot-Era Inventory (REI) may represent a first attempt to construct a tool able to include all the metrics of relevance for assessing the acceptability of SARs in the older population, in contrast to the scales already described, and that can be easily personalized based on of the specific services offered. In particular, dimensions, such as usability, social presence, services' acceptability, the personality of the robot, and interaction capabilities, are considered pillars in the field of social robotics assessment, but the relationships among these concepts, the robotic features and human abilities, need to be deeply investigated, to design a model that takes into account the characteristics of the target, i.e., older people, and the peculiarities of the services offered through the robotic solutions and, consecutively, also a tool for measuring and understanding the impact of using SARs.

MATERIALS AND METHODS

To build the Robot-Era Inventory, we started with the analysis of the results of the first experimental phase, as clearly described in a study by Cavallo et al. (2018). In light of the results obtained and the literature in the field (Heerink et al., 2008, 2009; Heerink, 2010), the first step was represented by the theoretical design of the model, including all the relevant domains, followed by the drafting of the items to be included in the Inventory. For the development of new concepts for the assessment model of the Robot-Era platform, the starting point of the analysis was represented by the Venkatesh UTAUT model (2003). As the second step, the Robot-Era Inventory was administrated to 21 older people during an experimental setup described in par 2.4, together with the UTAUT questionnaire. The internal validity of the construct of the new scale was evaluated using Cronbach's alpha. The final version of the Robot-Era Inventory is composed of 5 scales.

To build the Robot-Era Inventory, the steps proposed in a study by Boateng et al. (2018) were followed regarding: (a) the Item Development phase (through experts' workshops for identifying the domains and literature reviews on models, tools, and dimensions, described in the following paragraphs) and (b) the Scale Development phase (i.e., pretesting of the items with 21 older participants, first items reduction, and initial analysis of content validity). As the authors already suggest, the steps for scale validation may vary based on the purpose of the study, resources' constraints, and use of existing scales for item generation in contrast with "*de-novo*" tools. For the Robot-Era

Inventory, the items were grouped based on already available scales (see Section The Robot-Era Model), plus a customized section related to the Robot-Era platform's services. However, the full validation of the Inventory should include a higher number of participants and a deeper statistical investigation to assess the overall validity and reliability.

Social Presence and the Human–Robot Interaction

As it is well known from the literature (Lee et al., 2006; Heerink et al., 2008), social presence can be considered a determinant of the acceptability and usability of socially assistive robots. This particular dimension has received much interest both in the field of social psychology and human–robot interaction (Biocca et al., 2004). Many definitions of this concept have emerged, but it can be said that the term "social presence" can be referred to as "the sense of being there" (Witmer and Singer, 1998; Biocca, 2004) or the feeling of being in the company of someone as "the perceptual illusion of nonmediation" (Lombard and Ditton, 1997). From the psychological perspective, the social presence can be ascribed to the "theory of mind" paradigm (Gordon, 1986; Carruthers and Smith, 1996). Following this theory, it can be said that when interacting with a robot, the users expect the robot to respond socially, to be able to express affection and appropriate responses to the person's social input, and, thus, to stimulate emotional reactions (Damiano et al., 2015). In this way, it is possible to assess the social presence of a SAR, by determining how the robot can interpret social stimuli and how humans perceive and interpret the robot socially (Fiore et al., 2013).

In 2004, Lee classifies three types of presence:

- The physical experience of entities or environments.
- The social experience refers to the experience of social actors (both the humans and human like).
- The self-experience refers to the experience of one's self or selves.

Out of the three types, the social presence plays a crucial role for the human–robot interaction and it could be considered the ultimate goal of any designer of SARs (Breazeal, 2003; Fong et al., 2003; Lee and Nass, 2003). It is, therefore, important that through social signals, the robot conveys its social presence (Fiore et al., 2013), to allow the person to consider the robot as a social agent, able to influence the sociocognitive processes of the individuals (Biocca and Harms, 2002; Fiore et al., 2013). Finally, Biocca et al. (2004) suggested the need to contextualizing the theory of social presence and its measurement, matching the insights from the literature with the research objectives.

