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A Methodological Outline and Utility Assessment of Sensor-based Biosignal Measurement in Human-Robot Interaction

A System for Determining Correlations Between Robot Sensor Data and Subjective Human Data in HRI

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Abstract Sensor data taken during a human-robot interaction (HRI) have high potential for usage as new, objective measures of an interaction, either replacing or supplementing survey techniques that are currently most common in HRI research. Sensor data can be taken in large quantities quickly, naturally, and discreetly. They also have the potential to reflect a user's biosignals—information about the user's inner state (such as stress and attention) when interacting with the robot. We previously conducted three studies attempting to use sensor data as a measurement in HRI, with methodological differences in three different experimental environments. In this paper, we reanalyze and add new data to the previous findings under a consistent methodology, consolidate what correlations we find, and can conclude that sensor data is a useful metric in HRI across a wide range of experimental setups and subject pools. We fully describe the methodology we determined to be most effective, from selection of sensors to data analysis techniques to HRI experiment setup, as a basis for how this methodology can be used in other HRI studies. We describe necessary steps in the analysis of a large amount of sensor data (over 100,000 sets) and how sensor data can be compared with survey and behavioral data. Based on these correlations, we find that the most effective sensors are temperature sensors, tactile sensors, and face distance measurements. We also find that higher measurements across all of these sensors are more correlated with both survey and behavioral measurements reflecting positive thinking towards a robot (including non-technophobia, reciprocal behaviors, and positive ratings of the robot) during an interaction. Based on these results, we argue that robot sensor usage is an important and objective metric for HRI research.

Keywords Biosignal · Sensor data · Human-robot interaction · HRI measurement · Handshake · Touch-based interaction · Hand temperature · Tactile measurements · Face distances

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1 Introduction

Human-robot interaction (HRI) research is facing the same questions today that psychology once did in the past—how can one measure people's innermost feelings and motivations in the most accurate, objective way? A large portion of psychology research measures the human condition through explicit measures such as surveys or behavioral analysis. Similarly, HRI research has largely depended on these external measures to analyze people's reactions to a robot. Although subjective and explicit measures such as surveys are easy to prepare and analyze, they are unnatural and lengthy for the subject, and have high potential for response bias, where subjects answer based on irrelevant motivations [1]. In recent decades, psychology has tended towards quantitative methods that get at more objective, unbiased measures of people's cognitive states, including biosignal measurement. One example is lie detection machines, which measure a person's skin conductance to get at thoughts that are concealed from that person's outer behavior [2]. Along with skin conductance, other biological measurements that are frequently used in psychology research include hand temperature [3], brain waves measured by electroencephalography (EEG) [4], heart rate [5], and several others. Higher skin conductance means more hand sweat, which is linked with higher stress [6]. Higher hand temperature (as well as lower heart rate and lower blood pressure) has been linked with relaxation [7]. Lastly, EEG data and eye contact and focus data can give insight on attention. Although biosignal usage is now a well-accepted methodology in the field of psychology, this methodology has been surprisingly overlooked in HRI research, with only a few studies in the field. Strauss et al. are developing natural sensor systems, such as gloves and bracelets, to collect biosensor information during long-term psychology and human-computer interaction experiments [8]. Munekata et al. conducted research on having a robotic bear react to information taken from external skin conductance sensors [9]. However, little work has attempted to directly attach biosignal sensors to humanoid robots. In this study, we use a robot to directly take biosignal measurements, and we examine whether such biosignals are useful, how they can be used, and what we can interpret from their measurement.

The measurement of biosignal data by robots affords many benefits that surveys and behavioral analysis alone do not: it is fast, natural, and data-rich. First of all, no preparation is required from the user or the experimenter; there is no attachment of sensors or training. At most, one would need to calibrate the robot's sensors to match a subject's baseline. Subjects can thus have a quick, casual interaction with the robot and the robot can still collect meaningful data. The robot can take thousands of blocks of data per minute—even a quick thirty-second interaction can take a good enough sample to make comparisons of inner state across different types of people.

Second, the usage of robot sensors to collect data is extremely natural. Modern-day sensors are very discreet—they are small and can be flawlessly integrated into a robot's design. Theoretically, subjects do not even need to know that data are being collected from them (within human subjects requirements). The currently proposed methodology also allows humans to interact with robots in an ecologically valid environment with no surveys to interrupt the pacing of the interaction. Adding these sensors makes the robot sense in a more "human" way—not just by vision sensors, but also by touch. Humans use multimodal sensing—they regularly form first impressions of people based on tactile measurements from interactions such as handshakes [10]. People also feel a stronger connection with a robot if they are able to touch it—it helps them understand the robot better and become less afraid [11].

Lastly, sensor information is very data-rich. A survey only collects data at one point in time for a subject and has high potential for bias [12]. Biosignal sensing, however, takes constant measurements over time and can be sensitive to minute changes in a person's biosignal information while also being robust against anomalies. Sensor data usage also allows robots to integrate multimodal data (visual, tactile, auditory, etc.) to create a full picture of their human partner.

This paper explores the potential for such biosignal data to be used by robots to interpret human feelings towards an interaction. We previously conducted three separate studies [13–15] looking at using sensor data in HRI. Each study was conducted consecutively, working to build upon the results of the previous study and also to adjust the methodology and subject pool to create a cleaner experiment. Each study in itself acts as a support of using robot sensor data within a specific environment, but does not go into detail for a methodology that can be applied to a wider range of experiments. In this paper we combine the results and previously unreported data from these three studies, seeing what generalizations we can make about the usage of biosignal data. We reanalyze the results of these three studies using a consistent methodology. We then use what we have learned from these three studies to propose a general methodology for collecting biosignal data from robots, which we believe can be useful to other researchers wishing to replicate the methodology with their own robot systems. Specifically, we believe this methodology is applicable to any social, entertainment, or caretaking robot that comes in physical contact with a human, as it provides additional data useful for creating a more comfortable interaction with a human partner. Additionally, to serve as a guide for data design and to provide a large database of several subject's interactions with robots, the data from our studies will be publicly available online.

