The Impacts of Unreliable Autonomy in Human-Robot Collaboration on Shared and Supervisory Control for Remote Manipulation

Tsung-Chi Lin, Achyuthan Unni Krishnan, and Zhi Li

Abstract—**This work compared human-robot shared and supervisory control of remote robots for dexterous manipulation, and examined how the reliability of robot autonomy affects human operator performance, workload, and preference for robot assistance. Specifically, we implemented two human-robot collaboration (HRC) paradigms for remote manipulation: (1) shared control, where humans controlled gross manipulation and the robot autonomy controlled precise manipulation actions, and (2) supervisory control, where the robot autonomy controlled both gross and precise manipulation actions but relied on humans to detect and correct errors. We conducted two user studies: one to compare the effectiveness of the two HRC paradigms when assistive autonomy is reliable, and the other to examine the impact of error type and frequency on tasks and human operators in the two HRC paradigms when assistive autonomy is unreliable. Our results show that: (1) the interface with a higher level of reliable autonomy yields significantly better performance, lower workload, and higher user preference but lower engagement, and (2) the frequency and type of the error have significant impacts on the task performance and human workload but only partially affects the operator's preference and usage of autonomy.**

Index Terms—**Telerobotics and teleoperation, human factors and human-in-the-loop, human-centered automation.**

I. Introduction

TELEOPERATION via human motion tracking interfaces (e.g., motion capture systems, exoskeletons, hand-held controllers) enables humans to efficiently and intuitively control remote manipulator robots to perform dexterous, freeform manipulations. Robot autonomy is utilized to reduce operator workload by providing perception and action assistance, such as object detection and recognition, intent inference, motion planning, and control. Assistive autonomy improves human-robot

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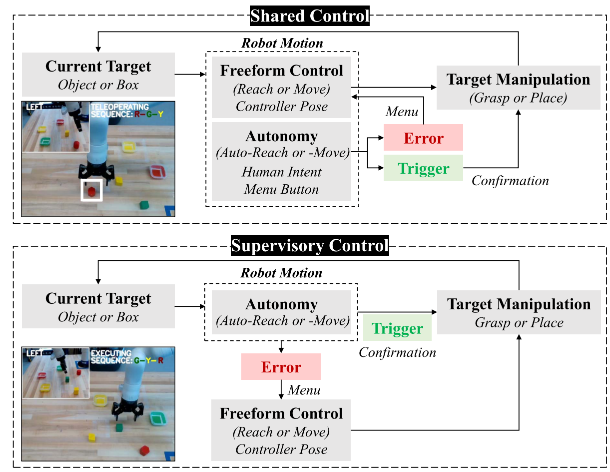

Fig. 1. Shared vs supervisory control for assisted remote robot manipulation.

collaboration (HRC) in remote control by providing varying levels (ranging from shared to supervisory control) and types (from perception to action) of assistance. However, the robot autonomy may not be consistently reliable due to the perception and action uncertainty of the robots, and the complexity of the manipulation tasks. It is still unclear *how the level and type of robot assistance be adjusted if the reliability of the robot autonomy may vary*.

This paper aims to investigate how to adjust HRC when the robot autonomy is reliable to different extents (with respect to the task). We focus on unstructured dexterous manipulation tasks that rely on general-purpose gross and precise manipulation actions to approach, move, grasp, and place objects. Unstructured tasks demand flexibility, adaptability, and reasoning as they often entail manipulating unknown objects or moving a robot arm through cluttered or unfamiliar environments. This requires human involvement at action levels, e.g., moving the end-effector close to the object to be manipulated during the task, or selecting the sequence of objects and manipulation actions to be executed later under supervisory control. They may also require humans to detect errors (e.g., due to the incorrect choice of object or action, low precision of autonomous action execution) using the remote camera visual feedback, and correct them using the control at the action or motion level.

Shown in Fig. 1, we implemented two HRC paradigms to effectively assist humans to control robots to perform these dexterous manipulation tasks using a motion tracking interface. (1)