As for humans, the communication "rules" should guide the development of social robots defined as "an autonomous or semi-autonomous robot that interacts and communicates with humans" (Bartneck and Forlizzi, 2004). In fact, to date, robots are not seen as simple tools anymore, but also as companions, thus able to interact socially with humans (Cobo Hurtado et al., 2021). To do that, the robot must be able to understand what the user is saying or doing, understand natural language, and should be capable of establishing complex dialogs with its human. As described also by Fong et al. (2003), the social robots should have the following characteristics:

- Express and/or perceive emotions
- Communicate with high-level dialog
- Learn/recognize models of other agents
- Establish/maintain social relationships
- Use natural cues (gaze, gestures, etc.)
- Exhibit distinctive personality and character
- May learn/develop social competencies.

Responsiveness and prompt support are mostly requested in emergency conditions, in which the user expects to receive coherent and rapid feedback on the circumstance, to act appropriately. For this purpose, the HRI may be supported by multichannel sensory features, which generally include auditory, visual, and tactile capabilities. Also, the esthetical parts of the robots are relevant for communication, such as eyes, dimensions, and shape (Bonarini, 2020). To appreciate and measure the quality of the HRI, key elements of the interaction should be defined during the setup of any experimentation or the design of a new product: the human, the robot, their interaction, and the context (Collins, 2019).

Regarding human characteristics, five personality traits of the user are strong predictors of a positive HRI, namely, extroversion, agreeableness, conscientiousness, neuroticism, and openness to experience (Esterwood and Robert, 2021).

Acceptability

The acceptance of technology represents more complex phenomenon with respect to the analysis of older people's needs *per. se* and it could be defined as "the demonstrable willingness within a user group to employ technology for the task it is designed to support" (Mynatt et al., 2000; Al-Youssef, 2015).

In general, there is a tendency to think that older adults are less interested in technological advances and the use of technology (Knapova et al., 2020). To understand the kernel of the older people, rejection of new technological artifacts means to understand deeply the person beliefs that characterized the elderly and that can determine their closure to the innovation. Although there are advantages to the use of technology by older people, it is possible to notice a rejection of the artifacts, caused by the low motivation to use technology, little knowledge about the computer/technological world, and also the cognitive and physical changes that older people undergo as they age (Wildenbos et al., 2018). This last factor specifically leads to a psychological condition known as "technostress," a construct that indicates how the difficulty of older people in using technology leads to anxiety and depression about technology and, therefore, a low level of acceptance of it (Nimrod, 2018).

The acceptance of a device is linked to intrinsic or extrinsic factors related to the technology (Flandorfer, 2012), such as living environments, social relationships, and needs, and it may lead to the diffusion and exploitation of the systems, supporting new markets and discovering new segments of consumers.

There are numerous studies (Wagner et al., 2010; Magsamen-Conrad et al., 2015; Vroman et al., 2015; Knapova et al., 2020; Zaman et al., 2022) that have researched and identified factors