2 General Methodology

2.1 Robot System

All three studies used the HRP2-JSKNT humanoid robot, a version of the HRP-2 robot by Kawada Industries, modified by our laboratory. The robot is 154 cm tall, weighs 58 kg, and has 30 Degrees of Freedom (DOF). There is added stereovision in the head, which has seven DOF. There are also additional three-fingered hands on each arm, with 2 DOF in the thumb, 3 DOF in the index finger, and 1 DOF in the large "middle" finger of the hand. The joints in the robot are made compliant when interacting with people, so that they adjust to a person's movement—for example, when holding a person's hand, the robot's joints adjust to the user's hand size without causing any discomfort. The robot's fingers are covered in a thin layer of black foam at the fingertips and black tape along the finger, so that the sensors underneath are inconspicuous and the hand is not unpleasant to touch or see. Auto-balancing in the robot's legs is also activated, so that even if a subject pulls or pushes the robot during an interaction, the robot does not fall over. Refer to Fig. 1 for a picture

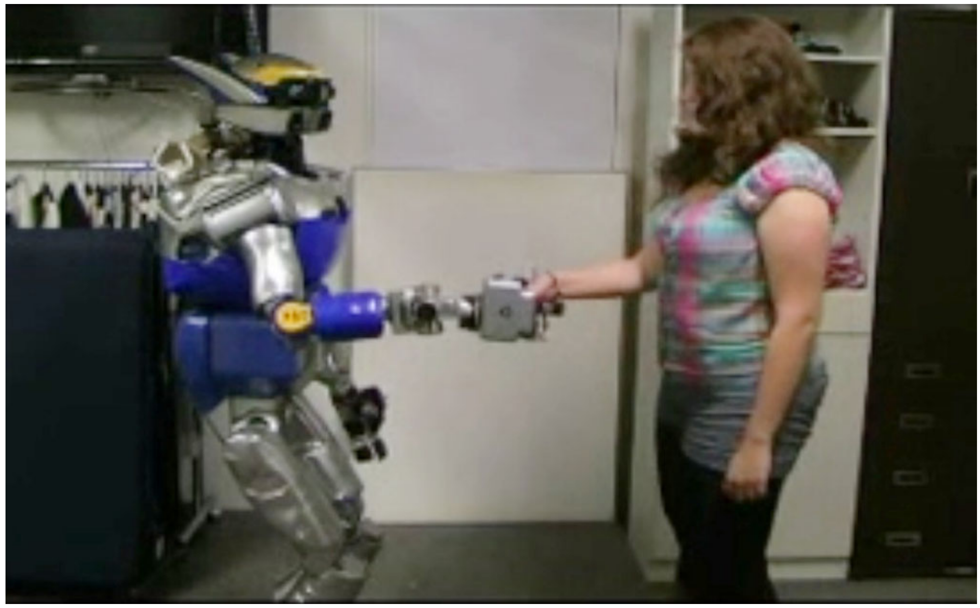

Fig. 1 A photograph of a user shaking hands with the robot during an experiment

of the robot in the middle of a handshake—one of the key data-taking points in the studies described in this paper.

The robot's programming is done in Euslisp, an object-oriented version of LISP developed by the JSK Laboratory [16]. The programming also uses a Robot Operating System (ROS) framework [17], to control multiple motor streams (specifically, asynchronous control of the robot head and arms) as well as to save sensor data in a uniform format. Simple speech synthesis is also implemented in Studies 2 and 3, allowing the robot to utter set phrases to the user to make the interaction more natural. Japanese speech synthesis is done using the AquesTalk plugin developed by Aquest [18], while English speech synthesis uses the open-source plugin Festival [19]. The robot is given a cute, feminine cartoonish voice, as selected by the general public in an open-campus survey [13].

2.2 Sensor System

These studies focus on the data from four types of sensors: temperature sensors, tactile sensors, force sensors, and cameras. A diagram of the sensors on the robot's hand can be seen in Fig. 2. Force sensors and cameras were already included in the robot, while the temperature sensors and tactile sensors were added by our laboratory. There are force sensors in each of the robot's joints, measured in six directions: x, y, z, roll, pitch, yaw. The robot uses one camera in its eye region to conduct face tracking and to measure the distance to a subject's face, based on a face recognition plugin in the robot's software framework. The temperature sensors are SEMITEC 0.5 mm thick high-precision thermistors with a sensing range of −50 °C to 125 °C, with 1 % accuracy. There are three on each hand: one on the palm, one on the thumb, and one on the index finger. The tactile sensors are 0.35 mm thick Standard 400 single-zone force sensing resistors, with a sensitivity range of .1 N to 10 N and accuracy of 2 %. There are eight on each hand: two on the palm, two on the thumb, two on the index finger, and two on the middle finger.

We selected the above four sensors for various reasons. It is intuitive to use sensors already built into the robot, specifically the force sensors and cameras. For newly attached sensors, the temperature and tactile sensors have several qualities that make them ideal for HRI. We propose keeping these properties in mind when selecting sensors to use in HRI:

1. They should be small, ideally inexpensive
2. They should be easy to integrate with the existing circuitry in a robot's hand
3. They should take data at a high frequency
4. Their data must be stable, requiring infrequent calibration and be resistant to disturbance
5. They should be useful for many applications (object grasping and sensing)
6. They should require no external attachments on the user

While other sensors are frequently used in psychological biosignal testing, there are still hurdles that prevent their smooth usage with humanoid robots. The most common sensor in psychology research is the skin conductance sensor, or galvanic skin response sensor [6]. Our laboratory experimented with using a skin conductance sensor, but it did not fit with the above for several reasons: skin conductance sensors require two continuous attachments to the user (leads taped to two fingers), miniaturized versions are rare, and their data are unstable, with a constant need for readjustment of sensitivity. Heart rate, EEG, and similar sensors also

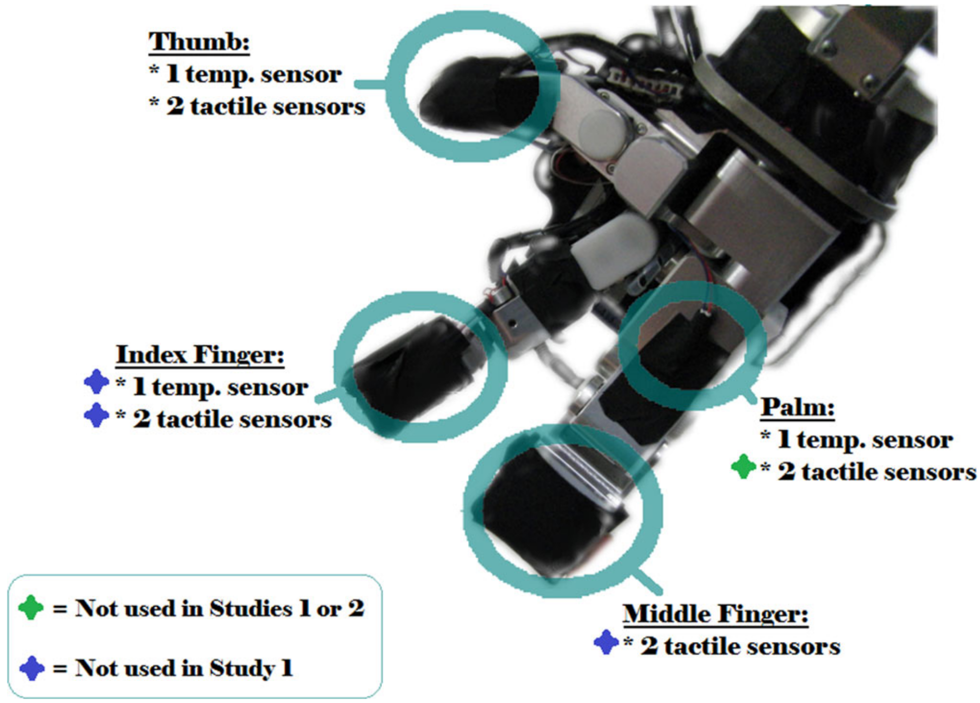

Fig. 2 A diagram of the sensors on the robot's hand, and which sensors were used for which studies. There are also force sensors on all joints of the robot's hand

require external attachments to the subject, which would diminish the naturalness and discreetness of the experimental environment. We encourage researchers to explore how these sensors or other sensors could be adapted to fit into a good HRI sensing system.

