Input Matters: How Telepresence Control Devices Affect Performance, Sense of Control, and User Experience*

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Abstract

Control devices are essential in shaping the user experience of telepresence robot operators. This is especially true for mobile telemanipulator robots (MTRs), which offer greater opportunities for social interaction compared to mobile or tabletop telepresence robots, but are more difficult to control. This increased difficulty can diminish key aspects of user experience, such as sense of control (SoC), which many users value over performance. However, the usability of telepresence control devices has been critically overlooked in HRI research. In a between-subjects study (n = 63), we investigate how three widely used control devices (mouse, gamepad, haptic controller) affect critical aspects of teleoperation: perceived SoC, safety, usability, and cognitive load; and task performance. Participants remotely controlled an MTR (Stretch) to wait on a customer in a social telepresence setting (cafe). We found that the type of control device significantly impacts both task performance and SoC in direct teleoperation, with the mouse having the best performance/SoC. There were notable tradeoffs in speeds, errors, and task completion times, and participants with higher SoC performed significantly better than those with lower SoC. We provide participant-informed suggestions for future control device design, such as allowing users to reconfigure its physical form, input sensitivity, and controls to align with video game conventions. By foregrounding the role of control devices, our work contributes to ongoing conversations in HRI around the tradeoffs between autonomy, usability, and user agency in social telepresence.

CCS Concepts

• **Computer systems organization** → **Robotics**; • **Human-centered computing** → **Interaction design**; **Interaction devices**.

Keywords

Human-Robot Interaction, Teleoperation, Control Devices

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1 Introduction

Telepresence robots hold significant promise for overcoming barriers to in-person participation, particularly as demand for hybrid modes of interaction grows [1–7]. However, despite decades of teleoperation research, these robots continue to present substantial control challenges for users without specialized training [8–11].

Users often lack situational awareness and struggle to understand control mappings from low-dimensional control devices to different robot components [8, 12, 13]. These challenges are further exacerbated in robots with high degrees of freedom (DOF), like mobile telemanipulator robots (MTRs), which include a mobile base and one or more manipulators. While high-DOF robots offer a broad range of user and environmental interactions, they also introduce greater control complexity, imposing significant cognitive workload [14]. Users may issue incorrect robot commands, possibly leading to task failure, user frustration, and harm to remote interactants.

Such challenges are especially significant given recent findings in teleoperation research which emphasize the importance of improving the experience of direct teleoperation. This is because users frequently prefer direct control over autonomous assistance [15–20]. This preference challenges the dominant emphasis on shared autonomy as the way forward in teleoperation research, and highlights the need to reexamine how direct control systems are designed. One important step is to examine the choice, design, and implementation of the robot's control device [8, 9, 14].

Control devices are a critical factor in user experience, because they serve as the primary medium through which users act in remote environments during direct teleoperation. No single device is universally suited for all robots, tasks, and contexts, as each

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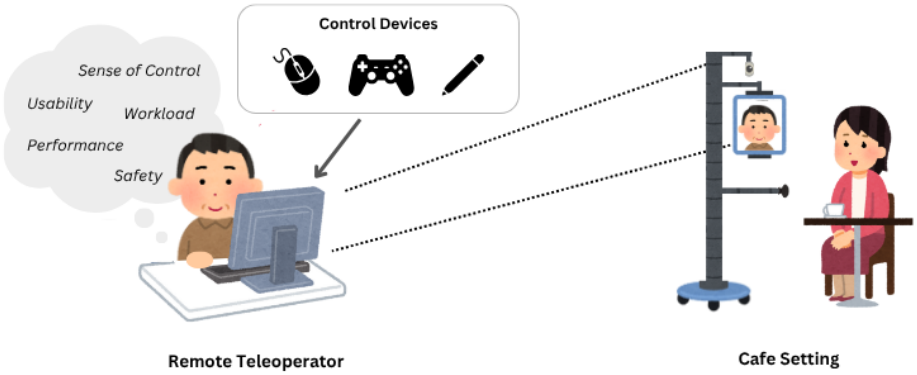


Figure 1: In this work, we investigated the effect of different types of control devices (mouse, gamepad, Touch) on key aspects of remote teleoperation: perceived sense of control, safety, usability, and cognitive load; and task performance.

combination presents unique interaction demands [14, 21–23]. Yet, we still have a limited understanding of the relationship between control devices and various factors that impact the remote user's experience of direct teleoperation.

While prior work has explored control devices in direct teleoperation, several gaps remain. First, there is a lack of understanding of how different devices influence key aspects of user experience, such as sense of control (SoC) and perceived safety (PS). Existing studies primarily focus on task performance, cognitive load, and system usability, but do not explore SoC or PS (c.f. [11, 14, 24]). They also tend to be situated within virtual, instead of real-world environments [25–27]. When situated in the real world, much prior work focuses on data collection for machine learning instead of user-centered design (c.f. [28, 29]).

Second, empirically grounded comparative studies of control devices are relatively scarce. Much of the literature evaluates a single device tailored to a specific population or context [30–32]. While such studies offer important insights, comparative studies are essential for uncovering performance and user experience tradeoffs across different devices and interaction styles.