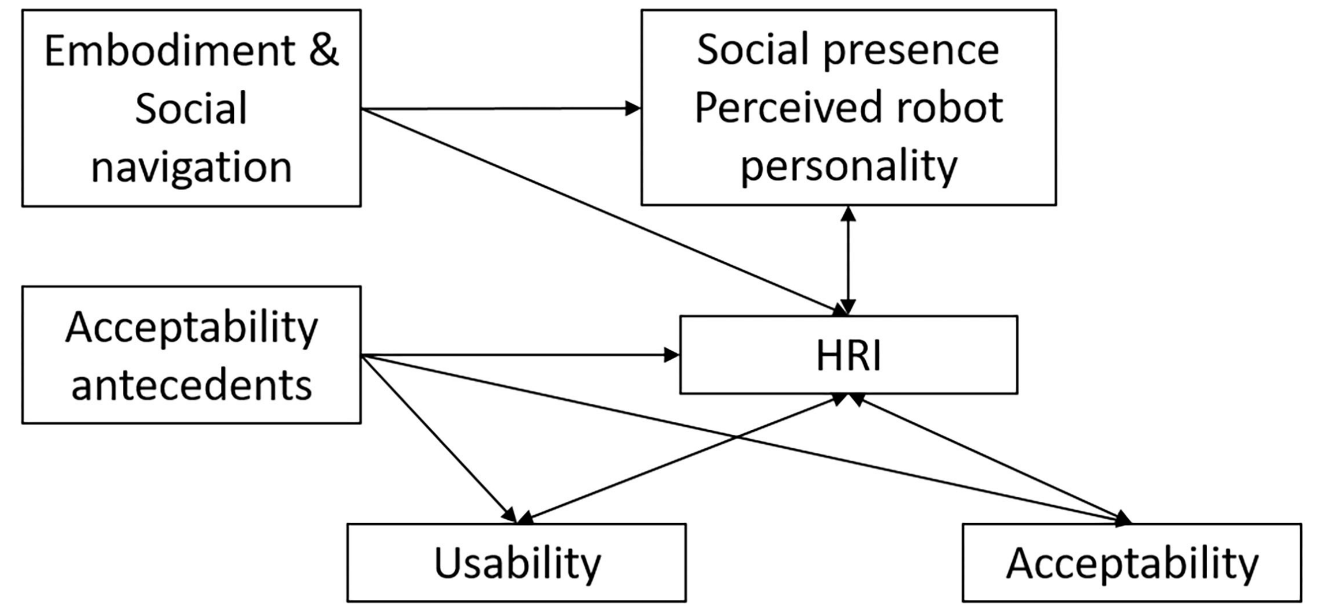

FIGURE 1 | The Robot-Era theoretical model that summarized the direct influences within the different factors.

that explain the level of technology acceptance by older people. Personal factors, such as age and education level (Magsamen-Conrad et al., 2015; Vroman et al., 2015; Vorrink et al., 2017), psychological factors, such as motivation to use technology, perceived anxiety, and cognitive abilities (Venkatesh et al., 2003; Macedo, 2017), and environmental factors, such as financial support and assistance from friends and family (Wagner et al., 2010), come into play. Finally, personality-related factors also play an important role (Vroman et al., 2015).

In this regard, Svendsen et al. (2013) have investigated the degree to which users' assessment of the core constructs of the Technology Acceptance Model (TAM) is influenced by personality as measured by a short version of the Big Five Inventory (John et al., 1991). A web-based survey was used where 1,004 users read a description of a software tool before completing personality and the TAM inventories. The results indicate that personality influences behavioral intention (BI). In particular, the extraversion trait has significant, positive relations to BI and this relation is fully mediated by the TAM beliefs, in addition to the openness to experience, significantly and positively related to perceived ease of use.

In this case, the analysis of the acceptability of the three robotic platforms was mainly based on the administration of the UTAUT questionnaires and *ad-hoc* questions on anxiety and perceived enjoyment, and the evaluation of the acceptability oriented to the services, employing through observations. Moreover, the analysis of two personality traits, namely, the novelty-seeking and the introversion/extraversion traits, will be added to the preliminary questionnaire, while Anxiety, Attitude, and Perceived Adaptability scales from the UTAUT were selected. Among them, it was found that perceived adaptability is a crucial dimension for evaluating the acceptance of social robots in older people (Heerink et al., 2008).

Usability

Older people are often considered "technophobes" due to their scarce knowledge and lack of accessibility to technology (Joshi et al., 2020). The use of a robotic assistant for daily activities can be felt by older people as a real challenge. Furthermore, long-term use of robots is also rare because little research has tested them in real human operating environments, where both the needs and difficulties of interaction emerge (Cobo Hurtado et al., 2021).

Understanding the role of usability in the field of robotics is not trivial, as the technical features of the robots are inextricably connected with factors, such as social presence, empathy, and feeling of being in a relationship (Rogers, 2009).

Following the principles of universal design, a product and an environment should be usable by all the people, avoiding, as much as possible, the need for adaptation or specialized design, through the application of principles, such as equitable use, flexibility, simplicity, and intuitive use, perceptible information, tolerance for error, low physical effort, and size and space for approach (Burgstahler, 2001). This means that the technology should be built for as wider a range of users as possible and also for secondary and tertiary end-users, most of all for the informal caregivers (Van Den Broek et al., 2010). Technological malfunctioning and limitations of robots represent two of the most important barriers to the adoption of social robots. Moreover, it can be stated that the usability of a robotic system is a major concern among older adults (Papadopoulos et al., 2020).

Robots are smart objects that can be distinguished from other similar products due to their navigation and manipulation skills, in addition to the interaction modality. The usability is influenced strongly by interactions that are executed by hardware and moving parts, not only by software. Robots can move around autonomously, they can interchange or manipulate objects with users, and due to their stronger interaction skills, they can be not

TABLE 1 | Items selected for the inventory.

