Interact With Me: An Exploratory Study on Interaction Factors for Active Physical Human-Robot Interaction

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Yue Hu[1,*], Mehdi Benallegue[1], Gentiane Venture[1,2], Eiichi Yoshida[1]

***Abstract*— In future robotic applications in environments such as nursing houses, construction sites, private homes, etc, robots might need to take unpredicted physical actions according to the state of the users to overcome possible human errors. Referring to these actions as active physical human-robot interactions (*active pHRI*), in this paper, the goal is to verify the possibility of identifying measurable *interaction factors* that could be used in future active pHRI controllers, by exploring and analyzing the state of the users during active pHRI. We hypothesize that active physical robot actions can cause measurable alterations in the physical and physiological data of the users, and that these measurements could be interpreted with users' personality and perceptions. We design an experiment where the participant uses the robot to play a visual puzzle game, during which, the robot takes unanticipated physical actions. We collect physiological and physical data, as well as outcomes of two state-of-the-art questionnaires on the perceptions of robots, CH-33 and Godspeed Series Questionnaires (GSQ), and a pre-experiment personality questionnaire, to relate the collected data with the users' perceptions and personality. The experiment outcomes show that we can extract a few factors related to personality, perception, physiological, and physical measurements. Even though we could not draw very clear correlations, these outcomes give fundamental insights for the design of novel pHRI experiments.**

I. Introduction

Physical contact is an inevitable feature of many future robotics applications, where often, the interaction actions cannot be planned beforehand due to unpredicted events. Examples of environments and situations in which this may occur daily are nursing houses, construction sites, packaging lines, cooking help, and personal care.

When using robots in direct physical contact with humans, safety is one of the most important concerns. In 2016, the safety standards for collaborative robots ISO/TS 15066 [1] was introduced to ensure the physical safety of the users [2], [3]. However, physical safety should not be the only concern in human-robot interaction (HRI). As well known, humans give importance to emotions and perceptions, which are fundamental in human-human interactions, therefore perceptions and mental safety should also be considered in HRI [4].

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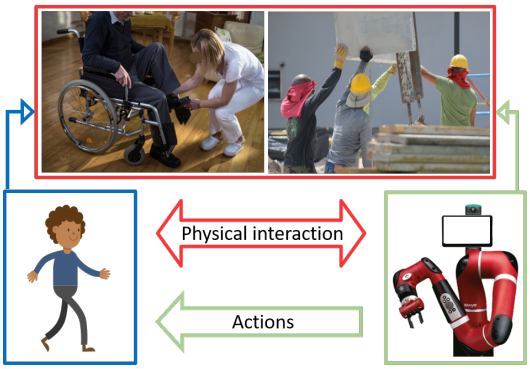


Fig. 1: Two possible scenarios for active pHRI: a robot helping in a nursing house and in a construction environment. In both cases, possible unpredictable events may occur and autonomous physical actions might be necessary.

In examples shown in Fig. 1, a collaborative manipulator could be used in nursing houses to help people in daily tasks such as wearing shoes, where the user could be uncooperative or need special care due to, e.g. mood swings, distraction, loss of stability, etc. In a construction site, robots could help the workers lifting and positioning pieces, where unpredicted events caused by wrong evaluations may occur. In both environments, people may be unaware of surrounding risks, make wrong decisions, and feel uncomfortable for being handled in certain ways. In our opinion, the robot should take actions that are corrective, taking into account the physical and mental states of the person, while still achieving the original task. As these could be unpredicted physical actions, the robot should also take into account the state of the users by "observing" their reactions to such probing actions.

The current safety standard imposes strict constraints on the performance of robots, inducing the robots to become rather "passive" and "slow" during interactions, moreover, it does not take into account users' mental state. We believe that new factors should be taken into account to boost the efficiency of human-robot interactions from both the robot and the human side. This means that the robot should become more *active*, i.e. with a controller that allows active interactions not only depending on users' physical state, but also perceptions and mental state.

In the context of HRI, robot controllers and human perceptions have been mostly treated in two main research directions, i.e. physical (pHRI) and social (sHRI), which have been evolving mostly in parallel without much intersections. In order to achieve our goals, we think it is necessary to combine tools from both sides.