With the robot's cameras, the only data taken during these studies are face distances (calculated by face size). The cameras used for this study are too low-resolution to do more complex analysis. However, with more high-resolution cameras, there are several measures that could serve as useful biosignal information, including amount of eye contact, pupil size, and emotional valence of facial expression, and we also encourage researchers to explore the integration of computational vision and multimodal information in HRI.

2.3 Data Analysis

The main hurdle in data analysis for this methodology is the large amount of data. A flowchart of the general data analysis steps can be seen in Fig. 3. In this paper, these steps were reapplied to the three studies mentioned below, which previously used inconsistent methodologies. Through the following steps, an experiment that begins with millions of lines of data can be pared down to tens or hundreds of thousands of lines of data, depending on the number of subjects and experiment length. Each minute, the robot collects over 1,700 lines and approximately 1 gigabyte of data, which include sensor data, program output data, point cloud data, image data, and sound data. Data are stored in a *ROS-bag*, the data format used by ROS to store the various data types aligned to a timestamp from when the data was saved. At each point in the experiment, the robot's software is also creating a *ROS-msg* (a String stream of data outputted in the same way as the sensor data), which we call "*experiment-action*," which describes the point in the experiment for that timestamp (for example: "*begin-handshake*"). Several steps are necessary to pare the data down to a manageable level:

1. *Create a text-file of relevant data through a parser.* A parsing script takes the sensor values and *ROS-msgs* from all timestamp-aligned data for the relevant *experiment-actions* and outputs them as comma-separated values into a text file (a CSV file). No image or audio data were included in the output file. The experimenter specifies as a parameter which *experiment-actions* (such as "*begin-handshake*") have useful data to be parsed. For these experiments, we used instants only when the user was firmly gripping the robot's hand, such as the *experiment-action* "*start-handshake*". The frequencies of data output differed across sensors on the robot. To solve this, our parser found moments when the sensor data were outputted a few nanoseconds apart, and synchronized these to an average timestamp. All outputted lines had full sets of sensor data, except for the more infrequent face distance measurements.
2. *Add optional data through a video tagger.* A video tagger script allows the experimenter to replay video of the experiment, pause it at key points and add *ROS-msgs* related to the video points. For example, if a subject waved at the robot, the experimenter could use this tagger to mark the beginning and endpoints of the wave. The *ROS-*

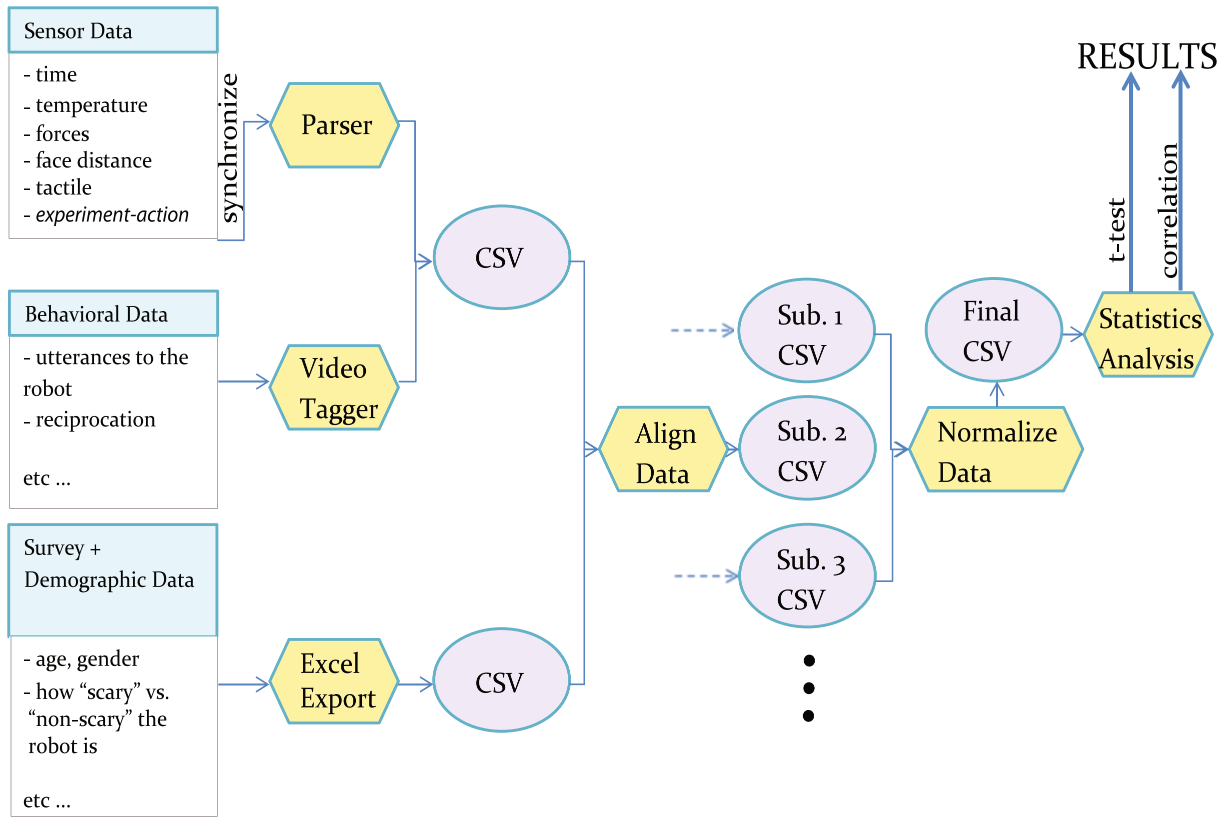

Fig. 3 A flowchart showing the steps involved in turning sensor data into biosignal interpretation. *Blue boxes* indicate data types, *yellow hexagons* indicate script or software processing, and the lavender ovals indicate output files. *CSV* indicates a comma-separated value file. "*Sub.*" stands for Subject and demonstrates the combination of multiple subjects' data

msg is then outputted as a timestamped user-specified String (for example, *subject-greeting* = "*wave*"), which is aligned with sensor data of the same timestamp.

