TeleDriver: A Driving Simulator-Inspired Technique for Steering Telepresence Robots

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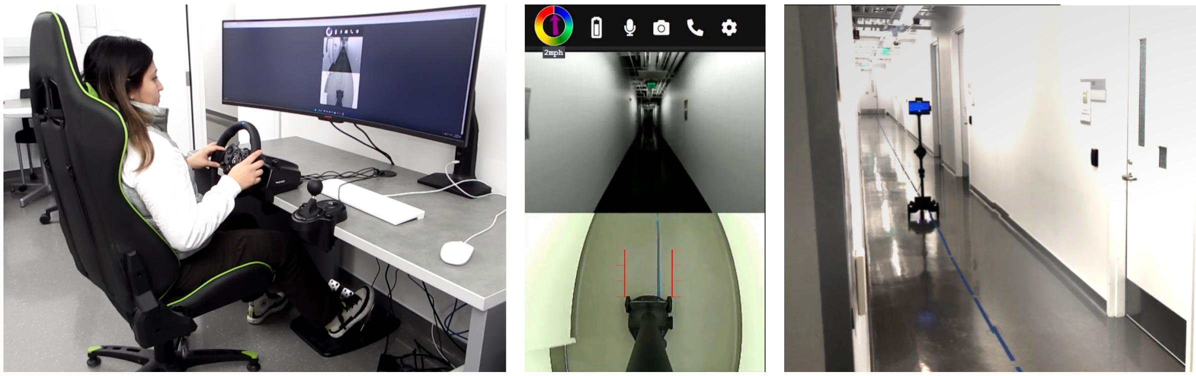


Figure 1: TeleDriver allows operators to control telepresence robots using a driving simulator, mapping the steering wheel, gear shifter, gas pedal, and brake pedal to robot actions. The figure shows an operator, the control interface, and the robot in action.

Abstract

We introduce TeleDriver, a system inspired by driving simulators that maps motor vehicle controls to corresponding telepresence robot actions. We conducted a study to compare TeleDriver with a traditional desktop interface among both drivers and non-drivers. The study revealed that drivers could effectively transfer their driving skills to TeleDriver, completing tasks 23% faster and with 39% fewer errors compared to the default method. In contrast, non-drivers were 26% slower and made 147% more errors using TeleDriver. Performance was comparable between drivers and non-drivers when using the default method. Notably, both groups demonstrated learning with TeleDriver. By the final trial, drivers were 17% faster and 58% more accurate, while non-drivers were 13% faster and 63% more accurate compared to their initial performance.

Keywords

Control Interface, Embodiment, Maneuver, Out-of-sight Robots, Racing Wheel, Remote, Robotics, Skill Transfer

ACM Reference Format:
Ghazal Zand and Ahmed Sabbir Arif. 2025. TeleDriver: A Driving Simulator-Inspired Technique for Steering Telepresence Robots. In *The PErvasive Technologies Related to Assistive Environments (PETRA '25), June 25–27, 2025, Corfu Island, Greece.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3733155.3733208

PETRA '25, Corfu Island, Greece

ACM ISBN 979-8-4007-1402-3/25/06
https://doi.org/10.1145/3733155.3733208

1 Introduction

Telepresence robots equipped with videotelephony allow people with limited mobility to visit places and participate in events remotely using robots as avatars [14]. Although these robots can be owned personally, they are also envisioned as shared resources [31]. For example, a hospital can maintain a fleet of telepresence robots for patients to operate remotely to consult physicians. This shared usage model can improve accessibility for people with limited mobility and those in rural areas with limited transportation options, while also expanding access to education, healthcare, rehabilitation, and other essential services for economically disadvantaged communities [14, 45, 51]. However, a significant challenge for the widespread adoption of telepresence robots is the difficulty in operating them effectively [50]. Users often find tasks such as adjusting and maintaining speed, turning, and reversing the robot tedious and cognitively demanding, leading to errors such as robots backing into walls or colliding with obstacles [3, 23, 33, 37].

This work proposes a contemporary approach to operating telepresence robots. Instead of relying on conventional desktop and mobile applications that use keyboards, mice, joysticks, or touchscreens, it envisions a dedicated control station equipped with a driving simulator. Such stations could be set up at home or in shared spaces such as libraries or local community centers for communal use. The aim is to exploit the existing driving skills of user by allowing them to control telepresence robots using a driving simulator equipped with a steering wheel, pedals, and gear shifter.

Although driving cars and operating telepresence robots involve some similar actions, people are generally more proficient at maneuvering automobiles than at remotely controlling telepresence robots. This disparity has been linked to the idea that automotive interfaces become extensions of our embodied cognition, encompassing not only the driver's mind and body, but also the automobile itself [40, 52]. Automotive interfaces employ different physical controls for specific actions, such as a steering wheel for navigation, a gear shifter for transmission and reverse motions, and pedals for speed control, which engage different parts of the body. This physical interaction fosters a sense of embodiment and supports intuitive control. In contrast, telepresence robots often depend on virtual controls, which lack the tactile and distributed engagement of automotive systems. Therefore, we hypothesize that operating a telepresence robot through a driving simulator can evoke a sense of embodiment similar to driving an automobile. This could enable faster learning while providing a more effective and enjoyable interaction experience [21, 34].

The contribution of this work is thus threefold. First, we design TeleDriver, an interactive system inspired by driving simulators that maps driving controls to telepresence robot actions. Second, we examine whether the driving analogy facilitates faster learning by transferring automotive skills to telepresence robots. Finally, we explore whether operators without driving experience can learn the method with some practical practice.

2 Related Work

This section reviews various control systems for telepresence robots and studies examining skill transfer between different systems.