In pHRI, it is implied that direct or indirect contacts

between human users and robots may occur. Current state-of-the-art pHRI features topics such as co-manipulation [5], [6], collaborative object carrying [7], [8], the development of controllers with human-in-the-loop [9], [10], [11]. In most of these works, the main focus is given to the robot, i.e. the development of control frameworks in which the human is treated either as an external noise, an external force, or another "robot". Or, in the case of therapy and rehabilitation robotics [12], [13], focused on specific rehabilitation goals for the patient.

In contrast, sHRI focuses mainly on the human counterparts, trying to analyze their mental state, comfort, sense of safety, sociability, and in general users' perceptions. These are often studied via specially designed experiments involving little or no physical interactions with the robot, and a popular evaluation method is to use post-experiment questionnaires [14], [15], [16], [17]. Physiological measurements also proved to give useful insights, e.g. galvanic skin response (GSR) and electrocardiography [18], [19], [20] have been investigated to evaluate factors such as stress and anxiety, and eye gazing has been analyzed for engagement and proactiveness [21], [22]. Similar signals have also been used in Affective Computing to understand human emotions [23] and endowing machines with emotional intelligence.

A few works involved both physical and social interactions: evaluation of touch in a nursing situation [24], responses to hugging [25], rhythmic activities for teamwork [26]. The main focus of these works remains the evaluation of social perceptions, where the robot is designed as "social". In our case, we are interested in using tools from sHRI to evaluate the social aspects of people using also robots which have not been specially designed as "social", e.g. industrial manipulators, where the robot does not have to necessarily display social behaviors or emotional intelligence.

A. Hypotheses and contributions

We define *active physical human-robot interaction* (active pHRI) as an interaction during which robots may take physical actions on the human without prior notifications. Until now, in HRI there has been generally little or no expectation that the robot may take unpredicted physical actions, so the first step is to address the impact of such active actions on the user. For the robot to take the proper actions, the physical and mental state of the user needs to be *measurable*, i.e. a set of identifiable and quantitative *interaction factors*. For example, in a nursing house, if we were able to quantify and measure in real-time the anxiety of the user related to their perception of the robot actions, the robot could tune the motions to achieve different types of contact (softer, closer, stronger, etc), while maintaining the objective of achieving a specific task (e.g. helping to stand up).

The goal of this paper is to identify a first possible set of interaction factors by means of an active pHRI experiment. Our target is not the assessment of single perceptions (e.g. fear, satisfaction) or specific objectives (e.g. workload assessment, energy consumption). Rather, inspired by behavioral psychology, we hypothesize that it is possible to break down a more comprehensive human state into measurable factors, and that we can find relationships between the physical and physiological data and the perceptions and possibly the personality [27]. We formulate the following hypotheses:

- **H1** Unpredicted robot actions cause measurable alterations in the users' physical and physiological data;
- **H2** Measurable physical and physiological data could be explained with users' personality and perceptions of the robot.

To easily isolate possible factors, we designed an active pHRI experiment in which the user uses the robot to play a visual puzzle game. During the game, the robot takes active physical actions on the user similar to simple disturbances, of which the user is not informed beforehand, such that a natural reaction can be assessed. For the analysis, we collect physical and physiological data, personality, and post-experiment questionnaire outcomes related to the users' perceptions.

To avoid cultural dependencies, the experiments have been carried out only with Japanese nationals born and raised in Japan. We collected data from 23 participants (among which 17 were retained in this paper), then, we extracted a series of factors by post-processing the data. The major contributions and outcomes of this paper are:

- To the best of our knowledge, the first experiment addressing the analysis of the human state during active pHRI;
- First insights on measurable factors, despite the outcomes showing just a few relevant correlations between personality and user perceptions with physical and physiological data;
- Important insights for active pHRI scenarios and experiments analysis and design.

B. Paper organization

This paper is organized as follows: in section II we describe the details of the experiment, including the design choices, the control of the robot, the description of the setup, and the experiment protocol; in section III we illustrate the performed experiments, the factor extraction, and relevant factors; in section IV we analyze and discuss the obtained results; in section V we summarize the outcomes and give an outlook of our next steps.

II. Experiment description

The experiment has been designed to allow the users to have an intuitive direct physical interaction with the robot, and at the same time, allowing them to feel the action of the robot on the users. In the following subsections, we will illustrate the design choices, the control of the robot, the hardware equipment, and the experimental protocol.