3. *Code behavior/survey data.* The experimenter manually inputs survey and behavior data (such as utterances of the user) into a spreadsheet, which is then exported as a CSV file.
4. *Align behavior/survey data to sensor data.* A file-concatenating script attaches the relevant survey and behavioral data to the sensor data of the same subject, based on a *ROS-msg* indicating subject number in the sensor data.
5. *Normalize the data amounts per subject.* Amount of data varies based on the amount of time a subject interacted with the robot. This creates a bias where subjects who interacted longer with the robot have more effect over the data tendencies. For example, subjects who like the robot may interact with it longer, causing them to skew the data (temperature, tactile, etc.) to have stronger significant differences than there actually are between positively and negatively feeling subjects. To eliminate this bias, a script normalizes the data amount across subjects. First, subjects with data inconsistencies (mainly, subjects where there was a network error during the experiment that prevented successful saving of the data) are eliminated from the pool. Then, for each *experiment-action*, the script finds the minimum number of lines of data in a subject. The same number of lines is then taken as a random sample from each subject, so that all subjects have the same number of lines of data, and the same amount of influence over the final data analysis.

The final comma-separated text file produced from this processing is then outputted to statistical analysis software. Person's correlations are used between the full set of sensor data and the full set of behavioral/survey data from each study to look at correlations between biosignals and behavioral reactions to the robot. Independent samples t-tests are used to compare the full set of sensor data in a study between two groups (such as by gender). Unless otherwise noted, all statistical tests reported in the results for the following three studies passed a significance level of $p < 0.001$. Measurements are not reported for a group if they are not below a $p < 0.05$ level of significance, or if multiple measures for one biosignal (for example, the measures from the eight tactile sensors) do not show a majority tendency in one direction. Specifically, temperature is only reported if all three temperature sensors agree, tactile measurements if at least four of six or five of eight agree, and force measurements if at least four of six, or all three x, y, and z agree. Face distance measurements sometimes differ in sample size because the robot only outputted face distance data when it detected a face, at a much lower frequency than other sensor output.

Some abbreviations will be used to identify the data from different sensors. The force sensors will be reported as x, y, z, r (roll), pt (pitch), and yw (yaw). The tactile data will be reported as $tc0$, $tc1$, $tc2$, $tc3$, $tc4$, $tc5$, $tc6$, and $tc7$, as the eight tactile sensors on the robot's right hand. The temperature data will be reported as $t0$, $t1$, and $t2$ as the three temperature sensors on the robot's right hand.

One important methodological aspect to note is that the sensors need not be calibrated for each subject in a multi-subject experiment; subjects' baseline measurements are unnecessary. This is due to the fact that because there are several subjects, individual differences should even out and not have an effect on correlations of the data. For example, it is unlikely that subjects who like the robot all happen to participate in the experiment when the room is warm that day. Because of this, we did not have to look at the average or baseline temperatures for subjects as a part of the data analysis—we only include them here for reference. When this methodology is readapted for single user sensor reading and prediction, then deviations from a baseline will have to be monitored.

3 Study 1

3.1 Methodology

We reported initial findings and very preliminary hypotheses in a workshop paper [13]; however the results have been reanalyzed and solidified for the current paper. The goal of this study was to see whether sensor data could produce any statistically significant differences between groups of people, as a first step in investigating this methodology. The robot greeted people who visited our laboratory as a part of a laboratory alumni open-house. The robot tracked people's faces and then selected a random greeting of a wave, a bow, or a handshake when a person came into view. The most biosignal data was taken during the handshake. 27 people shook hands with the robot (24 male, 3 female), and all had extensive experience with robots (though not necessarily with the HRP-2). Subjects did not interact with the robot for more than a few minutes. For this study, temperature data and tactile data were only measured from two sensors each. There was no time to administer a survey, so information was collected on group differences that were easy to identify—specifically, gender, lab membership, and content of verbal utterances. Verbal utterances were coded blindly from the video data for the existence of a clearly positive word (such as "cool") or a clearly negative word (such as "scary").

3.2 Results

In the original version of the study, we analyzed the data as-is. However, in this study, the data was reanalyzed in accordance with the methodology outlined in Sect. 2.3. The average temperature readings were $t0: M = 27.2$ °C, $SD = 1.7$ °C and $t1: M = 26.2$ °C, $SD = 2.0$ °C, tactile measurements were unitless, and the average face distance was $M = 1354.25$ mm, $SD = 345.1$ mm. In terms of gender, males had lower temperatures than women ($t0: t(3070) = 14.306; t1: t(3070) = 5.078$) and farther face distances ($t(201) = 3.229$, $p < 0.005$). Tactile, temperature, and face distance readings, however did not have significant differences. Current members of the laboratory (seven subjects) versus alumni who were not current members (twenty subjects) had higher forces ($x: t(3192) = 2.721$, $p < 0.01$; $y: t(3192) = 4.574$, $z: t(3192) = 2.527$, $p < 0.05$), lower hand temperatures ($t0: t(3192) = 10.023; t1: t(3192) = 8.873$), and farther face distances ($t(305) = 3.343$, $p < 0.005$). People who spontaneously made positive remarks during the interaction (four subjects) versus negative remarks (three subjects) had lower hand temperatures ($t0: t(824) = 30.673; t1: t(824) = 32.409$).

3.3 Discussion

The main purpose of this study was to act as a pilot study, testing the concept of using sensor data to identify differences between people during HRI. Subjects spent very little time with the robot, and there was a small number of subjects in each group, which makes it difficult to make any strong conclusions about the groups themselves. Perhaps the comparison of current members versus alumni has the most reliable measure because of the larger subject pool (seven and twenty respectively), but we believe the results here on gender and positive versus negative remarks have too low subject numbers to be meaningful. However, we include this study in this paper because it serves as the starting point to the creation of this methodology, and demonstrates that significant correlations can come out of sensor data. It also serves as a point of comparison to the results of Study 2 because of the similarities in methodology.

4 Study 2

4.1 Methodology

We reported the main content of these findings in a Japanese domestic conference paper [14]. The main purpose of this study was to build upon the ideas established in the pilot study (Study 1) and to establish basic tendencies in how feelings towards a robot correlate with sensor data. The methodology of Study 2 is similar to Study 1: the robot greeted people with either a wave, bow, or handshake—with the data analysis mainly focused on the handshake. However, instead of having the robot interact only with people experienced with robots, the robot was put outside on the University of Tokyo campus and it greeted people who walked by. The robot interacted with a wider range of people, most of them people with no robotics experience at all. This study also ran for a longer period of time—the robot was outside for three hours, and greeted 70 people (49 male, 21 female). Of these 70, a full set of data was successfully collected from 62 subjects. Instead of focusing on solely demographic group differences (gender, laboratory relationship, etc), we also looked at behavioral cues related to feelings towards the robot. While we did collect surveys, the fast pace of the experiment forced us to keep the survey collection and the robot interaction separate, so we could not match the survey data to the sensor data. From the sensors, measurements were taken from all three temperature sensors, six out of eight of the tactile sensors, and face distance data was not taken, although percentage of eye-contact was hand-coded by an experimenter by reviewing the video footage.

