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***Abstract*—Unanticipated physical actions from the robot on humans (*active pHRI*) may be inevitable with the deployment of robots in human-populated environments. However, it is still unclear how humans would perceive such actions and how the robot should execute them in a physically and psychologically safe manner. The objective of this paper is to explore the possibility of quantifying the humans' physical and mental state during an active physical interaction with a robot, by means of a laboratory experiment. We hypothesize that the active robot actions could cause measurable alterations in users' data, which could be related to their perceptions and personalities. In the experiment, the user plays a visual game using the robot, which has a hidden task that results in active physical actions on the user. We collect data from physical and physiological sensors, and the perceptions and personalities via questionnaires and a semi-structured interview. Statistical analysis and clustering of the data collected from a total of 35 participants showed relationships between participants' physical and physiological data and their age, gender, perception, and personalities. Further developments based on these exploratory outcomes can be used to implement an active pHRI controller that can account for both the physical and the mental state of users.**

***Index Terms*—Physical Human-Robot Interaction, Human Factors, Human-Centered Robotics**

I. Introduction

We define *active physical human-robot interaction* (active pHRI) as a type of interaction during which the robot may take a physical action on the user without prior notifications. This type of physical interactions will be inevitable when robots will be used in close contact with humans. If we consider environments such as the ones illustrated in Fig. 1, where robots could be used to help humans in nursing houses, construction sites, assembly lines, or just cooking at home, unexpected situations may occur due to several reasons, ranging from human errors to uncooperative behavior due to mood changes.

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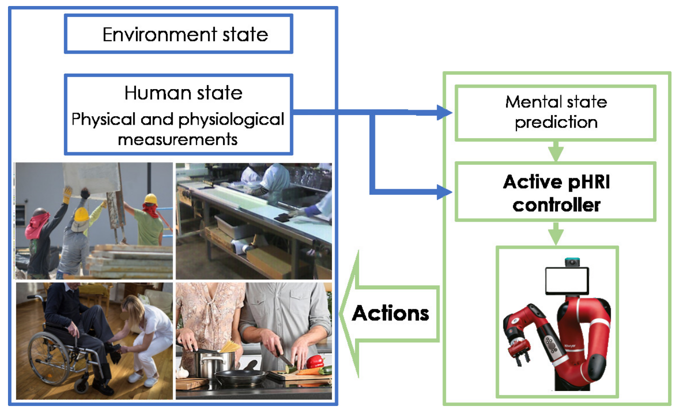


Fig. 1: Active pHRI may occur in several scenarios, in these situations the robot should take actions based on the human state, both physical and mental, where mental state could be predicted/inferred from measurable physical and physiological data.

Often, in a physical interaction scenario, the focus is given to the physical safety of the user [1], [2]. However, physical safety and comfort do not necessarily guarantee the same from a psychological point of view. Psychological safety and user perception should be regarded as equally important [3], [4], as guaranteeing a comfortable mental state is also imperative in both working and domestic environments.

In our view, addressing both physical and psychological safety is fundamental in achieving an optimal interaction in an active pHRI scenario. The control of the robot should adapt depending on different factors, including the state of the environment, the physical and the mental state of the users, where with mental state we refer to their perceptions of the robot and possibly mental load and stress. Few works have addressed the perception of users with respect to physical actions from the robot, and even less have addressed the matter when the action is not notified to the user beforehand.

In this paper, we are interested in conducting an exploratory study to investigate how users perceive active pHRI, and how these perceptions could be quantified with sensors and information that can be acquired beforehand, such that they can be used in an active pHRI control framework to adapt the control not only based on environment and physical states, but also on the mental state.

A. Related works

In the state-of-the-art, there has been interest in the human perceptions of robots related to physical interactions. In particular, touching has been proven to increase the trust and comfort of human users with regard to robots [5], [6], where often the robot touch tries to imitate the human touch. Robot initiated touch has also been investigated with respect to psychological stress and social bond [7], [8], as well as in nursing situations [9]. Hugging has also seen increasing interest from the research community as it can relieve stress and increase comfort, where active hug from the robot has been shown to provide good user experiences [10], though the hugging action alone is not necessarily perceived positively [11]. Physical interactions also occur in studies involving robots performing exercises with the user [12], where social-physical exercises improved user experience and engagement. Rehabilitation robots are used to perform exercises [13], [14], mostly coupled with games, but more focused on rehabilitation goals rather than user perceptions. Robot-initiated actions are considered in the case of dancing robots [15], [16], where long-term analysis on the perception of the user shows that adaptation of the robot increases comfort.

However, in these works, the physical contact and/or actions, even when initiated by the robot, are not unanticipated, or when not formally pre-announced, could still be anticipated due to the setting of the experiment (e.g. exercising and dancing). Whereas in our case, we are interested in unanticipated and not necessarily predictable physical actions from the robot. In these situations, it is important for the robot to be able to predict and/or measure the human state.

For instance, predicting human behavior and motions can increase the efficiency of the task [17], [18], this adaptation can vary according to the purpose of the task based on human behavior measured from the cardiac activity and eye-tracking [19]. It has also been demonstrated that human behavior can be predicted based on their attitude towards robots [20], where preferences could be predicted from their attitude [21] and social cognition [22]. In Van Zoelen et al. [23], human-robot team behavior was used to extrapolate interaction patterns by means of an experiment performed with an indirect physical action via a leash attached to a robot. Personality has been demonstrated to be predictable from non-verbal movements in a human-robot interaction scenario [24], and personality, in general, has been demonstrated to play an important role in HRI [25], [26].

In these works, the relationship between measurable data and perceptions is still treated in a limited way, and most studies are yet to be improved to target physical interactions and real-time measurements. For instance, while Van Zoelen et al. [23] created a model consisting of an interaction pattern language that could be used as a library of interactions to design human-robot interactions, it still needs further investigation on the relationship between real-time measurable data with the perception and behavior of users with respect to active robot actions. It is, therefore, crucial to perform a study that targets this missing piece in the context of pHRI, and to analyze how to obtain quantifiable data so that they could be integrated into the measurement of the human state in real-time and to build a model that can be used in future control frameworks of robots.

