Impact of Different Interfaces on Trust During Authority Shifting in Collaborative Robotics

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***Abstract*—Real-time authority handovers in human–robot collaboration demand predictable post-takeover control. This study compared keyboard control with a wrist-mounted position tracker following a common gesture-based authority switch. Thirteen participants (within-subjects, counterbalanced) performed a collaborative pick-and-place task with a cobot while trust (primary outcome) was measured using a 10-item, 5-point scale. The keyboard control produced higher trust than the tracker: mean paired difference 0.362 (1–5 scale; 95% CI [0.078, 0.646]), $t(12) = 2.774$, $p = 0.0169$; corroborated by Wilcoxon $p = 0.0234$ (rank-biserial 0.758; Hodges–Lehmann 0.300). Results indicate that during handovers, predictability and low input variance foster greater operator trust than embodied pose-based control. Design implications include handover human–machine interactions that make mode changes unmistakable, apply early damping/noise rejection after takeover, and use hybrid strategies that anchor the handover with discrete inputs before reintroducing embodied control.**

***Index Terms*—Human-Robotic Interaction, Authority Switching, Trust, Teleoperation, Smart Manufacturing**

I. Introduction

Trust is a fundamental element in Human-Robot Interaction (HRI), especially in collaborative settings where humans and robots share responsibilities [1], [2]. Effective cooperation requires that humans trust the robot's autonomy while retaining the ability to intervene when necessary [3]. This balance between autonomy and manual control is managed through mechanisms such as authority switching, which allows human operators to override or adjust robot behavior during task execution [4].

This publication has emanated from research conducted with the financial support of Taighde Éireann under Grant Number SFI/12/RC/2289-2 - Insight Centre for Data Analytics. Aspects of this work have been supported under the following Grant Numbers: CONNECT Centre for Future Networks and Communications (13/RC/2077), and 16/RC/3918-CONFIRM and [21/RC/10303_P2]–VistaMilk. All work is co-funded under the European Regional Development Fund. For the purpose of Open Access, the author has applied a CC BY public copyright licence to any Author Accepted Manuscript version arising from this submission.

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Control interface design strongly shapes user trust and usability in HRI [5]. Gesture-based interfaces (instrumented gloves with motion tracking) are often proposed as alternatives to keyboards or touchscreens. Schött et al. [6] note that transparency in co-located HRI is often monomodal, bolt-on, and underuses haptics, motivating handover HMIs that emphasize legible, predictable, low-variance control. Mohebbi [7] emphasizes human-centered design, multimodal sensing, and shared control in assistive HRI, while highlighting open issues such as fatigue, interface robustness, and systematic modality comparisons. Together, these reviews link operator state and interface reliability to successful authority transitions and highlight a lack of controlled comparisons at the moment of handover (e.g., gesture vs. keyboard).

In high-stakes or precision-critical tasks, assigning the non-dominant hand to gesture-based authority switching keeps the dominant hand free for fine control. This study adopts that pattern: the non-dominant hand triggers the handover, while the dominant hand executes the post-takeover corrections.

A. Problem Statement and Research Questions

Wearable hand-tracking interfaces (instrumented gloves) offer intuitive, embodied control via familiar hand motions, yet their impact on trust, perceived authority, and performance relative to discrete interfaces (e.g., keyboards) remains unclear. This study examines (i) whether gesture-based control alters operator trust, (ii) how modality (gesture vs. keyboard) shapes perceived authority, confidence, and controllability, and (iii) whether it affects task success or user satisfaction. Trust is quantified with a validated HRC questionnaire under counterbalanced modalities, complemented by post-trial qualitative feedback.

We intentionally contrast a standard, deterministic keyboard interface with a single, commercially available 6DoF pose tracker mounted at the wrist. The goal is not to claim that keyboards are universally superior to all embodied interfaces, but to probe two ends of the design space—discrete, low-variance commands versus continuous, potentially noisy pose control—at the instant immediately following an authority handover. The task and setup are deliberately simple to isolate this moment, so the findings should be read as an initial, controlled comparison rather than a definitive prescription for all HRI scenarios. Future work will extend this comparison to richer tasks and alternative embodied controllers (e.g., other gesture devices, joysticks, or exoskeletal interfaces).

II. Methodology

A. Participants

Thirteen adults from a university/research community participated. Demographics (age, gender, prior robotics/VR experience) were collected post-experiment (Fig. 1); prior automation experience can influence trust [4]. All gave written informed consent. Inclusion: normal/corrected vision; ability to operate a keyboard and a wearable glove; no musculoskeletal issues affecting hand motion. Exclusion: current hand injuries or musculoskeletal impairments. All participants were proficient in English for instructions and surveys.