2.1 Control Interfaces

Most interactive systems for controlling telepresence robots rely on desktop setups with keyboards and mice [50]. Bazzano et al. [4] introduced a keyboard-based method in which operators used arrow keys to manually steer the robot and a point-and-click approach in which operators selected a destination on the robot's camera feed for autonomous navigation. Their study showed that the keyboard-based method allowed for faster task completion with fewer interactions compared to the autonomous approach. Similarly, Mishra et al. [27] developed a keyboard-based method along with an autonomous approach that first identified the face of a person and then followed them. However, these methods were not evaluated in user studies. Mosiello et al. [28] improved the point-and-click method by projecting the dimensions of the robot onto the driving surface, enhancing the spatial awareness of the operators. Macharet and Florencio [23] proposed semi-autonomous and autonomous control methods to reduce collisions. The semi-autonomous approach used keyboard arrow keys for steering while the robot avoided obstacles automatically. The autonomous method allowed operators to select a direction with a mouse, and the robot navigated autonomously. In an evaluation, the autonomous method achieved the fastest task completion time and the fewest collisions. In a different study, Rae et al. [38] compared Skype videoconferencing on a tablet with telepresence robots controlled through a desktop application. The results indicated that the telepresence robots increased trust between the operators and the participants. Naseer et al. [30] employed deep reinforcement learning and deep deterministic policy gradient algorithms to address delayed signal scenarios, with simulation results suggesting reduced control tracking errors and improved training effectiveness.

Although joysticks and gamepads are widely used to control surgical, mining, or delivery robots, they are rarely used for telepresence robots [50]. However, academic research has investigated their potential for telepresence and other remotely operated robots. Zalud [48] developed a two-handed joystick system for robot teleoperation, while Promsutipong et al. [36] combined a joystick with a treadmill for directional control. Neither method was comparatively evaluated. Zhang and Hansen [51] demonstrated that joystick control in virtual reality (VR) outperform gaze tracking, resulting in fewer collisions and reduced workload. Kratz et al. [17] improved the control of telepresence robots by integrating a joystick with a VR headset, and immersion by utilizing stereoscopic video and head tracking. Xu et al. [46] found that a gesture-based motion glove enabled faster task completion than joystick controls, but users preferred joysticks for ease of use. In a broader comparison, Björnfot [5] evaluated input devices such as keyboards, mice, game controllers, and dance pads, and concluded that keyboards are the most reliable, but game controllers offer the fastest performance.

Some researchers have used gaming steering wheels and floor pedals to remotely control out-of-sight robots. Kružić et al. [18] developed two control systems: one using a gamepad and another employing a gaming steering wheel with integrated keys. However, a comparative study found no significant differences in task completion time or precision between these methods. Similarly, Megalingam et al. [26] created a steering wheel-based control system, though it was tested only in simulations. Halme et al. [12] explored five configurations of steering wheels and floor pedals, combined with various sensory setups including stereo and monovision, with/without display, head tracking, and fixed cameras. Their findings suggested minimal performance differences between the systems once the operators mastered the task. Ott et al. [32] explored two methods for robot operation: one using arm motion and the other combining a steering wheel and throttle with a haptic device for force feedback. Their findings showed that the arm motion method led to improved task completion times. Likewise, Yang et al. [47] used a force feedback steering wheel to navigate a tank-type rescue robot, although this was not tested in a user study. These studies used gaming steering wheels as substitutes for traditional controllers, either relying on built-in keys and triggers or enhancing them with motion sensors and head trackers. Most systems omitted the use of a gas pedal. In contrast, our approach seeks to replicate an authentic automobile-like driving experience by meticulously mapping automobile controls to robot operations.

Many researchers have developed interfaces for controlling telepresence robots using mobile devices. Ainasoja et al. [1] introduced a tilt-based control method where operators tilted their mobile device to move the robot and rolled it to turn. Although this method achieved a faster task completion time, users preferred a touch-based alternative. Similarly, Zand et al. [50] designed a one-handed tilt-based method in which operators simultaneously tap the screen and perform directional tilts to steer the robot. This method outperformed a conventional touch-based interface in speed, accuracy, and user preference. Kashi et al. [15] proposed a voice command method for smartphone-based telepresence robot control, but it has not yet been evaluated. Zand and Arif [49] developed a finger-wearable mouse to map typical mouse actions to robot operations. This approach required fewer actions to complete tasks, significantly reducing task completion times compared to a keyboard-based method. Most of these studies focused on task completion times and subjective feedback, with little attention to error rates. In contrast, our work takes a holistic approach, incorporating quantitative and qualitative analyses while assessing a broader range of errors, including collisions, wrong turns, and speed maintenance.

2.2 Skill Transfer

Cognitive psychology suggests that humans can transfer skills learned from one context to new situations [19]. This transfer is more effective when a task has been practiced extensively, allowing for the adaptation of learned techniques to different scenarios. In fact, transferring skills from related tasks can be more effective than direct training in a new task [22]. Such as Komar et al. [16] showed that people with prior experience in striking skills perform better in softball batting than novices without such experience. In computer systems, metaphors facilitate skill and knowledge transfer, making complex systems more intuitive [25]. For example, Fels et al. [10] used musical metaphors in a digital sound tool to clarify device operation, while Siio and Tsujita [43] implemented a paperweight metaphor for mode switching in mobile devices, both improving user understanding. Rakhmetulla and Arif [39] demonstrated that users can transfer their keyboard layout skills to a new layout when using the other as a metaphor. Here, we concentrate on metaphor-driven skill transfer in driving interfaces.

