2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
October 14-18, 2024. Abu Dhabi, UAE

Reducing Performance Variability and Overcoming Limited Spatial Ability: Targeted Training for Remote Robot Teleoperation

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Abstract— **In this paper, we present a targeted training approach for remote teleoperation aimed at achieving consistent proficiency levels across users with varying capabilities. Our approach begins by assessing users' abilities to perform robot motion control, workspace adaptation, and gripper control. It then provides tailored training based on identified skill gaps to enhance the learning effectiveness and user experience. To demonstrate our approach, we conducted a user study, with one group undergoing conventional, free-form training and the other engaging in targeted training in accordance with their skill gaps; after the training phase, participants teleoperated a robotic arm in a simulated medication preparation task for performance evaluation. Our results show that the targeted training approach effectively reduces performance variability and mitigates the influence of spatial ability on both training and task completion time. We discuss the implications of our results for practical teleoperation training and future research.**

I. INTRODUCTION

Robot teleoperation plays a pivotal role in scenarios in which a human presence is either difficult or dangerous and in the complex and unstructured environments where autonomous systems often encounter challenges. Ensuring the competence of teleoperators is crucial, as human direct control provides real-time responsiveness of the robot action that impacts the task performance and remote environment. Yet teleoperators with diverse backgrounds, varying experience with robotic systems, and differing spatial abilities exhibit varied performance in robot teleoperation.

Conventional teleoperation training is mostly free-form and unstructured; this lack of specificity contributes to inconsistencies in skill development among teleoperators and poses a significant challenge in both achieving uniform competence levels and in accurately calibrating acquired skills. Varying proficiency levels could negatively influence the success and quality of task performance. Furthermore, research on robot teleoperation may not progress productively if study participants lack uniform proficiency levels, leading to poor comparisons of new teleoperation methods with baselines under confounding effects. While prior research in space telerobotic systems and surgical-assisted robots has explored structured training approaches [1], [2], these methods involve prolonged training modules due to the critical consequences of operational errors, and are thus inefficient for the general applications that involve robot teleoperation.

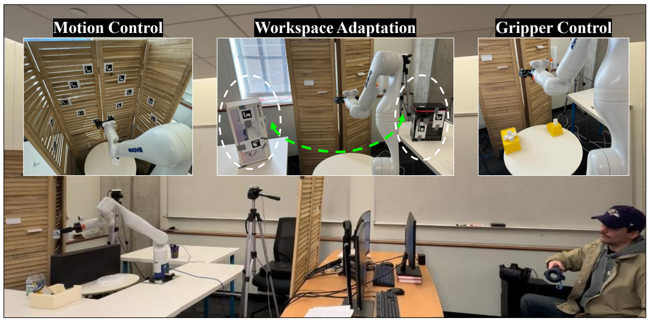

Fig. 1: Our proposed targeted training paradigm includes three distinct modules: robot motion control, workspace adaptation, and gripper control.

This paper presents a novel targeted training paradigm for remote teleoperation (Fig. 1). Our proposed approach utilizes distinct manipulation modules to systematically identify users' weaknesses in teleoperation based on predetermined proficiency criteria before offering specific training to bridge their individual skill gaps. The modules are comprised of pre-tasks that focus on fundamental teleoperation skills, such as robot motion control (translation and rotation), workspace adaptation (reconfiguring pose for arm ergonomics), and gripper control (grasping and releasing), together covering a wide range of general-purpose remote manipulation tasks. To evaluate our proposed training paradigm, we conducted a user study in which one group of participants engaged in free-form training and the other attempted targeted training. During the study, participants controlled a Kinova robotic arm using a motion tracking device (i.e., HTC Vive controller) and were provided with a graphical user interface that combined multiple video feeds from stationary cameras and a dynamic eye-in-hand camera. To deepen our understanding of the factors influencing teleoperation performance, spatial ability assessments were conducted alongside performance evaluations to explore the correlation between an individual's spatial ability and their performance in remote teleoperation.