A. Design and tools choices

Active pHRI scenarios could involve a high variety of factors, so we designed the first experiment to be a simple one, to allow for a straightforward identification of possible

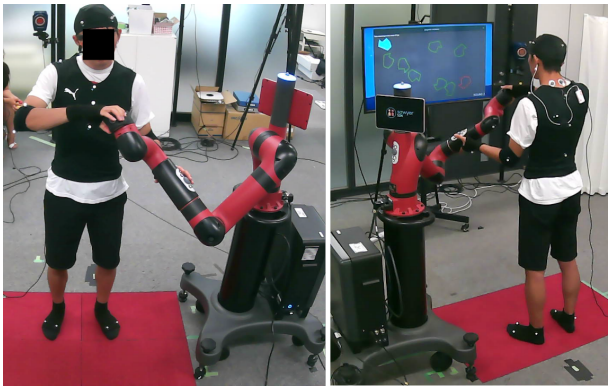


Fig. 2: The user uses the robot as a joystick to play the visual puzzle game.

factors. As shown in Fig. 2, during the experiment, the user has to use the robot as a joystick to play a visual puzzle game, shown on a screen. The user has to match the pieces by moving the end-effector (EE) of the robot in space, coming into an intuitive direct physical contact with the robot. During the interaction, the robot performs actions on the user by pushing or pulling with an active force. The game and the action can be seen in the video attachment. The visual game approach is similar to rehabilitation robots [12], where patients often play visual games using a robot arm with direct physical contact. However, in these cases, the interaction is guided and the objective is to perform specific rehabilitation programs via the game, with little focus on social perceptions and mental state.

As stated in the hypotheses, we aim at measuring the physical and physiological data of the users. Among the available physiological measurements, we decided to adopt GSR, Photoplethysmography (PPG), and eye-tracking. GSR is a well-known indicator of arousal, its variations allow us to measure the intensity of arousal to stimuli [28], [29]. The PPG measurement is used as an alternative to the Heart Rate Variation (HRV), which is another popular indicator. From the PPG signal, it is possible to extract the Pulse Rate Variability (PRV) [30], which is related to mental stress, where higher PRV (with respect to the baseline conditions) indicates higher mental stress [31], [32]. Eye blinking frequency (EBR) and eye blinking duration (EBD) have been related to mental load, where higher EBR and shorter EBD correspond to higher mental load [33], [34]. From a standard eye tracker, it is also possible to obtain the gazing direction, which is another important indicator [21], [22].

For the physical data, we collect motion data, ground reaction forces, and interaction forces with the robot. From these data, it is possible to extract a series of information regarding the overall behavior of the user towards the robot (e.g. distances, forces exerted).

One of the most common tools used in sHRI to evaluate the post-experiment perceptions of the users towards the robot is questionnaire. Among the questionnaires available in the literature, we decided to adopt CH-33, which has been established as a measurement of psychological safety towards robots [4], and the Godspeed Series Questionnaire (GSQ) [35], which is one of the most popular questionnaires in HRI [36]. As personality has been shown to be relevant in HRI [27], [37], we decided to adopt a simplified version of *the Big Five*, one of the most commonly used personality traits questionnaire [38]. All the questionnaires are available online at [39].

B. Robot control

To play the game using the robot, the user has to come into contact with its EE. The users are free to move the robot in any direction, and the 3D Cartesian space motion of the robot EE is projected into the 2D movement of the target piece. The rotation of the piece is a direct mapping of the joint angle of the last joint before the EE. If the robot is released, it stops all the motions.

We assume the robot to be torque-controlled when the user is in contact, and in position control otherwise. We implement a controller that runs at a frequency of 100 Hz, implemented using a Quadratic-Programming (QP) [40] formulation which allows us to take into account joint limits, joint velocity limits, and joint torque limits. During the game, the robot takes a timed action on the user, i.e. every ΔT, an *active force* $\mathbf{f}_a$ is applied. The direction of $\mathbf{f}_a$ is opposite to the estimated EE velocity direction at the instant the active force starts to be applied. The magnitude is proportional to the force exerted by the user on the EE, bounded in specified minimum and maximum, to ensure that the force is perceived yet at the same time safe for the user.