Regan et al. [41] found that the driving skills developed in a simulator generalize effectively to real-life traffic situations, applicable in both similar and unfamiliar scenarios. Pradhan et al. [35] also noted that those trained in a simulator exhibit enhanced risk awareness, even in situations not covered during training. Fisher et al. [11] compared the skills of novice drivers trained with a driving simulator to those without such training, observing better performance, increased hazard awareness, and a reduced likelihood of crashes among the trained group. Allen et al. [2] reported significant improvements in novice driving behavior after PC-based training. Furthermore, de Winter et al. [9] identified a significant correlation between novice drivers' performance in simulators and their on-road driving test results, suggesting a transfer of skills and behaviors from the simulator to real-world driving. Beyond automobiles, Dannenhoffer and Green [8] demonstrated that flight simulation training leads to a deeper understanding of aspects like aircraft stability. Large et al. [20] compared the performance of novice and experienced train drivers in a simulation, discovering that while the simulated performance of novices was comparable to that of experienced drivers, their actual train handling skills were less developed. Another study on simulating the motion and field of view of real trucks found improvements in drivers' abilities to reverse park real trucks [44].

While most of these studies focused on transferring skills from computer simulations to real-world applications, our research takes a novel approach, aiming to transfer skills from the physical world to the digital domain, an idea that has received little attention in previous research.

3 TeleDriver

TeleDriver enables operators to control telepresence robots using a driving simulator, like driving an automobile. Its purpose is to exploit operators' preexisting driving skills, while providing a usable, easy-to-learn solution to non-drivers. It uses a "driving" metaphor by mapping driving interactions to corresponding telepresence robot actions: steering wheel to steer the robot, gear shifter for forward and reverse motions, gas pedal for increasing the speed, and brake pedal for decreasing the speed or a full stop. We mapped driving simulator controls to corresponding robot movements based on multiple lab trials.

The steering wheel and the pedals generate values in the range of $[-1, 1]$. The steering wheel's initial position is 0, and rotation in either direction generates a value up to 1 or -1 depending on the rotation direction. The values 1 and -1 are the results of full rotations. The pedals, in contrast, produce 1 in the initial position (not pressed) and -1 when pressed all the way down. The shifter has seven modes and their activation is identified by 0 (inactive) and 1 (active). We defined the gas pedal output as acceleration (*acc*) values and the brake pedal output as deceleration (*dec*) values, then mapped their output range $[-1, 1]$ to the robot's speed range $[-10, 0]$ and $[0, 10]$ for deceleration and acceleration values, respectively. We then determined the robot's current speed using the following equation.

$$V^t_{Robot} = (A * acc + B * dec)dt + V^{t-1}_{Robot} \tag{1}$$

Where V^t_{Robot} is the velocity of the robot at time t, $V^0_{Robot} = 0$, dt is a very small period of time $dt = 0.1$s, and A and B are constants. For safety, we set a bigger weight for the deceleration than acceleration, $A = 1$ and $B = 4$. Besides, lab trials revealed that these values better replicate automobile driving experience. Also, like an automobile, when the operator releases the gas pedal when the robot is at its maximum speed, it automatically slows down and makes a full-stop in 3 seconds. This time window was used for the safety of the robot and the bystanders, as immediate stops while at full-speed resulted in abrupt jumps forward in lab trials. The robot's direction is calculated directly from the steering wheel output (*stw*) using the following linear function.

$$\Theta^t_{Robot} = (450 * stw) \tag{2}$$

Where Θ^t_{Robot} is the robot's orientation at time t, and the steering wheel's full rotation angle is 450° in both directions. Table 1 summarizes the mapping between driving simulator controls and corresponding robot actions.

4 User Study

We conducted a user study to compare TeleDriver with the default Ohmni Telepresence Robot web application in terms of speed, accuracy, and perceived performance and workload. We selected the Ohmni web application as our baseline, reflecting the prevalent

Table 1: Mapping driving simulator controls to robot actions.

Simulator	Output	Robot Action	Mapping
Gas pedal	$[-1, 1]$	Increase speed $[0, 2]$ mph	Eq. 1
Brake pedal	$[-1, 1]$	Decrease speed or stop	Eq. 1
Steering wheel	$[-1, 1]$	Orientation $[0, 360°]$ Clockwise, counterclockwise	Eq. 2
Gear shifter (7 Modes)	0 or 1	Change direction of motion Forward, reverse, park	–

use of desktop applications operated with a keyboard and mouse for telepresence robot interaction. Our objective was not only to compare the performance between our proposed method and the most dominant approach, but also to explore the potential of drivers to transfer their driving skills to the system. Given this aim, we did not include input devices like joysticks or game controllers in the study as they were not pertinent to our study's goals.

4.1 Participants

We recruited 24 volunteers for the study. They were pre-screened for driving experience to form two groups: drivers and non-drivers. There were 12 participants in the drivers group. Their age ranged from 19 to 25 years (M = 20.67 years, SD = 2.1). Six of them identified as women and six as men. They all owned and drove cars for at least the last two years (M = 4 years of experience, SD = 2.4). The non-drivers group, too, had 12 participants. Their age ranged from 18 to 38 years (M = 21.58 years, SD = 5.8). Nine of them identified themselves as women and three as men. None of them had driving experience or had learned to drive or used a driving simulator prior to the study. All participants received US $10 for volunteering.

4.2 Equipment

We used an Ohmni Telepresence Robot in the study, consists of a 4K forward-facing camera, a wide angle downward-facing camera, and a 256.54 mm HD IPS touchscreen (Fig. 2). We developed a custom web application for controlling the robot's movements with TeleDriver. The baseline condition used the default Ohmni Telepresence Robot web application, described in Zand and Arif [49]'s work. Both apps were viewed on a Google Chrome browser on a Viotek 49 inch 32:9 curved monitor at 3840 × 1080 pixels. Although we could have used the full display to show the camera feeds in the custom app, we kept its dimension fairly comparable to the default app to eliminate a potential confound. We could not use the same interface for both methods because they require different controls and, consequently, different feedback mechanisms.