Our results show that: (1) targeted training minimizes the variability of task performance in terms of task efficiency (completion time and robot trajectory) and control ergonomics; (2) users who underwent targeted training reported higher confidence, not only in general teleoperation but also in each specific aspect of telemanipulation; (3) perspective-taking ability demonstrates a stronger correlation with performance in telemanipulation pre-tasks compared to mental rotation ability; and (4) targeted training mitigates the impact of spatial ability on training duration and the time required to complete the evaluation task.

This work was supported by the Malone Center for Engineering in Healthcare at the Johns Hopkins University.

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II. BACKGROUND AND RELATED WORK

A. Training Methodologies for Remote Teleoperation

Remote teleoperation training methodologies encompass a diverse range of approaches. *Self-guided training* empowers operators to independently acquire skills through interactive simulations and immersive environments, fostering autonomy and adaptability [3], [4]. However, a limitation of this method lies in the potential for knowledge gaps and the necessity of self-motivation, as operators may miss critical aspects without structured guidance. *Expert-guided training,* which involves mentorship from experienced practitioners, accelerates the learning curve and promotes skill transfer [5], [6], but is limited by its dependence on the availability of experts, which may hinder its scalability and accessibility. *Curricula-based training* follows structured programs, ensuring a comprehensive understanding [7], [8], but can be less efficient and sometimes redundant, as predefined curricula may not readily address diverse user demographics. *Proficiency-based training* tailors tasks based on demonstrated skills, thereby ensuring competency [1]; however, current studies using this method typically concentrate on highly specific tasks, which can pose a challenge in establishing common proficiency metrics. In this paper, we exploit a hybrid curricula- and proficiency-based approach by incorporating a “skill calibration” process, which offers targeted training to effectively address specific skill gaps. This approach enables the seamless execution of real-world tasks, such as those frequently seen in remote health care.

B. Impact of Spatial Ability on Teleoperation Performance

Numerous studies have investigated the correlation between spatial ability and teleoperation performance. In the domain of space teleoperation, studies have examined the influence of spatial abilities on performance outcomes. Positive correlations were identified between total task time and observation time with mental rotation ability; additionally, an inverse correlation with perspective-taking ability was observed [9]–[11]. Additional research has explored the reliability of spatial ability test scores within a logistic model for predicting training outcomes, suggesting their applicability for planning training schedules or identifying the need for additional training [12]. In the domain of surgical robots, researchers have explored the impact of spatial ability on the acquisition of operational skills and identified partially significant correlations across evaluation tasks, primarily during the initial learning phase [13], [14]. Additionally, recent research has investigated the response to virtual signals in excavator teleoperation, revealing a notable inverse relationship between spatial ability and response time [15]. While the link between spatial ability and teleoperation performance is well-established across various domains, a detailed exploration of how spatial ability specifically influences essential remote control skills is still lacking; further research is required to unravel this relationship and enhance our understanding of spatial ability’s role in building the specific competencies required for remote teleoperation.

III. TARGETED REMOTE TELEOPERATION TRAINING

We first describe the implementation of a motion-tracking interface for remote teleoperation and then the design of telemanipulation modules to provide targeted training.

A. Remote Teleoperation System

Robot and Control Interface: We used an HTC Vive handheld controller to capture natural hand motions as the input for controlling a 7-DoF Kinova Gen 3 manipulator with a two-fingered Robotiq gripper, shown in Fig. 1. Our approach involved utilizing a motion-tracking control interface that incorporated a Relaxed-IK solver [16], [17] to address inverse kinematics for the robot manipulator, enabling the generation of seamless and viable robot motions while averting joint-space discontinuities and kinematic singularities and adeptly managing self-collisions. This approach proved to be more intuitive for novice users in robot teleoperation when contrasted with other interfaces [18], rendering it a suitable selection for studying training paradigms. To perform remote teleoperation tasks, users activated the default control for Cartesian translational movement by pressing the grip (side) button on the controller. Rotational control was initiated with the menu button and gripper control was managed via the trigger button. The robot control could be paused at any moment by pressing the grip button again.