B. Objective and contributions

The objective of this paper is to carry out an exploratory study on the human state with respect to active pHRI, with the aim of using the outcomes to better understand the human perception and behaviors, and towards building a human-state model that is based on quantifiable data, so that future active pHRI control frameworks will be able to take into account both physical and mental state of the human from measurable data. In particular, we are interested in the general human state that could be explained by means of several measurements, therefore we carry out a laboratory experiment to gather as much data as possible from both the user and the robot to obtain a broad insight into the human state.

This paper is based on the same hypotheses of our previous work [27], where we conducted a preliminary analysis on the possibility of extracting *interaction factors* from an active pHRI experiment, by relating the measurable data to participants' perceptions and personalities. The formulation of the hypotheses has been slightly changed for the sake of clarity, and are as follows:

- **H1** Unanticipated robot actions cause measurable alterations in the users' physical and physiological data;
- **H2** Physical and physiological data measured during the interaction could be explained with users' personalities and perceptions of the robot.

In this context, the term *unanticipated* refers to an action that the user might not be expecting or not knowing when it is being executed. Further details will be clarified in the description of the experiment in section II-B

In our previous study, the experiment presented several disadvantages: the randomness and difficulty of interpreting the actions of the robot, and the low number of participants (23). By taking into account the advantages and drawbacks of the previous work, we designed a new experiment, consisting of a simpler game, clearer robot actions, improved data analysis, and an almost doubled number of participants (40) which allows obtaining more solid outcomes. Furthermore, we added a semi-structured interview of each participant after the experiment that gives a qualitative insight into their perception and understanding of the experiment. While the semi-structured interview addresses the understanding of the robot's actions, the goal of this study is not to make the robot's actions legible and explainable (i.e. explainable artificial intelligence), rather, we aim at understanding the human with respect to physical actions taken by robots.

We kept the game as a task for the user, as it represents an easy physical approach to the robot and was one of the main advantages of the previous experiment. We measured the same physical and physiological data as in [27]: Galvanic Skin Resistance (GSR), which allows measuring arousal [28], Photoplethysmography (PPG), which can be converted to Pulse Rate Variation (PRV) and is an indicator of mental stress [29], Eye Blinking Rate (EBR), Eye Blinking Duration (EBD), and Pupil Diameter (PD), which are indicators of mental load [30]. In comparison to [27], we use different questionnaires to quantify users' perceptions and attitudes towards robots, more details can be found in section II-E.

Despite being based on the same hypotheses and a similar set of measurements, this paper represents a completely stand-alone and in-depth study on active pHRI, with insightful results and solid perspectives for future pHRI developments. The contributions of this paper are:

- Active pHRI experiment that allowed to gather a large set of data on the human state;
- Systematic analysis of the data that shows the relationship between measurable data, personality, and perceptions; this analysis allows to obtain a set of factors that can be used to build a human-state model and as input of an active pHRI controller that can predict and adapt to human perceptions based on measured data;
- To the best of our knowledge, except for our previous work, the only experiment targeting active pHRI and systematic analysis of a large pool of factors.

C. Paper organization

This paper is organized as follows: in section II we describe the details of the experiment, including the design of the game, the control of the robot, the equipment and sensors that were used, the full protocol of the experiment, and the recruited participants. In section III we explain the data processing, and in sections IV and V we illustrate the results obtained using statistical and clustering analysis respectively. In section VI we analyze and discuss the results with reference to our initial hypotheses. In section VII we briefly summarize the outcomes and illustrate possible future developments and perspectives.

II. Method

A. Experiment overview

We designed an active pHRI experiment that involves both direct physical *contacts* between the user and the robot and direct physical *actions* from the robot on the user and vice-versa. In the experiment, the user is asked to play a visual game, displayed on a large screen, using the robot, as shown in Fig. 2. To play the game, the user has to move the end-effector (EE) of the robot in space. If the user releases the end-effector, the robot stops any movement. Therefore, a direct physical *contact* is required to play the game. During the game, when a physical contact is established, the robot can take physical *actions* on the user, which are similar to push and pull motions. The users are not informed beforehand of these actions. This allows us to quantify the change in their perception and behavior towards unanticipated robot motions. The reader can see the experiment in the multimedia attachment.

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 (N. 2019-0544). Before the experiment, participants have received proper information and were given informed consent to participate in the study.

B. Game and action design

In our previous work [27], the game consisted of a puzzle game where the user had to match a puzzle piece in a destination that was randomly generated at every game and had also to use the wrist rotation of the robot to match the different orientations. The action was introduced as a push/pull force on the user, recurring at constant time intervals. This type of action did not have specific interpretations, and as a result, was more similar to a disturbance. Furthermore, the necessity of moving the piece in 2D and rotating the wrist joint at the same time resulted in a complex motion that may have affected the interaction more than we had expected.

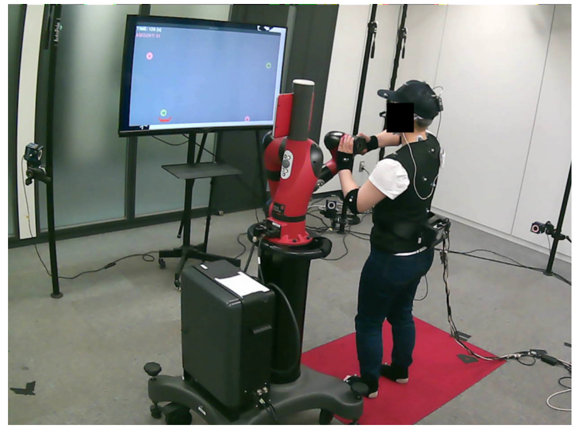


Fig. 2: Experiment setup, the user uses the robot to play a visual game.

In designing the new game, we considered those disadvantages and focused on: simplifying the game, defining a specific task for the robot, reducing randomness to obtain comparable data. The new task consists of a coin-catching game where the motion of the end-effector in 3D space is projected to move a catcher horizontally in 1D, to catch coins falling from the top, as can be seen in the multimedia attachment. The falling coins have four different values: 1, 5, 10, and 20. To give additional motivation to the users to engage in the game, the sum of the caught coins corresponds to a real bonus payment. The coins fall at regular time intervals, but at different speeds (1 and 5 at different speeds, 10 and 20 always at maximum speed), i.e. there are multiple coins on the field at the same time. We use a pre-generated sequence of coins and speeds, so every user plays exactly the same game, which allows for a better comparison of the collected data.