The **shared control** paradigm allows robot autonomy to control precise manipulation actions but relies on humans for gross manipulation control and error correction; (2) The **supervisory control** paradigm allows robot autonomy to control both the gross and precise manipulation actions and only relies on humans for error correction. The shared control paradigm integrates robot autonomy, including: (1) human goal *intent inference* based on human gaze, robot status, and task states; (2) *autonomous actions* for precise manipulation which tend to cause high cognitive and physical workload for human control (e.g., object grasping and placing actions [1]). The design of assistive autonomy, including intent inference, autonomous actions, and methods for estimating human engagement and workload, can be readily applied to various other remote manipulation tasks. We conducted a user study to evaluate the effectiveness of the proposed HRC paradigms when the autonomy is reliable (User Study I). We also investigated how the unreliable assistive autonomy (User Study II) that results in errors of different types and frequencies during the tasks may influence the performance, workload, human preference, and usage of autonomy for the two HRC paradigms. Shown in the control flow in Fig. 1, the errors may happen to the autonomous actions triggered by the operator, at the action-level (e.g., picking up the wrong object) or the motion-level (e.g., missing to grasp an object). The operator needs to switch to manual control to correct the error. Our results show that: (1) *When the autonomy is reliable*, the supervisory control is the easiest to use for remote manipulation because it leads to the best performances, workloads, and preferences despite the lowest engagement. (2) For both shared and supervisory control with *unreliable autonomy*, higher error frequency leads to worse performance and workload, but may not increase user preference or usage of lower autonomy levels; users also prefer to use the robot autonomy if the effort for error correction is lower. This work contributes: (1) a comparison of HRC paradigms that integrate various types and levels of autonomy for effective control of freeform, dexterous manipulation; (2) a simple and effective implementation of intent inference for guiding robot autonomy; (3) an assessment of the impact of unreliable assistive autonomy on users' autonomy preferences; and (4) offer new knowledge about leveraging the design of HRC paradigms to mitigate the adverse impacts of unreliable autonomy.

II. Related Work

A. Autonomy to Assist Motion Tracking Teleoperation

Human motion tracking interfaces enable human operators to control the dexterous manipulation of remote robots (e.g., manipulators [2], mobile manipulators [3] and humanoid robots [4]) using the natural motion coordination of their body, arms, and hands. These motion tracking interfaces include various motion capture systems (vision-based [5] vs IMU-based [6]), stylus/joysticks [7], exoskeletons (soft [8] and rigid [9], passive [10] vs actuated [11]), virtual reality systems (hand-held controllers [2]), and the custom integration of multimodal control interfaces [12]. Our prior research shows that, while motion mapping interfaces are more effective and intuitive for dexterous manipulation control than gamepad control or stylus inputs [1], assistive autonomy is still required to improve precision and reduce workload for human operators. Among all human-robot collaboration paradigms (refer to different levels of autonomy in [13]), shared autonomy [1], [14] and supervisory control [15], [16] are both proven to be effective for handling complex, unstructured and error-prone manipulation tasks. However, during comprehensive manipulation, the operator's preference for the level of assistive autonomy may vary based on the reliability of the autonomy specifically for "the current sub-task" of the dexterous manipulation task. Investigating how this preference varies with the reliability of the autonomy will enable us to adjust the human-robot collaboration paradigms (more shared or supervisory control) to provide ideal assistance to the operator.

B. Causes and Effects of Unreliable Autonomy

Related work in the literature has analyzed the causes and effects of the failures in human-robot interactions and how to mitigate possible negative impacts (see the review in [17]). In general, robot failures may differ in their functional severity, social severity, relevance to general or specific robot systems, frequency, condition (when the failure happens), and symptoms (that indicate the failure). The failures of robots may affect task performance (e.g., task completion time), human workload and comfort, and human perception of robot intelligence, transparency, safety, and influence human's trust, satisfaction, impression, and attitude toward robots. When failures happen, robots are preferred to communicate the errors to help humans to better perceive and comprehend the failures, and to leverage human help to resolve the failures. In this work, we focus on the failures common to general-purpose robot manipulation tasks, and common to both shared or supervisory control. At high-level, the robot may apply the wrong action to the wrong object, due to errors in the prediction of goal or action intent [18], [19], [20], or detection of object-action affordance [21], [22], [23]. At low-level, the robot may not successfully perform the manipulation motions (e.g., missing to grasp or place an object) due to errors in perception, motion planning, and execution. Thus far, it is still unclear how the types and frequency of errors may affect human performance, workload, perception, and preference for the level of autonomy for assistance This work aims to identify the factors that should inform the adaptive shared autonomy for dexterous manipulation.

III. Assisted Tele-Manipulation System With Unreliable Autonomy

Remote Manipulation System: Fig. 2 shows the tele-manipulation system we integrated to perform the pick-and-place task. We used the hand-held controller of the HTC virtual reality system to track human hand motion to control a 7-DOF (degrees of freedom) Kinova Gen 3 robotic manipulator with a two-fingered Robotiq gripper. The scaling of human-to-robot motion mapping is 5:3:3 for the linear velocity in x-, y- and z-axes to provide more manipulability to the front of the robot arms where most of the manipulation is performed. We constrained the robot's rotational motions because this work focuses on investigating the impact of unreliable robot autonomy instead of the controllability of teleoperation. A desktop monitor displayed a graphical user interface (GUI) of Unity 3D window (1440 $\times$ 1080 pixel) to stream the video from the workspace cameras

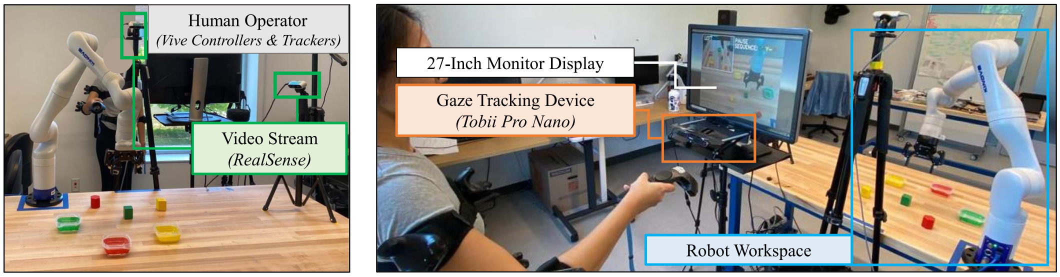

Fig. 2. Assisted Tele-manipulation System.