Dimension	Acronym	ITEMS
Perceived Robot Personality	PRP	The robot is unsociable-sociable The robot is insensitive-sensitive The robot is incompetent-competent The robot is unintelligent- intelligent The robot is moving rigidly- moving elegantly The robot could be a friend of mine I would like to have a friendly chat with the robot I would trust the robot if it gives me advice I have confidence in the robot ability to get the job done I'm afraid the robot can hurt me I feel safe when the robot moves around me
Human Robot Interaction	HRI	The robot was able to communicate his intention clearly to me When talking with the robot I felt like I'm talking to a real person The vocabulary of the robot is appropriate The robot talks fluently The robot is able to manage communication failures How do you feel when the robot was moving his arm? agited-calm How do you feel when the robot was moving his arm? quiescent-surprise How do you feel when the robot speech? agited-calm How do you feel when the robot speech? quiescent-surprise I think talk to the robot is very easy
Perceived Benefit	PB	The robot is appealing and I really would like to use it more I do not have the technical competences to make a good use of the robot I think I could have a good use of the robot Robot services match the needs I have The robot is able to fulfill the goal I have settled I feel more independent if supported by the robot in my daily activities
Easiness of use	EU	I couldn't get anything accomplished with the robot I will be able to use the robot without any support I think the overall RE platform can be used only by people with no limitation I have had fun using the robot I was relaxed during the use of the robot I feel nervous while using the robot
Perceived usefulness	PU	Reminding appointment Communicate with carers Carrying objects Giving the sense of security in the home Accompany inside the homeh36pay I could use Robot-Era system only if necessary I am willing to my living environment to be able to use the robot.

only perceived as machines, but also personal assistants or even friends. For this reason, it was decided to maintain the concepts expressed by ISO 9241 and the UTAUT dimensions of perceived usefulness and perceived ease of use as relevant references for the usability evaluation, both largely described in the literature.

Robot-Era Model

The Robot-Era model is designed in light of the literature in the field and the lessons learned from the first testing experience with the Robot-Era platform. In particular, the adaptation of available tools seemed necessary to include a more comprehensive approach to social presence and the HRI, determined by the robotic capabilities and characteristics.

The relevant factors behind the model are divided into: *intrinsic. characteristics* and *interaction. factors*.

For *intrinsic. characteristics*, we defined all those end-users and robots' characteristics that influence the interaction condition, determined by embodiment and social navigation for the robotic agent and acceptability antecedents, such as attitude toward technology, personality traits, age, gender, technology representations, eHealth, and health literacy, for the human agent.

Regarding the robotic agent, the embodiment and social navigation establish a basis for structural coupling by creating the potential for mutual perturbation between system and environment, a prerequisite for any robotic agent to be perceived as a social being (Fong et al., 2003). On the human agent, the acceptability antecedents represent a core set of essential information to be collected, as largely reported in many studies and theoretical approaches in the field (Bevilacqua et al., 2014).

As *interaction. factors*, we have defined all the key dimensions to assess the overall acceptability of social robotics in any experimental setup that required contact with older people to cooperate in daily activities. These factors are:

- *Perceived. robot. personality*, including all the characteristics related to social presence, trust, and feeling of being in company with someone.
- *Human–robot. interaction*, including the assessment of communication skills and speech, perceived safety, and physical contact.
- *Usability*, intended as ease of use and perceived usefulness.
- *Acceptability*, intended as attitude toward the system (in this case, the Robot-Era, but these should be customized based on the robotic services or technology), perceived benefit, and adaptability to the needs and wishes of the participants.

Even if all the dimensions are strictly connected, **Figure 1** summarizes the direct influences of the different factors: the robotic agent's intrinsic characteristics, for example, directly influence the social presence and the HRI capabilities, while the human agent's acceptability antecedents may have a direct effect on the perception of usability and acceptability of SAR, and on the evaluation of the HRI features themselves. As observed, the HRI plays a central role in the model, as it is the domain in which the robotic agent and the human agent' dynamics converge together, in the co-construction of the social interaction.