Visual Interface: The visual interface displayed cropped RGB video streams from remote cameras, including: (1) two stationary RealSense D435 cameras to provide primary and unobstructed viewpoints, (2) the dynamic eye-in-hand camera attached to the robot end effector, and (3) a Logitech C930e webcam used as the scanning camera for the evaluation task described in Sec. IV. Fig. 2 shows the graphical user interface (GUI), which integrated the visual interface, overlaid text to indicate the robot’s operational state (“CONTROLLING,” “PAUSED,” “ROTATION: ON/OFF”), and incorporated AruCo marker features for interaction.

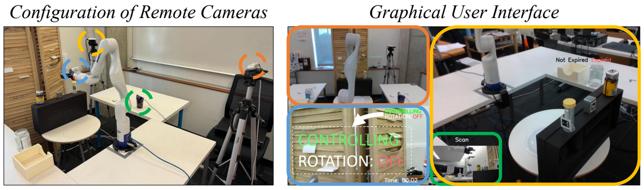
Configuration of Remote Cameras *Graphical User Interface*

Fig. 2: The configuration of remote cameras and corresponding graphical user interface for the evaluation task (medication preparation).

B. Telemanipulation Modules

Users engaged in three telemanipulation modules structured as a set of pre-tasks to evaluate their initial performance of various aspects of remote robot teleoperation (Fig. 3).

Robot Motion Control (Module 1): Users began by executing the movement-only pre-task, directing the robot to interact with markers on a flat plane. Users subsequently engaged in the full control pre-task, which involved both moving and rotating the robot to interact with markers on multiple flat planes. Both pre-tasks made use of the GUI,

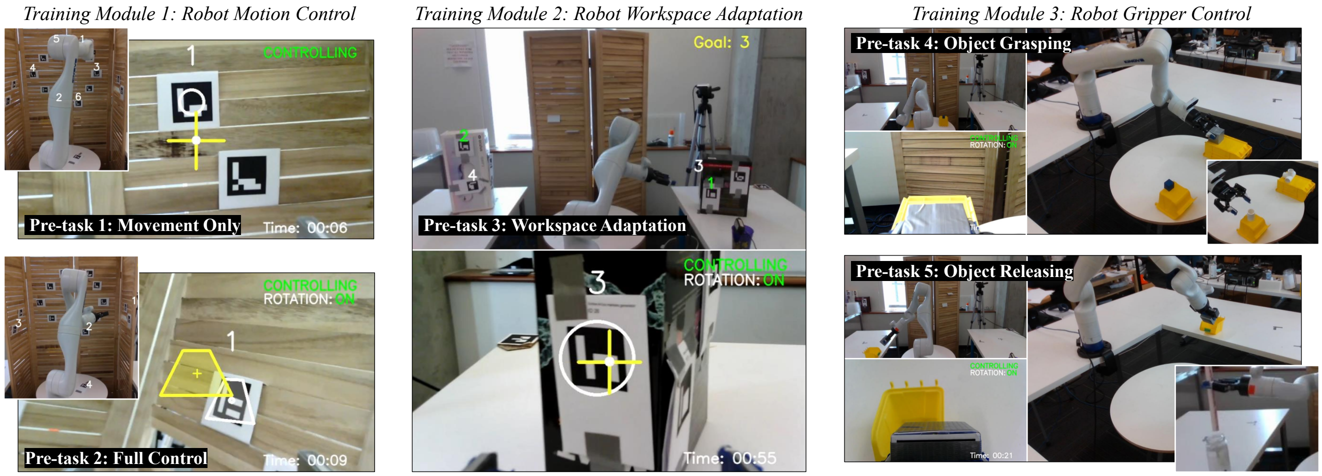

Fig. 3: We developed three interactive remote teleoperation training modules to assess and enhance telemanipulation capabilities. The robot motion control module, comprised of two pre-tasks, focuses on the aspects of movement and full control. The robot workspace adaptation module aims to improve arm ergonomics during remote teleoperation. The robot gripper control module includes two pre-tasks that focus on manipulating objects of various sizes and shapes and dropping them into a bin or precisely aligning them for insertion.

offering visualization through stationary global (workspace camera) and dynamic local (eye-in-hand camera) views.