4.2 Results

The data analysis methodology used in the initial version of the study without data normalization [13] showed similar tendencies to the results of Study 1, however after a reanalysis using normalization, stricter sensor agreement rules, and the video-tagger to label positive and negative behavioral data as outlined in Sect. 2.3, the data tendencies changed as reported below, becoming more significant, and helping us to establish our hypotheses for what to expect in sensor data. For this study, the average temperature readings were $t0: M = 21.8$ °C, $SD = 2.4$ °C; $t1: M = 22.4$ °C, $SD = 2.8$ °C; and $t2: M = 21.8$ °C, $SD = 1.2$ °C. Tactile measurements as well as eye contact were unitless.

As in Study 1, we looked at demographic differences and how they related to the sensor data. In terms of gender, women had stronger forces than men ($y: t(12862) = 8.009$; $z: t(12862) = 3.155$, $p < 0.005$; $r: t(12862) = 10.121$; $pt: t(12862) = 5.919$; $yw: t(12862) = 7.863$), lower tactile measurements ($tc0: t(12862) = 10.530$; $tc1: t(12862) = 13.810$; $tc2: t(12862) = 10.40$; $tc3: t(12862) = 11.650$; $tc4: t(12862) = 10.464$; $tc5: t(12862) = 12.127$), lower hand temperatures ($t0: t(12862) = 20.541$; $t1: t(12862) = 17.598$; $t2: t(12862) = 4.883$) and less eye contact ($t(12862) = 5.166$). Subjects were coded for nationality, and people of Asian descent versus Western descent were found to have significantly lower tactile measurements ($tc0: t(12862) = 2.492$, $p < 0.05$; $tc2: t(12862) = 3.111$, $p < 0.005$; $tc3: t(12862) = 4.390$; $tc5: t(12862) = 4.403$) and less eye contact ($t(12862) = 16.271$). Some laboratory members also interacted with the robot, and compared to those without robot experience, they had lower tactile measurements ($tc0: t(12862) = 3.237$, $p < 0.005$; $tc1: t(12862) = 6.532$; $tc2: t(12862) = 4.936$; $tc3: t(12862) = 4.385$; $tc4: t(12862) = 4.474$; $tc5: t(12862) = 5.248$) and more eye contact ($t(12862) = 10.126$).

We also analyzed video of the interaction and recorded several behavioral measures that reflect subjects' views towards the robot. While these measures were hand-coded by the experimenter, they were obvious true/false values, and we expect no experimenter bias:

1. *Whether they returned non-handshake greetings (the wave and bow) to the robot or not (20 subjects versus 14 subjects).* Greeting reciprocation was correlated with higher forces ($y: t(7033) = 6.242$; $z: t(7033) = 11.829$; $r: t(7033) = 10.621$; $pt: t(7033) = 8.197$; $yw: t(7033) = 4.412$), lower temperature ($t0: t(7033) = 12.38$; $t1: t(7033) = 9.03$; $t2: t(7033) = 10.71$), and more eye contact ($t(7033) = 7.11$).
2. *Whether they stopped the handshake with the robot midway (5 subjects versus 57 subjects).* "Giving up" on the handshake was correlated with lower forces ($y: t(12862) = 4.709$; $z: t(12862) = 2.996$, $p < 0.005$; $r: t(12862) = 2.627$, $p < 0.01$; $pt: t(12862) = 6.645$; $yw: t(12862) = 2.087$, $p < 0.05$), lower temperature ($t0: t(12862) = 18.465$; $t1: t(12862) = 16.337$; $t2: t(12862) = 7.949$), and less eye contact ($t(12862) = 18.827$).
3. *Whether they spontaneously made an obviously positive (ex: "cool!") or an obviously negative remark (ex: "scary!") about the robot (19 subjects versus 13 subjects).* More positive remarks were correlated with higher tactile measurements ($tc0: t(6430) = 7.435$; $tc1: t(6430) = 6.828$; $tc2: t(6430) = 5.936$; $tc3: t(6430) = 5.318$; $tc4: t(6430) = 6.746$; $tc5: t(6430) = 5.560$), higher temperature ($t0: t(6430) = 6.522$; $t1: t(6430) = 11.346$; $t2: t(6430) = 2.952$, $p < 0.005$), and more eye contact ($t(6430) = 15.547$).
4. *Whether they spontaneously conversed with the robot or not (10 subjects versus 52 subjects).* People who conversed with the robot were correlated with higher tactile measurements ($tc0: t(12862) = 6.562$; $tc1: t(12862) = 5.496$; $tc2: t(12862) = 4.222$; $tc3: t(12862) = 4.822$; $tc4: t(12862) = 4.553$; $tc5: t(12862) = 5.633$) and more eye contact ($t(12862) = 21.923$).

4.3 Discussion

This study managed to expand upon the methodology established in Study 1, by including a more general population of people, with more subjects and more sensor data.

Table 1 Example questions from the four sections of the technophobia survey administered before the experiment, along with the scale on which subjects responded. *Sections 1–3* were adapted from Weil et al.'s [20] survey, while *Sect. 4* was created for the experiment. All questions had five choices, and were scored ranging from +2 for the most technophobic response down to −2 for the least technophobic response. All items' scores were then summed to produce a total technophobia score

Section 1: Computer Anxiety Rating Scale	
How anxious would each item make you?	
Thinking about taking a course in a computer language.	Not at all—Very much
Getting "error messages" from the computer.	Not at all—Very much
Section 2: Computer Thoughts Survey	
How often do you think each item when using a computer?	
I am going to make a mistake.	Not at all—Very much
I enjoy learning about this.	Not at all—Very much
Section 3: General Attitudes Towards Computers Scale	
Circle your level of agreement.	
Computers are taking over.	Agree—Disagree
Computers are essential to life in modern society.	Agree—Disagree
Section 4: General Attitudes Towards Robots Scale	
Circle your level of agreement.	
Humanoid robots are a potential threat to society.	Agree—Disagree
I would like to buy a humanoid robot.	Agree—Disagree

This study also establishes a pattern of how sensor data can be interpreted positively or negatively. In general, behaviors with positive tendencies tend to have higher temperature, higher tactile measurements, higher forces on the robot's arm, and more eye contact (see Fig. 4). There is one exception in the lower temperature of subjects who reciprocated non-handshake greetings. Perhaps these subjects were more comfortable interacting with the robot at a distance (waving and bowing rather than shaking hands), however further investigation would be needed to test this hypothesis. Many measures still had a small number of subjects, such as the number of subjects who gave up the handshake halfway. This study also found different sensor data tendencies from Study 1 in terms of demographic data—however, these two samples (engineering alumni versus the general public) are possibly too difficult to compare and make generalizations from. After finding strong correlations in Study 2, we designed Study 3 to test whether the same tendencies repeat themselves in a more structured and controlled experimental setting designed to take larger amounts of data per subject.