To draft the items of the inventory, the tools and scales from the literature were selected (Interpersonal Attraction Scale; McCroskey and McCain, 1974; UTATU, Venkatesh et al., 2003; Godspeed questionnaire, Bartneck et al., 2009) and then customized for the Robot-Era robotic services. **Table 1** shows the items selected for the inventory.

Sample Description and Procedure

To assess the internal validity of the Robot-Era Inventory, a preliminary test with 21 participants was performed, to be replicated with a larger sample in a more advanced stage, in case of initial positive evidence.

Sample Description

The study population consisted of 21 volunteers from a local recreational center of the municipality, 13 men and 8 women, with a mean age of 69.2 ± 3.9 years. Information about their educational level, working situation, and monthly income are given in **Table 2**.

Procedure

The first version of the Robot-Era Inventory was composed of 41 items to be rated on a 5-point Likert scale. The statistical validation of the inventory was conducted in a piloted session in the IRCCS INRCA facility with 21 older people, to test the validity of the scales concerning the goal standard scale (the UTAUT questionnaire). After the presentation of Robot-Era objectives and the main functionalities and characteristics of the three robots, the researchers have shown a video of Robot-Era platform operating in indoor and outdoor contexts, to give a concrete idea of the potential use of the robots. Before starting the test, informed consent was signed by each participant and the subjects' anonymity was guaranteed. After they saw the video, the Robot-Era Inventory and the UTAUT questionnaire were administrated. This video may be found here: https://www.youtube.com/watch?v=XVJXdIZ6GVA.

TABLE 2 | Sample description.

Variable	
Age, mean ± SD	69.2 ± 3.9
Gender, *n* (%)	
Male	13 (61.9%)
Female	8 (38.1%)
Educational level, *n* (%)	
Primary	9 (42.9%)
Secondary	7 (33.3%)
Tertiary	5 (23.8%)
Education in years, mean ± SD	11.2 ± 4.1
Working situation, *n* (%)	
Retired	16 (76.2%)
Working full time	2 (9.5%)
Working at home	2 (9.5%)
Monthly income, *n* (%)	
0–500 €	1 (5.3%)
501–1,000 €	2 (10.5%)
1,001–1,500 €	7 (36.8%)
1,501–2,000 €	6 (31.6%)
2001–2500 €	3 (15.8%)

Statistical Analysis for the Development of the Robot-Era Inventory

The reliability of the Robot-Era Inventory scales was analyzed with Cronbach's alpha. Cronbach's alpha is a coefficient of internal consistency reliability and a solid construct would have an alpha of at least 0.7 (Nunnally, 1978). The interpretation of Cronbach's alpha is (Gliem and Gliem, 2003): *a.* ≥. 0.9 Excellent; 0.8 ≤ *a.* <. 0.9 Good; 0.7 ≤ *a.* <. 0.8 Acceptable; 0.6 ≤ *a.* <. 0.7 Questionable; 0.5 ≤ *a.* <. 0.6 Poor; and *a.* <. 0.5 Unacceptable. Based on the criteria observed in the literature and the analysis, 41 items were developed and grouped in different scales (**Table 1**). In addition, the same analysis was performed on the UTAUT results to verify the reliability of the scale in the experimental setting. Finally, the internal validity of the constructs has been tested using the correlation analysis between the Robot-Era Inventory and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) subscales. The Bonferroni correction has been applied to correct the multiple comparisons. A confirmatory principal component analysis (PCA) using Varimax rotation method with Kaiser normalization is conducted.

RESULTS

Cronbach's alpha values of the Robot-Era Inventory (REI) scales and the UTAUT scale are given in **Tables 3**, **4**, respectively. In **Table 3**, an adequate level of reliability is shown by the scores that are all > 0.6. **Table 4** shows that the UTAUT scales also have good internal consistency within this study, except social influence (SI). The correlation coefficients, after the Bonferroni correction, between the Robot-Era Inventory scales and the UTAUT scales

TABLE 3 | The Cronbach's alpha values of the Robot-Era Inventory scales.

Dimension	Acronym	Cronbach's Alpha
Perceived Robot Personality	PRP	0.7416
Human Robot Interaction	HRI	0.6947
Perceived Benefit	PB	0.8480
Easiness of use	EU	0.6784
Perceived usefulness	PU	0.7064

TABLE 4 | The Cronbach's alpha values of the Unified Theory of Acceptance and Use of Technology (UTAUT).

