Inference of User Qualities in Shared Control*

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***Abstract*— Users play an integral role in the performance of many robotic systems, and robotic systems must account for differences in users to improve collaborative performance. Much of the work in adapting to users has focused on designing teleoperation controllers that adjust to extrinsic user indicators such as force, or intent, but do not adjust to intrinsic user qualities. In contrast, the Human-Robot Interaction community has extensively studied intrinsic user qualities, but results may not rapidly be fed back into autonomy design. Here we provide foundational evidence for a new strategy that augments current shared control, and provide a mechanism to directly feed back results from the HRI community into autonomy design. Our evidence is based on a study examining the impact of the user quality "locus of control" on telepresence robot performance. Our results support our hypothesis that key user qualities can be inferred from human-robot interactions (such as through path deviation or time to completion) and that switching or adaptive autonomies might improve shared control performance.**

I. Introduction

As we move towards a future in which humans will increasingly be asked to share control with autonomy in interactions with teleoperated technologies such as telepresence robots, aerial vehicles, and autonomous cars, the onboard control may be suboptimal without considering the person on the other end of the interaction. Through investigating the impact of personal qualities that can be sensed in interactions and adapting the autonomy based on that sensing, system performance can be improved as measured by key metrics of shared control performance such as time to completion, distance in transit, error from optimal, and computational efficiency. Based on these anticipated improvements, this work is applicable to researchers in human-robot interaction, cyber-physical systems, control theory, and robot planning and behavior.

The specific research question being addressed by this work is *Can user qualities be observed through interactions with a shared autonomy system and can that system adapt based on these observations?* This question is addressed through a user study on interactions with a Double telepresence robot (seen in Figure 1) in an obstacle avoidance task with two distinct obstacle avoidance regimes. The hypotheses in this work relate to the user performance and behavior under autonomies that offer tradeoffs between user control versus collision protection–of particular important to applications of telepresence robots and autonomous vehicles in the future.

Personality is the determinant of individual's characteristic behavior caused by dynamic organization of psychophysical systems and differences in personality traits among individuals lead to differences in their response to similar events [1]. In this paper, personality traits of users are referred to as user qualities. The user quality investigated in this paper is locus of control which is defined as the degree to which people feel that they have control over the events in their life [2].

Many shared control strategies adapt to user performance by adapting to force [3], intent [4], [5], or similar extrinsic indicators, but do not consider intrinsic qualities the user may have that implicitly determine user performance. In contrast, the human-robot interaction and human factors communities have examined user traits [6], [7], qualities [8], [9], and the impacts of systems on user trust [10], presence [11], and awareness [12]. However, it is often the case that results from these studies are left to designers to incorporate into future designs, leaving a large gap in feedback of user studies into robot autonomy. In this work we aim to extend research in shared control and provide a mechanism for tighter integration of feedback from user studies into robot autonomy by providing evidence that user qualities can be inferred from interactions so that future autonomies can be adjusted to improve shared control performance.

Fig. 1: Double Telepresence Robot.

This work is novel in its investigation of personal qualities identified in human-robot interaction work to understand how these different users may be classified to allow better shared control strategies and improved system performance. There were more command conflicts under the restrictive control regime than under the relaxed control regime for all users, resulting in wasted computational resources and suboptimal system performance. On the other hand, users with a high external locus of control issued fewer commands under the relaxed control regime but drifted further from the optimal path and had a higher completion time, resulting in wasted energy. These results indicate that it might be beneficial to opportunistically switch modes based on resource scarcity for users with high external locus of control. This work also offers methods for researchers to investigate the impact of user qualities on user interactions and operationalize these findings in future work to allow systems that adapt to the

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current user rather than being designed for an ideal user.

II. Related Work

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

A. Shared Control in Telemanipulation

In telemanipulation, force from the user is used to apply force to the robotic manipulator, or predict intent [13]. A primary research topic is how well users perform with different shared control strategies. A few studies have been conducted that examine how shared control can be improved if user traits are known. Leeper et al. [14] analyzed the performance of participants using four different grasping strategies based on successful grasps, major collisions, and minor collisions in a ten minute time period. They found that strategies with increased autonomous control performed better because the operators were able to grasp more objects and caused fewer unwanted collisions. You and Hauser [15] ran five groups of users, each using a different control strategy. They concluded that users were willing to tolerate loss of control, slower reaction times, and less predictable motions only for significant improvements in performance and convenience, which was provided by one of their control strategies.