The action of the robot consists of a ”hidden” objective, which is to catch the coins with the highest values, i.e. 10 and 20. Every time a high-value coin falls, the robot would move its end-effector to move the catcher towards that coin, until it is caught or falls out of the field. The action of the robot starts immediately after the coin appears on the screen, i.e. it happens before the participants realize that a coin of high value has appeared. The actions are sequential, i.e. if multiple high-value coins are present on the field, the robot would aim at the first one that appeared, then once it disappears, it would aim at the second one in the sequence that is still on the field, and so on. The robot does not position the catcher at an exact point, rather it directs the user, who has to refine the positioning. In the experiment, a single game lasts 150 seconds. The coins sequence consists of 86 coins, of which 15 coins of value 20, 16 of value 10, 36 of value 5, and 19 of value 1. Therefore, the robot takes action for a total of 31 times out of the 86 coins falling.

These actions are ”hidden” because, as explained in section II-A, before the active session starts, the participants are completely unaware of them. This means that when the robot starts to take physical actions, the participants are not expecting them and do not know the meaning of the robot’s actions (intention). After a few actions, the participants should be aware that the robot may take actions, but the unanticipated nature of the actions remains, as the actions happen before the participants can realize that a coin of high value has appeared, therefore the participant would not be able to predict when the next action is taking place, independently from the participant understanding the intention of the robot or not.

C. Robot control

To ensure safety, when the user comes into contact with the end-effector of the robot, the robot is controlled in torque, while when the interaction is not intended, e.g. the user releases the robot, the robot is controlled in position. To implement the controller, we use a Quadratic-Programming (QP) formulation [31], which allows further safety by taking into account the joint limits, joint velocity limits, and joint torque limits of the robot. The controller runs at 100Hz.

The action of the robot is implemented using a position task in the QP formulation, i.e. the controller has the objective of minimizing the distance between the current position of the end-effector and a target position. In this case, the target position is the location of a high-value coin. When a high-value coin appears, the stiffness of the position task is incremented, increasing the effect of the objective of reaching the target position on the generated joint torques, resulting in the robot exerting a higher force to move its end-effector towards the target position. However, as we use torque control, the user could still exert high enough opposition forces on the robot and prevent it from moving towards its target.

D. Equipment details

We use equipment similar to the one from our previous experiment [27]. We use the Sawyer (Rethink Robotics) collaborative manipulator, which has 7 degrees of freedom and joint torque sensors in all the joints, which allows us to implement the torque control and estimate the interaction forces at the end-effector. In addition to our controller, we also use the default self-collision avoidance of the robot. The user has to press the cuff button located on the end-effector in order to move the robot, i.e. to switch to torque control mode. To start the game, the user has to press a second button, which is also located on the end-effector. As illustrated in Figs. 2 and 3, the setup of the experiment includes the following:

- Photogrammetric motion camera system with 13 cameras from Motion Analysis;
- 4 force plates (red area in Fig. 2) from Bertec that measure both forces and moments;
- EMR-9 eye tracker from NAC Image Technology, which features a cap on which the world camera and the two eye cameras are mounted, and a controller box that allows to record the data and synchronize with the motion capture system; compared to [27], this new eye-tracker ensures better data as it uses two eye cameras;
- Shimmer3 GSR+ for measuring GSR via single-use electrodes positioned on the back of the neck, and PPG via an earlobe clip.

We use a total of 27 reflective markers for the motion capture system: 7 markers on the head are required for synchronizing the gaze data from the EMR-9 to the motion capture system, 8 markers on the torso and the back, 3 markers on each arm, and 3 markers on each foot. This set is similar to the one used in [27], which represents a minimal set of markers to detect the most important body movements to describe the human behavior in our experiment. All markers are positioned exclusively on the dedicated suit as illustrated in Fig. 3. During the experiment, the users are asked to stay as much as possible on the force plates (however, the experiment is not paused in case they step out).

The motion capture system, force plates, and EMR-9 are all plugged into the same software, Cortex (Motion Analysis). The motion camera and eye data are recorded at 60Hz (maximum allowed by EMR-9), while the force plates are recorded at 5 times the frequency, i.e. 300Hz. The GSR+ sensor is recorded at 100Hz as the robot controller. All the data, including the above-listed sensors and robot data, are synchronized via the Cortex recording signal, which triggers a module dedicated to data recording.

Fig. 3: Sensors setup: 27 motion capture markers, EMR eye-tracker with cap and battery bag, Shimmer3 GSR+ sensor with earlobe for PPG measurement and single-use gel-type electrodes for GSR measurements.

E. Questionnaires

In our previous work [27], to quantify human perceptions towards robots, we used state-of-the-art questionnaires: the Godspeed Series Questionnaires (GSQ) [32] and the CH33 [33]. GSQ was chosen due to its popularity in the HRI community, however, [34] noted pitfalls, that we also found in our results, Animacy and Anthropomorphism were highly correlated though supposedly on independent factors.

In this experiment, we decided to drop GSQ and keep CH33, which is a good measurement of psychological safety towards robots in 6 factors. In addition, we also use the Negative Attitude towards Robot Scale (NARS) [21] to understand the attitude of participants towards robots before the experiment, which results in 3 factors. We also use the well-established visual Self Assessment Manikin (SAM) [35] on a 9 points scale to assess the variations in emotional responses during the experiment. As for the personality, we use the simplified version of the Big Five personality questionnaire [36] consisting of 15 questions that were used in [27]. The reader is redirected to [27] for the full versions of the personality and CH33 questionnaires adopted in this study, while NARS and SAM can be found in [21] and [35], respectively.

F. Experiment protocol

The experiment follows a strict protocol as follows: during each experiment, two to three experimenters are present for one participant. One supervising experimenter (and one translator when necessary), who has the role of explaining the participant's rights (by reading the same document to all participants) and getting their consent, and one instructor, who is the one carrying out the experiment. In addition, an interviewer is connected from a remote at the end of the experiment.

To reduce the interaction between the experimenters and the participant and keep the most similar condition possible for all participants, each participant reads a file containing the full protocol of the experiment (see it in the attached material), then watches an instructional video which explains the game and how to use the robot to play the game (see multimedia attachment). The instructional video contains the minimum information necessary to play the game, no further instructions about how to approach the robot, how to grasp the robot, and in general, how to behave during the interaction, are given.