Third, the few comparative studies of control devices that examine direct teleoperation in real-world social contexts (e.g., [11, 14, 24]) typically focus on either mobility or manipulation tasks, but not both. They also had small participant pools, which can make it difficult to account for individual differences.

Collectively, these gaps make it difficult to 1) determine how different devices perform across diverse users and tasks, and 2) identify specific device characteristics that shape the experience of directly teleoperating MTRs.

In this work, we addressed these gaps by conducting an in-person between-subjects study to systematically investigate the impact of three control devices on the direct teleoperation of a high-DOF MTR (Stretch). Participants were asked to complete key tasks involving mobility, manipulation, and communication with people in a social setting (cafe). We explored the following research questions (RQs): What was the impact of the type of control device on: task performance (RQ1), cognitive load (RQ2), system usability (RQ3), perceived safety (RQ4), sense of control (RQ5), and user perceptions (RQ6)? These questions address areas that have been growing in relevance within Human-Robot Interaction (HRI) research [20, 33, 34].

We also investigated relationships between these factors, such as between SoC and task performance. By including these metrics in a large-scale study, our work provides a deeper understanding of the effects of different control devices across diverse users.

We examined three control devices: a mouse, a gamepad, and a haptic controller. The mouse and gamepad are widely available and familiar to most users, while the haptic Touch controller represents an area of ongoing interest in teleoperation research [35–37]. We built a direct teleoperation system, **NOvice-centered Remote TEleoperation (NORTE)**, to support flexible switching of control devices across 63 participants. Each participant was assigned one control device to remotely teleoperate the robot for about 1 hour.

Contributions: First, we demonstrate that for direct teleoperation, the choice of control device affects the relationship between task performance and sense of control. Participants who reported a significantly higher sense of control with a control device performed better when using it, and vice versa. Participants using the mouse generally performed best and reported the highest SoC. Gamepad and haptic controllers reported lower SoC and demonstrated tradeoffs in speed, accuracy, and completion rates. Given the growing emphasis in HRI research on the importance of supporting user agency when controlling robots [17, 18, 20], our results indicate a need to improve direct teleoperation systems through better control device design.

Second, we highlight how factors like kinematic dissimilarity, force feedback, input scaling, and users' prior experience can influence users' interactions and overall experience with a device. We draw on these findings to recommend ways HRI and robotics researchers can make control devices more user-centered.

Our work on control devices offers valuable insights for future teleoperation systems that prioritize user experience and agency.

2 Related Work

2.1 Telepresence Robots

Telepresence robots have been explored in many settings, including conferences [6], hospitals [38], museums [7], and schools [39]. MTRs can be particularly useful as telepresence robots, as they can

provide affordances like patient examination or pressing elevator buttons [40]. However, MTRs' high DOFs significantly increase their control complexity. To simplify this control complexity, researchers have developed many systems to support shared autonomy [9, 14, 25, 26, 31, 41–45].

However, shared autonomy can reduce transparency, and be unsuitable due to the potential for unreliable or unsafe behaviors [44, 46]. Also, recent HRI research shows users may prefer direct control instead of autonomous assistance, even if the assistance improves their task performance [17, 18, 20**?**]. Thus, it is necessary to specifically examine how to improve direct teleoperation systems. One important component of such systems are control devices, as they directly mediate the user's interaction with the robot.

2.2 Control Devices for Direct Teleoperation

The choice of control device can significantly impact the experience of controlling a robot [14, 21, 22]. Prior work has explored control devices for telepresence, including: keyboard/mouse [21, 24, 31, 41], joysticks [14, 21, 22], haptic controllers [14, 47], and gaze- and motion-tracking systems [14, 48]. However, few studies empirically compare the impacts of different devices on task performance, usability, and other factors that impact telepresence experience.

Existing comparative studies present conflicting findings. For example, Bjornfot [21] found that keyboards were generally effective for mobile robot teleoperation, though gamepads are preferable for tasks requiring high precision. Meanwhile, Gliesche et al. [24] found that a haptic controller was more suitable than a keyboard/mouse for quickly executing tasks with a stationary manipulator. In contrast to both works, Lin et al. [14] found that motion tracking systems performed best compared to haptic and gamepad controllers for manipulation with a bimanual mobile manipulator. However, they also noted that motion mapping causes users significant physical fatigue, which may be unsuitable for many users.

Given the differences across these studies, it is important to examine these control devices with increased task complexity and larger participant pools to account for individual differences.We chose to explore them on Stretch, a robot platform that is increasingly being used in HRI to support teleoperation research [49]. In addition to common performance and usability metrics, we evaluated user experience in terms of SoC and PS, which were not studied in prior work. Additionally, we provide qualitative feedback from participants and their perspectives on the need for autonomy.

With our work, we hope to provide a deeper understanding of the impacts of control devices on telepresence experience.

2.3 Sense of Control in HRI

The role of autonomy in assistive robots has been a subject of ongoing debate in HRI, particularly regarding its impact on a user's sense of control (SoC), or agency [1] [20, 50–52]. SoC refers to an individual's perception of how much control they have over the robot. Diminished SoC can cause users to feel unsafe and can occur when robots behave unpredictably or in unwanted ways [20, 51, 53]. In recent work, [20] found that higher levels of autonomy can diminish a user's SoC, despite increasing their performance, demonstrating that higher autonomy is not always ideal.