TABLE I
HUMAN-ROBOT COLLABORATION PARADIGMS

Autonomy *(Level)*	**Perception** *(Option)*	**Decision** *(Selection)*	**Motion Planning** *(Action)*
Manual	Human	Human	Human
Shared	Human/Robot	Human	Robot/Human
Supervisory	Robot	Robot/Human	Robot

(back and side views, using picture-in-picture display to trivialize the impact of the loss of depth information) at 30 Hz frame rate. The GUI also used overlay text to indicate the control status (“TELEOPERATING”, “EXECUTING”, “PAUSED”) and sequence of objects to manipulate.

Shared and Supervisory Control: Table I shows the three HRC paradigms we implemented for remote robot control based on task allocation between human and robot for sensing the environment, making action decisions, and executing the planned motion [13]. In the *supervisory control* mode, the robot performs all aspects of the task which autonomously picks and places the object following a pre-planned sequence based on the general procedure to perform this type of task. The human operator who supervised the robot can confirm the robot’s selected actions if they are appropriate, or control the robot’s actions and motions to correct any errors. In *shared control* mode, humans can use hand motions to control the robot to reach the target object and to move it close to the desired location, and can trigger a button to control the robot’s actions to precisely grasp and place an object. This HRC paradigm, which was implemented and evaluated in our prior work in [1], enables humans and robots to complement each other’s skills and strength to perform unstructured remote manipulation tasks. While humans can intuitively and efficiently control the robot’s freeform manual and shared control gross manipulation motions to navigate the robot across a cluttered workspace and approach targets. On the other hand, robot autonomy performs precise manipulation actions, which can place a considerable workload on humans, based on inferred human goals and action intent.

We infer human goals and action intents, by tracking human gaze fixation (using Tobii Pro Nano eye tracking device) and robot states (i.e., distances to each object and container in the workspace, the opening and closing of the gripper). Specifically, the location where the gaze is fixated for a duration longer than 0.1 seconds is inferred as the object/box the operator intends to manipulate. When the end-effector is close enough to the target object (identified by gaze fixation) to pick or location to place (within 50 mm for our task), the robot will determine

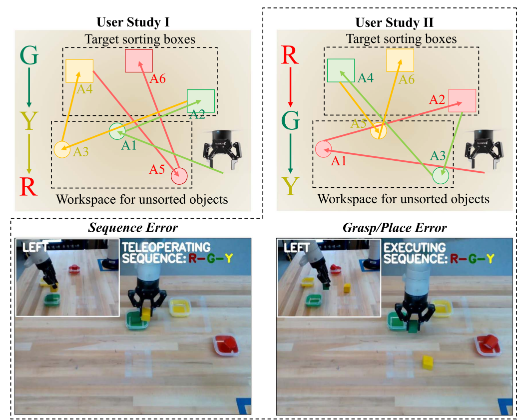

Fig. 3. (Top) Task and action sequence in each user studies; (Bottom) Sequence and grasp/place errors.

the appropriate autonomous action and execute it after the operator triggers a button on the hand-held controller to approve autonomous action. The object is identified to have been grasped or placed based on whether the gripper is opened or closed. We trivialize object detection by pre-defining the object and container locations. To correct errors, humans can press the menu button on the controller to undo a completed action or switch to *manual control* mode in order to directly control the robot’s motions.

Unreliability of Robot Autonomy: We manipulated the reliability of the robot autonomy by introducing errors at the action- and motion-level that are common to manipulation tasks (see Fig. 3 (Bottom)). When a *sequence error* happens, robot autonomy may pick up a wrong object (given the pre-defined object manipulation sequence) or place it into a container that does not match its color. When a *grasp/place error* happens, robot autonomy may miss grasping an object or placing the object with an offset from the desired location. Once a sequence error (picking up the wrong object in the sequence) or a grasp/place error (missing the grasp or placing the object) occurs and is allowed to complete, it becomes irrecoverable and cannot be corrected. We also manipulated the frequency of errors that occur (as seen in Section IV).