- ***Pre-task 1 (Movement Only).*** This task aimed to assess and enhance users' awareness of the optimal controller movement speed to align with the robot's maximum velocity. Inspired by Fitt's Law [19], we implemented an interactive goal-directed movement test. In this test, the center of the eye-in-hand camera view was marked with a crosshair; users were tasked with positioning this crosshair inside a circle generated from the AruCo markers for six different targets. Note that the circle appeared only when the robot was in proximity to the AruCo markers. Performance was gauged by calculating the average index of difficulty (derived from the distance and the target's size) over movement time across all pairs between targets, ranging from 0.05 to 0.2 bits/second[1].
- ***Pre-task 2 (Full Control).*** This pre-task introduced full control, requiring control over both the translation and rotation of the robot's end effector. We implemented a shape-fitting test in which the center of the eye-in-hand camera view was marked with a trapezoid; the objective of this test was to accurately match the size and angle of the trapezoid for four different targets attached to various flat planes. Performance was assessed on two indices: average accuracy (computed as the mean intersection over union and offset angles, ranging from 0 to 100 percent) and average movement time across all pairs between targets.

Robot Workspace Adaptation (Module 2): In this module, users had full control, allowing them to interact with targets within a larger workspace. This often required frequent reconfiguration and repositioning of their control workspace to maintain optimal arm ergonomics, ensuring adaptability in the maneuverability and reach of the robotic arm. The GUI remained configured as in Module 1, providing stationary global and dynamic local views.

- ***Pre-task 3 (Workspace Adaptation).*** Similar to pre-task 1, the dynamic view was overlaid with a crosshair that users were to move across two distant workspaces in order to select four different targets sequentially. Performance was evaluated using the same performance index as in pre-task 1 (ranging from 0.01 to 0.08 bits/second) and by measuring the percentage of time the arm spent in the ergonomic workspace. The ergonomic workspace was defined as the weighted region offset from the reachable workspace [20] as determined via user-specific calibration, which involved users annotating the farthest distance they could reach by pressing the trackpad in five directions as shown in Fig. 4. The ergonomic index ranged from 0 to 100 percent.

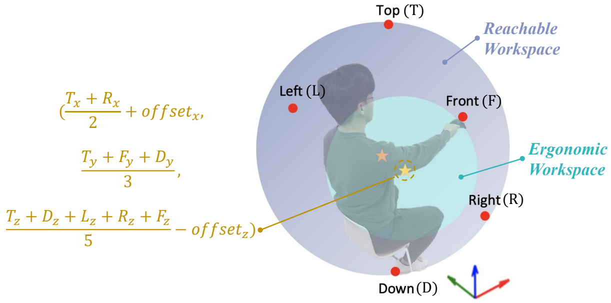

Fig. 4: Illustration of the reachable and ergonomic workspaces. Red dots represent recorded poses in various directions. The orange star marks the center of the estimated reachable workspace, while the yellow star marks the center of the ergonomic workspace.

Robot Gripper Control (Module 3): Lastly, users manipulated objects of varying shapes and sizes with a gripper and performed different types of object release, from simple dropping to precise alignment for insertion. In addition to the stationary primary view and dynamic eye-in-hand view, the GUI in this module offered another stationary viewpoint

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[1] The index of difficulty is inherently unitless, with the bit serving as a measure representing the quantity of information conveyed through motion.

that reduced visual collisions during object manipulation.

- ***Pre-task 4 (Object Grasping).*** This task assessed users' manipulation skills in effectively grasping and holding objects of varying sizes and shapes for at least 3 seconds. The task was comprised of two trials: picking up small (1 inch on each side) and large (2 inches on each side) cubic objects and picking up regular (coupling) and irregular-shaped (side-outlet tee) pipe fittings. Performance was evaluated based on errors made and total time taken to complete the task.
- ***Pre-task 5 (Object Releasing).*** This task involved placing a successfully picked-up object in scenarios of varying difficulties; specifically, the task included two trials: dropping a large cubic object into a bin and precisely aligning a pipe for insertion into a jar. Performance was assessed based on success rate and total time taken to complete the task.