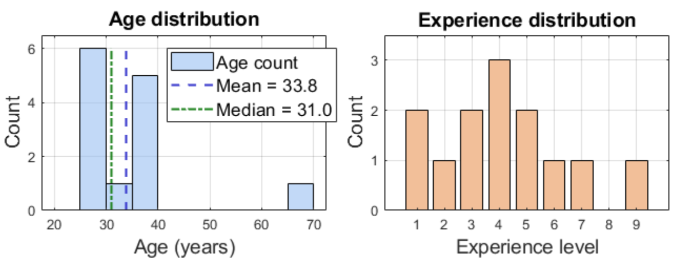

Fig. 1. Participant demographics and self-reported prior experience with robotics and VR ($N = 13$). Bars summarize the distribution of age, gender, and ordered experience categories (from "none" to "extensive") for the university/research participant cohort.

B. Experimental Apparatus and System Architecture

The experimental setup comprised an UR16e collaborative robot fitted with a RG6 gripper (OnRobot, Odense, Denmark) performing a pick-and-place task at a workstation (Fig. 2). Participants wore a data glove (Quantum Metaglove, Manus Technology Group, Geldrop, The Netherlands) on the non-dominant hand to issue an authority-switch gesture recognized by the system: an open hand signaled the robot to continue its planned trajectory, whereas a closed fist transferred control of the end-effector to the operator. The dominant hand guided the end-effector trajectory, via discrete key inputs in the keyboard modality, or via a wrist-mounted position tracker (Vive Tracker 3.0; HTC, Taiwan, R.O.C.) in the tracker modality.

The hardware was selected to ensure high-fidelity interaction. For example, the low latency of the Manus gloves ($\leq 7.5\,\mathrm{ms}$) and the high repeatability of the UR16e ($\pm 0.05\,\mathrm{mm}$) indicate that performance variations were more likely due to human factors and interface design than hardware limitations.

The software architecture was based on ROS2 Humble Hawksbill running on Ubuntu 22.04. Dedicated nodes handled

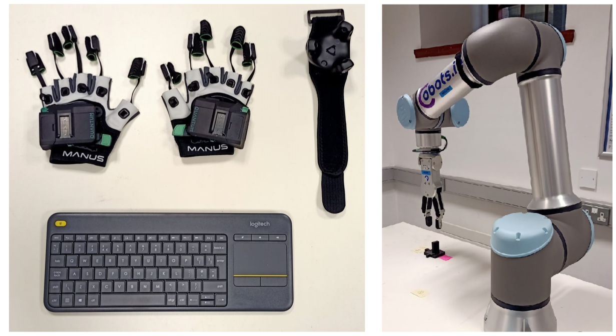

Fig. 2. Overview of the experimental apparatus. Left: input devices used in the study (Manus Quantum Metaglove for authority switching, HTC Vive Tracker 3.0 for pose-based control, and wireless keyboard for discrete control). Right: UR16e collaborative arm with RG6 gripper at the shared workstation used for the pick-and-place task.

(i) gesture recognition from the Manus glove via a pre-trained classifier, (ii) 6DoF pose streaming from the Vive Tracker through a SteamVR–ROS2 bridge, (iii) mapping keyboard inputs to velocity commands, and (iv) managing the current control mode (autonomous vs. manual) and routing inputs accordingly. The official `ur_robot_driver` translated ROS2 commands into low-level control for the UR16e arm.

C. Trust Assessment Questionnaire

Subjective trust was measured after each modality using a modified version of the Charalambous et al. [3] HRC trust questionnaire, previously validated in industrial HRI. The scale comprised 10 items on a 5-point Likert format, coded such that strongly positive = 5 and strongly negative = 1. Total scores thus ranged from 10 (lowest trust) to 50 (highest trust). Negatively worded items (questions 1, 3, and 7) were reverse-scored prior to computing per-modality trust indices.

D. Task and Procedure

A within-subjects design was used: each participant experienced both control modalities, with counterbalanced order (tracker vs. keyboard), as shown in Fig. 3.

1) Collaborative pick-and-place scenario: The UR16e autonomously picked custom 3D printed blocks from a start area and placed them into color-coded slots on the workbench. At a randomized point, a scripted misplacement occurred, implicitly signaling an opportunity for intervention.

2) Authority switching protocol: Participants could assume manual control at any time, especially after the fault, by performing a closed-fist gesture with the instrumented glove. The Gesture Recognition node detected the gesture and the *Robot Control Manager* stopped autonomy and transferred control to the operator.

