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Inference of User Qualities in Shared Control of CPHS: A Contrast in Users ⋆

Lucas Hall * **Urja Acharya** * **Justin Bradley** *
Brittany Duncan *

* *All authors are affiliated with the Department of Computer Science & Engineering, University of Nebraska, Lincoln, NE 68588, USA (email:* {lhall, uacharya, jbradley, bduncan}@cse.unl.edu*).*

Abstract: Most cyber-physical human systems (CPHS) rely on users learning how to interact with the system. Rather, a collaborative CPHS should learn from the user and adapt to them in a way that improves holistic system performance. Accomplishing this requires collaboration between the human-robot/human-computer interaction and the cyber-physical system communities in order to feed back knowledge about users into the design of the CPHS. The requisite user studies, however, are difficult, time consuming, and must be carefully designed. Furthermore, as humans are complex in their interactions with autonomy it is difficult to know, a priori, how many users must participate to attain conclusive results.
In this paper we elaborate on our work to infer intrinsic user qualities through human-robot interactions correlated with robot performance in order to adapt the autonomy and improve holistic CPHS performance. We first demonstrate through a study that this idea is feasible. Next, we demonstrate that significant differences between groups of users can impact conclusions particularly where different autonomies are involved. Finally, we also provide our rich, extensive corpus of user study data to the wider community to aid researchers in designing better CPHS.

Keywords: Shared control, autonomous mobile robots, telerobotics, human robot interaction

1. INTRODUCTION

Allowing autonomous control to be supervised by and shared with users can greatly improve performance by allowing users to complete complex tasks and assure that all tasks are completed safely. In these cases, most designs rely on users "learning" or being trained on how the autonomy behaves and adapting their behavior accordingly. We contend that this paradigm is backwards. Collaborative autonomies should infer user qualities and use this knowledge to adjust autonomy in an effort to improve the performance of the combined user/autonomy system. In this way cyber-physical human systems (CPHS) learn and adapt together.

Accomplishing this objective is very difficult as it requires a tight feedback loop in which a CPHS learns and infers intrinsic qualities about a user and adapts to them in a short period of time using interactions. While the human-robot interaction (HRI) and human-computer interaction (HCI) communities have a rich knowledge base, studies, and data on user qualities and their relationship with systems, these data may not make their way to designers of cyber-physical systems (CPS). Moreoever, in the event tight collaboration is achieved between these communities, collecting the data to close the design loop on user-based design is fraught with difficulties. For example, user studies are time consuming, require institutional review board (IRB) approval, recruitment of participants, tight monitoring of the study process to ensure data integrity, etc.

Additionally, humans are complex and small numbers of users may be inadequate to draw conclusions, making it difficult to identify how many users are needed to ensure significant results. Even if the data is collected, designers of CPS may not consult the data to incorporate user study information into their designs.

Fig. 1. Double Telepresence Robot

We have been correlating user interactions and robot autonomy and performance with intrinsic user qualities with the goal of building adaptive robot autonomies as reported in Acharya et al. (2018). We initially conducted a user study with 28 participants investigating the impact of the intrinsic quality Locus of Control as described by Rotter (1966) on the performance of a Double telepresence robot (seen in Figure 1). These original 28 participants, supplemented with two more for 30 total, were insufficient to draw firm conclusions due to the limitations of the platform and our autonomy. We then recruited an additional 30 users to participate in the study allowing us to draw much stronger conclusions. The differences between these user groups was pronounced and instructive. This data was difficult to obtain and required expertise from those in the HRI and CPS community and represents a large effort

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toward our ultimate objective of a user-adaptive autonomy for robots.

In this paper, using data from the aforementioned study, we make three key contributions to address the several issues elucidated above. First, we showcase data from the participants that demonstrates that it is possible to infer intrinsic user qualities from user interactions with a robot. Second, this data is split into two groups, a first group of 30, and a second group of 30 participants. We compare and contrast those two groups to demonstrate the differences in conclusions that can be drawn from different groups of random users, as well as whether they hold for a larger group of 60. This helps provide insights to the community for the circumstances under which more participants may be needed, but also the variability of data gathered from groups of users in human subjects studies. Finally, we provide a corpus of our data [1] allowing other researchers to avoid the need to run such time consuming and complex studies. Our data correlates intrinsic, unchanging user qualities with robot autonomy principles such that other researchers can download and mine the data to find answers for particular design challenges.

2. RELATED WORK

We briefly summarize work related to user qualities and preferences in shared control in telepresence systems and then discuss user qualities studies related to our work to set the stage for our study.