C. *Proficiency Criteria*

To define the baseline criteria for each manipulation pre-task, a pilot study was conducted with two experts (both male, aged 24 and 33) and two novice users (both female, aged 26 and 34). The experts, each having accumulated over 100 hours of interaction and teleoperation with the robot in question, demonstrated a retained proficiency level in remote teleoperation, whereas the novices represented individuals with limited prior experience in the domain. Each participant completed five repetitions of each pre-task and their performances were recorded. Our proficiency criteria, listed in Table I, were established by calculating the average performance across both experts and novices with a weighting coefficient of 7 to 3.

TABLE I: Proficiency criteria of each telemanipulation pre-task.

—— Motion Control ——			—— Gripper Control ——	
Movement Only	**Full Control**	**Workspace Adaptation**	**Object Grasping**	**Object Releasing**
> 0.13 bits/s	$> 80\ \%^{1}$ $< 35\ \mathrm{s}^{2}$	> 0.05 bits/s $> 65\ \%^{3}$	< 2 errors < 2 mins	$100\ \%^{4}$ < 2 mins

[1] The accuracy of shape fitting.
[2] The time taken to move between targets.
[3] The duration of maintaining an ergonomic arm pose.
[4] The success rate of task completion.

IV. User Study

To evaluate our targeted training paradigm, we conducted a human participant study and tested the following hypotheses:

H1. Users with targeted training will exhibit significantly less variability in evaluation task performance compared to a user group that only received free-form training.

H2. Users in the targeted training group will report higher confidence in their teleoperation skills and performance compared to those in the free-form training group.

H3. Users' spatial abilities will correlate with their performance in manipulation pre-tasks prior to any training.

H4. Targeted training will mitigate the impact of spatial ability on training time and evaluation task performance.

Participants and Evaluation Task: We recruited a total of 22 participants, with 11 individuals assigned to each of the free-form (6 males, 5 females, age = 25.45±2.39) and targeted (6 males, 5 females, age = 26.1±3.53) training groups. Participants reported limited prior experience with robots (*M* = 2.05, *SD* = 1.25, measured on a five-point scale) and the amount of time they spent playing video games ranged from 0 to 15 hours per week. To ensure the practical relevance and generalizability of our findings, both groups of participants were tested on controlling the robot to complete a medicine preparation task, inspired by prior work on a telenursing robot [21]. In this task, participants controlled the robot to pick up three medications of varying sizes and shapes, scanned the attached marker using a stationary camera, and sorted them into bins based on the marker reading (expired or not). The medications were positioned in front of the robot, with the scanning camera and sorting bins placed to the right and left, respectively (Fig. 2).

Experimental Procedure: After obtaining informed consent, participants completed a demographic survey and assessed their spatial abilities using the Purdue Spatial Visualization Rotation Test and Vandenberg Mental Rotation Test, which are both relevant to remote teleoperation [9]; each test is composed of ten questions with respective time limits of five and four minutes. Next, the experimenter explained and demonstrated how to control the Kinova manipulator using the motion tracking controller and screen-based visual interface. Once participants expressed readiness, they performed the telemanipulation pre-tasks outlined in Sec. III-B to assess their initial performance and determine their weaknesses as compared to the proficiency criteria described in Sec. III-C for subsequent targeted training. During the training phase, participants in the free-form training group had the flexibility to specify the modules or pre-tasks they wished to focus on during practice. Conversely, participants in the targeted training group were informed by their initial performance and required to meet the proficiency criteria for each pre-task during the training phase. This phase was limited to 30 minutes. Following training, participants were introduced to the evaluation (medicine preparation) task. Upon completing the evaluation task, participants filled out a questionnaire to provide feedback on their experience.

Measures and Analyses: To compare task performance between groups, we measured completion time, the trajectory length traveled by the robot end effector, and the duration of maintaining an ergonomic arm pose during the evaluation task. We conducted the F-test to analyze the variability and both Student's (equal variance) and Welch's (unequal variance) t-tests to determine statistical significance for all performance measures. We assessed participants' confidence in general robot teleoperation and specific telemanipulation skills through a post-study survey with a five-point rating scale (5 indicating the highest confidence), and the results were analyzed using one-way analyses of variance. We used a mixed regression model to assess the correlation between spatial scores and pre-task performance.