The active force is applied only when the user is interacting, therefore when the robot is in torque control. The time interval ΔT is counted only over the time during which the cuff is pressed, i.e. for the user, the interval between each active force is unknown. The active force is not applied instantaneously, but over a duration of $\Delta T_a \ll \Delta T$.

C. Equipment and sensors

The robot we use for the experiment is a Sawyer collaborative robot (Rethink Robotics), which has 7 degrees of freedom. It is torque-controlled and equipped with Series Elastic Actuators, and it complies with the safety standards ISO/TS 15066. The robot can avoid self-collisions, it has joint torque sensors in all the joints, which are also used to estimate the external wrench at the EE. With Sawyer, to trigger the torque control mode, the user has to press the cuff button located at the EE, as shown in Fig. 2.

To measure the user's state during the experiment, we use the following equipment and sensors:

- GSR and PPG sensor, Shimmer3 GSR+ Unit (*Shimmer Sensing*), a wireless sensor with Bluetooth that records GSR and PPG data locally on an SD card. The GSR is recorded via two single-use gel-type electrodes, while the PPG via an earlobe clip optical sensor;
- Eye tracker, *Pupil Core* (from *Pupil Labs*), which is an open-source eye-tracking platform connected via USB-C. We use a single eye tracker on the right eye;
- Camera-based motion capture system from *Motion Analysis*, with 11 cameras;
- 4 *Bertec* force plates, synchronized with the motion capture system.

Fig. 3: Motion capture markers (23 in total), Pupil Core eye tracker, and Shimmer3 GSR+ Unit for GSR and PPG.

Typical locations for the electrodes of the GSR are the palm of the hands, however, given the interactive nature of our experiment, the electrodes have been positioned at the back of the neck (see Fig. 3), which also provides reliable measurements [29].

For the motion capture, we use a set of 23 markers: three on the head, one on each hand and two on each elbow, two on the front of the torso, four on the back and one on each shoulder, and three on each foot. All the markers are pre-positioned on wearables: gloves, shirt, cap, and socks that can be worn on top of the users' clothes, such that the users can feel more comfortable without the need of changing clothes. The positioning of all the sensors and markers is shown in Fig. 3. All the data are synchronized via the Cortex software (Motion Analysis) and sampled at 100 Hz, except for the eye tracker which is sampled at 125 Hz and the force plates at 500 Hz.

D. Experiment protocol

Every experiment follows strictly the same protocol. Before the experiment, the participants read the experiment protocol which explains the setup and the procedure by themselves, to minimize the interaction with the instructor. The participants are then asked to watch a pre-recorded video with audio and subtitles in Japanese, explaining how to interact with the robot and how to play the game. The participants are not informed about the possibility of the robot to perform independent actions, as we are interested in the natural reaction to unexpected actions by the robot on the user. The protocol is provided online at [39].

Then the experiment proceeds as follows:

1) The participant completes the simplified version of the Big Five personality traits questionnaire consisting of 15 questions.
2) The participant is equipped with sensors and markers.
3) The participant rests for about 10 minutes during which the GSR and PPG baselines are recorded.
4) The participant performs two *trial sessions*, during which the robot is completely passive, i.e. no active force is applied. These sessions serve the user to get used to the robot.
5) The *active session*, involving the active force, is performed three times consecutively. The number of sessions has been chosen as a trade-off between making the users used to the experiment and keeping them motivated to play the game.
6) At the end of all sessions, the two questionnaires about robot perception are asked to be completed, CH-33 [4], and GSQ [35], one after the other, with the questions of each presented in a randomized order.

During each session, the record of the data starts about 10 seconds before the participants start the interaction with the robot, and ends about 10 seconds after the last interaction. This is to ensure that signals such as GSR and PPG are at their baseline levels before and after each session.

The total of 5 sessions lasts about 20 minutes, where a single session (trial or active) lasts about 2-3 minutes, during which the participants play the game that consists of 3 rounds, lasting 30 seconds each. The game can be restarted and the participants are asked to keep playing until instructed otherwise. Since the game is a task for the participants to interact with the robot, the winning and/or losing is not the goal of the experiment. In this paper, we set $\Delta T_a = 1$ and $\Delta T = 5$, so during each session, about 5-15 active forces may occur. Each experiment is video-recorded from two perspectives, from the front and the back.