[1]We use SoC and agency interchangeably, as there has yet to be a clear distinction on how they are individually used and evaluated in HRI [20, 34].

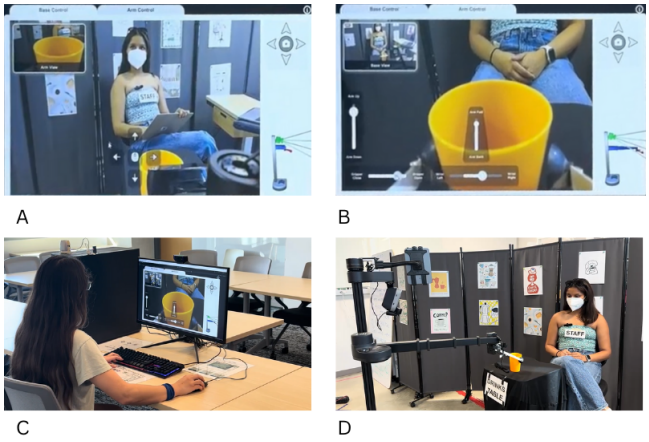


Figure 2: The NORTE system used in our study had base (A) and arm (B) control modes. Participants used this system (C) to remotely operate the robot to interact with people in a cafe setting (D).

Hence, one open question is what this relationship between SoC and performance is like during direct teleoperation of telepresence robots in social contexts, a question we explore in this paper.

3 Robot Teleoperation System (NORTE)

To explore our research objectives, we built the NORTE system, the result of a multi-year collaboration with key stakeholders of social telepresence systems (e.g., clinicians and chronically ill users) [2, 38]. NORTE consists of an MTR (Stretch), supports three control devices (mouse, gamepad, and haptic controller), provides software that maps inputs to robot motion, and has a UI that provides real-time visual feedback (Fig. 2).

3.1 Platform and Software

We used Stretch 2 [49], a mobile manipulator with a non-holonomic base, an arm with a wrist and gripper, and a camera. We replaced its dexterous wrist (3-DOF) with the standard wrist (1-DOF) to enhance usability. To provide operators with a wider field of view, we attached two wide-angle webcams, one to the head camera and another to the gripper. We also attached a small tablet near the robot's head to display the operator's face and enable two-way audio-visual communication. Our current implementation supports a mouse, gamepad (EasySMX [54]), and haptic device (3D Systems Touch [55]), though it is easily extensible to support others.

NORTE has three main software components. The Robot Control and UI modules manage operator commands and visual feedback of the robot's pose and camera views. The Device Specific modules enable control for the gamepad and Touch. We implemented the system using ROS Noetic, Python 3, C#, and Unity.

3.1.1 Robot Control Modules: The Robot Control modules handle the robot's movements. The *Operator Command Manager* module processes operator commands from the control interfaces, enabling real-time robot movement either to an absolute position or an incremental adjustment. The *Robot State Manager* module then reads the robot's updated pose and reflects this new state in the UI.

3.1.2 UI Modules: We used Unity to create UI modules for all three control devices based on our design requirements (Sec. 3.1.4).

The *Device Manager* module governs switching between control devices (mouse, gamepad, and haptic device), and handles device-specific communication. It works with the *Visual Feedback* module to dynamically update the UI for each control device, providing tailored visual feedback for the selected input.

Through the *Visual Feedback* module, we incorporated on-screen buttons that light up when the head camera or base moves. It also has sliders with fill bars that reflect the arm's real-time position (see Fig. 2). We also developed an animated 3D model of the Stretch robot that updates its pose in real-time to reflect the actual robot's pose. Finally, the module helps display the robot's two camera feeds.

3.1.3 Device Specific Modules: Our system also has modules to manage inputs from specific control devices. The mouse directly interfaces with the *Device Manager* module. The *Gamepad Control Module* manages gamepad inputs sent from the UI to the robot.

The *Haptic Device Control Module* enables the Touch to teleoperate the robot. It uses the OpenHaptics software [56] to obtain the state of the Touch's joints and buttons to render restoring forces and generate control commands. The restoring force allows operators to feel discrepancies between their input position command and the robot's actual gripper position. It helps prevent operators from moving the stylus faster than the robot can move.

3.1.4 Control Devices Mouse Control: On-screen buttons send the robot incremental commands for moving the base in *Base Control* mode. Sliders control the arm in *Arm Control* mode. Buttons control the head camera in both modes.

Gamepad Control: In *Base Control* mode, a joystick moves the robot's base, and in *Arm Control* mode, the joystick, along with other buttons, moves the arm. In both modes, a set of directional buttons controls the head camera.

Touch Control: In *Base Control* mode, a restoring force drives the Touch stylus' tip to the center of the Touch's workspace, where the robot will not move. Moving out of this center position will move the robot's base. In *Arm Control* mode, moving the stylus up and down moves the arm up and down, and moving it forward and backward extends and retracts it. The buttons on the stylus open and close the gripper. Pressing and holding both buttons simultaneously allows operators to move the head camera. Clicking both buttons once can engage and disengage the controls, allowing people to move the stylus freely without moving the robot. This allows users to reposition the stylus or step away from the robot.