IV. EXPERIMENT

Participants and Task: We conducted two user studies (with the same 13 participants, 10 males, 3 females, age $= 26 \pm 4$) to investigate the effectiveness of the two implemented HRC paradigms and evaluate the influence of different types and

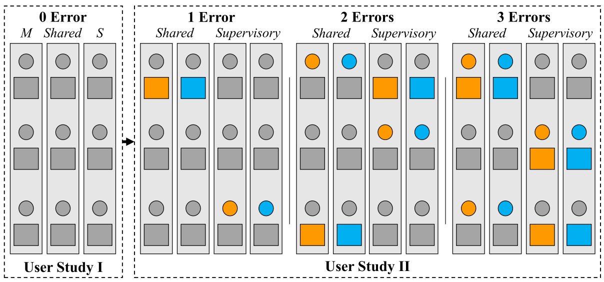

Fig. 4. Experimental conditions for User Study I and II. The circles and squares represent reach-to-grasp actions and move-to-place actions respectively. Orange (blue) highlights denote the sequence (grasp/place) errors.

frequencies of the error on the tasks and human operators. The experimental protocol was approved by WPI's Institutional Review Board (IRB-21-0004). As shown in Fig. 3 (Top), participants were required to perform a general-purpose multi-object manipulation task in which they collected objects and placed them in the correspondingly colored box following the sequence of green-yellow-red (User Study I) and red-green-yellow (User Study II). Note that each object in the workspace requires 2 actions: reach-and-grasp (i.e., A1, A3, A5) and move-to-place (i.e., A2, A4, A6).

Experimental Procedure: Before the user studies, the experimenter explained and demonstrated how to control a robot manipulator using the motion tracking controller and how to trigger robot autonomy. In the study, participants were asked to practice single object pick-and-place tasks using three different interfaces: manual control, shared control, and supervisory control. Each participant had a maximum of 10 minutes to practice with each interface. The participants were then asked to look at a blank screen for 30 seconds and had their pupil diameters recorded for the calibration required to estimate their cognitive workload. After User Study I and II, the participants answered generic surveys (the NASA-TLX and System Usability Scale) and reported their preferred control interfaces via a customized questionnaire.

a) User Study I: The first user study aims to investigate the effectiveness of the two HRC paradigms. Participants performed a multi-object sorting task, in which they controlled the remote robot manipulator to grasp and place the objects in the box following the green-yellow-red color sequence. The order of the interfaces was randomized of manual, shared, and supervisory control to minimize the impact of the learning effect. Note that the autonomy in this user study is reliable without errors. The participants performed a total of 6 trials (3 interfaces $\times$ 2 repetitions). Repeating the task helps eliminate the variation and ensure consistency.

b) User Study II: We further manipulated the reliability of robot autonomy by varying the type and frequency of the errors and evaluated their influence on the tasks and human operators. Participants performed the same multi-object sorting task in a red-green-yellow color sequence by using the randomized order of the shared and supervisory control. Shown in Fig. 4, we implemented at least one and up to three errors in 6 actions for both the sequence (orange marks) and grasp/place type errors (blue marks). The participants are allowed to correct the errors only before the confirmation of the grasping and placing action.

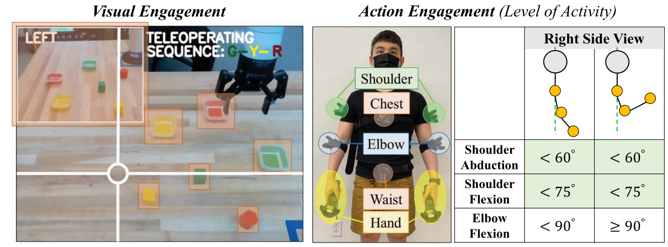

Fig. 5. Visual engagement and level of activity estimation.

If a participant made a sequence error during the task and mistakenly picked up the wrong object, the subsequent placing box should match the color of the wrongly grasped object. After placing the object, a new color sequence would be assigned based on the priority of the original red-green-yellow sequence. The participants performed a total of 12 trials (2 interfaces $\times$ 3 frequencies of the error $\times$ 2 types of the error).

Evaluation Metrics: In both user studies, we measured the *task performance* using task completion time and the length of the trajectory traveled by the robot end-effector (which indicates the motion efficiency). Additionally, the *task success* was measured by the number of times a participant successfully grasped/placed an object, picked the wrong object in the sequence or placed the object in the wrong box. A task was considered to be a failure if any of the above errors occurred due to autonomy or manual control.

We measured the users' *utilization* in the robot autonomy objectively using how many of the tasks the participants completed with autonomy and how many times the participants switched from autonomy to manual control, assuming fewer human interventions indicated more trust.

We also analyzed how participants' behaviors change due to varying robot autonomy to estimate their levels of engagement in visual perception and actions to control robots. Shown in Fig. 5 (Left), we tracked human eye movements using Tobii Pro Nano and calculated the percentage of the task for which the gaze fixation was in the area of interest (i.e., targets and picture-in-picture) to estimate *visual engagement*. To estimate the *action engagement* (level of activity), we tracked the positions of the two handheld controllers and 6 body trackers (Vive Tracker 3.0) attached to the operator's upper arms, forearms, chest and waist. The locations of the handheld controllers and body trackers were used to measure the shoulder and elbow joint angles (namely, shoulder abduction θ_{SA} on the frontal plane, shoulder flexion θ_{SF} on the sagittal plane and elbow flexion θ_{EF}) using the inner product formula. Our prior work [1] shows that: the muscle efforts of the anterior, lateral deltoid, and bicep muscle groups, caused by shoulder flexion, abduction, and elbow flexion, contributes most to the physical workload when human controls tele-manipulation using their arm and hand motions. Fig. 5 (Right) shows the gesture demonstrations and the threshold we defined for the low level of activity given the motion range of each joint angle ($0^\circ < \theta_{SA} < 120^\circ, 0^\circ < \theta_{SF} < 150^\circ, 0^\circ < \theta_{EF} < 150^\circ$). User feedback indicated that humans have more relaxed arm postures and are less ready for robot control.