E. Control Modalities

1) Tracker-based control: In this condition, the participant controlled the robot's end-effector directly through their dominant hand's motion. The 6DoF pose from the Vive Tracker was mapped to the target pose of the robot's tool center point. A separate, distinct gesture (e.g., making a claw) was used

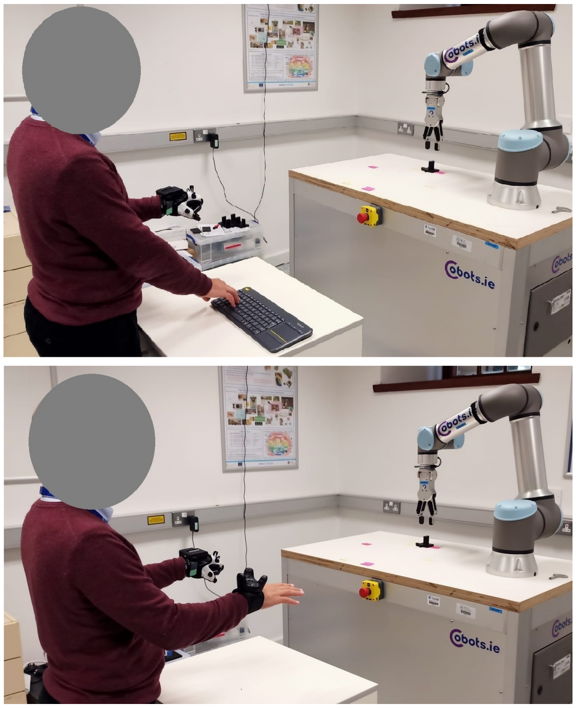

Fig. 3. Experimental protocol for the two post-handover control modalities. Top: keyboard condition - after authority handover via a closed-fist gesture with the non-dominant hand, the operator steers the end-effector using WASD and arrow keys, and uses numeric keys to control the gripper. Bottom: tracker condition - after the same authority handover, the operator guides the end-effector using the wrist-mounted HTC Vive Tracker 3.0 and distinct hand gestures to open/close the gripper.

to command the OnRobot RG6 gripper to close, and another (e.g., opening the hand) to command it to open.

2) Keyboard-based control: In this condition, the participant used standard keyboard keys with the dominant hand to control the robot. The `W` and `S` keys controlled forward/backward motion along the X-axis, `A` and `D` controlled left/right motion along the Y-axis, and the `Up` and `Down` arrow keys controlled vertical motion along the Z-axis. The `1` and `2` keys toggled the gripper state (open/close).

F. Data Acquisition Protocol

Each participant provided written informed consent and received a brief overview of the study without disclosure of specific hypotheses. They then completed standardized training on both the gesture-based and keyboard control systems in a nonexperimental sandbox until comfortable. The experiment used a within-subjects, counterbalanced design: participants performed two blocks of the pick-and-place task, each under one modality. In every block they monitored the robot, invoked the gesture-based authority switch at the scripted fault, and completed the placement using the assigned interface. Immediately after each block, they completed the modified Charalambous HRC Trust Scale.

III. Data analysis

For each participant, we computed a mean trust score per modality (keyboard, tracker) by averaging the 10 items. To test whether input modality affected trust, we applied a paired-samples t-test to the per-participant means and, as a nonparametric check, a Wilcoxon signed-rank test [8]–[10]. We report the mean difference with 95% confidence interval, Cohen's d_z for the t-test, and the matched rank–biserial correlation for the Wilcoxon test. Internal consistency of the 10-item scale was assessed with Cronbach's α [12], and boxplots with overlaid participant trajectories visualize the distribution of trust scores across modalities.

IV. Results

Table I summarizes the trust questionnaire responses, showing consistently higher mean scores and lower variability for the keyboard interface across multiple trust dimensions, including reliability, ease of use, and perceived safety.

TABLE I
Statistics per questionnaire item across participants

Item	Tracker		Keyboard	
	Mean	SD	Mean	SD
A: Comfortable Movement (R)	3.69	0.95	4.08	0.86
B: Reliable Robot	3.38	0.87	4.00	0.82
C: Ease with Speed (R)	3.54	0.88	4.00	0.91
D: Felt Safe	4.08	0.49	4.08	0.76
E: Confident Gripper Resp.	3.15	1.07	4.31	0.95
F: Not Intimidated by Size	4.08	0.76	4.00	0.91
G: Reliable Gripper (R)	4.15	0.80	4.23	0.83
H: Comfortable Not Hurt	4.46	0.66	4.62	0.51
I: Trusted to Cooperate	4.00	1.00	4.38	0.65
J: Trusted Behavior	3.92	0.86	4.38	0.87

(R) denotes reverse-scored items.

A. Quantitative Analysis

The paired difference in per-participant mean trust (Keyboard–Tracker) was 0.362 points on the 1–5 scale (95% CI [0.078, 0.646]), indicating a consistent advantage for the keyboard modality. Normality of paired differences was supported (Lilliefors, p = 0.50). A paired-samples t-test showed a statistically significant modality effect, $t(12)$ = 2.774, p = 0.0169, with Cohen's d_z = 0.769 (moderate-to-large within-subject effect). A Wilcoxon signed-rank test was likewise significant (p = 0.0234; matched rank–biserial correlation 0.758), indicating higher trust for the keyboard condition for most participants. The Hodges–Lehmann estimator of the typical paired difference was 0.300.