In Dragan and Srinivasa [16] users performed robot manipulation tasks with an aggressive controller and a timid controller that attempted to predict user behavior based on current and past trajectories. They found that users generally preferred the autonomy that provided the best performance. However, some preferred the timid controller even after admitting that the aggressive controller was more helpful, saying they preferred having more control of the robot. The results suggest that the degree to which users are willing to adapt to autonomy varies among individuals. Human adaptability was taken into consideration to design a human-robot adaptation model in a shared autonomy setting by Nikolaidis et al. [17] where robots planned their actions based on the degree to which users were willing to adapt to the robot's autonomy. It was observed that mutual adaptation of users and robots led to a balance between optimized task performance and user trust. The results of the study highlight the importance of user adaptive shared autonomy for human-robot collaboration tasks.

B. Shared Control in Telepresence

In telepresence robotics, some studies have examined the utility of assisted autonomy and correlated it with improved performance. Other examined user preferences and their relation to shared control performance. Several studies have identified that autonomous navigational assistance is essential in telepresence robots to provide better control of the robot and also reduce cognitive load of users [18]–[21]. In a similar study Bruemmer et. al [22] 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 [23] 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. [24]. 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 [25] 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 more internal locus of control fought against the autonomy and hence required more time to complete the tasks in comparison to people with 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.

C. User Qualities

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 [2] 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 [26], expect their actions to result in outcomes that can be predicted, and are more satisfied with situations allowing personal control [27] than people with external locus of control. Similarly, a study by Klein [28] which examined the effect of user control and media richness in virtual telepresence suggested that user qualities such as locus of control or desire to control may have an impact on an individual's use of control. A study by Samana et. al [11] 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 [29] 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 different behavior based on a user's locus of control and the impact that has on a user's performance with a robot to draw correlation between interactions and system performance. 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.

III. Hypotheses

Based on Takayama's previous work [25] which found varied performance across users with different locus of control when operating a telepresence robot with shared control, we formulated following hypotheses:

Hypothesis 1: Users with 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 have different behavior given a robot autonomy.

IV. Autonomy Description

We desire a static autonomy to investigate the ability to adapt to what is best for an individual's locus of control. The results in [25] demonstrate that although autonomous assistance helps improve performance, users with a high internal locus of control took longer to complete tasks suggesting they wrestled with the autonomy for control of the robot. This gives rise to our Hypothesis #1 above, and motivates the testing of autonomies for users based on their locus of control.

A. Autonomy Overview

Following a similar experimental setup to [25] we investigate the use of a telepresence robot on an obstacle course. The goal of the autonomy is to aid the user in getting to the end of the course without hitting obstacles. Hence we focus on autonomy that mixes with user commands with the objective of avoiding obstacles (i.e. "shared control").

We made hardware and software modifications for a customized shared control mechanism on a Double telepresence robot. An iOS application was developed to provide telepresence capabilities (i.e. provide video, send commands) to the user, and a vendor provided SDK [30] was used to introduce a layer of autonomy onboard the robot. A laser range finder was added to the robot to detect obstacles providing information to an obstacle avoidance algorithm. Commands from this algorithm and the user were then combined by the autonomy providing a shared control scheme.

B. Obstacle Avoidance System

Many advances in deliberative and reactive planning [31], [32] and obstacle avoidance [33]–[35] in robots have been made in recent years, and the limitations of potential fields are well known [36], though they are still in an active research area [37]. Our objective is a proof-of-concept shared autonomy that can be designed to adapt to user qualities inferred solely from interactions between the user and robot. As a result, we seek an obstacle avoidance strategy that is easy to implement, conducive to combining with user commands, and has common algorithmic adaptations that can be adopted for users with either internal or external locus of control.

Artificial potential fields are a reactive planner comprised of repulsive and attractive forces, represented by vectors with magnitude and direction [38]. Repulsive vectors represent undesirable locations or obstacles, and attractive vectors represent goal locations or rewards. At the robot's current location the forces are summed to determine travel direction and velocity. As part of our shared control scheme, we do not employ attractive forces relying on the user to provide goal seeking behavior. This leaves repulsive forces generated by nearby obstacles which push the robot away.