A Logitech G923 racing wheel and pedals for PlayStation 4 and PC (Fig. 2) were used to get control commands from operators (wheel size: 270 × 260 × 278 mm, pedals size: 167 × 428.5 × 311 mm). The wheel had the capability of a hall-effect steering sensor, 900 degrees rotation lock-to-lock, and an overheat safeguard. The pedals feature a nonlinear brake pedal, textured heel grip, and self-calibrating capability. Both systems were launched on a desktop computer (Intel Core i7, 16GB RAM) running on a Windows 11.

The default app used an HP Pavilion Keyboard and Mouse 200. The up and down arrow keys were used to move the robot forward and backward, respectively, and the left and right arrow keys were used for turning the robot left and right, respectively. The app also enabled adjusting the robot's velocity by dragging a horizontal slider at the left bottom corner of the app.

Figure 2: The robot and the setup used in the study.

4.3 Design

We used a 2 × 2 × 4 mixed-design for the study. There was one between-subjects variable with two levels (experience: drivers, non-drivers), and two within-subjects variables with two and four levels: method (default, TeleDriver) and trial (4 trials). The methods were counterbalanced to eliminate any potential effects of order. In each trial, participants navigated the robot through an obstacle path to the target, then brought it back to them (Fig. 3). This path was proposed in a previous work [50] to assure that participants are forced to use all robot control operations. The dependent variables were: **task completion time** (minutes), which signifies the average time operators took to navigate the robot to the target then bring it back to the initial position, and **error rate** (%), which signifies the average errors committed per task. An error was recorded when the robot collided with an obstacle, bumped into the corridor wall, took a wrong turn, or deviated one foot (~0.3 m) from the path.

4.4 Procedure

The study was carried out in a laboratory. The telepresence robot was out-of-sight in a nearby empty corridor. On arrival, we described the study procedure to the participants and collected their informed consent forms. Then, they completed a short demographic questionnaire and a questionnaire on technology usage.

In the study, participants operated a telepresence robot using the default method and TeleDriver in counterbalanced order. We demonstrated the methods ahead of use, and enabled participants to practice with each for 2–3 minutes. In each of the four trials, participants guided the robot through an obstacle path to the target, then brought it back to the initial position (Fig. 3) relying on the video feeds from the robot's forward and downward facing cameras. The ideal path was clearly marked with blue tape (Fig. 1). Participants were asked to complete the trials as fast and accurately as possible. Specifically, they were instructed to avoid collisions with obstacles and not to deviate beyond one foot from the path.

Upon completion of the study, participants were asked to complete two post-study questionnaires. One System Usability Scale

(SUS) [6] inspired custom questionnaire that asked participants to rate statements on the examined methods' speed, accuracy, learnability, ease-of-use, confidence, and enjoyment on a 5-point Likert scale. And the NASA-TLX questionnaire [29], where participants rated the examined methods' perceived workload in terms of mental, physical, and temporal demands, effort, and frustration on a 20-point scale. Both questionnaires included an open-ended section allowing participants to expand on their responses, offer comments on the methods evaluated, or give feedback.

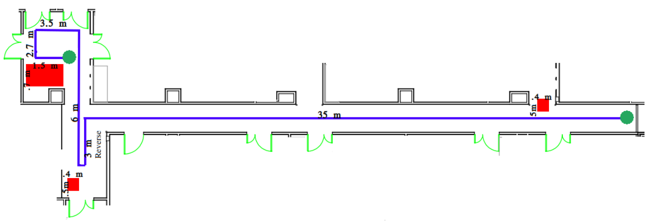
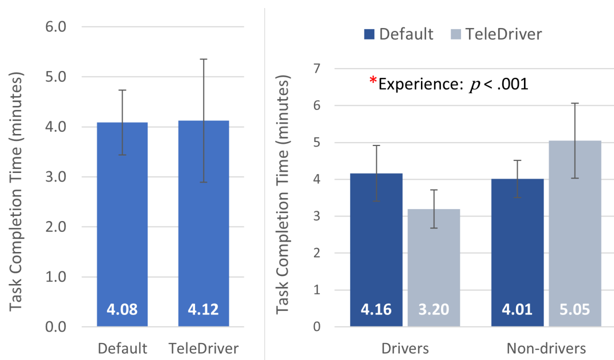


Figure 3: The obstacle path used in the user study. The blue line represents the path the robot followed, the red rectangles are obstacles placed on the floor, and the green dots represent the start point (right) and the target (left).

5 Results

A full study session, which included introduction, demonstration, breaks and questionnaire, lasted 45–60 minutes. Specifically for the experimental tasks, drivers averaged 29.4 minutes, while non-drivers took an average of 36.2 minutes.

A Martinez-Iglewicz test revealed that the response variable residuals were normally distributed. A Mauchly's test indicated that the variances of populations were equal. Therefore, we used a mixed-design ANOVA for all analyses. We used a Wilcoxon Signed-Rank test for the subjective data. We also report effect sizes for the statistically significant results, namely eta-squared (η^2) for ANOVA and Pearson's r for Wilcoxon Signed-Rank test.



(a) Overall **(b) By user group**

Figure 4: Average task completion times (minutes) with the two methods. The red asterisk indicates statistically significant difference. Error bars represent ±1 standard deviation.