5 Study 3

5.1 Methodology

We reported some findings in an international conference paper [15]; however there are added demographic results in this current study that are not included in the original paper. While Studies 1 and 2 focused on interactions in a multi-user, unstructured environment, Study 3 focuses on a one-on-one, structured setting, where subjects teach the robot how to play rock-paper-scissors by directly moving the robot's arms and fingers to form each gesture. 38 people (14 female, 24 male) of diverse backgrounds participated in the study, and 34 subjects' data were used in the final analysis (four subjects' data were removed due to network errors resulting in unrecorded data). Subjects shook hands with the robot before and after the study, filled out a survey measuring technophobia before the study (adapted from the Technophobia Measurement Instrument developed by Weil et al. [20]), and completed a survey measuring general views towards the experiment and robot after the study. Table 1 shows examples of questions in the pre-experiment technophobia survey, while Table 2 shows examples of questions from the post-experiment survey. The subject's hand temperature was also measured before meeting the robot, to serve as a baseline measurement. For this experiment, temperature was taken from all three temperature sensors and all eight tactile sensors. Temperature growth was also calculated for each subject. Temperature growth measures how much a subject's temperature grows over the time of the experiment based on a regression line calculated across the temperature data, and it is marked by six metrics: the regression slope of the measures from the three temperature sensors ($t0s, t1s, t2s$) and the regression's correlation coefficient of the measures from the three temperature sensors ($t0r, t1r, t2r$).

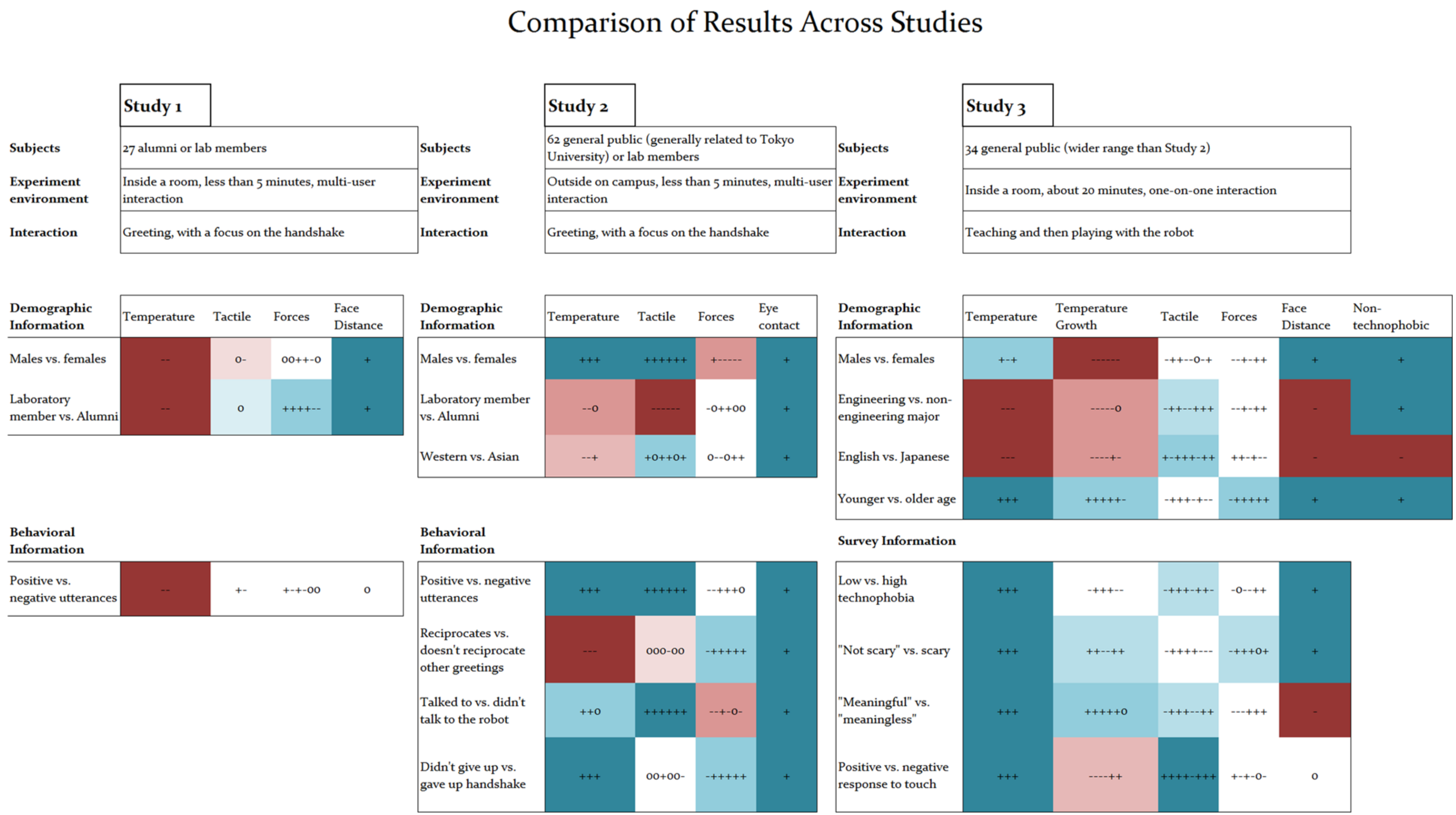

Fig. 4 A chart of the correlations for all sensors for each study. Blue and (+) indicate positive correlations, red and (−) indicate negative correlations, and white and (0) indicate no correlation. Multiple values indicate values from multiple sensors for one measure. The depth of color indicates degree of sensor agreement (a *darker color* means more sensor agreement, and thus a stronger tendency in that direction). Related measures (for example, nationality in Study 2 and experiment language in Study 3) are located on the same row, and sensors are listed in the same order

Table 2 Examples of the types of questions on the post-experiment survey, along with the scale on which subjects responded

Demographics								
Gender, Age, Nationality, University / Occupation, Field of Study								
Interaction with the Robot								
How did you feel about your interaction with the robot?								
Scary	3	2	1	0	1	2	3	Not Scary
Interesting	3	2	1	0	1	2	3	Boring
Meaningful	3	2	1	0	1	2	3	Meaningless
Exciting	3	2	1	0	1	2	3	Unexciting
Open-Ended Questions								
What would you name the robot?								
What was missing from the robot that would make it feel more alive?								
How did touching the robot affect your feelings towards it?								