Subscale	ACRONYM	Cronbach's Alpha
Anxiety	ANX	0.9269
Attitude	ATT	0.8341
Facilitating conditions	FC	0.8627
Intention to use	ITU	0.9305
Perceived adaptability	PAD	0.7386
Perceived enjoyment	PENJ	0.9232
Perceived ease of use	PEOU	0.6393
Perceived usefulness	PU	0.8369
Social influence	SI	0.4942
Trust	Trust	0.8773
Social presence	SP	0.8846
perception of sociability	PS	0.8909

are shown in **Table 5**. As expected, there is a high value of the correlation coefficients between the REI and UTAUT subscales, even if only some correlations are significant. Several UTAUT subscales do not show a significant correlation coefficient with the REI subscales, probably due to the low sample size. Two of the most important subscales in the literature and also in our model are the TRUST and PS subscales. Both have a positive and significant correlation with all of the HRI and PB subscales, respectively. In fact, in both the models, importance is placed on the robot's ability to interact with the person. However, the limitation of the UTAUT is that it was not built for the elderly person, as opposed to the REI. Another important scale is the intention to use (ITU), which is considered an essential scale for technology usage adoption. In our case, it has two correlations with our inventory with the perceived usefulness and with the human–robot interaction.

Table 6 reports the analysis of the sociodemographic characteristics of the sample, concerning the score obtained on the REI and the UTAUT scales. As it is observed, no significant differences in age, class, and gender were found for the REI scales, while for the UTAUT, there is a significant positive correlation between gender and facilitating condition, suggesting a positive perception of available personal resources to use the robot from the male respondents, and a higher perception of social influence for the older people, underlying a probable positive role of the environment to foster the system acceptability.

The factor loading obtained from the confirmatory principal component analysis is reported in **Supplementary Materials**.

TABLE 5 | Correlation coefficients with the Robot-Era Inventory scales and the UTAUT scales after the Bonferroni correction.

		REI				
		PRP	**HRI**	**PB**	**EU**	**PU**
UTAUT	**ANX**	−0.3306	−0.4631	−0.4630	0.0142	−0.3617
	ATT	0.4618	0.5797	0.5046	0.3914	0.6134
	FC	0.2738	0.5755	0.5165	0.433	0.5552
	ITU	0.6865	0.7454*	0.5497	0.4498	0.8175*
	PAD	0.5301	0.7392*	0.6647	0.3933	0.5345
	PENJ	0.5166	0.7654*	0.5173	0.4665	0.3527
	PEOU	0.3548	0.6693	0.6404	0.6857	0.6621
	PU	0.3024	0.4866	0.5566	0.6427	0.6507
	SI	0.3973	0.2222	0.2311	−0.0265	0.3135
	Trust	0.6042	0.7479*	0.6952	0.5511	0.5700
	SP	0.6619	0.5817	0.6304	0.3305	0.5869
	PS	0.6166	0.5070	0.7678*	0.5892	0.6496

ANX, Anxiety; ATT, Attitude; FC, Facilitating conditions;ITU, Intention to use; PAD, Perceived adaptability; PENJ, Perceived enjoyment; PEOU, Perceived ease of use; PU, Perceived usefulness; SI, Social influence; Trust, Trust; SP, Social presence; PS, Perception of sociability; PRP, Perceived Robot Personality; HRI, Human Robot Interaction; PB, Perceived Benefit; EU, Easiness of use; PU, Perceived usefulness.
** =$r < 0.05$.*

This analysis confirms the validity of the theoretical subdivision in subscales reported in this article. The PCA showed 5 components: the first component corresponds to perceived benefit, the second component corresponds to perceived robot personality, the third component corresponds to the human–robot interaction, and the fifth component corresponds to perceived usefulness. The second component is the only one that has not immediate correspondence with our model. Correlations among PCA components and the REI subscales are tested with Pearson's coefficients, which range from 0.3751 for factor 4 to 0.8807 ($p < 0.05$) for factor 1 corresponding to the REI PB.

DISCUSSION

Given the rising number of older people in nowadays society, it is essential to understand the acceptability of social robotics to support them in daily activities. The pervasiveness of robotics in the healthcare context requires a deeper analysis in terms of impact on the quality of life and cost-effectiveness of the innovative solutions, but the successful diffusion of such devices is strongly determined by their acceptability, in the short and long term.