5.1 Task Completion Time

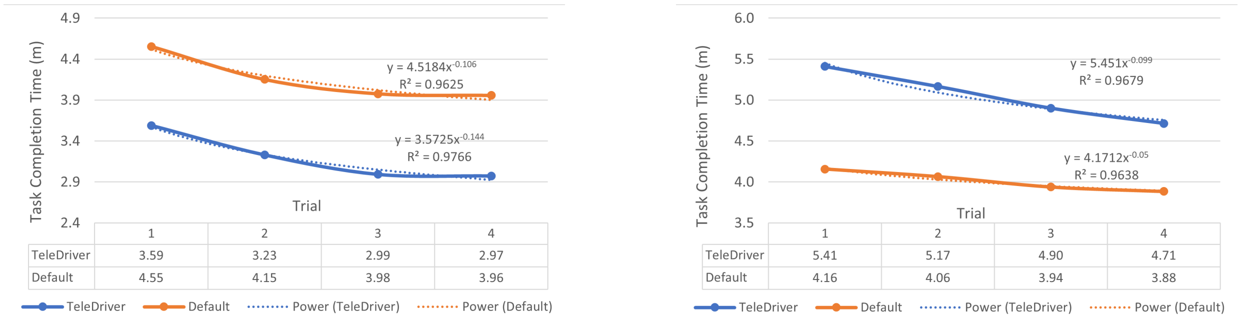
An ANOVA failed to identify a significant main effect of method on task completion time ($F_{1,22} = 0.05, p = .82$). The average task completion times with the default method and TeleDriver were 4.08 minutes (SD = 0.65) and 4.12 minutes (SD = 1.23), respectively (Fig. 4a). However, the main effect of experience ($F_{1,22} = 14.74, p < .001, \eta^2 = 0.19$) and the interaction effect of experience × method ($F_{1,22} = 40.02, p < .00001, \eta^2 = 0.26$) were statistically significant. Drivers required on average 4.16 minutes (SD = 0.76) and 3.2 minutes (SD = 0.52) to complete a task with the default method and TeleDriver, respectively. While, non-drivers took on average 4.01 minutes (SD = 0.51) with the default and 5.05 minutes (SD = 1.02) with TeleDriver to complete a task. Fig. 4b illustrates this. A Tukey-Kramer multiple-comparison test revealed that drivers were significantly faster with TeleDriver, while non-drivers were significantly faster with the default method. Relevantly, the test identified three distinct groups: {Drivers × TeleDriver}, {Non-drivers × TeleDriver}, and {Non-drivers × Default, Drivers × Default}, where {Drivers × TeleDriver} was significantly faster.

An ANOVA identified a significant effect of trial on task completion time ($F_{3,66} = 31.48, p < .00001, \eta^2 = 0.05$). A Tukey-Kramer multiple-comparison test revealed that both drivers and non-drivers were significantly faster in the last trial with both the default method and TeleDriver compared to the first trial. Fig. 5 illustrates average task completion times by trial for both drivers and non-drivers, fitted to power trendlines.

5.2 Error Rate

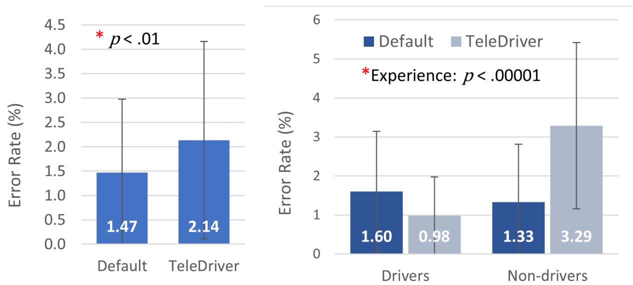
An ANOVA identified a significant main effect of method on error rate ($F_{1,22} = 8.22, p < .01, \eta^2 = 0.03$). The average error rates with the default method and TeleDriver were 1.47% (SD = 1.51) and 2.14% (SD = 2.02), respectively (Fig. 6a). The main effect of experience ($F_{1,22} = 9.96, p < .005, \eta^2 = 0.08$) and the interaction effect of experience × method ($F_{1,22} = 30.86, p < .00001, \eta^2 = 0.13$) were also statistically significant. Drivers committed on average 1.60% errors (SD = 1.54) with the default method and 0.98% errors (SD = 1.0) with TeleDriver. While, non-drivers committed on average 1.33% errors (SD = 1.48) with the default method and 3.29% errors (SD = 2.13) with TeleDriver (Fig. 6b). A Tukey-Kramer multiple-comparison test revealed that non-drivers committed significantly more errors with TeleDriver than the default method. However, no such effect was identified for drivers. The test identified two distinct groups: {Non-drivers × TeleDriver} and {Non-drivers × Default, Drivers × Default, Drivers × TeleDriver}, where the former committed significantly more errors than the latter. A deeper analysis of the data did not identify any significant difference in error distribution between the two user groups and the two methods (Fig. 7).

An ANOVA identified a significant effect of trial on error rate ($F_{3,66} = 24.41, p < .00001, \eta^2 = 0.15$). A Tukey-Kramer multiple-comparison test revealed that non-drivers were significantly more accurate in the last trial with both the default method and TeleDriver compared to the first trial. While, no such effect was identified with drivers. Fig. 8 illustrates average error rates by trial for both drivers and non-drivers, fitted to power trendlines.



(a) Drivers **(b) Non-drivers**

Figure 5: Average task completion times (minutes) by trial for the two methods fitted to power trendlines. Error bars represent ±1 standard deviation.



(a) Overall **(b) By user group**

Figure 6: Average error rates (%) for the two methods. Red asterisks indicate statistically significant differences. Error bars represent ±1 standard deviation.