Control Interface: We designed the interfaces to meet the following requirements: 1) Provide a visually coherent interface with icons for control device components and on-screen "cheatsheets" that illustrate control mappings, 2) Offer visual feedback on the range of motion for each DOF, and how user inputs alter the MTR's current pose, 3) Provide a modal interface to limit simultaneous commands and minimize the risk of unsafe actions, and 4) Provide multiple camera views for situational awareness.

4 Methodology

We ran an in-person, mixed methods study with 63 participants to evaluate the effects of different control devices (mouse, gamepad, Touch) on task performance, system usability, cognitive load, perceived safety, and sense of control. Participants remotely operated an MTR (Stretch) with an assigned device in a cafe setting, completing tasks requiring navigation, manipulation, and interaction. Following the recommendations of [57], we chose a between-subjects design, to minimize participants' time commitment and reduce confounding factors that come with repeated interactions, such as fatigue, frustration, and learning effects. This study was approved by the UC San Diego IRB. Participants received a gift card ($25 USD) for their participation.

4.1 Participants

We conducted a power analysis using the G*Power software [58] for a linear multiple regression F test to detect potentially medium effect sizes ($f^2 = 0.15$) [59] for one predictor with power of $\beta = 0.80$ and $\alpha = 0.05$. To ensure equal numbers of participants used each control device, we aimed to recruit at least 57 adults. We recruited 64 adults through word of mouth and social media, with one excluded due to a system error. All provided informed oral consent.

Participants were of different ages (18-24: 55.6%, 25-34: 30.2%, 55-64: 11.1%, 65+: 3.2%), genders (male: 38.1%, female: 58.7%, transgender: 1.6%, prefer not to answer (PNA): 1.6%), and ethnicities (asian american/asian: 49.2%, white/caucasian: 25.4%, hispanic/latine: 11.1%, middle eastern/north african: 3.2%, multiple: 7.9%, PNA: 3.2%). 32 participants reported prior experience controlling robots. 18 reported being current gamers, while 38 had played video games in the past. 38 participants had prior experience with gamepads. Participants were randomly assigned to test only one control device while using NORTE. We will refer to participants who used Mouse, Gamepad, and Touch as M#, G#, and T#, respectively.

4.2 Procedure

The study took about 1.5 hours, and was split into three parts: training, teleoperation with an assigned control device, and surveys.

First, participants learned about Stretch, and how to teleoperate it with their assigned control device by watching short videos. Then, participants practiced using it to complete a sample task: picking up and replacing two objects on a table. They also practiced using the robot's camera to look around the remote environment. After the structured training, participants continued practicing the controls until they felt comfortable. In total, training took about 35 minutes.

Then, participants were briefed on the main tasks they would need to complete. Participants received a paper checklist and were told to check off tasks as they went. For our study scenario, we chose a cafe context, similar to [60–62], as it is a familiar social setting for most people. Participants were asked to imagine they worked at a cafe but could not work in person, so they would serve customers via a telepresence robot. The mock cafe included a host station, a customer table, and a drinks table. Two experimenters acted as a customer and staff member at the cafe. Participants remotely operated the robot in the mock cafe from a different room.

Participants conducted three types of tasks, each repeated three times. **Navigation tasks** involved going to an X-marked spot at the customer's table, the drinks station, and the host station. **Interaction tasks** included greeting the customer, taking their order, telling them their order would be ready soon, and conveying their order to the staff. **Manipulation tasks** included handing a menu

to the customer, picking up a cup from the drinks station, and placing the cup on the customer's table. To reduce order effects, we had three versions of the scenario, with the task types in different orders. Participants were randomly assigned to each version.

Participants had 30 minutes to complete the scenario, and were given a list of reminders for controlling the robot, a cheatsheet with the control mappings, and a map of the cafe. The researcher left the room to avoid the Hawthorne effect. After the scenario, participants completed a demographics form and a questionnaire that consisted of NASA-TLX [63], System Usability Scale (SUS) [64], the perceived safety (PS) scale [34], and the sense of control (SoC) scale [34]. They also answered open-ended questions about their experience with the system and opinions on automation.

4.3 Data Collection and Analysis

Task performance was measured by two experimenters, who recorded task completions, time taken, and the number of errors. We predefined the evaluative criteria before running the study through extensive piloting. To be considered complete for *Navigation*, *Interaction*, and *Manipulation*, participants had to reach the designated location, speak to the correct person, and successfully manipulate the correct object, respectively. Errors included: arm and base collisions, dropping or dragging items, moving in the wrong direction, making the customer reach off the table for the menu, forgetting the customer's order, and doing the tasks out of order. If a participant did not complete a task, we recorded either the errors made during their attempt or the maximum errors observed among those who completed the task, whichever was greater, following a worst-case scenario imputation strategy as suggested by [65].

Two experimenters independently reviewed video footage of each participant, recording task start and stop times, as well as any unrelated actions or interventions. They compared times, and noted and rechecked discrepancies that were over 10 seconds until they were resolved. Each participant's time was calculated as the average of both experimenters' recorded times. Any intervention time was subtracted. If a participant did not complete a task, we recorded either the time they spent attempting it or the maximum time taken by those who completed it, whichever was greater.

Statistical analyses were conducted using RStudio (v2024.4.2.764) and Jamovi (v2.3) [66, 67]. Participant feedback from open-ended questions was analyzed using reflexive thematic analysis [68].