To estimate the *physical workload*, we utilized a predictive model that we had developed in a separate research project [24]. The model contains the learned mapping between joint angle and muscle effort. The muscle effort was calculated based on surface Electromyography (EMG) measurements. Specifically, we calculated the shoulder muscle efforts by taking a weighted sum of the anterior and lateral deltoids, with a ratio of 3:4 based on their force generation capabilities [25]. The elbow effort was based on bicep flexion. The overall physical workload was estimated by averaging the shoulder and elbow muscle efforts for each arm and taking a weighted sum of the dominant and non-dominant arms (at the ratio of 9:1), for tasks that required extensive movement of the dominant arm for robot motion control. We also estimated the *cognitive workload* caused by stress (C_{str}) and error complexity (C_{err}) from the operator's pupil diameter, gaze fixation, and movements. We tracked variation in the operator's pupil diameter and estimated the cognitive workload caused by stress as the difference between average pupil diameter during a task and the operator's calibrated pupil diameter calculated before the task's start. Pupil diameter is expected to increase with the increase in stress [26]. This result was normalized with respect to the maximum cognitive workload across all the trials for that subject. The cognitive workload caused by error complexity (C_{err}) was computed as the ratio between the average distance in pixels of the operator's gaze fixation motion (S_{tsk}) and the maximum distance of fixation motion across all the trials for the participant (S_{max}). Complex errors are expected to result in greater gaze motion distances as they are assumed to use other visual cues to compensate. The overall workload (C_{task}) of the entire task is the average of the workloads caused by stress and error complexity.

For each user study, we collected the *subjective feedback* from the participants using a NASA-TLX questionnaire on a scale from 1 to 20 and the System Usability Scale (SUS) survey on a scale of 0 to 100. The NASA-TLX score is calculated as the overall workload by weighting six sub-scales (mental demand=5, physical demand=4, temporal demand=0, performance=2, effort=3, frustration=1). The weighting coefficients were generated by choosing from a series of pairs of rating scale factors that were deemed to be important based on the official instructions. Participants also answered our customized questionnaire on the preferred interfaces considering different factors (i.e., reliability of robot autonomy, frequency, and type of error) at the end of the user study.

Evaluation Hypotheses: Our user studies aim to evaluate the following hypotheses: *[H1]*-When the autonomy is reliable, the supervisory control interface will have the best task performance, the lowest workload, and the highest user preference, even with a loss of engagement; *[H2]*-When the robot autonomy is unreliable, a higher error frequency will lead to worse performance and higher workload, and increases the operator's preference and usage of a lower level autonomy. *[H3]*-When the robot autonomy is unreliable, users will not lose the preference for using the robot autonomy if the effort to correct the error is lower.

V. Results

This section will present the results obtained from the comparison between different factors: (1) levels of robot autonomy, (2) error frequency, and (3) error types. For all the comparisons, we analyzed data from all evaluation metrics using one-way repeated-measures analysis variance (ANOVA), including HRC paradigms for User Study I, and error frequency and type for User Study II, as a within-participants variable. All pairwise comparisons used Holm-Bonferroni correction to control for Type I error in multiple comparisons. In all the figures, $p < .05$, $p < .01$, and $p < .001$ are represented by one star (*), two (**), and three (***) stars respectively.

A. User Study I: Effectiveness of HRC Paradigms

Fig. 6 compares the manual, reliable shared, and supervisory control in terms of task completion time (on average 116±44, 83±12, and 44±2 seconds), traveled trajectory lengths (on average 4.5±0.9, 3.1±0.6, and 1.9±0.02 meters), physical workload (on average 76±21, 58±10, and 26±10 percent), cognitive workload (on average 77±19, 50±13, and 33±12 percent), NASA-TLX (on the average score of 65±15, 37±13, and 7±2), SUS (on the average score of 57±21, 77±10, and 93±7), visual engagement (on average 71±3, 63±11, and 48±12 percent), and action engagement (on average 76±13, 82±17, and 19±11 percent). Post hoc comparisons showed that the supervisory control outperformed both shared and manual control with a significantly faster task completion time (both with $p < .001$), shorter traveled trajectory (both with $p < .001$), lower physical (both with $p < .001$), cognitive ($p < .01$ and $p < .001$), and subjective overall workload (both with $p < .001$), and higher system usability score (both with $p < .001$). However, supervisory control exhibited a notably lower percentage of visual and action engagement compared to shared (both with $p < .001$) and manual (both with $p < .001$) control, implying that constant visual attention and control focus were not necessary. Subjective results (Fig. 8) indicated that 12 out of 13 participants rated supervisory control as the most preferred interface. Overall, the findings from User Study I support *H1* even if it leads to reduced engagement.