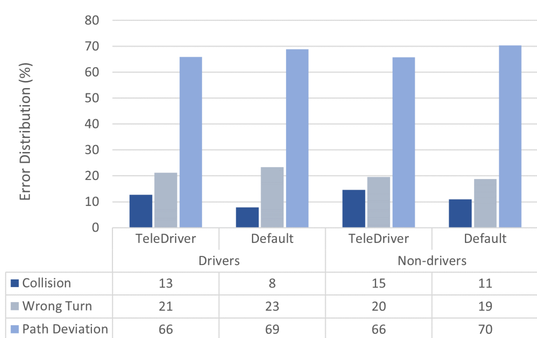


Figure 7: Average percentage of the types of errors committed by the two user groups with the two examined methods.

5.3 Perceived Performance

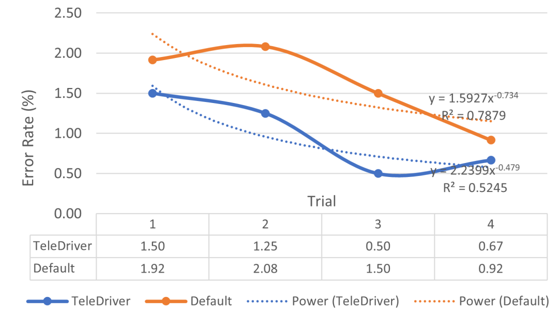
In regard to drivers, a Wilcoxon Signed-Rank test identified a significant effect of method on perceived speed ($z = -2.69, p < .01, r = 0.78$) and enjoyment ($z = -2.06, p < .05, r = 0.59$). However, there was no significant effect on accuracy ($z = -1.01, p = .31$), learnability ($z = -0.37, p = .71$), ease-of-use ($z = -0.37, p = .71$), or confidence ($z = -1.41, p = .16$). Fig. 9a shows the median perceived performance ratings of the methods by drivers. In regard to non-drivers, a Wilcoxon Signed-Rank test identified a significant effect of method on learnability ($z = -2.83, p < .005, r = 0.82$), ease-of-use ($z = -2.83, p < .005, r = 0.82$), and confidence ($z = -1.98, p < .05, r = 0.57$). However, there was no significant effect on perceived speed ($z = -1.75, p = .08$), accuracy ($z = -1.73, p = .08$), or enjoyment ($z = -1.13, p = .26$). Fig. 9b shows the median perceived performance ratings of the methods by non-drivers.

5.4 Perceived Workload

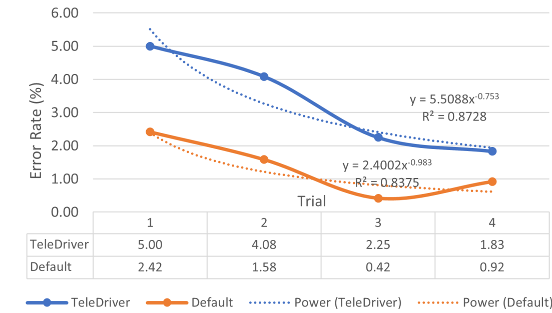
This section presents raw NASA-TLX scores by analyzing the sub-scales individually, which is a common practice in the literature [13]. In regard to drivers, a Wilcoxon Signed-Rank test identified a significant effect of method on performance ($z = -2.32, p < .05, r = 0.67$) and frustration ($z = -2.53, p < .05, r = 0.73$). But there was no significant effect on mental demand ($z = -1.08, p = .28$), physical demand ($z = -1.18, p = .24$), temporal demand ($z = -1.47, p = .14$), or effort ($z = -0.85, p = .39$). Fig. 10a shows the median perceived workload ratings of the methods by drivers. In regard to non-drivers, a Wilcoxon Signed-Rank test identified a significant effect of method on all sub-scales: mental demand ($z = -2.90, p < .005, r = 0.84$), physical demand ($z = -3.06, p < .005, r = 0.88$), temporal demand ($z = -2.95, p < .005, r = 0.85$), performance ($z = -2.44, p < .05, r = 0.70$), effort ($z = -2.80, p < .005, r = 0.81$), and frustration ($z = -2.04, p < .05, r = 0.59$). Fig. 10b shows the median perceived workload ratings of the methods by non-drivers.

6 Discussion

Results revealed that drivers were significantly faster in performing the tasks with TeleDriver than with the default method (23% faster). In contrast, non-drivers were significantly slower with TeleDriver (26% slower). Consequently, drivers were significantly faster than non-drivers (37% faster) in performing the tasks with TeleDriver, while their performances with the default method were somewhat comparable (~4 minutes, Fig. 4b). This was further substantiated by the rejection of both null hypotheses in an equivalence test ($p < .05$). Similar trends are also evident in error rates. Drivers committed significantly fewer errors with TeleDriver than the default method (39% fewer), while non-drivers were significantly more

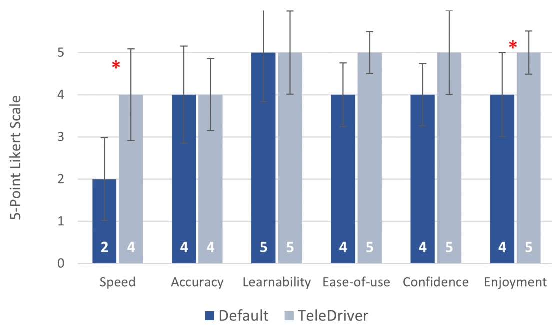


(a) Drivers

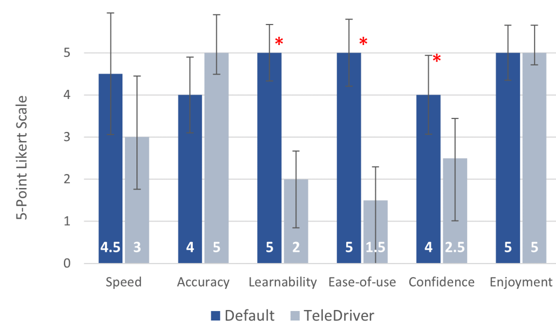


(b) Non-drivers

Figure 8: Average error rates (%) by trial for the two methods fitted to power trendlines. Error bars represent ±1 standard deviation.