In telepresence robotics, several studies have identified that autonomous navigational assistance is essential in telepresence robots to provide better control of the robot and also reduce the cognitive load of users (Desai et al., 2011). In a similar study, Bruemmer et al. (2005) found that participants performed better with shared control through reduction in task completion time, reduction in errors, and increase in number of items found by users during a search task. Riano et al. (2011) conducted human studies with shared control implemented on telepresence robot in order to assess the improvement of user performance with shared control. They observed that with shared control in obstacle avoidance, people made less mistakes in navigation, and felt more comfortable to drive the robot and maintain conversation simultaneously.

The role of shared control has also been evaluated on Brain Computer Interface (BCI) based telepresence systems by Tonin et al. (2010). The study used shared control on a telepresence robot (Robotino) to provide its operators a feeling of control over the robots while ensuring safe navigation in a remote environment. It was observed that shared control with low-level obstacle avoidance enabled operators to complete the task faster than without shared control.

Even though shared control has been found to improve user performance with telepresence robots, the performance has been found to vary with user qualities. Takayama et al. (2011) conducted human studies to evaluate the effectiveness of shared control implemented on telepresence robots by comparing performance of users based on system dimensions (shared control and manual control) and human dimensions (gaming experience, locus of control, and spatial cognitive ability). It was observed that even though shared control was effective over manual control, user performance varied based on their locus of control. People with a more internal locus of control fought against the autonomy and hence required more time to complete the tasks in comparison to people with a more external locus of control. The results of their study suggest that shared control should be adaptive based on the user qualities to improve performance.

Finally, we summarize work related to the specific quality, locus of control, we study in this work, demonstrating that locus of control helps define how a person interacts with the world, and by extension, will interact with a robot. Rotter (1966) divides people into two groups, internal locus of control and external locus of control. People who perceive that outcomes are based on one's own actions are labeled as having internal locus of control whereas those who believe that outcomes are dependent on luck, fate or other external forces are labeled as having external locus of control.

Studies have shown that people with internal locus of control believe in their ability to control their life events, expect their actions to result in outcomes that can be predicted, and are more satisfied with situations allowing personal control (Brenders, 1987; Phillips and Gully, 1997) than people with external locus of control. A study by Samana et al. (2009) found locus of control to be one of the better predictors of presence in virtual environments. With an increased sense of presence in virtual environments people's behavior in virtual environments could be similar to their behavior in the real world (Mestre et al., 2006) which could lead to improvement in performance. As a result, we expect that differences in locus of control of individuals will lead to difference in performance with different obstacle avoidance settings invoked in shared control.

Our work here is differentiated from this related research by leveraging the impacts of a user's locus of control on the robot toward development of a shared control strategy. We show there is high likelihood that locus of control can be predicted from these interactions, and as a result, an autonomy could be adapted to that user quality to improve shared control performance.

3. STUDY DESCRIPTION

In this section we provide a condensed description of our hypotheses, the autonomy used in the study, and the user study experiment reported in Acharya et al. (2018).

3.1 Hypotheses

Takayama et al. (2011) found varied performance across users with different locus of control when operating a telepresence robot with shared control. Based on that work we formulated following hypotheses:
Hypothesis 1: Users with a more internal locus of control will perform better with an autonomy more responsive to user inputs than a more restrictive autonomy.
Hypothesis 2: Users with different locus of control will have different performance given a robot autonomy.
Hypothesis 3: Users with different locus of control will

[1] `https://nimbus.unl.edu/projects/cyphuas/`

have different behavior given a robot autonomy.

3.2 Autonomy Description

We created two modes of a static autonomy in order to explore the effects of locus of control and autonomy on performance. The results from Takayama et al. (2011) show that autonomous assistance improved performance, but for users with highly internal locus of control, the tasks took longer to complete. They suggest that these users fought with the autonomy for control of the robot leading to our Hypothesis #1 above. This also provides the reasoning for two modes of autonomy tested on users separated into groups based on their locus of control.

Autonomy Overview We studied the navigation of a telepresence robot through an obstacle course, similar to Takayama et al. (2011). Our goal is for the autonomy to aid the user in traversing the course while avoiding obstacles. To acheive this goal, we focus on an autonomy that works together with user commands (i.e., "shared control").

We used a Double telpresence robot and made changes to the hardware and software to create a customized shared control mechanism. The user interacted with our iOS application that provided telepresence capabilities such as a live video feed, and command input. We added a laser range finder to the robot to detect obstacles, which sent information back to an obstacle avoidance algorithm. The obstacle avoidance algorithm then combined the user input with sensor data and sent commands through a vendor provided software development kit (SDK)[2] to command the robot under a shared control scheme.