In literature, it is widely recognized the paramount importance of the TAM and the UTAUT models, aimed at providing insights on how to support the use of innovative systems, especially robotics in the latter case. However, the authors suggest the need to adapt the model and the questionnaires to the requirements of the experimental setting, and the technological artifacts (Heerink et al., 2008). Moreover, as the research in the field is becoming more and more multidisciplinary, understanding the impact of technology acceptance on the quality of life of older people is a central

TABLE 6 | The Robot-Era Inventory scales and the UTAUT by the gender and age groups, mean ± SD.

Scales		Total	Gender			Age group		
			Male	Female	p	<70	70+	p
REI	**PRP**	37.6 ± 5.7	37.8 ± 6.3	37.4 ± 5.2	0.883	37.3 ± 5.3	37.1 ± 6.4	0.938
	HRI	34.9 ± 4.5	36.2 ± 3.4	32.8 ± 5.5	0.088	35.0 ± 4.7	35.0 ± 4.8	0.999
	PB	22.8 ± 4.9	23.5 ± 5.5	21.6 ± 3.7	0.398	22.9 ± 3.4	21.8 ± 6.5	0.903
	EU	17.7 ± 2.4	18.4 ± 2.0	16.6 ± 2.8	0.106	17.5 ± 2.8	17.5 ± 1.3	0.999
	PU	28.9 ± 4.0	29.2 ± 3.9	28.4 ± 4.2	0.642	29.2 ± 3.7	27.6 ± 3.8	0.376
UTAUT	**ANX**	9.2 ± 5.0	8.5 ± 4.9	10.5 ± 5.3	0.379	9.8 ± 4.9	9.0 ± 5.5	0.725
	ATT	11.0 ± 2.5	11.5 ± 2.0	10.3 ± 3.1	0.290	11.3 ± 2.0	10.0 ± 2.8	0.228
	FC	6.4 ± 1.9	7.2 ± 1.3	5.0 ± 2.2	**0.013**	6.3 ± 1.7	6.3 ± 2.4	0.989
	ITU	7.8 ± 3.1	8.3 ± 2.9	6.9 ± 3.5	0.337	8.4 ± 3.1	6.5 ± 2.8	0.198
	PAD	10.2 ± 2.4	10.8 ± 1.8	8.9 ± 3.0	0.075	10.4 ± 2.3	9.6 ± 2.6	0.526
	PENJ	17.7 ± 2.7	18.3 ± 2.5	16.9 ± 3.1	0.295	17.9 ± 2.7	17.6 ± 3.2	0.811
	PEOU	17.3 ± 3.9	18.4 ± 2.1	15.5 ± 5.4	0.097	17.2 ± 3.5	17.0 ± 4.7	0.928
	PU	10.3 ± 2.6	11.1 ± 2.1	9.0 ± 2.9	0.071	10.3 ± 2.7	9.9 ± 2.2	0.751
	SI	8.1 ± 1.9	8.1 ± 2.1	8.2 ± 1.6	0.940	9.0 ± 1.0	7.0 ± 2.4	**0.038**
	Trust	7.2 ± 2.1	7.6 ± 2.0	6.5 ± 2.3	0.250	7.5 ± 2.2	6.6 ± 2.1	0.389
	SP	11.8 ± 4.3	13.0 ± 4.5	9.9 ± 3.2	0.130	10.8 ± 4.0	12.9 ± 4.9	0.353
	PS	11.9 ± 4.9	12.5 ± 4.9	10.9 ± 4.9	0.479	11.3 ± 4.8	12.1 ± 5.3	0.719

p-values from unpaired t-test.
ANX, Anxiety; ATT, Attitude; FC, Facilitating conditions; ITU, Intention to use; PAD, Perceived adaptability; PENJ, Perceived enjoyment; PEOU, Perceived ease of use; PU, Perceived usefulness; SI, Social influence; Trust, Trust; SP, Social presence; PS, Perception of sociability; PRP, Perceived Robot Personality; HRI, Human Robot Interaction; PB, Perceived Benefit; EU, Easiness of use; PU, Perceived usefulness.
Bold values indicated statistically significant differences.