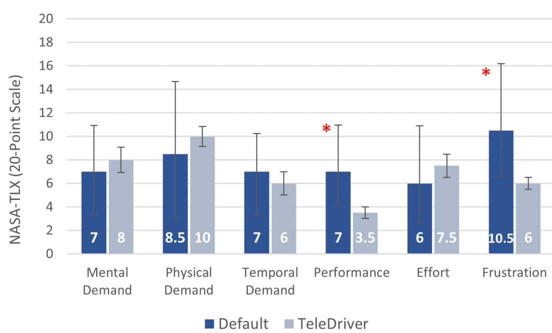


(a) Drivers

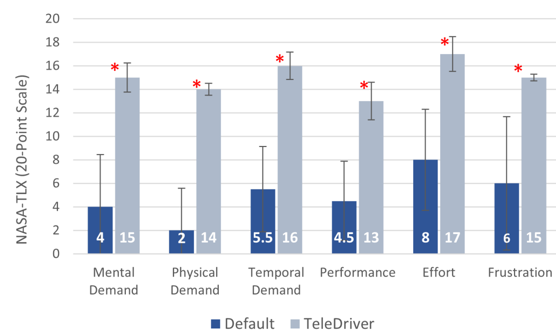


(b) Non-drivers

Figure 9: Median perceived performance of the default method and TeleDriver by (a) drivers and (b) non-drivers on a 5-point Likert scale, where "1" to "5" signified "strongly disagree" to "strongly agree". Error bars represent ±1 standard deviation.



(a) Drivers



(b) Non-drivers

Figure 10: Median perceived workload of the default method and TeleDriver by (a) drivers and (b) non-drivers on a raw NASA-TLX 20-point scale, where "1" to "20" signified "very low" to "very high", except for the Performance sub-scale, where "1" to "20" signified "perfect" to "failure". Error bars represent ±1 standard deviation.

erroneous with it (147% more). Likewise, drivers were significantly more accurate with TeleDriver than non-drivers (70% fewer errors), while their error rates with the default method were not statistically different (1.6% vs 1.3%, Fig. 6b). These results indicate towards the possibility that drivers can transfer their driving skills to TeleDriver, facilitating a faster transition from novice to expert. In the post-study questionnaire, we included an extra question for those with driving experience, asking whether the "driving" metaphor helped them master the new method. All participants (N = 12, M = 4.8, SD = 0.4) responded that it was really helpful. One participant (P07, male, 19 years) commented, *"As Someone who drives a lot and plays a bunch of racing games the indications on the driving simulator helped guiding me through the track."*

Both user groups' task completion times over trial with the two methods conform to the power law of practice [42] ($R^2 > 0.95$). Drivers were faster with TeleDriver from the very start, yielding a 21% lower task completion time than the default method in the first trial. Yet, they demonstrated learning with TeleDriver. Their task completion time with the method was 17% faster in the last trial compared to the first. However, not much learning was observed in the last two trials. Drivers' task completion time with TeleDriver was only about 1% faster in the last trial compared to the third, which suggests that they most probably came closer to the method's theoretical lower bound on task completion time. Task completion time with the default method demonstrated similar trends. Driver were consistently slower with it, but yielded a 13% faster task completion time in the last trial compared to the first. But the difference between the last two trials was merely 0.5%, suggesting that with the default method, too, drivers' reached closer to its lower bound on task completion time. For context, drivers were 25% faster with TeleDriver than the default method in the last trial. The trends observed with non-drivers are different. Initially, they were 30% slower with TeleDriver compared to the default method, but made significant improvements across the trials. Their task completion time with TeleDriver improved by 13% in the last trial compared to the first. Most importantly, they yielded a 4% faster task completion time with TeleDriver in the last trial compared to the third, which suggests that it is likely to improve further with practice. Learning was also observed with the default method, but the improvement in the last trial compared to the third was not as compelling (1.5%). This suggests that non-driver's task completion time with the default method is unlikely to get much faster with practice. In fact, driver and non-drives yielded comparable task completion times with the default method in the last trial (3.96 minutes vs. 3.88 minutes). This was also substantiated by an equivalence test ($p < .05$). Relevantly, an exponential smoothing (ETS) model forecasted that non-drivers' task completion time with TeleDriver to cross the same with the default method by the 10th trial, yielding a 3.3 minutes task completion time.

Drivers were consistently more accurate with TeleDriver than the default method (31% fewer errors overall and 27% fewer errors in the last trial). Yet, their error rates with TeleDriver dropped by 58% in the last two trials from the first two trials. In the last two trials, they yielded only 0.5% and 0.7% error rates with TeleDriver (Fig. 8a). Accordingly, error rates over trial with TeleDriver did not fit well to a power trendline ($R^2 = 0.52$). This further supports the claim that drivers transferred their driving skills to the method, which enabled them to maintain modest error rates throughout the study. Non-drivers, in contrast, demonstrated learning with TeleDriver ($R^2 = 0.87$). Their error rate with the method dropped by 63% in the last trial compared to the first (Fig. 8b). Not only that, they yielded a 19% reduction in error rate in the last trial compared to the third, indicating to the possibility that it is likely to get much lower with practice. Both drivers and non-drivers demonstrated some learning with the default method ($R^2 = 0.79$ and 0.84). Drivers' error rates with the default method dropped by 39% in the last trial compared to the third. Non-drivers, in contrast, yielded the lowest error rate with the method in the third trial (0.42% error rate). After studying the data carefully, we believe this to be purely by chance. Interestingly, both drivers and non-drivers yielded the same 0.92% error rates with the default method in the last trial.