5 Quantitative Findings

5.1 Descriptive Statistics

5.1.1 Task Performance Times are reported in minutes (min) and seconds (s). On average, participants took 16 min 11 s (±11 min 2 s) to complete approximately 89% of tasks across all devices and task types. Task-specific information is as follows: *Navigation* (84% ± 25%; 5 min 34 s±3 min 23 s), *Manipulation* (92% ± 23%; 9 min 11 s±8 min 29 s), and *Interaction* (92% ± 18% 37.2 s±20.3 s).

Mouse (11 min 37 s±4 min 17 s) users were the fastest overall, followed by the gamepad (15 min 49 s±11 min 40 s), and then the Touch (21 min 7 s± 13 min 14 s) users. Gamepad (9 min 7s± 8 min 30 s) and Touch (12 min 33 s± 10 min 52 s) users required almost double the time for *Manipulation* tasks compared to those using the mouse (5 min 54 s±3 min 11 s).

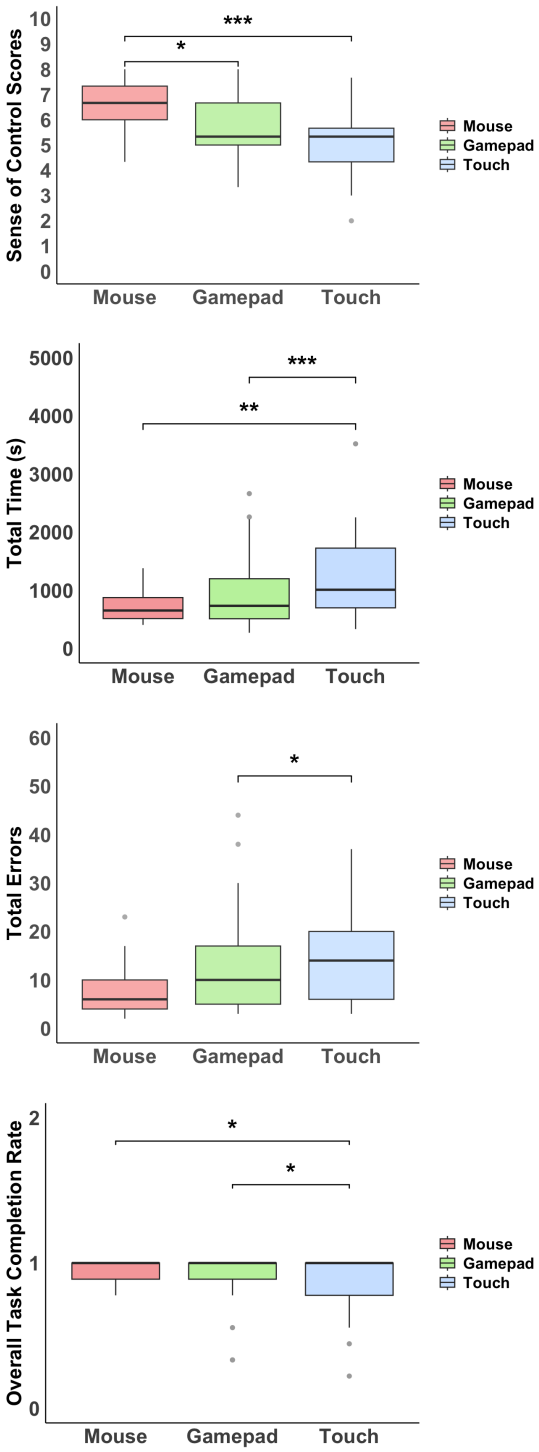


Figure 3: Descriptive Statistics of (from top to bottom) Sense of Control scores, Total Time taken, Errors made, and Completion Rate for each of the three control devices (Mouse, Gamepad, Touch). Statistical significance is marked based on results from multiple linear regression, adjusted for covariates.

On average, participants made 11.7 errors (±9.4). Most errors occurred during *Manipulation tasks* (8.2 ± 6.4). Participants made fewer overall errors with the mouse (7.7 ± 5.1), followed by the gamepad (13.5 ± 11.7), and then the Touch (13.9 ± 9.2). This trend appeared in *Manipulation* and *Interaction* tasks; however, in *Navigation* tasks, participants made the most errors with the gamepad.

5.1.2 Sense of Control (SoC) and Perceived Safety (PS) Average SoC score was 5.7 (±1.3). Mouse users had the highest SoC (6.5±0.9), followed by gamepad (5.7±1.2), and then Touch (5.0±1.3). Average PS score was 3.3 (±0.8). Mouse (3.6 ± 0.7) users had the highest PS, followed by the gamepad (3.2 ± 0.8), and then Touch (3.2 ± 0.7).

5.1.3 System Usability and Cognitive Workload Average SUS scores were 58.6 (±17.4). Mouse (63.8 ± 15.5) was the highest, then gamepad (56.9 ± 15.9), and finally, Touch (55.1 ± 19.9). Average raw NASA-TLX score was 36.9 (±17.0), with the Touch (42.3 ± 15.4) yielding the highest cognitive workload, followed by gamepad (38.5 ± 16.9), and mouse (29.8 ± 16.8).