The experiment then proceeds with the following steps:

1) Measurement of the participant's height and weight;
2) The participant fills in the preliminary questionnaire, the Big Five personality questionnaire, and the NARS questionnaire;
3) The participant is equipped with the EMR-9 and performs the eye-tracker calibration;
4) The participant is equipped with the motion capture markers and the Shimmer3 GSR+ sensor performs the motion capture template acquisition, and rest for 5-10 minutes to collect baseline data for GSR and PPG;
5) The participant performs 2 times the *trial session*, during which the robot does not take any action, and the caught coins do not account for the bonus payment;
6) The participant fills in the CH33 and the SAM;
7) The participant repeats 3 times the *active session*, during which the robot takes actions (aims at high-value coins); after each session, the participant fills in the SAM, to assess the change in emotional state; after all 3 active sessions, one more time the CH33, to assess the change in perceptions; the sum of the coins caught during the 3 sessions is the final bonus payment;
8) The equipment is removed from the participant and they take the semi-structured interview with the researcher connected remotely on a laptop.

In total, each participant needs about 1.5 to 2 hours to complete the whole experimental procedure from instructions to interview. During each session, the participant plays only one game, therefore one session lasts about 3 minutes (150 seconds for the game, about 15 seconds at the beginning, and at the end for setting GSR and PPG at baseline levels). The entire time during which the participant is engaged with the robot is no longer than 30 minutes (including the time to answer the questionnaires). The semi-structured interview lasts about 10-15 minutes. The meaning of the actions of the robot is not disclosed to the participant unless explicitly asked at the end of the whole procedure.

G. Participants

A total of 40 participants participated in this study. The participants were recruited via a recruiting company to avoid any conflict in the process and ensure a uniform population. The following criteria were given for the recruitment:

- Japanese nationals, born and raised in Japan;
- Age between 20 and 50;
- Weight between 50kg and 80kg;
- Height between 150cm and 180cm;
- No prior experience with similar experiments;
- No health issues (heart issues, movement disorders).

Each participant received a reward based on the time they spent to conduct the experiment, plus the bonus payment from the game result. The reason for choosing only Japanese nationals is to avoid possible cultural-dependent variations, and due to the difficulty of recruiting a uniform population for a different nationality. Among the 40 participants, 35 have been retained for this study. A total of 5 participants had to be discarded due to accidental loss of data during the experiment, i.e. force plates not recording, eye-tracker falling. Of the 35 participants, 17 are females and 18 are males, 12 are in their 20s (5 females and 7 males), 12 are in their 30s (6 females and 6 males), and 11 are in their 40s (6 females and 5 males).

III. Data processing

The raw data collected during the experiment are post-processed to obtain a series of *factors* that are used for the analysis. We consider only data from the second trial session (referred to as the "trial session" hereafter), and the 3 active sessions. The first trial session is discarded as it is meant for the participants to familiarize themselves with the operation of the robot.

A. Motion and force data

The motion capture data are first processed with the Cortex software (Motion Analysis) to obtain smooth marker trajectories. Then by means of the DhaibaWorks [37] software package, we compute the joint angles of the human model and the poses of the body segment. In DhaibaWorks we use both the human and the robot model, for the human model, the positions of the recorded markers are matched to the virtual ones to perform inverse kinematics, while for the robot model, the joint angles recorded directly from the robot are used to obtain a precise reproduction of the movements of the robot. In this way, we can directly extract body segment poses and their relative distances to the links of the robot. We extracted features that can describe the general human behavior during the interaction, such as the orientation of the head, torso, and feet, the distance between the head, torso, and hands and end-effector of the robot, distance between the feet and the base of the robot, and extension of their hands. Distance between the feet, hands extension, and distance to the head are normalized with respect to the height of the participant. To obtain more precise information regarding the distance between the body segments and the end-effector of the robot, we used a collision detection algorithm [38], which is also used to automatize the detection of the hand that the participants used to press the cuff (the main hand) and to compute the distance from the other hand (the supporting hand). This information is relevant as participants interacted with the robot with many different body postures and hand placements, as can be seen in the multimedia material. The data from the force plates are used to obtain the ground reaction forces (GRF), which are normalized by the weight of the participant, and the position of the center of pressure (CoP) with respect to the base of the robot.

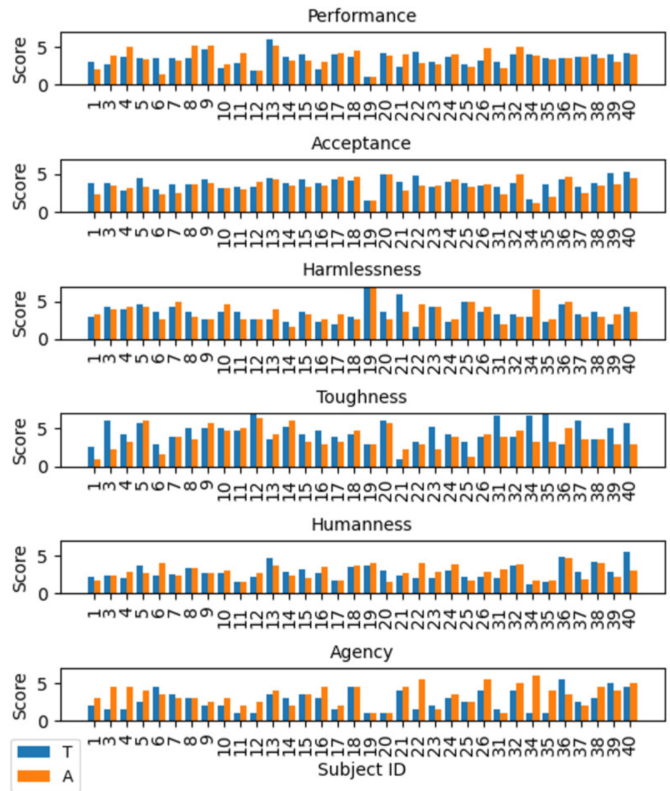


Fig. 4: CH33 scores after the trial session (blue) and the active sessions (orange), ordered by participants' ID number

B. Physiological data

From the eye-tracker, we extracted the eye blinking duration (EBD), the eye blinking rate (EBR), and the pupil dimension (PD), which are all normalized with respect to their baseline values to avoid differences due to biological factors such as age and gender. The gazing location is not considered as the participants looked mostly at the screen for the whole duration of the game. From the Shimmer3 GSR+ we obtained the baseline of the GSR and PPG signals from the resting period before the start of the experiment sessions, and also the signals measured during the sessions. We also post-process PPG into Pulse Rate Variability (PRV). Instead of using the GSR and PRV directly, we use the percentage difference between their baseline and the data measured during the sessions.