B. Reliability of the Trust Measure

Internal consistency of the 10-item trust scale was good in the keyboard condition (Cronbach's α = 0.842) and acceptable in the tracker condition (α = 0.726), supporting aggregation of item scores to a single trust index per modality. Fig. 4 illustrates the upward shift for the keyboard condition and the absence of extreme outliers in the paired differences.

V. Discussion

Trust was consistently higher with keyboard control than with the tracker modality, with statistically reliable effects and acceptable scale reliability in both conditions. The two

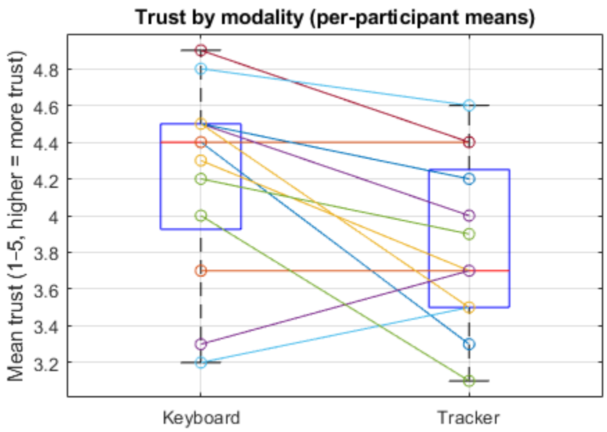

Fig. 4. Trust by modality with participant trajectories. Boxplots of per-participant mean trust for keyboard and tracker; colored lines trace each participant across conditions, illustrating within-subject changes. Higher scores indicate greater trust on the 1–5 scale (averaged across 10 items).

modalities shared the same gesture-based handover; differences arose only in post-takeover control. Discrete key inputs minimize early post-handover variance and ambiguous states, whereas pose tracking can introduce jitter, occlusion noise, latency, and drift. The tracker also maps a 6DoF hand pose to end-effector motion, increasing coordination demands relative to three decoupled translational axes on the keyboard. Under time pressure, such uncertainty and cognitive load plausibly erode trust more than any gain in perceived naturalness. Our results therefore provide quantitative evidence, in the specific context of gesture-triggered authority handovers, for the established HMI principle that predictable, low-variance interfaces facilitate trust.

A. Design Implications for Handover HMIs

Handover HMIs should make mode changes unmistakable, dampen the first seconds of input (rate limits/filters), and confirm intent before high-gain moves. Keep authority-switch gestures clearly separable from control gestures. A hybrid strategy is effective: discrete inputs anchor takeover and fine adjustments; embodied tracking resumes once the robot is stabilized. Exposing tracking confidence/occlusions and attending to ergonomics further stabilizes control.

B. Alternative Explanations and Boundary Conditions

Effect magnitude may vary with familiarity/training, task demands (precision vs. spatial mapping), system tuning (latency/smoothing/gains), and measurement timing (early calibration vs. post-acclimation). These qualify, but do not overturn, the claim that predictability dominates at the handover instant.

C. Limitations, Generalizability, and Future Work

The small sample size ($N = 13$) limits generalizability and the precision of effect-size estimates; although converging tests and confidence intervals support the observed effect, the study is underpowered for more subtle modality differences. Larger-scale validation with more heterogeneous operators and contexts is therefore required.

The comparison is also deliberately narrow: one cobot platform (UR16e with RG6 gripper), one gesture-based authority-switching mechanism (non-dominant-hand glove), and one specific pose-tracking device. Thus, we cannot fully disentangle whether lower trust in the tracker condition reflects continuous pose-based control in general, the specific device implementation (e.g., base-station placement, occlusions, tracking robustness), or our parameter choices (latency, smoothing, gains). Training was self-paced until participants felt comfortable, so training duration may have differed between modalities; future studies should either standardize or explicitly model training time.

VI. Conclusions

In a collaborative pick-and-place task with a gesture-based handover, keyboard control produced higher operator trust than pose tracking, with statistically reliable and practically relevant differences. During the handover window, predictability and low input variance outweighed perceived "naturalness".

Handover HMIs should make mode changes unmistakable, damp early inputs, and confirm intent before high-gain moves; in practice, discrete inputs can anchor takeover, with embodied tracking added after stabilization. Given the modest sample and single-platform, single-device setup, effects may vary with experience, task demands, and tuning. Future work should test these moderators and assess handover-aware tuning and hybrid interface timelines using both trust and performance metrics.

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