5.2 Statistical Analysis

5.2.1 Task Performance Metrics Task performance metrics violated normality assumptions (Shapiro-Wilk, all $p < .001$), and Levene's test indicated unequal variances for total task time and errors. Thus, we used non-parametric analyses.

Spearman's correlation, with Bonferroni correction, showed total task time was significantly correlated with completion rate ($r_s = -.64$) and errors ($r_s = .82$). Errors was correlated with completion rate ($r_s = -.60$; all $p < .001$). Partial correlation analyses suggested that the intercorrelations may be accounted for by total task time. The partial correlation between total task time and completion rate ($r = -.31$, $p < .05$), as well as with errors ($r = .71$, $p < .001$), was significant. Completion rate and errors were not partially correlated ($r = -.19$, $p > .05$).

5.2.2 Sense of Control and Perceived Safety SoC and PS scores correlated positively ($r_s = .68$, $p < .001$), consistent with prior work [34, 53].

5.2.3 Sense of Control and Task Performance SoC scores were significantly correlated with completion rate (r_s = .35, p < .01), errors (r_s = -.50, p < .001), and total task time (r_s = -.42, p < .001), indicating that those who performed better also reported a greater sense of control.

5.2.4 Task Version and Task Performance Kruskal-Wallis test showed efficiency ($H(2) = 0.67$), completion rate ($H(2) = 0.43$), and errors ($H(2) = .61$) were not significantly affected by task version (all $p > 0.05$), indicating no order effects.

5.2.5 Gamepad Experience and Task Performance With Wilcoxon rank-sum, we found that gamepad users (median=667.2s) were significantly faster than non-users (median=947.5s; $W = 617$, $p < .05$, $r = -.25$). Errors ($W = 580.5$, $p > .05$, $r = -.19$) and completion rate ($W = 394$, $p > .05$, $r = -.16$) did not differ between groups.

5.2.6 Robot Control Experience and Task Performance With Wilcoxon rank-sum, we found that participants with prior robot control experience (median = 573.8s) completed the task significantly faster than those without such experiences (median = 875.0s; $W = 311$, $p = .01$, $r = -.32$). They also made significantly fewer errors (median = 6 vs. 11; $W = 350.5$, $p < .05$, $r = -.25$). Completion rate did not differ significantly between groups ($W = 581.5$, $p > .05$, $r = .19$).

5.2.7 Video Game Experience and Task Performance We grouped participants by gaming experience: current gamers, former gamers, and never-gamers [69]. Kruskal-Wallis revealed significant effects of gaming experience on task times ($H(2) = 6.30$, $p < .05$) and errors ($H(2) = 8.08$, $p < .05$), but not completion rate ($H(2) = 3.59$, $p > .05$). Current gamers were significantly faster than former gamers and made fewer errors. Current gamers also made fewer errors than never-gamers (all $p < .05$). There was no major difference in task times between current and never-gamers, likely due to the lack of never-gamers among Touch users. The findings suggest that current gaming experience reduces errors.

5.3 Effects of Control Device on Performance and SoC

We used multiple linear regression (MLR) to assess the impacts of control devices. Initial models included all variables related to prior experience with various controllers. Non-significant variables were subsequently excluded to reduce overfitting. Here, we report results obtained from the final models (see Supplement).

5.3.1 Completion Rate Control device significantly affected completion rate, controlling for task times and prior gamepad experience ($F(4, 58) = 49.4$, $p < .001$, $R^2 = .773$). Gamepad ($\beta = -.074$, $p < .05$) and Mouse ($\beta = -.069$, $p < .05$) had significantly lower completion rates than Touch. Gamepad did not significantly differ from the mouse ($\beta = -.006$, $p > .05$).

5.3.2 Total Task Time Control device significantly impacted total task time, controlling for completion rate, errors, and gamepad experience ($F(5, 57) = 74.0$, $p < .001$, $R^2 = 0.867$). Relative to the Touch, both the mouse ($\beta = -241.8$, $p < .01$) and gamepad ($\beta = -296$, $p < .001$) were significantly faster. Mouse and gamepad did not significantly differ ($\beta = 54.2$, $p > .05$).

5.3.3 Task Errors Control device significantly affected errors, adjusting for task times and gamepad experience ($F(4, 58) = 49.9$, $p < .001$, $R^2 = 0.775$). Users made significantly more errors with gamepad than with Touch ($\beta = 3.76$, $p < .05$). Mouse did not significantly differ from gamepad ($\beta = -2.67$, $p > .05$) and Touch ($\beta = 1.08$, $p > .05$).

5.3.4 Sense of Control and Perceived Safety Control device significantly affected SoC ($F(2, 60) = 8.52$, $p < .001$, $R^2 = .22$), but not PS ($F(2, 60) = 1.72$, $p > .05$, $R^2 = .05$). Mouse users had significantly higher SoC than gamepad ($\beta = .87$, $p < .05$) and Touch users ($\beta = 1.49$, $p < .001$), while gamepad and Touch users did not differ ($\beta = .62$, $p > .05$).