5.2 Results

The baseline temperatures measured by a infrared thermometer reader averaged with $M = 32.45$ °C, $SD = 1.59$ °C for the palm of the hand, and $M = 30.95$ °C, $SD = 1.89$ °C for the back of the hand. The average temperature readings from the robot were $t0 : M = 36.4$ °C, $SD = 1.1$ °C; $t1 : M = 35.4$ °C, $SD = 1.5$ °C; and $t2 : M = 35.3$ °C, $SD = 1.3$ °C. Differences between the baseline measurement and robot measurements are likely due to differences in calibration, but have no effect on the results of the study. Tactile measurements and temperature growth measurements were unitless, and the average face distance was $M = 743.1$ mm, $SD = 179.3$ mm.

Demographic differences were analyzed to serve as a point of comparison with Studies 1 and 2. For gender, females versus males had closer face distances ($t(140095) = 86.598$) and also higher levels of technophobia ($t(140095) = 140.060$). Subjects were given a choice of conducting the experiment and surveys in either Japanese or English, based on the language most natural for them. The language choices mapped onto nationality differences (all Japanese subjects and most Asian subjects chose Japanese, while all Western subjects chose English). Based on this language dichotomy, subjects who chose Japanese (twenty subjects) over English (eighteen subjects) had higher hand temperatures ($t0 : t(140095) = 61.186$; $t1 : t(140095) = 88.405$; $t2 : t(140095) = 41.661$), lower tactile measurements ($tc0 : t(140095) = -3.128$, $p < 0.005$; $tc2 : t(140095) = 4.540$; $tc3 : t(140095) = 5.978$; $tc4 : t(140095) = 5.434$; $tc6 : t(140095) = 9.674$; $tc7 : t(140095) = 25.274$), farther face distances ($t(140095) = 33.589$), and less technophobia ($t(140095) = 45.128$). Subjects of older age were linked with lower hand temperatures ($t0 : r = 0.096$; $t1 : r = 0.189$; $t2 : r = 0.115$), lower temperature growth ($t0r : r = 0.237$; $t0s : r = 0.225$; $t1r : r = 0.254$; $t1s : r = 0.198$; $t2s : r = 0.153$), closer face distances ($r = 0.120$), and higher technophobia ($r = 0.349$). Lastly, there were strong correlations based on university field of study. Majoring in engineering, versus another subject (such as economics, theater, etc.) was more correlated with lower hand temperatures ($t0 : r = 0.072$; $t1 : r = 0.169$; $t2 : r = 0.145$), lower temperature growth ($t0r : r = 0.530$; $t0s : r = 0.525$; $t1r : r = 0.627$; $t1s : r = 0.437$; $t2r : r = 0.217$), closer face distances ($r = 0.015$), higher tactile measurements ($tc1 : r = 0.036$; $tc2 : r = 0.034$; $tc5 : r = 0.140$; $tc6 : r = 0.079$; $tc7 : r = 0.056$), and lower technophobia ($r = 0.090$).

Several survey measures stood out as being correlated with sensor data:

1. *Technophobia.* Subjects with higher technophobia (meaning they were more anti-technology, and anti-robot) had lower hand temperatures ($t0 : r = 0.215$; $t1 : r = 0.109$; $t2 : r = 0.140$), closer face distances ($r = 0.294$), and higher tactile measurements ($tc1 : r = 0.066$; $tc2 : r = 0.036$; $tc3 : r = 0.007$, $p < 0.01$; $tc5 : r = 0.025$; $tc6 : r = 0.019$).
2. *Rating the robot as "scary" versus "not scary".* Subjects who rated the robot as more "scary" also tended to have lower temperatures ($t0 : r = 0.254$; $t1 : r = 0.188$; $t2 : r = 0.061$), lower temperature growth ($t0r : r = 0.025$; $t0s : r = 0.048$; $t2r : r = 0.034$; $t2s : r = 0.066$), and closer face distances ($r = 0.055$).
3. *Rating the interaction as more "meaningless" versus "meaningful".* Subjects who rated the interaction as more "meaningless" tended to have lower temperatures ($t0 : r = 0.006$, $p < 0.05$; $t1 : r = 0.113$; $t2 : r = 0.133$), lower temperature growth ($t0r : r = 0.134$; $t0s : r = 0.149$; $t1r : r = 0.222$; $t1s : r = 0.309$; $t2r : r = 0.014$), and farther face distances ($r = 0.129$).
4. *Giving a more positive response (as scored by an experimenter blind to the subjects' other data) to the question "How did touching the robot affect your feelings towards it?"* Subjects who gave a more positive response

tended to have higher temperatures ($t0: r = 0.093$; $t1: r = 0.050$; $t2: r = 0.170$), lower temperature growth ($t0r: r = 0.167$; $t0s: r = 0.224$; $t1r: r = 0.262$; $t1s: r = 0.192$), and higher tactile measurements ($tc0: r = 0.038$; $tc1: r = 0.100$; $tc2: r = 0.018$; $tc3: r = 0.011$; $tc4: r = 0.014$; $tc6: r = 0.038$; $tc7: r = 0.034$).

5.3 Discussion

These demographic and survey data match the tendencies found in Study 2. Again, more positive opinions towards robots tend to be positively correlated with higher temperature, higher tactile measurements, higher temperature growth, and farther face distances (refer to Fig. 4). These results also show that survey data show the same correlation trends with sensor data as behavioral data do. In contrast to these trends, more positive responses to the robot's touch were correlated with less temperature growth (though were correlated with high temperatures overall). These subjects had significantly higher starting hand temperatures than subjects who gave negative responses (palm: $r = 0.102$, $p < 0.001$, back: $r = 0.144$, $p < 0.001$), indicating that there may have been less room for these subjects' temperatures to grow. Also in contrast with the general trend, subjects who found the experiment "meaningful" also had closer face distances than those who found it "meaningless". We believe face distance is a difficult value, and closer face distances in this case could reflect interest in the study. We discuss face distances in more detail in Sect. 6. In terms of usability for future research, it appears that temperature has the strongest and most stable correlations, followed by temperature growth and face distance, followed by tactile measurements, and then force measurements, based on sensor agreement levels and strength of correlations.

This study also introduces the new measure of "temperature growth". Temperature growth can be a useful measure, at it can tell researchers how a subject's feelings towards a robot change over time. When incorporating temperature growth in experiments, it is important to note that as a person interacts with a robot, both the person's hand temperature and the robot's motor temperature are likely to increase. Thus, it would be important to collect baseline data beforehand for human hand and robot motor temperatures. However, as the current study is comparative amongst a diverse pool of subjects, we expect no unrelated significant differences to emerge, and so such a baseline is not needed.