Obstacle Avoidance System In recent years advances have been made in deliberative and reactive planning (Ingrand and Ghallab, 2014; Kortenkamp et al., 2016) and obstacle avoidance (Minguez et al., 2016; Kim and Chwa, 2015) for robots. Limitations of potential fields are well known (Koren and Borenstein, 1991), although they are still an active area of research (Sharma et al., 2017). Our objective is a shared autonomy that can be later designed to adapt to user qualities entirely founded on interactions between the user and the robot. Due to these requirements, we want an obstacle avoidance strategy that allows combination of user commands with autonomy, is easy to implement, and has common algorithmic adaptations that can be employed for users with different locus of control.

Artificial potential fields fill all of the stated conditions. They are a reactive planner comprised of forces both attractive and repulsive that are represented by vectors giving the magnitude and direction of the force (Murphy, 2000). Undesirable locations correspond to repulsive vectors, while desirable locations are represented by attractive vectors. The autonomy sums the forces at the robot's location to determine direction and velocity of the next movement. In our particular shared control scheme, we rely on user input (rather than attractive forces) to provide the goal seeking behavior while obstacles detected by the laser scanner generate repulsive vectors. Repulsive vectors are then combined to take into account both user input and computer control.

In each phase of our experiment, one of two potential field strategies is chosen. One strategy was designed with a repulsive force that scales linearly with distance from an obstacle. We hypothesize this strategy will: 1) keep users further from obstacles despite a desire to approach them and 2) more quickly lead the user to the end goal by following more closely with an optimal path – if they allow the autonomy to guide them. These factors make the linear repulsive force more appealing to users with an external locus of control who should be less resistive to sharing control with the robot.

The other strategy was designed with a potential field scaling exponentially with decreasing distance from the obstacle. This strategy will 1) give users more control by allowing them to get closer to obstacles and 2) provide better insight on the user's capability because the user is almost entirely responsible for staying on the optimal path. This makes the exponential repulsive force more suitable for users with an internal locus of control.

To implement this strategy, obstacles in front of the robot are detected using a laser scanner. For each obstacle detected, repulsive forces are calculated based upon the angle to the obstacle and the distance to the obstacle. The force can be modeled by a "magnitude profile" function within a "sphere of influence" around the robot (Murphy, 2000).

Obstacle avoidance is only activated when at least one obstacle is within the sphere of influence of the robot. In our control scheme, the sphere of influence was tuned to a diameter of $D = 1\,\mathrm{m}$ based on robot capabilities and the size of our obstacle course.

Linear Magnitude Profile Let $d_{\min} = 0.15\,\mathrm{m}$ be the minimum obstacle detection distance of the laser scanner, and D be the sphere of influence, inside of which obstacles will apply a repulsive force. The magnitude of the repulsive force exerted by an obstacle is calculated to be

$$m = \frac{D - d}{\eta_{lin}}$$

where d is the distance from the obstacle and η_{lin} is a normalizing factor that represents the maximum repulsive force, which would occur at d_{min}.

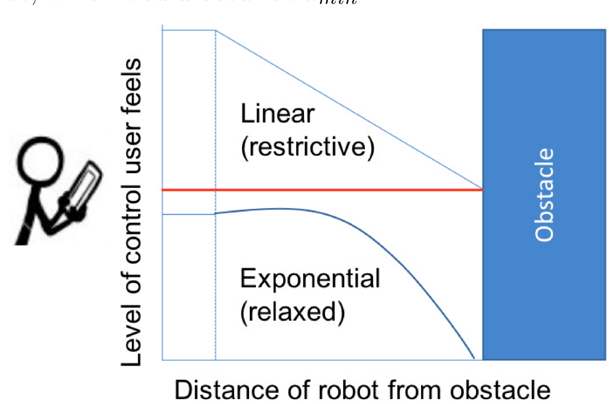

Fig. 2. Linear and Exponential Magnitude Profiles as a Function of Distance

[2] Double Robotics: Basic-Control-SDK-iOS (`https://github.com/doublerobotics/Basic-Control-SDK-iOS`)