topic, especially for geriatricians. However, there is still limited evidence of tools that assess the perceived improvement of the quality of life, in combination with the acceptance of technological services. This limitation is also due to the use of qualitative methods and/or clinical scales in technological trials, such as the Short Form-12, for example, to address the improvement of quality of life after the system use. These tools are designed for the clinical population in assistance and care settings (Ware et al., 1996) and not to understand the impact of technology for supporting active and healthy aging, for example, at home, as they include the assessment of a wide range of dimensions that are not the target of technological devices, as SARs. The same can be said for the independent living and autonomy domains. In this case the most used tools are activities of daily living and instrumental activities of daily living indexes (Lawton and Brody, 1969). These scales are designed by adopting a medical perspective to assess the functional and cognitive autonomy of older people, but those activities (i.e., dressing, bathing, managing, financing) are only partially addressed by the robotic solutions and require a more complex combination of technological and personal assistance to be supported. There are wider concepts and definitions of autonomy in aging that may open up to a profound understanding of the impact of technology and its acceptance, not only of the aging phenomenon. As the objective of any technological tool is the promotion of an optimal aging process, the definition of successful aging has the achievement of "high physical, psychological, and social functioning in old age without major diseases" (Fries, 1980; Cosco et al., 2014; Martin et al., 2014; Bevilacqua et al., 2020), seems to be more appropriate to unveil the activities that the older people consider of utmost importance for their quality of life and that may be supported through technologies. More recently, intending to promote a more comprehensive and appropriate assessment of the aging population, the WHO introduced the concept of intrinsic capacity (IC), defined as "the composite of all the physical and mental capacities that an individual can draw upon during his/her life" (Beard et al., 2016), open up to those intrinsic characteristics that the older people can put in place during the aging process and that play a crucial role in the technology acceptance and usage behavior.

In our model, we have tried to combine a wider approach to understand the impact on the quality of life of the personalized robotic services offered through the Robot-Era system, with the construct of acceptance of technology from a traditional model, like UTAUT. The Robot-Era Inventory includes the assessment of the personalized services, an adaptation already suggested in the literature (Heerink et al., 2008), with the evaluation of the perceived robotic capabilities, influenced by the end-users intrinsic characteristics. As it was designed, the dimension of the human–robot interaction (HRI) represents the kernel of the model, by including the evaluation of the robotic capabilities (i.e., speech) and the perception of those by the older users, representing a co-constructed space between the two agents that shape the relationship, influencing the use of the system.

This study represents an attempt to take a step further in the field of technology assessment with older people, concerning the SARs, and also a solution to the urgent need for the availability of customizable tools, to be adapted to different experimental setups and services.

As psychophysiological measures are considered one of the main methods of assessment used for human studies in the human–robot interaction together with self-report, behavioral measures, and task performance analysis (Bethel et al., 2007), future studies should take into consideration the use of the scale of acceptance in combination with biosignals, for example, related to anxiety during the use of the robot. As the physiology of the autonomic nervous system changes with age, the comprehension of the autonomic arousal concerning to stressful stimuli, such as the use of a SAR, is of paramount relevance in combination with traditional assessment tools, to understand the reactions of older people during the performance with the technology. Several studies on social robotics have used combined evaluation of quantitative and/or qualitative tools with biosignals, such as ECG, electrodermal activity, and the electric brain activity, with the aim of personalizing the behavior of the robot concerning to the emotional state of the older users (Fiorini et al., 2020).

Despite this, this study presents some limitations. First of all, a higher number of participants should be involved in the scale assessment, to collect data to refine the inventory. A shorter version of the inventory needs to be developed to be applied during any experimental setting, so as not to constitute a burden for the older respondents. Moreover, despite the validity of the video analysis as the methodology to evaluate the HRI, the opportunity of administrating the questionnaire after an effective interaction in a real or realistic setting can be relevant. In the future, a cultural validity of the inventory, by including older volunteers from different cultural backgrounds and equally divided by gender, should be conducted.

DATA AVAILABILITY STATEMENT

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

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

EM and RB: study concept and design. RB and EF: acquisition of data. RB and MD: analysis and interpretation of data. EM, RB, and MD: drafting of the manuscript. GP, GR, and FL: critical revision of the manuscript for important intellectual content. AM and GA: writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnbot.2022.883106/full#supplementary-material

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