For all the data in III-A and III-B, we compute the average during the interaction, i.e. the duration of one game, during which the participants are holding on the end-effector of the robot and therefore establishing a physical contact.

C. Questionnaires and interview

The questionnaires are processed to project the participants' answers to their respective factors. For personality and CH33, the reader can refer to [27], while for NARS and SAM, to [21] and [35], respectively. In the case of CH33, we compute also the difference between the outcome after the trial sessions and the ones after the active sessions, as this represents the change in the participants' perceptions after they have experienced the actions of the robot, shown in Fig. 4.

In this paper, we used partially the outcome of the semi-structured interview to categorize whether the participants have understood the meaning of the intention of the robot, i.e. catching high-value coins.

This categorization is not directly obtained with straight-forward questions but identified by the interviewer from the answers during the interview. We extract two categories: the robot intention understanding and the perception of the robot helpfulness. Of the 35 participants, 22 participants understood the intention of the robot, and 13 did not. 18 participants found the robot helpful while 17 did not or not completely. Another interesting aspect that has emerged is that the intention understanding and the perception of the robot helpfulness are likely dependent. For instance, among those who understood the robot's intention (22), 15 participants answered that the robot was helpful or cooperative, while among those who did not or not completely understand the intention (13), 6 answered that the robot was not helpful nor collaborative.

D. Data analysis

We perform two types of analysis on the post-processed data: statistical analysis, presented in section IV, and clustering detailed in section V. All the factors that showed relevant relationships in our analysis are reported in Table I. The statistical analysis serves to address our initial hypotheses. Specifically:

- **H1** stated that the unanticipated robot actions can cause measurable alterations in physical and physiological data, meaning that we need to look for possible differences between the data of the trial session and the active

session, and possibly across the active sessions as well; this is done via correlations considering the percentage differences, and variance tests.
- **H2** stated that these physical and physiological data measured during the interaction could be explained with users' personality and perception of the robot, meaning that we need to look for possible correlations between factors.

While the statistical analyses can verify and/or reject our initial hypotheses and explain the human behavior and perceptions when physically interacting with a robot, the clustering analysis aims at the further step of building a model of the human state that could be used with controllers. Via clustering, we attempt at building a model using data that can be collected beforehand and real-time measurable data as inputs, which could predict factors such as perception and psychological safety.

IV. Statistical analysis

A. Correlations

We perform Spearman's correlation for non-parametric data on the factors obtained from the post-processing. To verify hypothesis **H2**, correlations are performed between personal data (age, height), personality, perception, and the physical (body segment distances and orientations, forces), physiological (eye data, GSR, and PRV) data. To target hypothesis **H1**, in the correlations we consider the difference in percentage (indicated with Diff) between the data measured during the trial session, with the average of those measured during the three active sessions.

To select relevant factors, we use a threshold on the p-value, i.e. all correlations with p-value < 0.05 are considered relevant. This choice is due to the exploratory nature of the study, where our sample size is still small relative to the number of factors, and further constraints (e.g. on correlation coefficients) on the data may leave out factors that are significant. The retained factors are reported in Table II. The entries are split into two groups. The first group includes the factors that are measured at each session, and the second group includes those that are the percentage difference between the average of the active sessions and the trial session (except for CH33 that is not the average, but the percentage difference in scores). From Table II we can observe the following significant correlations:

- Personal information:
  - Height has a negative correlation with Diff PRV and positive correlation with Head Dist, indicating that taller people had higher PRV during the experiment and kept the end-effector further away from their head.
  - Age has a positive correlation with end-effector forces, indicating elder people exerted higher forces.
- Personality:
  - Extraversion has a negative correlation with Head Dist, indicating that more extroverted people kept the robot closer to their head. In *Group 2*, Extraversion has a positive correlation with Diff Supp Hand Dist, indicating that more extroverted people had their supporting hand closer to the EE during the active sessions compared to the trial session.
  - In *Group 2*, Conscientiousness has a positive correlation with Diff Head Dist and Diff Hands Ext, indicating that more conscientious people kept the robot closer to their head and with a smaller hand extension during the active sessions with respect to the trial session.
  - In *Group 2*, Openness has a negative correlation with Diff PD, indicating that the more people are open, the smaller their PD, therefore less mental load, during the active sessions with respect to the trial session.
- CH33 (perception, psychological safety):
  - Diff Acceptance has positive correlations with Diff GSR, indicating people who found the robot less acceptable after the active sessions, had lower GSR with respect to the baseline, meaning a possible higher level of anxiety.
  - Diff Agency has positive correlations with PD, indicating that people who found the robot less agent after the active sessions, also had smaller PD, which may indicate less mental load.
  - Diff Toughness has a negative correlation with end-effector force and positive correlation with GRF, indicating the people who found the robot as less tough after the active sessions, applied lower interaction forces at the end-effector and higher GRF.
  - Diff Performance has a positive correlation with Supp Hand Dist, indicating that the less performing the robot was perceived after the active session, the further the supporting hand was from the end-effector.
  - Diff Humanness has positive correlations with Supp Hand Dist and Hand Ext, indicating that the less human the robot was perceived after the active sessions, the further the participants kept their supporting hand and had larger hands extensions.
- NARS:
  - S3-Emotional interaction has a positive correlation with EBR, and in *Group 2*, negative correlation with Diff Harmlessness, indicating that the more people felt negative about emotionally interacting with the robot, the higher their blinking rate, so they may have had a higher mental load, and the less harmless they perceived the robot to be after the active sessions.
  - In *Group 2*, S1-Social interaction has a negative correlation with Diff EE force, indicating that the more people were negative towards socially interacting with the robot, the higher were their interaction forces during the active sessions with respect to the trial session.