6 General Discussion

Each study accomplished a separate goal: Study 1 established the ability of sensor data to recognize significant differences between groups during a short experiment; Study 2 examined connections between sensor data and behavior data with a more general subject pool; and Study 3 looked at connections between sensor data and survey data with a more focused interaction. Figure 4 shows a comparison of the sensor data tendencies across the three studies. With each study, the methodology has been refined and used in different environments: large, unstructured, multi-user environments, as well as one-on-one instruction-based interactions. While we looked at correlations in demographic groups (gender, nationality, and laboratory membership), it is still too early to make strong statements about the feelings of these groups towards robots. Looking at Fig. 4, there do seem to be some similar demographic tendencies across studies—for example, lower hand temperatures for those with more engineering experience across the three studies—however, finding demographic group differences is not a main point of this study. These differences in demographic groups would be a possible avenue for future study. In terms of the behavioral and survey data, there is general agreement in correlation direction and strength in data across studies. The few exceptions are discussed in the Discussion sections of the corresponding studies above.

In terms of general feelings towards robots, the same tendencies appear to play out across studies. Between the different modalities of behavioral measurement and survey measurement, there appears to be a link between positive attitudes towards robots and higher temperature, higher temperature growth, higher tactile measurements, and farther face distances. There does not appear to be any strong tendency related to force. Initially when forming the hypotheses for Study 1, we believed that higher hand temperature would be linked with stress or excitement. However, the sample size for Study 1 was small and we measured only a single behavioral measure (verbal utterances—with four in the positive group and three in the negative group). For Studies 2 and 3, we looked at more obvious and plentiful measures of views towards robots, including multiple behavioral measures and survey results. Study 3 was able to replicate the results from Study 2, despite the different experiment environment. Based on these results and also extensive psychology literature review, we have determined that high hand temperature is likely linked to positive thinking towards robots. Psychology research has similarly found a link between high hand temperature and relaxation, while lower hand temperature has been linked with anxiety and stress [3, 7]. Temperature also tended to increase over the time course of the experiment, which likely indicates a subject getting warmer as they use their hands during the experiment, and also a "warming up" in comfort to the robot over time. Higher tactile measurements likely indicate a willingness to touch a robot and lack of fear. In general, higher communication through touch with others has been linked with higher self esteem [21]. Lastly, face distance has two main possible interpretations. Based on previous research, we believe keeping a farther face distance indicates an affordance of personal space to the robot, and thus an attribution of the robot as a "social actor" rather than an "object" [22, 23]. This hypothesis could explain the consistent correlations between positive reactions to the robot and far face distances. However, a far face distance could also indicate fear and reluctance to get close to the robot. Both factors likely interact when a user determines the distance they should take from the robot.

In terms of the statistical results of these experiments, there is some question as to whether these correlations of sensor data, behavior data, and survey data only happen by chance—perhaps by data dredging [24]. Although some of these correlations may be weakly correlated, the results are all highly significant. Even when taking into account the potential for Type I error (to assume there is an effect when there isn't one, and running so many statistical tests that some are bound to come out significant just by chance), almost all of these correlations pass a Bonferroni correction test. The Bonferroni correction is a conservative statistical corrective method that adjusts alpha to account for the possibility of chance significant correlations. To perform it, one divides alpha by the number of tests (0.05 divided by 13 for the case of Study 3). Even so, almost all above statistical tests still pass the resulting adjusted alpha of 0.0038, ensuring that these correlations are in fact significant enough to be meaningful. These experiments also use multiple sensor measures and look at multiple behavioral and survey items, meaning correlations showing similar tendencies are more robust. However, in the above experiments, there were still times when some sensors did not show any significant correlations. When first using this methodology on a new robot system in a natural environment and without the use of surveys, multiple sensors and perhaps additional behavioral measures (such as eye contact, vocal utterances, human-like treatment of the robot, and reciprocation to the robot) should be combined to analyze the HRI experiment.

Now that this paper has found significant correlations between sensor data and subjects' feelings to a robot, the next step is to find causal data that will eventually lead to predictions of human behavior. Modeling of the data as well as experiments examining sensor data changes in a subject in different experimental conditions (mild stress, relaxation, attention, inattention, etc.) could lead to promising systems for a robot to predict and adjust to a single user's behavior. One could imagine several useful applications of this methodology. With only one subject, it would be easy to make a system that can detect changes in sensor data over time contrasted against a baseline learned over a acclimation period with the user. Using the data minimization techniques described in this paper, as well as consolidating less-salient data into lower frequency data logs, would allow such a system to be implemented with any normal computing capacity. If a robot reads the sensor data from a user frequently and suddenly detects a negative change in data, it could take actions to relax or cheer up the user. As another application of this methodology, a robot could potentially learn to predict a new user's level of technophobia based on their aggregate sensor data in a quick interaction. A robot could also combine biosignal information with already established visual processing; for example, recognizing a user based on handshake style when there is a potential for misidentification using solely face recognition software. The methodology presented in this paper can be useful for any robot that touches humans. Gaming robots could detect a user's stress through a game controller and give the user breaks. Caretaking robots could record patients' thermoregulation abilities to make inferences about a patient's stimulant intake [25]. Friend robots could adjust their actions until they sense the user is comfortable with them. With this methodology, there is also potential for other sensors to deliver similarly useful data—particularly skin conductance, EEG, and heart rate sensors, if they can be attached to the robot in a non-invasive way for the user. We propose that sensor data be incorporated into future HRI experiments, to act as an objective support to survey data being taken during the experiment, and also to add to our knowledge of how sensor data may vary across experimental setups and robotic systems.

7 Conclusion

Overall, the combination of these three studies confirms the usage of sensor data as viable biosignal data reflecting human views towards robots. This paper consolidates and reinterprets these three past studies to create a general methodology for how robot sensor data should be used as an objective measure in HRI, and outlines how to select sensors, how to manage the data, and different experimental setups that show proof-of-concept. These three studies show similar tendencies in the sensor data while also replicating the results with different subject groups and different experimental environments. Based on their results, in general, higher hand temperature, higher temperature growth, higher tactile measurements, and farther face distances indicate more positive feelings towards a robot. In order to facilitate future study, the data from these studies will made publicly available at the first author's research website. With these data, researchers can try new analyses with data in the database that were outside of the scope of the current paper using similar tests as described in this paper. For future research, robots could build personal sensor data profiles for each user and sense daily changes in stress, attention, and relaxation levels. These sensing methods could also serve as backup methods to sense user emotions when face recognition or voice recognition is difficult. Using sensor data as biosignal data opens up many possibilities for robots to develop as multimodal sensing creatures, and through its usage, HRI has the potential to become more efficient, objective, and natural.

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