All our experiments have been approved by the local ethics committee at the National Institute of Advanced Industrial Science and Technology (AIST) in Tsukuba, Japan. Before the experiment, participants have received proper information and given informed consent to participate in the study.

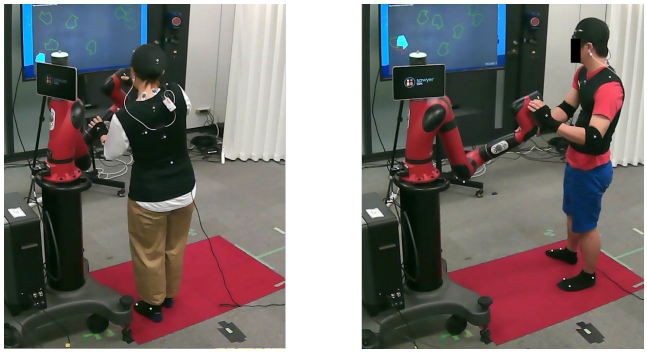
III. Method and Results

We performed the experiment with a total of 23 participants, of which only the data of 17 participants were usable due to technical issues, e.g. sensors not recording, unexpected external interferences. Of these 17 participants, 6 are females and 11 are males, with ages between 20 and 33 years old. All the participants are Japanese, born and raised in Japan. From a pre-experiment questionnaire (see additional material), all the participants have no or very little prior experience with robots in general.

A. Data collection and post-process

We collected data from the questionnaires presented in section II-A and all the sensors listed in section II-C, following the protocol detailed in section II-D.

Motion capture data have been processed with Cortex software (Motion Analysis) first, then post-processed with DhaibaWorks [41]. In DhaibaWorks we use a human model that is scaled according to the height, weight, and gender of each participant, and the Sawyer model that is the same used in the robot controller. The human model motions are obtained via inverse kinematics by mapping recorded marker positions to virtual markers, while the robot motions by using the recorded joint angles. From DhaibaWorks we



(a) Close (b) Far

Fig. 4: Two participants with different behaviors.

extracted the poses of the participants, including specific body parts such as head, hands, and feet, from which we computed distances between the participant and the robot. We are interested in these data as participants showed overall different attitudes to the robot. Fig. 4 shows two examples. The participant in Fig. 4a keeps the EE very close to the face during part of the experiment, prefers to stand facing the screen, and uses one hand on the cuff and one hand to hold the arm of the robot. On the contrary, the participant in Fig. 4b keeps a far distance from the robot by putting both hands on the EE, and prefers to face the robot looking at the screen by turning the head. This can be seen better in the video attachment.

From the eye tracker, we can extract data such as gaze direction, EBR, and EBD. The gaze direction is used to determine where the participants are looking at, i.e. at the robot, at the screen, or elsewhere. Specifically, we use collision detection [42] to categorize the gaze location, by modeling the gaze as a cone directed as the gaze direction with an angle of 10°. We compute the total gazing time to each location only during three time intervals: the play of the game, before starting, and after ending the interaction, given that for the rest of the session, the user may be looking at the robot due to the necessity of using the buttons to restart/reset the game, and this is not relevant for our analysis.

From the Shimmer3 sensor, we obtained the GSR and PPG data, the latter being post-processed to obtain the PRV. Differently from the rest of the data, for GSR and PPG we have a pre-experiment record of the baseline that is used to evaluate the changes that occurred during the experiment.

B. Factor extraction

From the above-mentioned data, we extracted a series of factors, mainly based on statistical analysis, including percentage differences between stimuli (i.e. active force application) and the average of each session or the baseline (GSR, PRV). Given **H1**, we considered the active force application by considering a window of 3 seconds from the start of the stimuli, to which we will refer as *action window*. For the analysis, only the second trial session and the 3 active sessions (4 out of the 5 sessions) have been considered, the first trial session has not been considered due to the high amount of other external stimuli that affected the experiment, e.g. frequent help from the instructor.