V. RESULTS AND DISCUSSION

This section presents the results from the comparison between user groups and discusses the implications of targeted remote teleoperation training and its impact on spatial ability. Note that there was variance in the initial performance of each pre-task among individuals in both groups; however, no significant difference was found between the groups.

A. Telemanipulation Performance Variability

Fig. 5 illustrates the comparison of variability in evaluation task performance between the free-form and targeted training groups. Our analyses revealed that the free-form training group showed significant variation in completion time ($p < .01$), duration spent in ergonomic arm pose ($p < .01$), and total length traveled by the robot end effector ($p < .05$) as compared to the targeted training group, which supports **H1**.

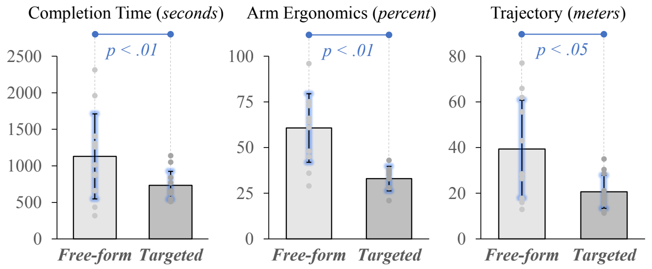

Fig. 5: Comparison of variability in completion time, duration spent in ergonomic arm pose, and robot end effector trajectory between user groups.

Discussion — Our findings suggest that integrating targeted training into standard teleoperation protocols can promote consistent skill development among novice users. This approach may ensure that participants reach a uniform proficiency level before testing or comparing teleoperation interfaces or augmentations (e.g., perception and action [22]); by mitigating learning inconsistencies, this approach may strengthen the reliability of study results in teleoperation.

B. Post-Training Confidence Level

The confidence levels obtained from the subjective survey are illustrated in Fig. 6. Comparisons showed that the targeted training group had significantly higher confidence than the free-form training group if asked to perform tasks that involve general remote robot teleoperation ($p < .01$) and specific telemanipulation skills; these skills include moving the robot manipulator translationally ($p < .05$) and combined with rotation ($p < .001$), reconfiguring the arm to adapt to the robot's workspace ($p < .001$), and successfully grasping ($p < .05$) and releasing ($p < .001$) objects. These findings provide support for **H2**.

Discussion — Users in the targeted training group reported significantly higher confidence in performing remote teleoperation not only in general teleoperation but also in each specific aspect of telemanipulation. We speculate that the proposed targeted training resulted in higher confidence because it was guided by objective proficiency criteria, providing a clear and measurable framework for skill development. This contrasts with subjective perception-based methods, which may not accurately assess the true weaknesses, especially for users who are new to robot control.

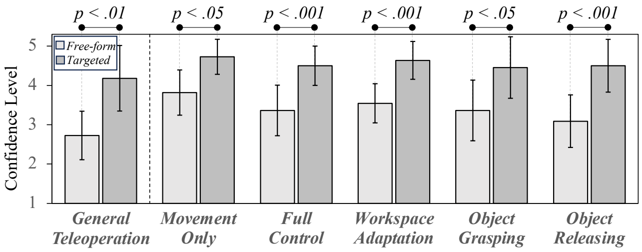

Fig. 6: Confidence levels in general teleoperation and specific telemanipulation skills across user groups, with error bars representing standard error.

C. Spatial Ability and Remote Teleoperation Correlation

We identified partial correlations between spatial ability and performance in telemanipulation pre-tasks as presented in Table II. Our linear regression analyses revealed that mental rotation ability significantly correlates with the efficiency of full control ($p < .05$) over the robot. Additionally, perspective-taking ability was found to significantly correlate with not only full control efficiency ($p < .01$) but also the accuracy ($p < .001$) and efficiency ($p < .01$) of object grasping, as well as the accuracy ($p < .001$) of object releasing. It was observed that spatial ability increased as performance improved across all correlations. These findings partially support **H3**, suggesting a correlation between spatial ability and pre-task (specific telemanipulation skill) performance.