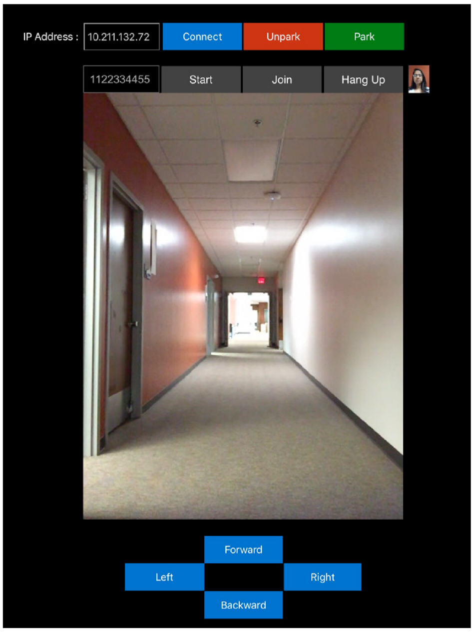

Fig. 3. Operator's User Interface with four blue buttons for forward, backward, left, and right controls

Exponential Magnitude Profile Using the previously defined parameters from the linear magnitude profile, the repulsive exerted by an obstace in the exponential magnitude profile is calculated as

$$m = \frac{\left(\frac{1}{d}\right)^{\alpha} - \left(\frac{1}{D}\right)^{\alpha}}{\eta_{exp}}$$

where η_{exp} is a normalizing factor and $\alpha = 0.18$ is a parameter that is tuned based on testing with the robot in the experimental environment and creates the curvature of the exponential function. Both magnitude profiles can be seen as a function of distance from an obstacle in Figure 2.

Shared Control In both magnitude profiles, all repulsive vectors from obstacles within the sphere of influence are averaged to make one total repulsive vector with a direction, ϕ_{total}, and magnitude, m_{total}, which is passed through the supplied SDK to the robot where it is combined with user input to determine the final movement.

3.3 Experiment

We designed the experiment to test performance with the shared control as well as to gain insight into key user traits. This section describes our setup, participants, and methodology for the user study.

Setup We conducted a two part study with a Double telepresence robot (Figure 1) with a weight of 6.8 kg and a constant height of 1.32 m. The robot is comprised of a mobile base and a vertical pole. At the top of the robot there is an iPad that is connected to the robot and acts as an interface. The video of the environment visible through the iPad's camera is streamed back to the operator in a similar manner to a standard videoconferencing application. The robot has a microphone and directional speaker on board that allow the operator to communicate in the remote environment. The robot has a box attached to the vertical pole near the base of the robot that houses the Hokuyo laser rangefinder, which sits approximately 7.62 cm above the mobile base and 35.56 cm above the floor. To give the operator control of the robot in the remote environment we built a custom iOS application and interface (seen in Figure 3) using the vendor supplied SDK. The interface has a live stream of the remote environment and has forward, backward, left, and right buttons to allow the operator to command the robot.