A list of factors is shown in Table I. The factors in Group 1 are computed for all sessions (considering each session independently), while the factors of Group 2 are computed only for the active sessions, as they refer to percentage differences between the action window and the average during the session. The participants' gender, personality, and questionnaire outcomes are also included as part of the factors (not shown in Table I). The post-experiment questionnaire CH-33 consists of 33 questions rated on a 7 points Likert scale and projected onto 6 factors, as shown in Fig. 5a, while GSQ is a series of 5 questionnaires rated on a 5 points semantic differential scale, resulting in 5 factors as shown in Fig. 5b. The personality test projects into 5 factors on a scale of 0-100, as shown in Fig. 5c. For the details of these factors, please refer to [4], [35], and [38], respectively. From Fig. 5 we can observe that there is no specific trend of the questionnaire outcomes, indicating that the participants had overall different perceptions of the robot. This confirms that it might be interesting to analyze the correlation between the factors to identify relationships between perceptions, personality, and measurements, as per **H2**.

C. Relevant correlations

As most of the collected data are not Gaussian, we used Spearman's correlation for non-parametric data. In particular, the following correlations have been carried out to test our hypotheses:

- Personality and gender with the questionnaire outcomes;
- Personality, gender, and questionnaire outcomes with all the extracted factors for all the sessions;
- Personality, gender, and questionnaire outcomes with the percentage difference between the average of each factor over the active sessions and the trial session (ED factors).

We considered as relevant those that scored correlation coefficient $|r| > 0.6$ and p-value $p < 0.05$, and that show interesting trends over the sessions (e.g. present in more than one session). These factors are reported in Table II. We ran the T-test for repeated samples on the factors of Group 1, for each active session with respect to the trial session, in order to verify possible significant changes when the active force is exerted. From the tests, most of the factors did not show significant differences, mostly with $p > 0.5$. A few factors showed significant difference with only one session with $p < 0.1$, while we verified that GSR diff showed $p < 0.1$ for all three active sessions.

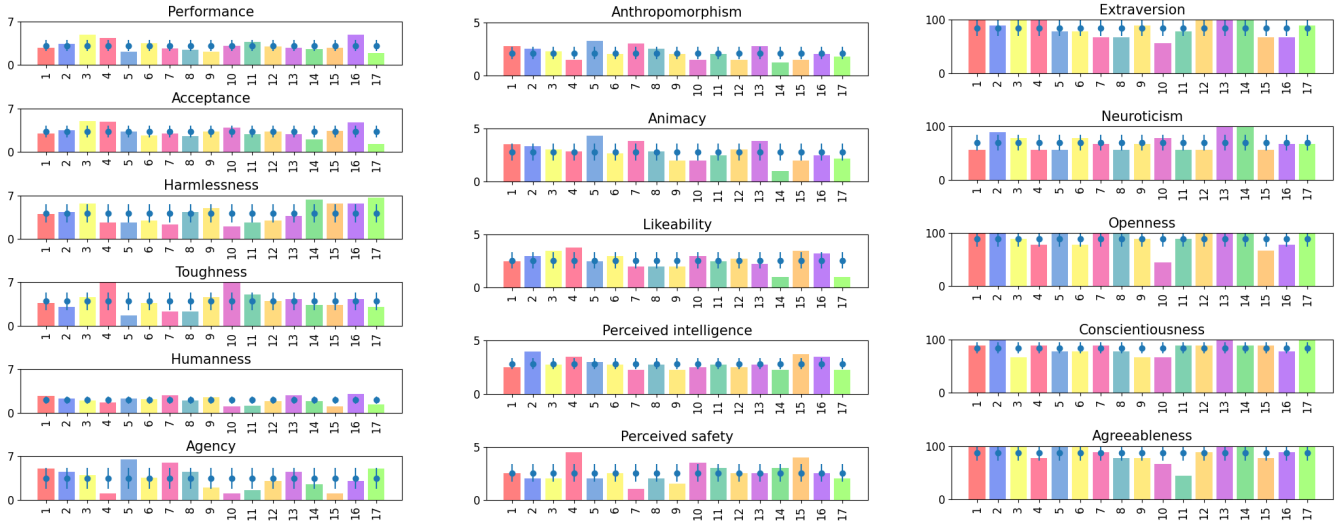
From Table II we can see that the correlation between Extraversion and CoP is consistent over all the sessions with negative correlation factors, indicating that extrovert participants approached the robot closer compared to the introvert ones. Anthropomorphism and Animacy from GSQ also show relevant correlation with GSR diff, with positive correlation indicating that the more the participants perceived the robot as anthropomorphic and animated, the lower their GSR level was during the sessions with respect to the baseline. However, the correlation weakens as the participants go through the sessions, with Anthropomorphism scoring