TABLE II: Inferential statistics for correlation between spatial ability and performance in each telemanipulation pre-task.

		Mental Rotation				*Perspective-Taking*			
Measure		***DF***	R^2	f	p	***DF***	R^2	f	p
Pre-Task 1	Performance	21	.02	1.27	.607	21	.10	1.60	.227
Pre-Task 2	Accuracy	21	.07	1.47	.239	21	.03	1.34	.569
	Efficiency	21	.23	5.13	< .05	21	.38	8.42	< .01
Pre-Task 3	Performance	21	.04	1.82	.355	21	.04	1.65	.434
	Ergonomics	21	.02	1.08	.892	21	.10	1.56	.232
Pre-Task 4	Accuracy	21	.06	1.83	.379	21	.52	15.2	< .001
	Efficiency	21	.10	1.62	.223	21	.36	7.88	< .01
Pre-Task 5	Accuracy	21	.11	1.70	.214	21	.50	14.2	< .001
	Efficiency	21	.02	1.22	.765	21	.03	1.48	.501

Next, we focused on analyzing the relationship between perspective-taking ability, training time, and evaluation task time, as perspective-taking ability has been shown to influence multiple aspects of telemanipulation skills (Table II). As shown in Fig. 7, perspective-taking ability was found to have a significant effect on the free-form training group only, in terms of both training time ($p < .05$) and the time taken to complete the evaluation task ($p < .05$). These findings imply that targeted training reduces the impact of spatial ability on training effort and task performance, supporting **H4**.

Discussion — Relationship analyses revealed that spatial ability correlates not only with the time taken to complete the evaluation task but also with various foundational skills of remote teleoperation; our findings suggest that for tasks involving both translation and rotation control in smaller workspaces and fewer viewpoints (i.e., pre-task 2), assessing both mental rotation and perspective-taking abilities can predict efficiency in performance, while for tasks requiring precise manipulation and coordination of multiple viewpoints (i.e. pre-tasks 4 and 5), only evaluating perspective-taking ability can predict accuracy in performance (Table II). Moreover, future work could investigate the possibility of developing targeted training based on individual's spatial abilities, rather than weaknesses identified through a series of telemanipulation pre-tasks.

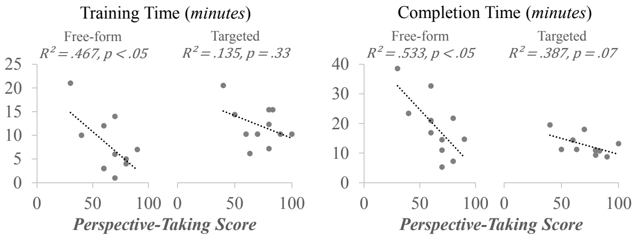

Fig. 7: The correlation between perspective-taking ability and both training time and evaluation task time for the free-form and targeted training groups.

VI. CONCLUSION

In this study, we introduce a remote teleoperation training approach addressing users' skill gaps across various telemanipulation modules to establish consistent proficiency levels. Through a comparative user study against conventional free-form training, we demonstrate the efficacy of our method. Our findings reveal significantly more consistent task performance and higher confidence in teleoperation within the targeted training group compared to the free-form training group. We explore the relationship between spatial ability and telemanipulation performance, identifying correlations for enhanced predictions. Additionally, we highlight targeted training's potential to mitigate the impact of spatial ability on training and task performance.

Limitations — While our targeted training proved effective in reducing performance variability, its applicability to more complex robot platforms has yet to be determined. We plan to expand our existing remote teleoperation training modules to encompass a broader range of functionalities, including bimanual manipulation, active telepresence, and navigation for both mobile manipulators and humanoid robots [17], [21]. Additionally, the current ergonomic arm workspace estimation requires calibration and is sensitive to upper body pose; therefore we plan to investigate wearable devices (e.g., motion trackers [23]) capable of capturing real-time poses to generate a human skeleton model, thereby enhancing the usability of ergonomic workspace estimation method.

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