We design two potential field strategies, and in each complete trial one of these two strategies is chosen for the duration. First, a potential field with a repulsive force linear in distance from an obstacle is designed. We hypothesize this repulsive force will: 1) keep users further away from obstacles despite their desire to get close to them, and 2) lead the user to the destination more quickly by following a path closer to the optimal path - if they allow it to guide them. This makes the linear repulsive force more amenable to users with more external locus of control who should be willing to share more control with the autonomy.

Second, we design a potential field with a repulsive force exponential in distance from an obstacle. This repulsive force will: 1) allow users to get closer to obstacles giving them more control, and 2) be a better reflection of the users capabilities as ability to follow the optimal path is primarily under the user's control. Conversely, this makes the exponential repulsive force likely to work better for those with a high internal locus of control - users wanting more control over the robot. We now describe the main parts of our strategy below.

We use a laser scanner to detect obstacles within the robot's field of view. The direction of each repulsive force is determined by the angle the obstacle makes with a line extending straight out of the sensor on the robot. The magnitude of the force depends on the robot's distance from the obstacle and can be modeled by a function called a "magnitude profile" and, within a "sphere of influence," increases with decreasing distance [38].

The obstacle avoidance behavior is only activated when the robot is within a predefined sphere of influence of at least one obstacle. In our design, a sphere of influence of diameter $D = 1\,\mathrm{m}$ was tuned to meet the objectives in our obstacle course given the size and movement capabilities of the robot.

a) Linear Magnitude Profile

Let $d_{\min} = 0.15\,\mathrm{m}$ be the minimum distance from which an obstacle can be detected by the laser scanner, and D be the sphere of influence within which an obstacle exerts a repulsive force. We calculate the repulsive force magnitude for the i^{th} obstacle as

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

where d is the distance to the obstacle returned from the laser scanner, and η_{lin} is a normalizing factor representing the maximum repulsive force (which would occur at $d_{\min}$).

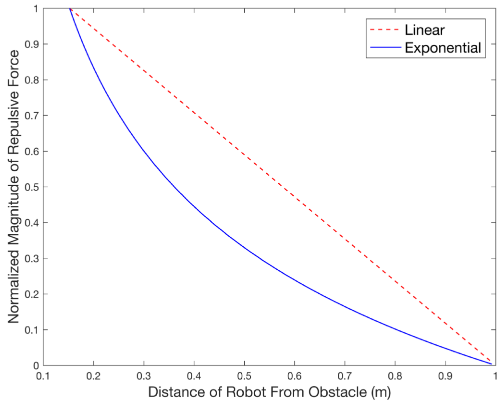

Fig. 2: Linear and Exponential Magnitude Profiles as a Function of Distance

b) Exponential Magnitude Profile

With parameters similar to the linear magnitude profile, we calculate the exponential repulsive force magnitude for the i^{th} obstacle as

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

where η_{exp} is a normalizing factor, and $\alpha = 0.18$ is a tuned parameter defining the curvature of the exponential function and determined by testing with the robot in the environment. Both the linear and exponential magnitude profiles can be seen in Figure 2.

c) Shared Control

Regardless of which potential profile is chosen for a particular run, all the repulsive vectors from obstacles within the sphere of influence are averaged to create a total repulsive vector with a magnitude, m_{total}, and direction ϕ_{total} which is then passed along to the robot via the vendor supplied SDK.

V. Experiment

We have designed the experiment to track shared control performance metrics as well as learn key user qualities. Here we describe our setup, participants, and methodology for the user portion of the study.

A. Setup

The study was conducted using a Double telepresence robot (shown in Figure 1) weighing 6.8 kg and, for this study, had a fixed height of 1.32 m. The screen of the robot consists of an iPad attached to the pole which in turn is attached to the mobile base of the robot. The interface on the iPad transmits the video stream of the robot's environment to the operator (similar to a standard videoconferencing application). The robot is also equipped with a microphone and a directional speaker enabling communication of the operator in the remote environment. To implement obstacle avoidance, a Hokuyo laser rangefinder was attached to the robot at approximately 7.62 cm above the mobile base (35.56 cm above the floor).

The robot was controlled using a custom built iOS application on an iPad Air 2 utilizing a vendor supplied SDK [30]. The user interface of the application (shown in Figure 3) allows the operator to drive the robot in the remote environment. The interface streams video of the remote environment and allows the operator to drive the robot using buttons for forward, backward, left, and right.