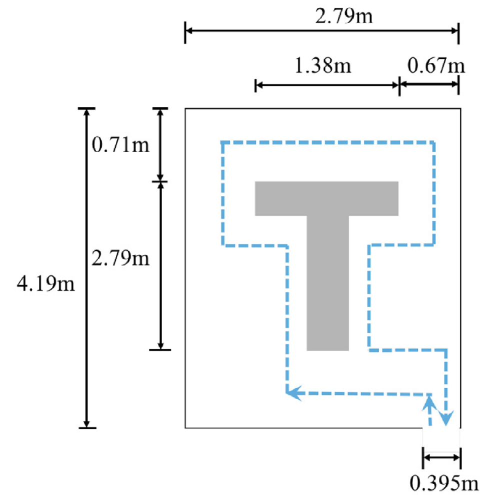

Fig. 4. Training Course

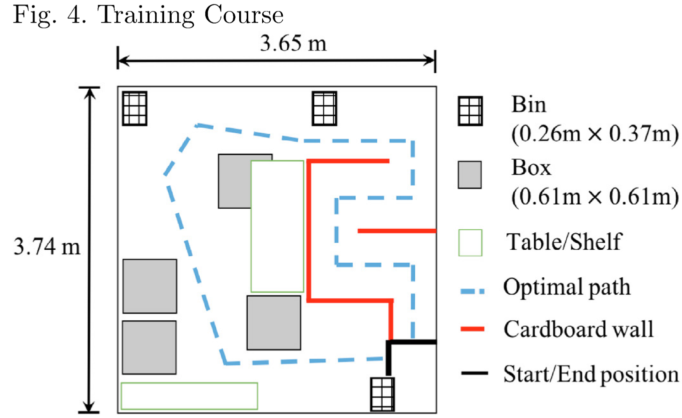

Fig. 5. Main Course

A T-shaped obstacle course (shown in Figure 4) was created in a 2.79 m by 4.19 m area made up of 0.85 m tall cardboard boxes. This training course was used for participants to practice driving the robot with a particular obstacle avoidance profile before being tested on the main obstacle course. The main obstacle course (seen in Figure 3.3.1) filled a 3.65 m by 3.74 m experiment room dedicated to the user study. This obstacle course was based on the study from Takayama et al. (2011) with modifications due to differences in room size, robot size, and sensor limitations. These included replacement of chairs with cardboard boxes and table leg coverings to provide a smooth continuous surface for the laser range finder. We computed an optimal path from start to end using an A* search to minimize distance traveled. A simplified version of this path is plotted on the figure using a dashed blue line. The start and end positions of the path are marked by thick black lines. The start and end positions will changed on a per trial basis, determined by the direction of movement (i.e., clockwise or counterclockwise). The robot's position was tracked with Vicon motion capture cameras through the obstacle course. This data was used to calculate metrics, such as the deviation of the user's path from the optimal path, velocity, and the number of collisions with obstacles.

Participants 60 participants (30 male, 30 female) with ages ranging from 19–74 were recruited through emails to campus mailing lists, and advertisements on- and off-campus. The first 30 participants were paid \$10 and the remaining 30 were paid \$20 as compensation for their time. Based on the value of locus of control, 23 participants were found to be "Highly Internal," six participants were found to be "Highly External," and 31 participants were found to be "Average."

Methodology This describes the questionnaires, performance metrics, and procedure used in the study.

Questionnaires:

(1) *Demographics Questionnaire:* This questionnaire consisted of questions regarding gender, age, handedness, computer experience, and robot experience.
(2) *Locus of Control Questionnaire:* An abbreviated version of the Locus of Control Questionnaire (LoCQ) (Valecha and Ostrom, 1974) with 11 items, each consisting of options for internal and external attribution was used in the study. This was used to group participants into three categories: strong internal locus of control ("Highly Internal", 0-3), mid-range locus of control ("Average", 4-7), and strong external locus of control ("Highly External", 8-11).

Procedure: The experiment was run in two parts with an identical procedure. Initially, the study was run with 30 participants, but after collecting and viewing the data, 30 more participants were recruited to verify and strengthen our findings. The procedure below was consistent for all participants in the study.

An experimenter welcomed the participants and provided them with consent forms, standard options to leave without penalty, and a pre-questionnaire collecting demographic information and assess their Locus of Control. Subsequently, the iPad interface was explained and the study was divided into two phases. Each phase would be conducted with either linear or exponential obstacle avoidance profiles in either a clockwise or counterclockwise direction. Both the direction and obstacle avoidance profile were randomly selected and counterbalanced to assure an equal number of males and an equal number of females in each configuration.

At the beginning of each phase, participants complete two laps on the training course (shown in Figure 4) in the direction and obstacle avoidance profile that they will use on the main course. Then, the participant completes one lap on the main obstacle course and their performance is tracked. Once the participant has completed the training and main obstacle courses, the first phase is complete, and they are asked to complete a questionnaire to gather feedback and insight into their experience with the robot. After the 2^{nd} phase, the participant completed a post-questionnaire to gather the same information as the questionnaire. The study was then wrapped up with a closing interview, again for feedback and a more personal discussion of their interaction with the robot.

Performance Metrics: We developed metrics to analyze user and robot performance in the shared control scheme. All metrics were computed from the time the robot crossed the start line to the time the robot crossed the finish line. To compile the data, we computed means across all six combinations of our defined locus of control categories and obstacle avoidance profile. For example, to measure the average duration of the "Exponential/Highly External" category, we took a mean of the duration of all runs from users having a highly external locus of control using the exponential obstacle avoidance magnitude profile.

We computed metrics to assess holistic CPHS performance. First, total duration, in seconds, to complete the main obstacle course. Next, total distance driven, in meters, during traversal of the main obstacle course. Both metrics give an overview of general task performance. The third metric is error from a optimal path through the main obstacle course, computed using an A* search to minimize distance while avoiding obstacles. This metric is measured as the average amount of perpendicular distance between the robot and the optimal path. The fourth metric is the number of collisions occured during a run. Any contact with an obstacle or wall counts as a collision. While the user remained in contact with the same obstacle, this count would not increase, but if the user broke contact and then contacted any obstacle, those would count as separate collisions.

The final metrics relate to the user input. First, total commands issued by the user via button presses while navigating the main course. Next, a conflicting command is defined as an instance where the final command executed by the robot differs from the user input due to the obstacle avoidance autonomy. Using this definition, we calculate the ratio of command conflicts to total commands. This indicates when the control scheme favors the input of the computer over the user, which provides insight into how often the user "disagrees" with the obstacle avoidance.