B. User Study II: Impacts of Unreliable Autonomy

Out of the 78 trials each of shared and supervisory control across the 13 participants, 5 and 7 trials were unsuccessful when using shared and supervisory control respectively. We summarize the findings of our data analysis, comparing different error frequencies and types under shared and supervisory control. A written summary of the results is provided below with the statistical details presented in Fig. 7 and Table. II.

Impacts of Error Frequency: The analysis indicates significantly longer completion time, traveled trajectory, and higher physical workload with the 3 sequence errors condition for both shared and supervisory control and 3 grasp/place errors condition for supervisory control. We found no significant difference in cognitive workload across the different frequency of errors for both shared and supervisory control. In Fig. 8, 12 out of 13 participants reported they preferred the supervisory control if errors occurred occasionally. However, when errors happened frequently, 5/13 participants prefer manual control and 5/13 participants prefer supervisory control, which indicates that some people still try to use a high level of autonomy even with frequent errors. We further analyzed the correlation between the usage of robot autonomy and manual intervention. We noticed that participants tend to let robot autonomy perform most of the

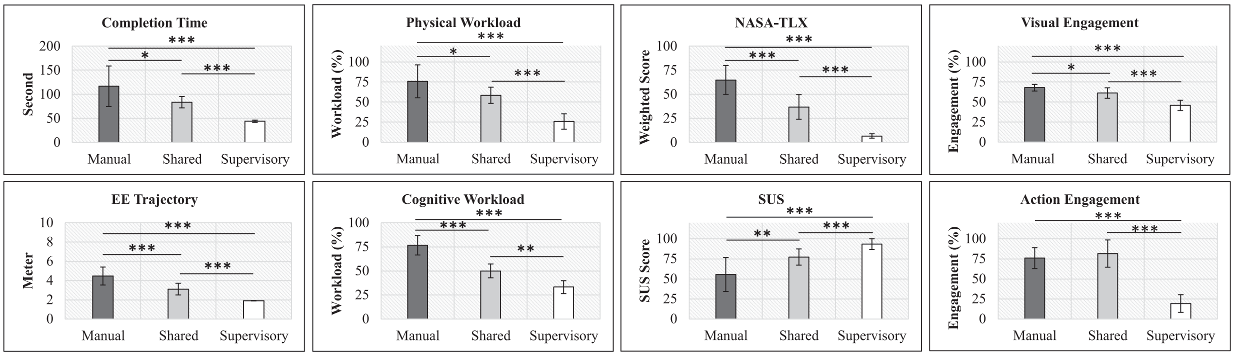

Fig. 6. User study I: comparison of manual, shared and supervisory control with reliable autonomy.

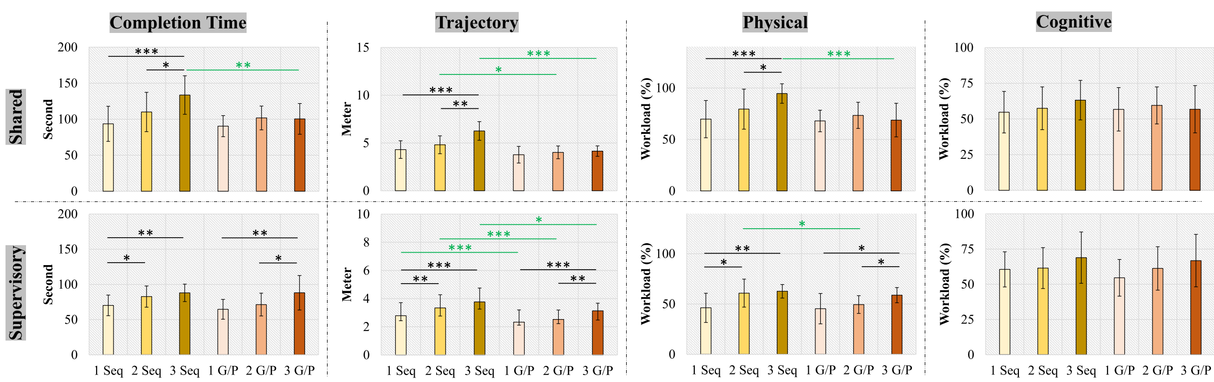

Fig. 7. User study II: comparison of completion time, trajectory, the physical and cognitive workload for shared and supervisory control with different error frequencies and types. The black and green lines indicate significant differences between different error frequencies and types of errors, respectively.