These results promote TeleDriver to be an effective method for steering telepresence robots for both operators with and without driving experience, as non-drivers are quick to adapt to the system.

6.1 Subjective Feedback

Drivers perceived TeleDriver to be significantly faster than the default method (which matches the actual results). They also enjoyed using TeleDriver significantly more than the default method. One participant (P05, female, 19 years) commented, *"I prefer the driving sim method because it gave a more natural feel to it, as if I am really moving something."* They felt that both methods were comparable in terms of learnability and ease-of-use, thus were confident in using both (Fig. 9a). Non-drivers, in contrast, found TeleDriver to be significantly more difficult to learn and use, thus were not as confident in using it as the default method (Fig. 9b). This is not surprising as they were more familiar with the keyboard/mouse controls than the driving simulator, and users tend to face similar challenges when adapting to new technologies [24, pp. 184–187]. Yet, encouragingly, non-drivers did not perceived the methods to be significantly different in terms of speed and accuracy, and enjoyed using both methods, which suggest that they are open to adapting it. One participant (P17, male, 27 years) commented, *"The driving sim method made a bigger impression that gave me a sense of the space of the robot, it felt like I was driving the robot, instead of a floating camera."* Non-drivers also acknowledged that they were getting better at using TeleDriver with practice. One participant (P19, female, 20 years) commented, *"The driving sim method was challenging at first, but it got easier to use."* Interestingly, almost all non-drivers commented on how TeleDriver inspired them to learn how to drive (P15, female, 18 years: *"This experience encouraged me to get my permit soon"*), reduced anxiety of driving (P23, female, 23 years: *"The driving sim [... reduced my] anxiety of crashing"*), and even recommended using it as a gateway to driving (P24, female, 19 years: *"It would be useful to put in the DMV [department of motor vehicles] and help beginner drivers get the feel of how to drive."*).

6.2 Perceived Workload

Drivers perceived TeleDriver to be significantly better performed and less frustrating than the default method (Fig. 10a). They found both methods to be not as demanding (≤ 10 out of 20) and somewhat comparable in terms of mental, physical, and temporal demands and effort. Non-drivers, on the other hand, found TeleDriver to be significantly more demanding in terms of mental, physical, and temporal demands. They felt that it required significantly more effort to use, not as well-performed as the default method, thus caused significantly more frustration during the study. One non-driver (P15, female, 18 years) commented, *"I was scared [when using TeleDriver] to crash into something and damaging the robot."* Another participant (P16, female, 18 years) commented, *"For me, it was a little harder using the driving simulator. I felt like I had to be more* *alert.*" Again, this is not surprising considering that they all were new users of the method, without any prior experience in driving or driving simulators or games.

6.3 Understanding & Presence

All respondents, both drivers and non-drivers, agreed that the driving metaphor enhanced their understanding and sense of presence in the system. One driver (P07, male, 19 years) noted that TeleDriver felt more *"realistic"* and enhanced his sense of actually being there. A non-driver (P17, male, 27 years) observed that TeleDriver provided *"a sense of the space"*, increasing awareness of the robot's environment. In addition, some mentioned how this increased sense of presence contributed to more effective operation. For example, a non-driver (P24, female, 19 years) mentioned that enhanced presence reduced her *"anxiety"* while operating the robot, as she felt more informed about the surrounding environment.

7 Limitations

A limitation of this study is the small and relatively young sample size, primarily due to challenges in recruiting adults (18 years or older) with no driving experience. Most older volunteers had some driving experience, so to maintain balanced age and gender ratios, we primarily included young adults in both groups. Therefore, the results may not be fully generalizable to an older population. However, the statistically significant results reported in this study yielded medium to large effect sizes ($\eta^2 \geq 0.05$ for a medium effect size and $r \geq 0.5$ for a large effect size [7]), suggesting that these findings could potentially persist in a more age-diverse sample.

8 Conclusion

We presented TeleDriver, a driving simulator inspired interactive system for controlling telepresence robot that maps driving interactions to corresponding telepresence robot actions. It uses a "driving" metaphor, with which operators use the steering wheel to steer the robot, gear shifter for forward and reverse motions, gas pedal for increasing the speed, and brake pedal for decreasing the speed or a full-stop. We conducted a user study to compare the method with a conventional desktop interface with both drivers and non-drivers. Results provided strong evidence in support of the hypothesis that drivers can transfer driving skills to TeleDriver, facilitating a faster transition from novice to expert. Drivers were consistently faster and more accurate with TeleDriver compared to the conventional method. They completed the tasks 23% faster and with 39% fewer errors with TeleDriver. Non-drivers, in contrast, were 26% slower and committed 147% more errors with TeleDriver compared to the conventional method. Both drivers and non-drivers yielded comparable performances with the conventional method. Most interestingly, both drivers and non-drivers demonstrated learning with TeleDriver. Drivers were 17% faster and 58% more accurate in the last trial compared to the first, while non-drivers were 13% faster and 63% more accurate in the last trial compared to the first.

9 Future Work

In the future, we will extend the work for a better, enhanced sense of embodiment by providing information on the robot's ambient environment using haptic feedback. For example, the steering wheel or the seat can vibrate slightly when the robot is going over rough terrain, just as it would when driving a vehicle. Likewise, a thermal diode could be added to the system to provide a sense of heat and wetness of the path by variating the temperature of the pedals. We will also optimize the video feeds for a widescreen monitor that resembles the windshield of an automobile to investigate whether it improves embodiment, learning, or performance. We will then investigate the effects of these systems on collaboration and productivity. We will also compare the proposed approach with alternative control interfaces that integrate joysticks, knobs, buttons, and gamepads to operate out-of-sight robots.

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