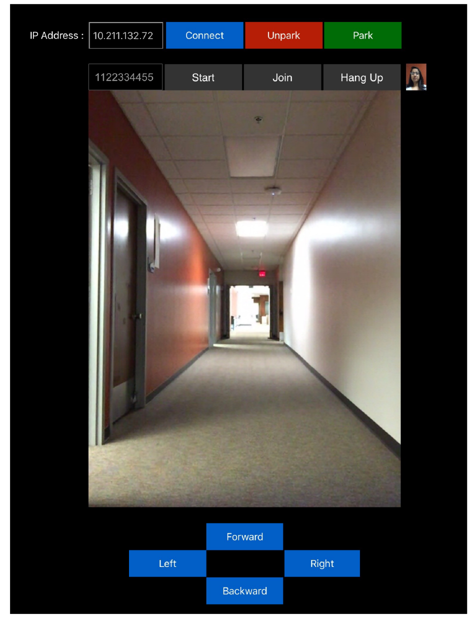

Fig. 3: Operator's User Interface with four blue buttons for forward, backward, left, and right controls.

A T-shaped training obstacle course (seen in Figure 4a) was constructed in an area 2.79 m by 4.19 m using cardboard boxes of height 0.85 m. It was used to train the participants to drive the robot with the specific obstacle avoidance profile prior to navigating the main obstacle course.

The main obstacle course (shown in Figure 4b) 3.65 m by 3.74 m was created inside an experiment room for the main study. The obstacle course in this study was inspired from a study by Takayama et al. [25] with some modifications due to limitations of sensors, size of the robot, and dimensions of the room. The modifications involved replacement of chairs by cardboard boxes and covering of the legs of the table by sheets of paper due to limitations of range finding sensors. As shown in the figure, the obstacle course consisted of trash cans, cardboard boxes, tables, and cardboard walls. A shortest distance optimal path was computed using a search strategy and is represented by the dotted blue line. Start and end positions of the path are represented by solid black lines connected to the optimal path. The start and end positions alternate based on the direction of movement (i.e clockwise/counterclockwise).

The ceiling of the main obstacle course was equipped with seven Vicon Bonita motion capture cameras in order to track the position of the robot throughout the obstacle course. The data from the motion capture system was used to determine the path of the robot, evaluate its deviation from the optimal path, and also to detect collisions with obstacles.

B. Participants

28 participants (fourteen male, fourteen female) with ages ranging from 19 to 68 (mean (M) = 29.18, standard deviation

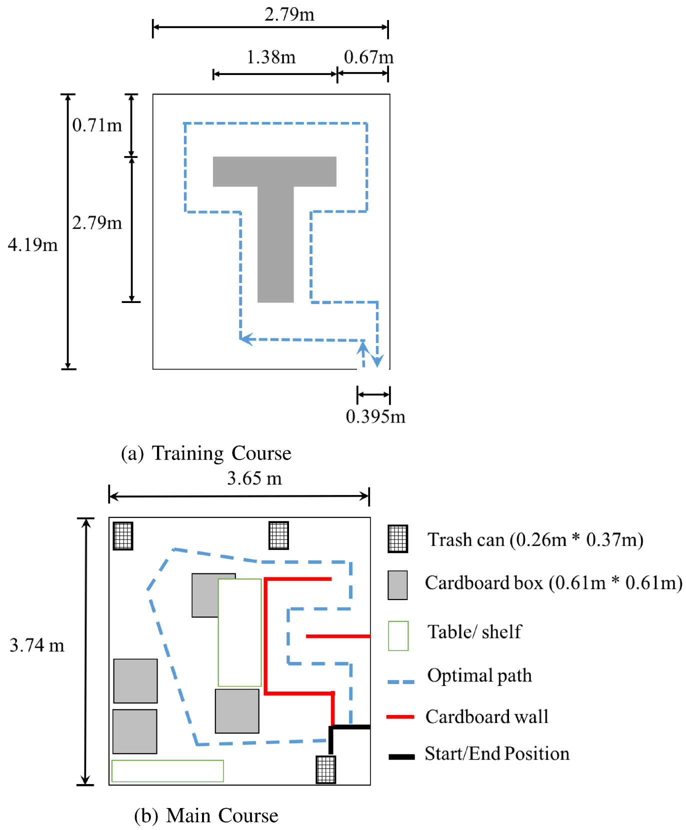

Fig. 4: Obstacle Courses

(SD) = 12.67) were recruited through emails to campus mailing lists, and advertisements on- and off-campus. The participants were paid $10 as compensation for their participation. Based on the value of locus of control, eleven participants (six male, five female) were found to be "High Internal," three participants (one male, two female) were found to be "High External," and fourteen participants (seven male, seven female) were found to be "Average."