4. RESULTS

We summarize and compare the data from both groups in order to understand the impact of the individuals on the collective results and discuss the consequences of running smaller versus larger participant groups. These results show that some trends, especially those relating to user behavior, require significantly larger participant groups to conclusively determine any trends from the acquired data.

Table 1 displays the results of both groups of participants. All data was sorted based on Locus of Control and autonomy mode. The table groups metrics and compares all user groups on each metric.

Our objective is to adapt the autonomy as we infer qualities about a user, thus we are interested in trends suggesting that one user group performs better on a particular mode of autonomy based on their locus of control. Following analysis by Takayama et al. (2011) and Samana et al. (2009), but observing trends in our data, we divided users into "Highly Internal," "Average," and "Highly External" Locus of Control categories. We added the "Average" category due to the relatively large number of users and their unique performance in the study. In Table 1 and later on in our

Table 1. Results grouped into the primary metrics, divided by user group. Lower values reflect better system performance in each category. High values for each metric for each group are bolded while low values are italicized.

Group 1	Total Commands	Command Conflicts	Path Length (m)	Deviation (m)	Time (s)
Highly Internal Exponential	540.2 (SD = 620.2)	189 (SD = 220.7)	13.4 (SD = 3.7)	.14 (SD = .04)	258.9 (SD = 145.3)
Highly Internal Linear	**647.6 (SD = 756.5)**	**278 (SD = 397.9)**	15 (SD = 3)	.12 (SD = .03)	378.5 (SD = 179.6)
Average Exponential	307.1 (SD = 268.4)	77.2 (SD = 63.7)	*12 (SD = 1.2)*	.11 (SD = .02)	*245.7 (SD = 87.6)*
Average Linear	465 (SD = 504.9)	181.2 (SD = 177.6)	13.2 (SD = 1.8)	.12 (SD = .03)	291 (SD = 87.7)
Highly External Exponential	*248.7 (SD = 168.3)*	*75.3 (SD = 41.3)*	13.6 (SD = 1.1)	**.42 (SD = .21)**	283 (SD = 80.6)
Highly External Linear	482.7 (SD = 352.7)	161.3 (SD = 90.7)	**15.4 (SD = 1.9)**	.11 (SD = .02)	**415.9 (SD = 92.1)**
Group 2					
Highly Internal Exponential	429.1 (SD = 172.8)	*95.3 (SD = 60.7)*	*13.5 (SD = 2.2)*	.18 (SD = .17)	*264.2 (SD = 80.1)*
Highly Internal Linear	647.7 (SD = 375.9)	224.1 (SD = 160.5)	17.3 (SD = 5.7)	.14 (SD = .04)	392.4 (SD = 141.5)
Average Exponential	593.4 (SD = 755.7)	188.4 (SD = 255.4)	15.2 (SD = 6.3)	**.19 (SD = .05)**	265.3 (SD = 147.4)
Average Linear	769.8 (SD = 630.6)	285.7 (SD = 270.9)	15.5 (SD = 3.1)	.13 (SD = .04)	364.5 (SD = 179.7)
Highly External Exponential	*414.3 (SD = 460.7)*	141 (SD = 170)	14.9 (SD = 3.7)	*.12 (SD = .14)*	321.4 (SD = 108.8)
Highly External Linear	**776 (SD = 715.9)**	**377.7 (SD = 435.43)**	**22 (SD = 6.3)**	.15 (SD = .05)	**482.3 (SD = 233.6)**
All					
Highly Internal Exponential	491.9 (SD = 474.5)	148.3 (SD = 193.9)	*13.4 (SD = 3.1)*	.16 (SD = .11)	261.2 (SD = 118.9)
Highly Internal Linear	**647.7 (SD = 608.2)**	254.6 (SD = 312.5)	16 (SD = 4.4)	.13 (SD = .04)	384.5 (SD = 160.8)
Average Exponential	464.1 (SD = 597.3)	138.2 (SD = 199.3)	13.7 (SD = 4.9)	.15 (SD = .11)	*256.4 (SD = 122.5)*
Average Linear	632.5 (SD = 588.4)	238.5 (SD = 235.8)	14.5 (SD = 2.8)	*.12 (SD = .04)*	331.3 (SD = 148.1)
Highly External Exponential	*331.5 (SD = 323.2)*	*108.2 (SD = 116.3)*	14.2 (SD = 2.5)	**.27 (SD = .21)**	302.2 (SD = 88.2)
Highly External Linear	629.3 (SD = 529.7)	**269.5 (SD = 305.2)**	**18.7 (SD = 5.5)**	.13 (SD = .04)	**449.1 (SD = 162.9)**

discussion, autonomy modes are abbreviated as "Linear" and "Exponential" referring to the magnitude profile of the potential field obstacle avoidance.