Factor	Explanation
Group 1: average over each session including the trial session	
CoP	Center of pressure distance between the participant and the robot base
Walking	Amount of walking as total number of steps/time
Head dist	Distance between head and robot EE
Head ort	Orientation of the head
Feet dist	Distance between the feet and robot base
Feet ort	Orientation of the feet
Hand ext	Extension of the arms as sum of distances from each hand to the torso, normalized by height
LHand loc	Location of the left hand, i.e. robot arm, wrist, or EE
Cuff frq	Frequency of pressing the interaction cuff
Gaze time diff game	Difference between gazing time at the robot and the screen during the game
Gaze time diff before	Difference between gazing time at the robot and the screen before starting the interaction
Gaze time diff after	Difference between gazing time at the robot and the screen after ending the interaction
GSR diff	Difference of GSR between the baseline and the session
PRV diff	Difference of PRV between the baseline and the session
Group 2: percentage difference between action window and the rest of the session, for each active session	
EBR diff AF	Eye blinking rate
EBD diff AF	Eye blinking duration
Pupil diff AF	Pupil dimension
EE force diff AF	Forces measured at the robot EE
GRF force diff AF	Ground reaction forces, normalized with body weight

TABLE I: All factors excluding personality, gender, and questionnaires. Factors in Group 1 are computed for all the sessions, while those in Group 2 excluding the trial session. In the table, "diff" means percentage difference, while "AF" refers to the average during the action windows.

Factor 1	Factor 2	Correlation coeff
Trial session		
Extraversion	CoP	-0.74 **
Anthropomorphism	GSR diff	0.71 *
Animacy	GSR diff	0.69 *
Active Session 1		
Extraversion	CoP	-0.73 *
Anthropomorphism	GSR diff	0.66 *
Animacy	GSR diff	0.72 **
Active Session 2		
Extraversion	CoP	-0.73 **
Animacy	GSR diff	0.65 *
Active Session 3		
Extraversion	CoP	-0.81 **
Difference between average of active and trial session		
Extraversion	Hand Ext ED	0.61
Performance	Walking ED	0.71 *
Acceptance	Walking ED	0.67 *
Toughness	Walking ED	0.65 *
Toughness	Feet Ort ED	0.65 *
Likeability	Walking ED	0.64
Animacy	PRV Diff ED	-0.67 *
Personality and questionnaires		
Openness	Toughness	-0.64
Openness	Agency	0.77 **
Openness	Likeability	-0.68 *
Agreeableness	Agency	0.67 *

TABLE II: Extracted relevant factors with correlation coefficient > 0.6 and p-value < 0.05. Those with * indicate p-value < 0.005, and ** indicates p-value < 0.001. "ED" refers to the percentage difference between the average of the three active sessions and the trial session.



(a) CH-33 (b) GSQ (c) Personality

Fig. 5: Results of the questionnaires CH-33 (a) on a scale of 1-7, GSQ (b) on a scale of 1-5, and personality (c) on a scale of 0-100, for the 17 participants considered in this study, the error bar shows the mean and standard deviations of the factor for all the participants.

$|r| < 0.6$ for active sessions 2 and 3, and Animacy for active session 3. This trend indicates that the participants had variations in the GSR level over the sessions that were not strongly related to their perception of the robot.

In Table II we can also observe a few correlations with the ED factors. In particular, more extrovert participants tend to have a wider extension of their arms during the active sessions with respect to the trial session. This may indicate that extroverts tend to impose on the robot more with their body with respect to introverts. Participants who perceived the robot as tougher (less likely to break down), more performant, acceptable, and likable, walked more during the active sessions. Also, those who perceived the robot as tougher, had feet more oriented towards the screen during the active sessions. High scores in these factors indicate overall a higher confidence on the robot capabilities as well as comfort they felt during the interaction with the robot, therefore, these correlations may indicate that the

participants who felt overall more comfortable and confident in the robot, felt more comfortable to walk around while manipulating the robot (e.g. the second participant shown in the video attachment) and/or also preferred to be more oriented towards the screen rather than the robot (e.g. the first participant shown in the video attachment), which may also indicate higher trust in the robot.