5.3.5 Sense of Control and Performance SoC significantly affected total task times ($F(5, 57) = 8.34$, $R^2 = 0.422$), errors ($F(5, 57) = 9.64$, $R^2 = 0.458$), and completion rate ($F(5, 57) = 8.57$, $R^2 = 0.429$) with all $p < .001$ after adjusting for control device and its interactions with SoC. Participants with higher SoC performed significantly better across all metrics: task times ($\beta = -395$), errors ($\beta = -5.39$), and completion rate ($\beta = .011$). Interaction effects between SoC and control device were significant for total task time and completion rate (all p<.05), but not for errors. These results

indicate that the type of control device moderates the significant effect of SoC on total task time and completion rate.

5.3.6 System Usability and Cognitive Load We found no significant effects of control device on SUS or raw NASA-TLX, even when controlling for gamepad experience.

6 Qualitative User Feedback

6.1 Control Device-Specific Feedback

6.1.1 Mouse Participants thought that they could "get the hang of [mouse controls] very quickly" (M59). Two participants noted the need to "complete each action individually," which "made [their] progress…very slow." Some participants also faced difficulties using the sliders for fine arm movements. M8 reflected, "while this robot system is very easy to learn, it is not at all intuitive."

6.1.2 Touch Several participants found stylus-based control "easy to learn." Others expressed difficulties with the restoring force of the stylus, describing it as "slippery" and that it "was fighting against me the entire time" (T13). Another stated, "hand felt strained […] felt like I was having to use a lot of force on the controls to get the robot to do what I wanted" (T7). To mitigate this, several suggested allowing users to "determine how sensitive certain inputs are" (T37). A few others mentioned that "holding up the stylus for extended periods" (T25) could "cramp the user's hand" (T6).

6.1.3 Gamepad Participants with gamepad experience found the controls straightforward and suggested aligning them more closely with familiar gaming conventions. Those without such prior experience thought it would be "more user-friendly for someone with experience in a [game] controller" (G36). Some also struggled with control sensitivity: "the UI did help me get used to the controls however […] felt as if my inputs would be more stronger than I anticipated and it took some time getting used to" (G45).

6.1.4 Alternate forms of control Several mouse and Touch users suggested controlling the robot with a keyboard, as it would be "more accessible," especially for gamers (T31).

Another participant suggested having a digital robot twin on screen, as "it would be cool if […] you stretch the arm out on your miniature robot then the arm on the actual robot would stretch out" (M56). Others wanted to leverage familiar forms of control inspired by daily life, such as a "steering wheel with a gas pedal" (T58).

6.2 Telepresence Should be Human Controlled

Overall, the findings indicate that if automation is to be included, it should be balanced with user control. Many strongly felt that "interacting with people should be fully controlled by the user" (M20) to "add the personal touch" (G27) and "retain the human-to-human interaction, even if it's through a computer" (G2). However, another participant felt "completing all the tasks manually required a lot of focus and all my people skills went away" (G5). One proposed that the robot could "auto-align itself" (M1) to maintain "eye contact [and] better preserve the sense of human customer service" (G45).

Some wanted to simplify navigation, similar to how "a Roomba [moves] by itself and I could be the one telling it when to stop moving" (T43). Participants also suggested features like force limiting the gripper to avoid "squeez[ing] the life out of things" (M8). However, "things that are harder to grab should still be done with someone controlling the device" (T46).

M38 thought that more time and experience with the robot is needed to "distinguish between not getting the hang of controls versus [needing automation as] a design choice that could make the user experience better."

7 Discussion

7.1 Control Device and The Role of Autonomy in Teleoperation

With our findings in mind, we reflect on a broader question: Is autonomy key to improving direct teleoperation, or can advancements in control device design play an equally vital role? This question is timely given ongoing debates in HRI on how to balance usability, task performance, and agency.

We contribute to this growing body of work by demonstrating that the relationship between task performance (in terms of speed, completion rate) and SoC is moderated by the type of control device used. We observed that mouse users had the best performance and SoC, while users of other devices had more variable tradeoffs in terms of errors, speed, and completion rate. There were no significant differences among them in terms of usability and cognitive workload.

Furthermore, participants with a higher SoC tended to perform better and have higher perceived safety in our study, and those with a lower SoC worse, regardless of the control device.

This suggests that carefully scrutinizing the usability of control devices and adopting a user-centered design approach could greatly improve the quality of users' direct teleoperation experiences in terms of both task performance and user experience. This is a promising path forward for HRI research, given that several studies have shown that users prefer having full control over the robot regardless of their performance improvements from shared autonomy [2, 17, 18, 20]. However, this focus on direct teleoperation is not mutually exclusive from research in shared autonomy.

Indeed, the correlation between performance and SoC raises interesting questions about when and how to provide users with direct control versus supporting them with carefully applied shared autonomy assistance. Building on our work, future research could examine how varying degrees of shared autonomy influence users' SoC and performance when teleoperating with different control devices. This may help us better understand the complex relationships between control devices, robot autonomy, and user experience.

Even so, the development of shared autonomy systems should not occur at the expense of increasing the usability of teleoperation interfaces and control devices. Direct teleoperation may be necessary in contexts where autonomous assistance may fail, or is inappropriate [2, 17, 18]. For instance, many of our participants strongly indicated that they should have full control over social interactions. In such cases, it will be important for users to have well-designed control devices that allow them to easily interact in the remote environment.

Ultimately, our results show that the medium through which users control the robot can have large impacts on both performance and SoC, highlighting the importance of improving device design.