We chose "Total Commands," "Command Conflicts," "Path Length (m)," and "Deviation (m)(from optimal path)" as the categories to focus on as they provide the most compelling data and could generally be sensed in real-time or through a short interaction lending themselves to in-situ autonomy adaptation. Of additional interest is the number of collisions in each trial, however, we found that collisions were consistent across all users in each of Linear and Exponential modes. Each of the categories provides a measure by which we will be able to switch the autonomy in future studies to improve performance. We now discuss each Locus of Control group across both user study groups.

Average. In Group 1, we found users in the Average group to be of primary interest. They performed better under Exponential control in all categories, except path length (as shown on the two middle bars for each metric in Table 1). A paired-samples t-test was conducted to compare total commands and conflicting commands under Linear and Exponential control schemes. There was significant difference in command conflicts for Linear (M=189, SD=170) and Exponential (M=77, SD=64) conditions; $t(13)=2.83$, $p=0.015$, two-tailed. Number of commands approached significance for Linear (M=465, SD=505) and Exponential (M=307, SD=268) conditions; $t(13)=1.86$, $p=0.087$, two-tailed. The Average participants drove shorter paths in both Linear (M=13.2 m) and Exponential (M=12 m) when compared to to the External participants (M=15.4 m and 13.6 m, respectively).

However, in Group 2, the Average user group sent more commands and had more command conflicts. When looking at command conflicts in the Linear condition, an Average user still has more conflicts (M=286 compared to M=188 in Exponential) and an increased number of commands (M=770 compared to M=593). There also appear to be some trends in this group that did not show up in the first group. In the Exponential condition, an Average or Highly Internal deviates the most. Highly Internal and Average have shorter Path Length using the Linear autonomy (M=17.3 m and 15.5 m, respectively, compared to M=22 m for Highly External), but while using the Exponential autonomy, Average and Highly External users drive greater Path Lengths (M=15.2 m and 14.9 m compared to M=13.5 m from Highly Internal).

Some conclusions have been consistent across the data. For example, from the first group of users, we correctly identified an important trend in command conflicts showing trends to be roughly the same across all groups. This suggests that some conclusions were sound with only 30 participants. However, other data have turned out to be significantly different. For example, in the first user group Internal and External users had similar total distances in Exponential mode but which were completely different in the second group.

Highly External. In Group 1, the Highly External group is clearly differentiable, among **all** user groups, because they have the largest deviation from an optimal path (M=0.42 m) and the fewest total number of commands (M=249) under the Exponential autonomy mode. They also have a much lower average error (M=.11 m) in the Linear mode but take the longest of all users (M=416 s) and travel the furthest (M=15.4 m), while having the fewest command conflicts (M=161) of any user group in that autonomy mode. Of note is that this group sent the lowest total number of commands in Exponential (M=249) of all groups suggesting their patience with autonomy.

In the second part of the study, the Highly External group is distinguishable in similar ways. Consistent with the first group, they take the longest to complete the course in both autonomy modes. However, in Exponential mode they switch from the highest deviation from the optimal path to the lowest (M= .42 m and .12 m, respectively). Unlike the first part of the study, in Linear mode, External users send the most commands (M=776), but in Exponential mode, they still send slightly fewer (M=414). In the Linear profile, Highly External users have the highest percentage of conflicts (48%) rather than being similar to other participants in the first part of the study (33%).

After just one group, the trends in the performance of these users seemed clear. However, without the second group of users, we would have come to false conclusions about these users' behavior. As shown in the differences between path deviations in the two parts of the study, the small number of users in this group causes the data to be highly variable.

Highly Internal. Finally, in the first group of users, the Highly Internal group has the highest percentage of command conflicts for both Linear (43%) and Exponential (35%) mode amongst all users (compared to Exponential Average 25% and Highly External 30%) in the first part of the study. Further, they also send the most commands to the robot (Exponential M=540, Linear M=678). As a group, they have a shorter total distance and duration, but higher error from optimal in the Exponential mode compared to Linear.

In the second group of users, this trend was reversed, with the Highly Internal participants having the lowest percentage of command conflicts in both Linear (35%) and Exponential (22%) amongst all users (compared to Exponential Average 34% and Highly External 32%). It is interesting to note in this comparison that the number of conflicts by Internal users were almost halved between the studies (M=189 in the first compared to 95 in the second) while the number of commands stayed roughly consistent (M=540 compared to 429). We also see that Highly Internal users take significantly less time to complete the course under the Exponential profile than the Linear (M=264 s and 392 s, respectively), and drive about 10–20% less than their External counterparts under the same conditions.