C. Methodology

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) [39] 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 ("High Internal", 0-3), mid-range locus of control ("Average", 4-7), and strong external locus of control ("High External", 8-11).

Procedure

Participants were greeted by an experimenter and were provided a consent form which informed them of the objectives of the study and their rights as a participant. They were also informed that they would not be penalized if they decided to leave the study at any point and would receive full compensation. After signing the consent form, the participants were asked to fill out a pre-questionnaire which consisted of the demographics and Locus of Control questionnaires.

After the pre-questionnaire, the participants were introduced to the interface that they would use throughout the study to drive the robot. The study was divided into two phases, where each phase was conducted with either linear or exponential obstacle avoidance profiles. In both phases, participants could drive the robot in either a clockwise or counterclockwise direction. Both the obstacle avoidance profile and the direction to drive the robot were based on random selection and were counterbalanced.

In each phase, participants completed two laps in the training obstacle course (shown in Figure 4a) in the given direction with an assigned obstacle avoidance profile after which they completed one lap in the main obstacle course (shown in Figure 4b) with the same direction and obstacle avoidance profile as in the training phase. After completion of each phase (i.e. training and main obstacle course), participants were asked to complete a questionnaire to collect their experience and feedback. After both phases, the study was concluded with a short interview.

Performance Metrics

We devised metrics to measure both user and robot performance in the shared control scheme. All metrics were analyzed from when the robot crossed the start line to when the robot crossed the finish line of the main obstacle course. To compile the data we computed averages across each of the six combinations of locus of control categories (i.e. High Internal, Average, and High External) for each shared control scheme. For example, to measure average duration for the category "Linear/High Internal" we averaged across all runs with users having a high internal locus of control using the linear magnitude profile shared control scheme.

The first metric is duration, which is the total time, in seconds, spent on the obstacle course. Second, we measured the robot's total distance traveled, in meters, during their navigation through the obstacle course. Both of these metrics can give a general idea of task accomplishment. Related to these, we computed an error measure to determine how close a user matched an optimal path. The optimal path was generated using an A* pathfinding algorithm that minimized the distance driven while still avoiding obstacles. Our metric is the average perpendicular distance that the robot was from this optimal path during their navigation through the course.

Next, we count the number of collisions that occurred during a run. A collision was counted as any contact with an obstacle or a wall. If the user remained in contact for an extended duration, this would only count as one collision, but if a user broke contact and then contacted the obstacle or wall again, these would be counted as separate collisions.

Finally, we count the number of total commands and conflicting commands from the user for each run. Each button press on the iPad corresponds to one command and the total is the sum of all of these commands during the run. A conflicting command is an instance where the final command after executing the obstacle avoidance algorithm does not match the command that the user sent. Using these we also calculate our conflict metric, which is a measure of the conflicting commands as a percentage of the total commands. This gives a good indicator for how often the obstacle avoidance takes control, and therefore, how often the user "disagrees" with the obstacle avoidance.

VI. RESULTS

Our results include traditional HRI community interests such as user preferences, spatial presence, and locus of control, as well as interests in autonomy in the robotics community such as system performance, reactive planning, and obstacle avoidance. Here, we focus exclusively on performance of the holistic system (i.e. combined user and robot).

Figure 5 illustrates the results related to autonomy performance. Data from all runs were sorted into categories based on locus of control and autonomy mode. The graph is grouped into five metrics and compares all user groups for each metric. On a per metric basis, each locus of control user group was normalized for consistency, yielding a percentage. Our objective is to eventually switch or adapt the autonomy as we infer a specific user quality. As a result, we are interested in trends that suggest that one autonomy mode is better for a particular user based on their locus of control. In keeping with the analysis in [11], [25], and adding some additional nuance, we divided users into "High Internal," "Average," and "High External" locus of control categories. This adds to previous results by treating those with scores near the halfpoint of the locus of control scale as their own category. Our results suggest this is an improved strategy given the relatively large number of users in that category, as well as their rather unique performance in the study. In our results we have abbreviated our modes of autonomy as "Linear" and "Exponential" referring to the magnitude profile of the potential field obstacle avoidance, and will utilize this abbreviation in our discussion.