B. Variance test by repeated sets

To verify **H1**, we performed T-test for repeated samples, by comparing the factors that are measured in each session. Specifically, we compared the trial session with the first active

Factor	Explanation
EE force	Interaction forces measured at the end-effector of the robot
GRF	Ground reaction forces, normalized with body weight
CoP	Distance between the center of pressure of the participant and the base of the robot
Head Dist	Distance between the head and end-effector of the robot
Supp Hand Dist	Distance between the supporting hand (the one not used to press the cuff) and end-effector of the robot
B Feet dist	The participant's intra-feet distance
Hand ext	Extension of the arms as sum of distances from each hand to the torso, normalized by height
GSR	Galvanic Skin Resistance, percentage difference between baseline and the session
PRV	Pulse Rate Variation, percentage difference between baseline and the session
EBD	Eye blinking duration
EBR	Eye blinking rate
PD	Pupil diameter
Diff *factor*	Percentage difference between the average of the active sessions and the trial session.

TABLE I: All factors excluding height, age, gender, personality, and questionnaires. All the factors above Diff *factor* are computed as the average for each session (in the case of GSR and PRV, it's the average of the percentage differences with the baseline values). Only those relevant in this paper are listed in the table.

Factor 1	**Factor 2**	**Corr. coeff.**			
Group 1: single session measurements		**T**	**A1**	**A2**	**A3**
Height	Diff PRV	-0.39	-0.35	-0.37	-0.37
Height	Head Dist	0.62**	0.61**	0.57**	0.63**
Age	EE force	0.51**	0.43*	0.49**	0.41
Extraversion	Head dist	-	-0.41	-0.35	-
Diff Acceptance	Diff GSR	0.47**	0.41	0.41	0.43*
Diff Agency	PD	-	0.41	0.44*	0.40
Diff Toughness	EE force	-0.48**	-0.48**	-0.49**	-0.49**
Diff Toughness	GRF	0.4	-	0.36	0.35
Diff Performance	Supp Hand Dist	0.36	0.39	0.40	0.38
Diff Humanness	Supp Hand Dist	0.41	0.53**	0.49**	0.41
Diff Humanness	Hands Ext	0.38	0.43*	0.47**	0.51**
S3-Emotional int.	EBR	-	0.33	0.4	0.51**
Group 2: differences					
Conscientiousness	Diff Head Dist	0.37			
Conscientiousness	Diff Hands Ext	0.40			
Openness	Diff PD	0.47**			
Extraversion	Diff Supp Hand Dist	0.44*			
S1-Social int.	Diff EE force	-0.42			
S3-Emotional int.	Diff Harmlessness	-0.38			

TABLE II: Relevant correlations (p-value $<$ 0.05). *Group 1* are those where the factors in **Factor 2** are measured for each session, with **T** being the trial session, and **A1, A2, A3** the three active sessions respectively. *Group 2* are the percentage difference between active sessions and trial session. The correlation coefficients marked with * are those with p-value $<$ 0.01, while those with ** the ones with p-values $<$ 0.005. Entries with "-" means p-value $>$ 0.05 and the correlation factor is not reported in the table.

session (T-A1), and the first active session with the third active session (A1-A3). For the SAM, we obtained p-values $<$ 0.05 for Pleasure and Arousal for T-A1, and Dominance for A1-A3. We can observe from Fig. 5 that Pleasure and Arousal did not change significantly from A1 to A3, while Dominance does not show a significant increase from the trial session to the first active session, but does increase significantly through the three active sessions. The EE forces also showed significant changes in both T-A1 and A1-A3, with EE forces increasing with the increasing number of sessions. The average distance between the feet also showed significant differences in both T-A1 and A1-A3, with increase distances.

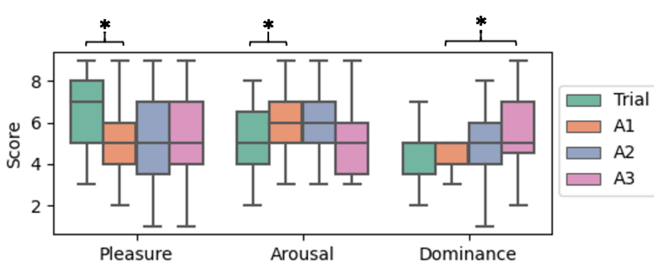


Fig. 5: Self Assessment Manikin (SAM) results after each session, "*" indicate the ones with significant difference (p-value $<$ 0.05).

C. Variance test by groups

We performed one-way ANOVA for different data groups, namely: age (20, 30, 40), gender (female, male), robot intention understanding (yes, no), robot helpfulness (yes, no). In the case of age groups, we found significant (p-value $<$ 0.05) differences for the EE forces, with forces increasing with age.

In the case of gender, we found a significant difference for EBD, with females having higher blinking duration (lower mental load) compared to males, and Hands Ext, where males have larger hands extensions than females.

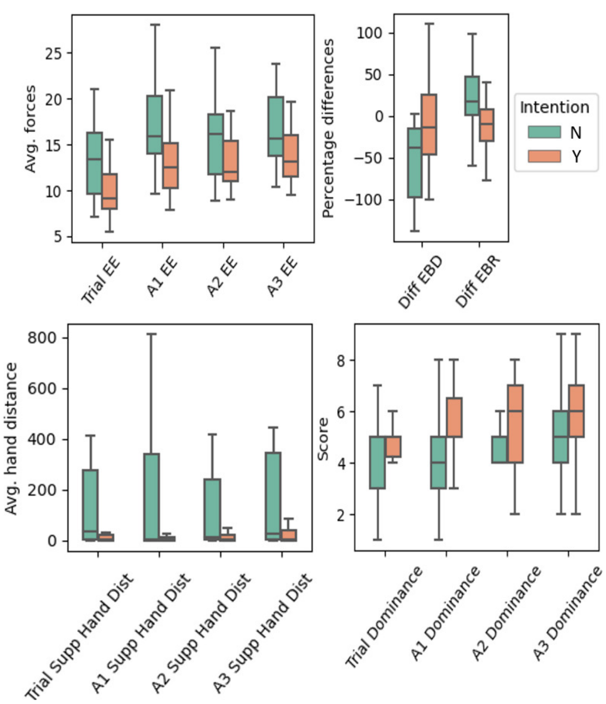


Fig. 6: Intention understanding class.