TABLE II
DESCRIPTIVE STATISTICS AND RESULTS OF SIGNIFICANT COMPARISON FOR ALL MEASURES

	Time (s)		Trajectory (m)		Physical (%)		Cognitive (%)	
Paradigms	**P1**	**P2**	**P1**	**P2**	**P1**	**P2**	**P1**	**P2**
Descriptive Statistics (M / SD)								
1 Seq	94 (24)	70 (15)	4.3 (0.9)	2.8 (0.4)	70 (18)	46 (15)	55 (15)	61 (12)
2 Seq	110 (27)	83 (15)	4.8 (0.9)	3.3 (0.6)	79 (19)	61 (14)	57 (15)	61 (15)
3 Seq	134 (27)	88 (12)	6.3 (1.0)	3.8 (0.5)	95 (9)	63 (7)	63 (14)	69 (18)
1 G/P	90 (15)	65 (14)	3.8 (0.9)	2.3 (0.2)	68 (10)	45 (15)	57 (15)	55 (13)
2 G/P	102 (16)	71 (16)	4.0 (0.7)	2.5 (0.3)	73 (13)	49 (9)	59 (13)	61 (15)
3 G/P	100 (21)	88 (25)	4.2 (0.5)	3.1 (0.7)	69 (16)	59 (8)	57 (17)	67 (19)
Pairwise Comparisons (P-value)								
1-2 Seq	.1316	.0406	.2030	.0092	.2162	.0247	.6573	.8731
1-3 Seq	< .001	.0037	< .001	< .001	< .001	.0025	.1592	.2047
2-3 Seq	.0437	.3669	.0012	.0639	.0231	.6978	.3411	.2812
1-2 G/P	.0858	.2860	.4466	.0785	.2677	.4458	.6380	.2630
1-3 G/P	.1904	.0082	.2071	< .001	.8831	.0150	.9916	.0752
2-3 G/P	.0984	.0493	.5792	.0075	.1641	.0140	.6627	.4359
1 Seq – 1 G/P	.0698	.3530	.1523	< .001	.7767	.8984	.7476	.2592
2 Seq – 2 G/P	.3753	.0885	.0249	< .001	.3739	.0320	.7273	.9702
3 Seq – 3 G/P	.0026	.9847	< .001	.0135	< .001	.2209	.3157	.7810

P1 and P2 denote shared and supervisory control, respectively.

actions (5-6 out of 6 actions) and only switch to manual control (1-3 depending on the frequency of the error) to correct the error if necessary while using supervisory control. The correlation for shared control in fewer errors condition is similar to supervisory control. This observation confirms that the participants might still utilize the high levels of autonomy for reducing operational effort even with frequent errors. However, certain participants tended to give up on the usage of autonomy (use autonomy for 1-2 out of 6 actions) and manually completed the task if errors were frequent. To sum up, we found *H2* was partially supported: the lower error frequency tended to show better performance, lower workload, higher preference and usage in high levels of autonomy; however, the user's preference and usage in the lower level of autonomy does not necessarily increase with the error frequency. This might be because operators tend to be more relaxed (minimal workload and engagement) if the tasks are not time sensitive or not extremely unreliable. As the participants

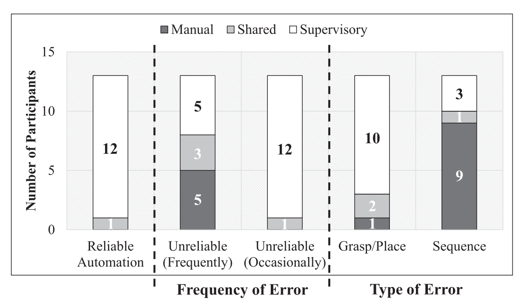

Fig. 8. The subjective feedback.

commented: *"...would like to use supervisory control to mitigate the control effort unless the success rate is very low."* and *"...higher autonomy levels is preferred since I can focus on other duties even if the robot is unreliable"*.

Impacts of Error Types: We also compared the impacts of error types across all the error frequencies for both shared and supervisory control. The analysis showed the sequence error results in a significantly longer traveled trajectory and higher physical workload for both shared and supervisory control in most of the error frequencies which aligned with our assumption that the effort to correct sequence errors is higher than grasp/place errors. The subjective feedback (Fig. 8) also indicated that 12/13 participants have a higher preference in the usage of robot autonomy (shared and supervisory control) if the error is the grasp/place error instead of the sequence error because it takes less effort to correct. This supports *H3* which predicts users' preference for usage of autonomy could be better retained if the effort for error correction is lower.