We have chosen "Duration," "Total Distance," "Total Commands," "Command Conflicts," and "Error from Optimal" as the categories to focus on as they provide the most compelling data. 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. As expected, since Exponential allows more user control closer to obstacles, users in Exponential mode hit more obstacles. Each of the categories provides a measure by which we will be able to switch the autonomy in future studies to improve performance.

Of primary interest is the users in the Average group, who performed better in the Exponential mode in all categories, except total distance (as shown on the two middle bars for each metric in Figure 5). To understand the user behavior, a paired-samples t-test was conducted to compare each of total commands sent and number of conflicting commands in Linear and Exponential conditions. There was a significant difference in command conflicts for Linear (M=190, SD=182) and Exponential (M=78, SD=66) conditions; $t(12)=2.83$, $p=0.015$, two-tailed. Number of commands approached significance for Linear (M=490, SD=516.89) and Exponential (M=320, SD=275) conditions; $t(12)=1.86$, $p=0.088$, two-tailed. As a result of the improved performance and reduced demand on computational resources, upon inferring a user's locus of control to be in the Average category, a switch to Exponential autonomy (i.e. an autonomy allowing more control) will result in improved performance. This could be assessed through looking at the number of commands sent, which would narrow the participants to those in either Average or High Internal.

Users in the High External group, among **all** user groups, 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, though they also have a much lower average error (M=.11 m) in the Linear mode. However, in Linear mode, also amongst all users, they take the longest (M=416 seconds) 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 $\sim 1/2$ the total number of commands in Exponential (M=249) of all groups suggesting their patience with autonomy. These results suggest neither mode suits this group of users all the time, and we recommend switching autonomy between the modes based on performance and commands sent.

Finally, the High Internal group has the highest percentage of command conflicts for both Linear (M=39%) and Exponential (M=34%) mode amongst all users (compared to Exponential Average 25% and High External 30%) . Further, they also send the most commands to the robot (Exponential mean=475, Linear mean=482). These results suggest this group may seek more control and grow frustrated with the robot's response. As a self-contained group, they have smaller total distance and duration, but more error from optimal in the Exponential mode compared to Linear. Overall performance for this group, however, does not justify an autonomy allowing more control. Rather, we suggest preference for Exponential to reduce computational overhead (and differentiate from Average users), which would likely be augmented by short stints in Linear to improve system performance.

When comparing between the groups, a Mann-Whitney test for central tendencies was conducted to compare each group (High Internal, Average, and High External) for each condition (Linear and Exponential) for each metric and the results are shown in Table I. Path deviation from optimal in Exponential was significantly different when comparing High Internal and High External groups and also when comparing High External and Average groups. In Exponential, High External and Average groups were significantly different on total distance travelled. When comparing time for Linear conditions, Average and High External groups were significantly different.

VII. DISCUSSION

This work has the potential to transform robot autonomy design by integrating ideas from human-robot interaction directly into the design of robot autonomy by inferring user qualities and adjusting algorithms at run-time.

A. Robot Design Implications and Recommendations

These findings provide insight into the design of robotic systems in which users are directly involved in control: user