7.2 Device Design Challenges and Recommendations

To improve control device design, we need to critically examine how users interact with different device characteristics. Drawing on our findings, we identify key challenges encountered by participants and offer design considerations for teleoperation control devices.

7.2.1 Scaling and Mapping User Input to Robot Motion In our study, mouse users generally outperformed. This may be in part due to the mouse only allowing inputs for one DOF at a time, whereas both the gamepad and Touch supported simultaneous, multi-DOF control across physically coupled input axes. While this design supports more fluid robot movements, it also increases the risk of unintended inputs. This is exacerbated by the challenges of scaling user inputs to robot motion in unconstrained settings; small hand motions can produce large robot movements, making fine control difficult. This oversensitivity leads to frequent corrections and thus, degraded SoC, PS and performance. *Recommendation:* Since there may be individual differences in sensitivity and preferences, we suggest providing users with customizable robot motion scaling based on device, task, and workspace constraints like [70], and options for single or multi-DOF control.

7.2.2 Kinematic Dissimilarity, Ergonomics, and Force Feedback in Haptic Devices Touch users generally had the longest task completion times and the least SoC compared to mouse or gamepad users. This may be because the Touch has 3 DOFs, and the MTR has 7 DOFs, which often caused participants to struggle with mapping stylus movements to the robot. In addition, participants reported substantial physical discomfort and fatigue, as users had to maintain their stylus position and overall posture to avoid unwanted robot movements, especially during precise manipulation tasks. These issues were exacerbated by its restoring force, which was intended to support mode switching and system transparency. Instead, participants felt they were "fighting" the device and needed to exert extra effort to perform desired actions.

Participants may have been unsure why the force was activated and what it means. This made it difficult for participants to effectively issue commands with the device and work with, rather than against, the restoring force. Ultimately, the lack of predictability made them feel less in control, causing lower SoC and poor performance compared to other devices. This aligns with [71], which found that increased jerk intensity reduces sense of agency/embodiment in human-machine interactions. Yet, it is also likely that it is this restoring force that enabled Touch users to more precisely control the robot, and thus have fewer errors and a higher task completion rate compared to gamepad users.

Recommendations: We recommend exploring how visual feedback may augment user interpretation of force feedback during teleoperation. While haptic feedback provides instantaneous information, combining it with visual cues leads to a richer and more contextual understanding of the robot's capabilities and remote workspace [72, 73]. This range of perceptual cues increases system transparency, and the visuo-proprioceptive synchronicity can lead to higher SoC as shown in [74]. It would also help support different interaction styles, as it is noted that a remote operator's spatial cognitive ability and temporal sensitivity affect teleoperation performance (c.f.[75–78]).

We also suggest drawing from Tangible User Interaction (TUI) to develop new user-centered, reconfigurable control devices alongside target populations. It would allow users to customize both the physical form of the device and their mappings according to their ergonomic preferences, the robot's kinematics, and the requirements of the specific task, improving SoC and overall user experience. For instance, the device could have an end-effector that is kinematically similar to the robot's (e.g., forceps, instrumentable tongs) [79–84]. To assess and adjust the ergonomic comfort of new device designs, we suggest performing physical fatigue analysis, similar to [14, 85].

7.2.3 Device Unfamiliarity and Einstellung Effect Several participants wanted other control devices or interaction schemes they were more familiar with. This may be explained by the *Einstellung effect*, a cognitive bias in which individuals default to known interaction strategies, even when unfamiliar options may be more appropriate [86, 87]. This bias can limit users' willingness to experiment with new or complex interfaces and to tolerate the short-term performance dips often required to develop expertise [88].

Recommendations: We suggest leveraging principles from video game tutorials for user training [89]. Users could begin with a simplified interface where certain controls are initially locked while they receive minimal, targeted guidance to complete proximal goals. As users demonstrate competence, additional functionalities can be gradually introduced. This approach supports skill acquisition while helping users overcome initial bias against unfamiliar controls.

7.3 Limitations and Future Work

Our study had a few limitations. First, SoC was assessed primarily through subjective self-reports, which may not fully capture the complexity of this phenomenon. In future work, we plan to explore additional methods to quantify users' SoC during teleoperation, such as the approach recently proposed in [90], which was published after we conducted our study. Second, while participants operated the robot for one hour, their perceptions of the robot may change as they operate it over even longer periods of time or repeated interactions. Thus, we plan to explore NORTE and its associated control devices with our collaborators in real-world settings (e.g., hospitals, museums) over longer durations in future work. We also hope to explore the generalizability of our findings across other robot platforms and contexts, though we note several of our gamepad/Touch findings are already consistent with [14].

7.4 Conclusion

In this paper, we presented findings from our study on social telepresence, evaluating the impacts of three control devices highly relevant to HRI to remotely teleoperate MTRs. Our results show that the choice of control device significantly impacts the relationship between task performance and sense of control during direct teleoperation. Additionally, participants with a higher SoC tended to perform better. Based on our findings, we discuss the role of autonomy in teleoperation and recommend paths forward for HRI researchers to improve control device design. By exploring the impacts of control devices, our work informs the HRI community on the design of future user-centered direct teleoperation systems, and contributes to ongoing conversations on the tradeoffs between usability, task performance, and agency in social telepresence.

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