As shown in Fig. 6, there are many factors that show significant differences between those who understood and those who did not understand the intention of the robot. In particular, those who understood the intention applied lower

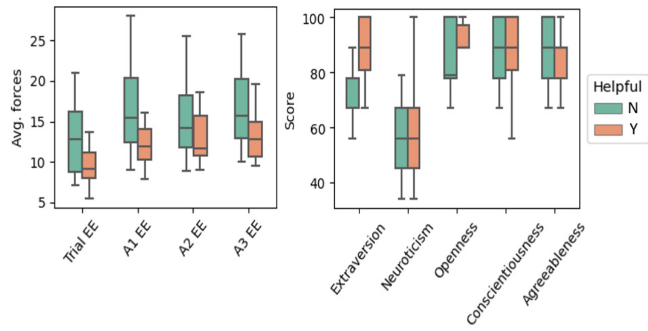


Fig. 7: Helpful class.

forces on the robot, had higher blinking duration and lower blinking rate (less mental load) during the active sessions with respect to the trial session, felt more dominant, and kept their supporting hands closer to the robot.

For those who found the robot to be useful or not, we also found significant differences on the forces applied on the EE, as in Fig. 7, with those who found the robot being helpful applying less forces. There is also a clear difference in Extraversion, where the more introverted people found the robot not/less helpful.

V. Clustering analysis

The statistical analysis shows many relevant relationships but does not give many insights if multiple factors are considered simultaneously, which can be done via clustering analysis.

Furthermore, in a realistic active pHRI scenario, the robot controller would need to use information that can be gathered beforehand and/or in real-time, to adapt its controller to specific users. Motivated by the results of the statistical analysis, where we could observe relevant relationships between the measurable data and perception, we divide the data into two groups before applying clustering:

1) Data that could be used to predict perceptions of the user:
   - Data that can be collected beforehand: personal information, personality, NARS.
   - Real-time data that can be measured in real-time with currently available or soon to be available non-invasive sensors that can be used in a realistic near-future scenario: postural data that depend mostly on the user (distance between the feet, location of the supporting hand), forces at the end-effector, and physiological signals (PRV, eye factors).
2) Data that could be predicted or adapted to based on the data from the group above:
   - Perception: CH33, SAM, robot intention understanding, robot helpfulness.
   - Postural data that the robot could adapt to (torso and head distances, torso, head, and feet orientations), e.g. by moving closer.

To reduce the number of factors and avoid redundancy, we use the differences rather than the measurements of each session. Factors that do not show significant changes were discarded (e.g. Diff GSR, Diff GRF). We use the data in the first group to perform clustering, with the aim to find out whether these clusters can lead to specific patterns of data in the second group, i.e. whether it would be possible to implement a controller that takes the data in the first group as input to predict the user's state represented by the data in the second group. We use agglomerative hierarchical clustering with Ward's linkage method. All data were standardized before applying clustering. We can see from the obtained linkage tree (dendogram) in Fig. 8 that it is possible to identify a total of 6 clusters, of which one cluster contains only one participant (n. 21). This participant is regarded as an outlier and not considered for further analysis. The obtained clusters are shown in Fig. 9, with the data used to obtain the clusters in Fig. 9a, and those in the relative clusters from the second group in Fig. 9b (gender is included only as reference). Further discussions will follow in the next section.

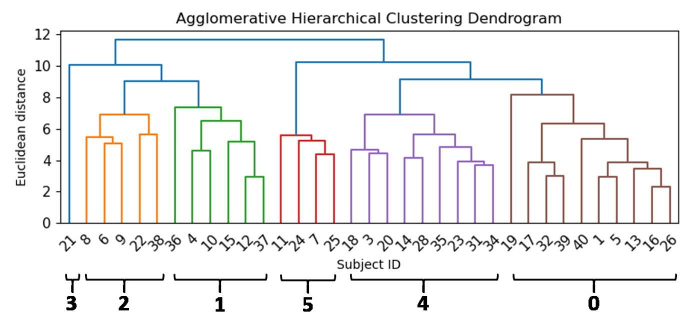
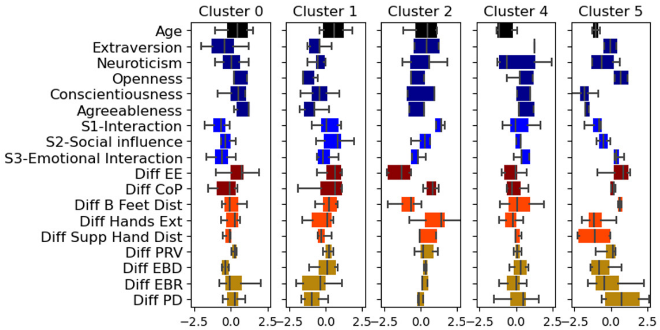


Fig. 8: Dendogram for agglomerative hierarchical clustering (bold numbers correspond to cluster number).

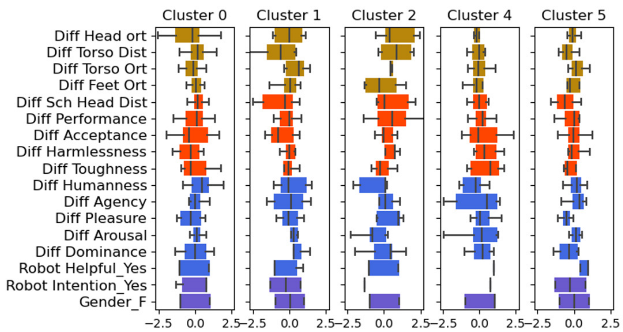
VI. Discussions

Our first hypothesis **H1** is that the unanticipated robot actions could cause measurable alterations in the participants' data. From the results, we can state that:

- From the semi-structured interview, it results that all participants considered for the analysis (35) except for two, clearly indicated that they felt that the robot was taking some action, independently from from their understanding of the intention of the robot (for the time being, these two participants were not considered outliers for the data analysis).
- From the differences of CH33 as in Fig. 4, we can clearly see that the perception of all participants changed after the active sessions with respect to the trial session.
- From the T-test we could observe that indeed their perception from SAM showed significant changes throughout the sessions, with decreasing pleasure, increasing arousal, and dominance after the first active session. However, pleasure also increases slightly for the remaining two active sessions, while arousal decreases. This may indicate that in the second and third active sessions, users started to get used to the actions and they feel a bit happier, less excited, and more dominant at the end of the experiment.
- From the physical data, end-effector forces, and distance between the feet showed significant increases between the trial session and the active sessions, indicating that



(a) Data used as input for clustering



(b) Data that could be predicted/interpreted from the cluster inputs

Fig. 9: Clustering results (excluding cluster n.3).

probably when the robot was taking actions, the users tried to adapt their forces and posture to the new situation.