We also obtained relevant correlations between participants' personality and the way they perceive the robot. Specifically, the more open the participants, the less they perceived the robot as tough and likable, and the more they perceived the robot as an agent. The more the participants are agreeable, the more they perceived the robot as an agent.

IV. Discussion

H1 states that the active force can cause measurable alterations in the participants' data. However, from the T-test, only the GSR diff showed significant changes, implying that possible alterations are not measurable via the other factors presented in Table I. This also may mean that the ED factors should be interpreted with caution. **H2** states that the measurable data can be related to the questionnaire outcomes. However, only two of the factors in Table I showed relevant correlations, namely the CoP and GSR diff. The former indicates that extroverted people seem to be approaching the robot from a closer distance, and the latter that the people who perceive the robot as anthropomorphic and animated could be more stressed/anxious when interacting with the robot with respect to resting conditions.

Even if we could not find an adequate number of factors satisfying our hypotheses, we cannot neglect the relevance of the obtained results. The outcomes give important insights into active pHRI experiments. We adopted a game-style task and a simple disturbance-style action in order to have a smaller number of variables for which the isolation of factors could have been less affected by random noise. However, this might have been the main limitation of our experiment, as the action seems to have not been strongly perceived by the participants. Therefore, in the design of active pHRI experiments, it could be advisable to use different types of "actions", for example, a collaborative one or one that has different objectives. We also tried to break down the different participants' attitudes observed in section III-A, however, these did not show up significantly in the resulting relevant factors, therefore, a different way of quantifying such attitudes may be advisable. GSQ was chosen due to its popularity in HRI, however, Animacy and Anthropomorphism showed high correlation, and as a matter of fact, it has been shown that there are some flaws in the GSQ [43]. We think this may affect the overall outcome of the questionnaire, so it may not be well suited for active pHRI. Personality appears to give interesting insights into the way participants approach and behave with the robot. As a matter of fact, the relationship between personality and personal spatial zones have been studied in literature [27], and the correlations between Extraversion and CoP and hand extension, both go in the direction of a possible relationship between the two. Therefore, we consider the investigation of personality and distances to be important.

It is also worth noting that none of the factors showed relevant correlations with gender, indicating that in active pHRI experiments, gender may not be influential. The restriction on cultural background has been introduced to avoid cultural dependencies, however, it also represents a limitation for which the outcomes may not be generalizable for different cultural backgrounds. Last but not least, the participants have been recruited via open calls, many of them seemed to have little interest in the content of the experiment itself, and many had several experiences with other types of laboratory experiments as well. We think that this has effects on the outcomes that are not negligible, therefore, we deem it important to consider also the participants' habituation levels and mindsets towards laboratory experiments.

V. Conclusions and future developments

In this study, we were interested in analyzing the perceptions and state of humans with respect to an active physical interaction with a robot. We hypothesized that this action can cause alterations in measurable physical and physiological data, and that these data can be related to personality, gender, as well as the perception of the users. However, results did not show many correlations with the extracted factors.

This study was an exploratory study meant as a first attempt to verify the possibility of identifying measurable *interaction factors* that could be useful for the development of active pHRI controllers, by combining tools from both pHRI and sHRI. Despite only a few factors having been uncovered, we obtained insightful observations and advice for the design of active pHRI, based on the advantages and pitfalls of our experiment. We consider these findings useful for researchers who may be interested in developing active pHRI experiments, while with future more consistent findings on interaction factors, we believe it will be fundamental for those who develop controllers for pHRI applications, as measurable quantities are necessary as inputs for controllers. Assuming that the interactions have specific objectives (e.g. helping to stand up or to lift pieces), the interaction factors could be used as weighted objectives to modify the motions of the robot according to the users' state. However, the inclusion of these factors in a control framework is out of the scope of this paper and will be considered for future work.

The findings of this paper will be taken into account in our next experiment. We will also target a higher number of participants to collect more consistent data, including qualitative data that were not considered in this study, which could help understanding better the results. To be able to identify as many factors as possible, we deemed necessary, for the time being, to use many sensors and equipment. However, to target real-world scenarios, less invasive setups will also be considered. From the future experiments, we expect to be able to extract further factors that can relate the human physiological, physical, and mental state with respect to different robot actions. Furthermore, Affective Computing methodologies, classification and/or factor analysis on the

data may lead to interesting outcomes and will be considered for further studies.

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