VI. Discussion: Contributions, and Limitations

A. Comparing HRC for Unstructured Remote Manipulation

The work in this paper compared two HRC paradigms (shared and supervisory control) that provide different levels of autonomy to assist humans to control unstructured remote robotic manipulation tasks. The *supervisory control* paradigm provides a higher level of assistive autonomy to plan and execute the entire task, but allows humans to use freeform reaching and moving motions to re-select the target location and objects during the task, and the action to apply. The *shared control paradigm* provides a lower level of assistive autonomy to perform the human-intended precise manipulation actions which tend to be difficult for human control, while the human operators use their hand pose to control the freeform gross manipulation. Our user studies discovered new knowledge about the effectiveness of HRC paradigms for unstructured remote manipulation: while the supervisory control paradigm with a higher level of assistive autonomy was more effective than the shared control paradigm for unstructured remote manipulation, some participants rated both paradigms similarly. This was because they felt more engaged and better able to detect and respond to robot errors with the shared control. We also found the intent inference based multi-modal inputs (human gaze, task, and robot states) to be simple and effective, and can be applied to various remote robot control and supervision compared to using these inputs individually ([27], [28]) or alternative inputs (user behavior [29], robot pose [30]).

While our user studies compared two HRC paradigms (shared and supervisory control), we are aware of the various levels of robot autonomy and human-robot collaboration paradigms (see the review in [13]) to be examined in future work. The levels of assistive autonomy may be adjustable or even adaptive, which implies the dynamic role arbitration in the human-robot collaboration [31]. Our user studies are also limited because most participants are experienced video game players. A further study with users of diverse backgrounds, ages, gaming, and VR interfaces is necessary for a holistic evaluation of the impacts of unreliable autonomy.

B. Influences of Unreliable Assistive Autonomy

In this work, we manipulated the error type and frequency and evaluate the impacts of unreliable autonomy on performance, workload, and user preference. We found that in general, more frequent and severe errors have more significant impacts on task performance, human workload, and the operator's preference to use autonomy (which may imply the user's trust). Particularly, we noticed that humans still prefer to use unreliable autonomy if the errors are easy to correct, which implies that an effective mechanism for error recovery may significantly improve the resilience and usability of robot autonomy. Thus the HRC paradigms must enable the operator to avoid errors. For instance, Augmented Reality (AR) prompts can indicate the autonomy's reliability in success, allowing the operator to make informed decisions on whether to use autonomy or not. Additionally, teleoperators can improve the reliability of the system and enhance their confidence by participating in the decision-making loop of the robot autonomy, which involves mitigating potential sources of errors. For instance, participants can mitigate the impact of errors in the object sorting task by indicating the colors of each object, which eliminates the need for object detection to locate the objects in the workspace. In the event of an error occurring, the HRC paradigm must allow participants the ability to easily correct the errors. For example, in the event of minimal corrective motion picking/placing errors in the user study, an interface that allows for discrete small motions (such as the trackpad of a handheld controller) can assist the operator in easily correcting the errors of robot autonomy within the HRC paradigm and minimize the impact of unreliable autonomy. We also noticed that compared to the shared control, supervisory control has significantly higher ($p < .05$) task performance and physical workload but comparable cognitive workload. Because the robot control in our task heavily relied on remote camera visual feedback, it is likely that a more unreliable robot autonomy has more adverse impacts on the cognitive workload (to track the task more carefully and detect the errors) than the physical workload (to correct the errors). Higher frequency of errors ($> 50\%$ of the task) could have a greater impact on the preference for autonomy and will be explored in future work.

Besides error types and frequency, other factors may influence the users' perception of robot autonomy, and preference to use a higher level of autonomy. Our post-study survey shows that the participants preferred supervisory control (higher level of assistive autonomy) when it is reliable, but only occasionally if the autonomy is unreliable. We also found most participants (9 out of 13) prefer using a higher level of robot autonomy if the errors happened at a later stage of the task, which implies the perception of the robot autonomy depends not only on the frequency and types of errors but also when the errors are likely to happen. Moreover, some participants (3 out of 13) indicated not preferring a higher level of robot autonomy since it is tedious to switch to a lower level of autonomy when they have to correct an error. Our future work will address the limitation of this work by examining the influence of these additional factors as well as the influence of the type of interface, workspace environment, and user background on human perception and trust in robot autonomy. Because trust is a complex construct that needs iterative establishment over time, we will choose objective measurements to assess trust levels. Moreover, we will refer to the related work that summarizes the attributes of robot autonomy (see the review in [32]), consider a more systematic approach to manipulate the errors, and consider errors caused by unreliable robot perception, decision-making, and action.

VII. Conclusion

This work investigated how unreliable autonomy affects the operator's performance, workload, and preference in the shared and supervisory control of unstructured remote manipulation tasks. We found that when the robot autonomy is reliable, supervisory control is the most effective despite low operator engagement. With unreliable autonomy, performance and workload becomes worse as the error frequency increases, yet the operator may still not prefer to reduce the level of autonomy due to the increasing efforts for robot control. Moreover, users may still prefer to use unreliable autonomy if it is easy to correct the errors. This paper also compared two HRC paradigms to effectively assist humans to control unstructured, error-prone remote robot manipulation, and proposed novel methods for the accurate intent inference for assistive autonomy. Our future work will evaluate the proposed approaches with a diverse participant population, and manipulate other attributes of robot autonomy. We also aim to consider vision-based remote manipulation tasks that involve more complex actions and motion control, and remote perception using dynamic viewpoint and multi-cameras.

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