From the results of the Highly Internal group, we see large variability in the conflicts between the first user group and the second. These users, by far, are the most inconsistent between groups. Their trends, especially total commands and conflicts, vary between the two groups. This shows that this group of users would need more study and perhaps even more users run before anything conclusive can be drawn *even though this group is larger than the External group* (with 10 participants compared to 3 in the second study).

5. DISCUSSION

The fusion of HRI/HCI directly into the design of robot autonomy by inferring user qualities and adjusting algorithms at run-time has the potential to transform robot autonomy design. But as the results here demonstrate, this process is fraught with difficulties in generalizing from small datasets.

5.1 CPHS Design Implications and Recommendations

These findings provide insight into the design of CPHS in which users are directly involved in control: user qualities can be inferred from a combination of system and user performance, and suggests that autonomy could be designed to switch or adapt to users on-the-fly based on observations made in real-time. It also means that such a strategy can augment the less explored adaptation mechanisms (Ranatunga et al., 2015) that supplement "human-in-the-loop" controllers such as impedance and admittance manipulation (Hogan, 1984). Despite these promises, the differences between the users in the first and second groups also highlights the fragility of designing to inherently noisy systems (such as those composed of individual humans with their own ideas and preferences). Due to these differences, it is likely that a third group would also produce different conclusions and researchers should be careful when drawing conclusions from small user studies.

We anticipate the largest gains will come when autonomy adapts to novice users and improves performance of the CPHS to make it comparable to performance with highly trained users. However, as these data show, these systems are unlikely to be seeded with data from a small number of participants. Recommendations for study design can be found in the HRI community (Bethel and Murphy, 2010) and can inform how many users it would likely take to support the amount of data required for training. But these guidelines can impart high costs for participant recruitment and payment, as well as student time for running studies. To do our part to mitigate this, and help the community build a shared repository for CPHS data, we offer our corpus of data of the user study described herein to aid researchers in furthering CPHS community goals [3].

In addition to sharing user-study data within the CPHS community, a recommendation moving forward would be to consider large, distributed studies collecting data from international locations that could inform some of the more basic adaptations of interest to the community. This would allow a magnification of efforts and would generally allow multiple research directions to be explored at once, if carefully designed.

5.2 Limitations

The Double telepresence robot used in the study is an inverted pendulum design. As a result, the robot oscillates to maintain balance resulting in non-smooth motion. This can affect user perception of what the robot is doing, and incidental collisions if the robot is near an obstacle and needs to balance. The platform also limits the rate and duration of a command to the robot. This means users must tap the command button for each command as opposed to holding the button down. This is due to limited access provided by the official SDK, and transmission of the commands through several systems, algorithms, and the network before reaching the robot base.

When looking at the results from both groups of users, one important note is the lack of significant differences between the Average and the Highly Internal groups. These groups are similar in all of the behaviors and metrics we tracked in this study, indicating not that Takayama et al. (2011) was wrong, but that there are likely other user qualities which are overriding the impact of LoC. As a result, a natural extension of this work would be to investigate other user qualities that might allow a differentiation between these groups. While the lack of participants in the Highly External group (only 10% of our population) could be a concern, we actually had a similar percentage

[3] `https://nimbus.unl.edu/projects/cyphuas/`

of the most extreme Highly Internal participants (7%) represented in this study when compared to findings by Valecha and Ostrom (1974) in a large population (5%). These distributions suggest that we should investigate how to further differentiate the >80% of people in the other groups.

From a study design perspective, because error, duration, and total distance do not always correlate, additional metrics such as idle time, thrashing, and additional optimal path metrics could augment our conclusions.

5.3 Next Steps

Based on our findings, two important next steps arise. First, studies similar to this one need to be conducted to establish 1) which other intrinsic user qualities can be inferred from user interactions, and 2) which ones are sufficiently predictive to allow for reliable categorization of a user to allow an autonomy to switch or adapt. We specifically plan to conduct a similar study focused on immersive tendencies and empathy as suggested by Samana et al. (2009) and spatial reasoning as suggested by Takayama et al. (2011). Second, of immediate interest is the development and implementation of a switching autonomy based on the larger set of both groups of participants, thereby smoothing the differences reported here. This will demonstrate that an autonomy that can infer user qualities and adapt accordingly will result in improved performance and user behavior.

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