With these results we could verify that the robot action does cause alterations in the participants' physical data and perceptions, but not in a significant way the physiological data.

Our second hypothesis **H2** stated that the physical and physiological data can be explained with perceptions and personalities. From the results, we could observe that:

- Personality traits can be related to several postural and physiological data. Specifically, more extroverted people seem to prefer to keep the robot closer, as also observed in our previous study [27].
- The attitude of participants towards robots also explain a few physical and physiological factors: people who felt overall more "positive" towards the robot (more acceptable, less tough, more performant, less agent, more human, and lower negative attitude), seem to have a more "relaxed" interaction with the robot (closer distances, lower forces, lower anxiety, lower mental load). This result emerges also from the variance test, where people who understood the intention of the robot are those who used less force, had less mental load, felt more dominant, and kept both hands closer to the robot end-effector. Also, those who found the robot being helpful used less force and were also those more extroverted compared to those who found the robot not or less helpful.
- There are significant differences in the forces applied at the end-effector in the 3 age groups, from both correlations and variance test. It has been demonstrated that significantly elder people (age range 70-80) use higher grip forces [39] with respect to younger people (20-40). Even if in our study the age difference is not as large as in these studies, we cannot exclude that this could be the reason for this finding.

We could verify that there exist relevant relationships between physical and physiological data and personalities and perceptions, and also between perception and personalities. Gender seems to play a smaller role, as the difference in hands extension could be due to cultural and societal reasons, and the possible lower mental load in females could be due to females being generally less addicted to gaming [40].

These results indicate that it is possible to adapt the robot controller from a set of measurable factors that explains the real-time perception of users. The clustering helps us identify possible patterns of these factors, which may lead to a model that can be used to adapt the robot motions based on measurable and known data, accounting also for the perception of the user. From the obtained clusters in Fig. 9, we could observe that clusters 4 and 5 are groups of younger subjects who are mostly extroverted but are very different in other personality traits such as Conscientiousness and Openness, and showed different attitudes towards robots. From the data shown in Fig. 9b, we can see that the difference in their posture may not be relevant, however, their perception varies significantly. Clusters 0, 1, and 2 are groups of elder participants and are distinguished mainly by their personalities, attitude towards the robot, forces, and postures. These differences mark variations in posture, understanding, and perceptions in Fig. 9b.

With respect to our previous study [27], we introduced a bonus payment to motivate the participants to interact with the robot, while we could not conclude whether the motivation of the participants was actually affected, the new game allowed for a better understanding of the relationship between the data, and the higher number of participants allowed to obtain statistically more significant outcomes. The number of factors, however, remains high, and not all possible behavior variations could be taken into account, therefore possible patterns could be missed. Even if the number of participants was doubled, it could still be premature to conclude on the usability of the cluster outcomes, which will be verified by implementing and testing a controller using the input data, however, this is out of the scope of this paper.

VII. Conclusions and Future Work

In this paper, we conducted an experiment to measure both the physical and mental state of human users in relation to active pHRI, i.e. a physical interaction during which the robot may take an unanticipated physical action on the user, based on the hypotheses that such actions can cause alterations in the users' state, and that physical and physiological measurements can be explained with personality and perceptions. We could verify both **H1** and **H2** by means of statistical analysis, even if **H1** could be verified only for a few factors. To be able to use the obtained results in a possible control framework, we performed clustering analysis to identify patterns in the data and obtained relevant classifications. For instance, users' perception of the robot (including understanding the actions of the robot and finding it helpful) could be predicted with their age, personality, and real-time measurable postural and physiological data.

The outcomes of this study indicate that mental state could be quantified by means of the relation between perception with physical and physiological signals, these findings could be used to build a human-state model for use in the control of robots during active pHRI. An important step will also consist in reducing the number of factors to be verified with respect to the number of participants of the experiment, in order to obtain more solid and statistically significant results. The clustering analysis is a first step towards reducing factors and building a model, where we will also consider Structural Equation Modeling (SEM) [41] to describe the relationship between factors. To implement an active pHRI controller that can take into account both the physical and mental state of the user in a real application, it is necessary to reduce the sensor load. In our experiment, a high amount of sensors was involved. Despite most of the participants did not feel interfered by the equipment (25 participants as resulted from the semi-structured interview), it does not represent a realistic setup. In future implementations, it will be necessary to focus on those factors that can be measured with existing non-invasive sensors and data that can be easily obtained, such as the ones that guide our clustering approach.

From the results, it appears that the interaction forces measured at the end-effector are highly relevant factors that vary depending on different factors such as age, personality, and perception. Personality seems to mark relevant differences in the participants' postures and perceptions. These outcomes are very encouraging as the end-effector forces are easily measurable with currently available sensors, personality can be easily acquired via a questionnaire before starting the use of the robot, and postures could be acquired via inexpensive cameras. In the next step, we will consider verification of the outcomes of this study with a minimal set of sensors. A more in-depth analysis of the semi-structured interview will also be performed from a social perspective but was out of the scope of the current quantitative analysis.

In future studies, the effect of long-term interactions and habituation should be considered, as the perception of users varies in time [42]. Also, we used a simple visual game to emulate the interaction with the robot, however, the type of task involved in the interaction may also affect perceptions and behavior. In this paper, we used a collaborative manipulator as it is the current state-of-the-art type of robot meant for physical interactions with humans, especially when considering industrial applications. However, this choice also represents a limitation of the study regarding the generalization of the outcomes. As a matter of fact, the type and also the shape of the robot inevitably influence the type of physical interactions with the human, whether direct or indirect, where the appearance of robots may influence human's perceptions [43]. While the outcomes of this study cannot be directly generalized for other types of robots (e.g. social robots, smaller size manipulators, manipulators with mobile bases, wheeled mobile robots, humanoid robots, etc.), the general framework of the paper (i.e. physical action from the robot, sensors adopted, and methods for data analysis) can be used to test similar settings for different types of tasks and robots, where dedicated experiments will be necessary to address each type of robot.

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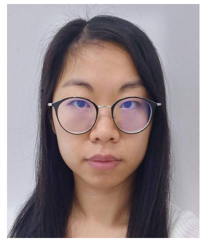

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