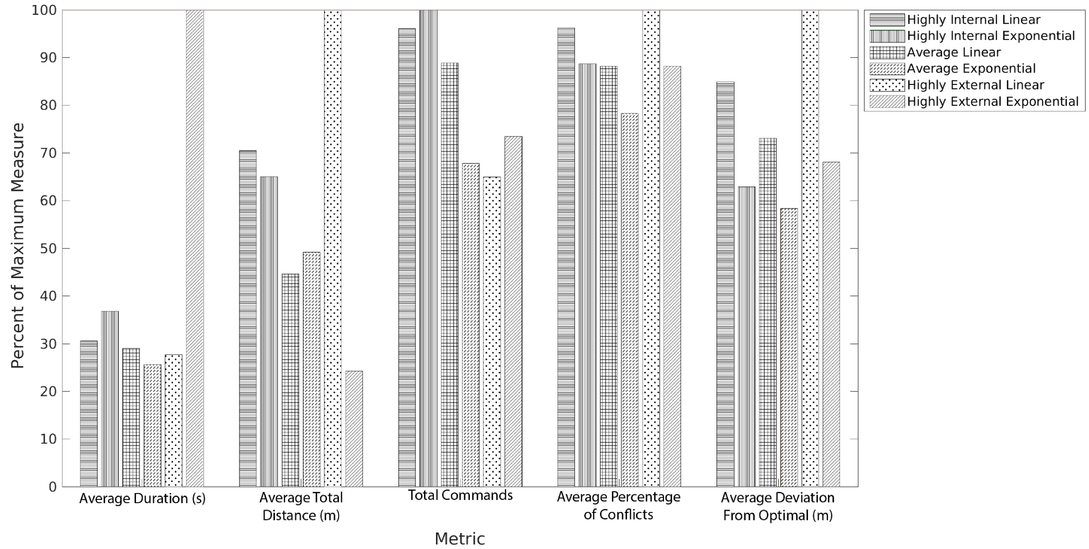

Fig. 5: Results grouped into the primary metrics, divided up by user group. Each metric group has been normalized according to the max to enable an easy comparison among all the user groups.

	Dependent Variable	Independent Variable	Median	Parameter (U)	Significance
Exponential	Path Deviation	**High Internal** **High External**	**0.12** **0.46**	**32.0**	***p* = 0.011**
		High Internal Average	0.12 0.10	39.5	*p* = 0.068
		High External **Average**	**0.46** **0.10**	**0**	***p* = 0.004**
	Distance	High Internal High External	12.20 13.26	22.0	*p* = 0.456
		High Internal Average	12.20 11.77	59.5	*p* = 0.505
		High External **Average**	**13.26** **11.77**	**4.0**	***p* = 0.039**
Linear	Time	High Internal High External	286.69 395.25	27.0	*p* = 0.126
		High Internal Average	286.69 243.48	61.5	*p* = 0.582
		High External **Average**	**395.25** **243.48**	**4.0**	***p* = 0.039**

TABLE I: Results of Mann-Whitney Tests

qualities can be inferred from a combination of robot and user performance, and suggests that robot 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 [13] that supplement “human-in-the-loop” controllers such as impedance and admittance manipulation [40].

As a first step this adaptation could be the result of precisely timed switches between types of planning or control strategies that could be categorized according to robot performance with users having a specific quality. In this work we have provided one example of two obstacle avoidance algorithms that could be used as part of an intelligent switching algorithm that switches according to inferred user locus of control and certain performance conditions. Alternately, schemes can be designed where key portions of the autonomy (e.g. planner, controller) adapt to performance objectives that stem from specific user qualities. While arguably more flexible, such a strategy will require a deeper understanding of how user qualities impact system performance and how users respond to the system and its performance. It also requires improvements in adaptive algorithms that: 1) model performance based on user qualities and can improve performance with long-term interactions, and 2) provide feedback to the user that helps them adjust behavior and expectations given current conditions.

We anticipate the largest gains will come when autonomy adapts to novice users and improves performance of the human-robot system to make it comparable to the system performance with highly trained users.

B. 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 between groups results, one important note is the lack of significant differences between the Average and the High Internal groups. These groups are similar in all of the behaviors and metrics we tracked in this study, so 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 High External group (only 10% of our population) could be a concern, we actually had a similar percentage of the most extreme High Internal participants (7%) represented in this study when compared to findings by [39] 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.

C. Next Steps

Based on our findings, two important next steps arise. First, of immediate interest is the development and implementation of a switching autonomy to demonstrate that an autonomy that can infer user qualities and adapt accordingly will result in improved performance and user behavior. Second, differences between the Average and High Internal groups were not as well defined as between High Internal and High External groups. More studies similar to this one need to be conducted to establish which other intrinsic user qualities can be inferred from human-robot interactions, and which ones are sufficiently predictive to allow for reliable categorizaton of a user in order to switch or adapt the autonomy. We specifically plan to conduct a similar study focused on immersive tendencies and empathy as suggested by [11] and spatial reasoning as suggested by [25].

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