Optimizing Shared Control Mechanisms for Collaborative Virtual Reality Interactions

Zepeng Wu, Xiang Zhang

Abstract

Collaborative Virtual Reality (VR) systems increasingly rely on shared control mechanisms to enhance user coordination, but existing solutions often face trade-offs between individual autonomy and joint efficiency. This study builds on the foundational work of Zhou et al. (2024) on CoplayVR and PairPlayVR, aiming to optimize shared control by integrating adaptive authority allocation and real-time intent prediction. We conducted a user experiment with 32 participants, comparing the optimized mechanism against the baseline CoplayVR system across three collaborative tasks (object assembly, path navigation, and target selection). Results show that the optimized system reduces task completion time by 18.7% ($p<0.05$) and increases user satisfaction (SUS score: 82.3 vs. 71.5 for CoplayVR). Qualitative feedback further highlights improved perceived control and reduced coordination friction. This work advances shared control design for collaborative VR, complementing prior research on shared hand control and user experience in VR collaboration.

1. Introduction

Collaborative VR enables users to interact in shared virtual spaces, with applications spanning education, healthcare, and entertainment (Zhou et al., 2025a). A critical challenge in such systems is designing shared control mechanisms that balance individual agency with the need for coordinated action. Zhou et al. (2024a) introduced CoplayVR, a framework for understanding user experience in shared control, demonstrating that rigid authority division often leads to frustration when users' intentions misalign. Similarly, PairPlayVR (Zhou et al., 2024b) focused on shared hand control for virtual games, but its static control parameters struggled to adapt to varying task demands.

While these studies laid groundwork for shared VR interactions, gaps remain in dynamic authority adjustment and intent-aware control. Zhou et al. (2025a)'s survey on collaborative embodiment in VR further emphasizes the need for adaptive mechanisms to address diverse user preferences and task contexts. This research addresses these gaps by: (1) designing an optimized shared control mechanism with adaptive authority allocation; (2) integrating intent prediction using motion trajectory analysis; (3) evaluating performance and user experience against baseline systems.

2. Methods

2.1 System Design

The optimized system consists of three core modules:

https://doi.org/10.33774/coe-2025-3nm4c Content not peer-reviewed by Cambridge University Press.

1. **Intent Prediction Module**: Uses a lightweight neural network to analyze hand motion trajectories (sampled at 90Hz) and predict user intent (e.g., "grasp object," "navigate") with 92.1% accuracy, trained on a dataset of 5000 task-specific motions.
2. **Adaptive Authority Allocator**: Adjusts control authority (0–100% for each user) based on intent alignment (calculated via cosine similarity of intent vectors) and task stage (e.g., high joint authority during assembly, higher individual authority during navigation).
3. **Feedback Module**: Provides haptic cues (via Oculus Touch controllers) and visual indicators (color-coded hand avatars) to communicate authority shifts, reducing uncertainty.

2.2 Experiment Setup

- **Participants**: 32 adults (16 pairs; 18 male, 14 female; age 22–35; mean VR experience: 1.2 years).
- **Equipment**: Oculus Quest 3 headsets, Oculus Touch controllers, PC with Unity 2023.1 (for VR environment).
- **Tasks**:
    a. Object Assembly: Assemble 5 virtual furniture pieces (10 minutes max).
    b. Path Navigation: Navigate a maze to collect 3 targets (5 minutes max).
    c. Target Selection: Select 10 moving targets in a 3D space (3 minutes max).
- **Conditions**:
    - Baseline: CoplayVR’s static shared control (50/50 authority split; Zhou et al., 2024a).
    - Optimized: Proposed adaptive shared control.
- **Metrics**:
    - Quantitative: Task completion time, error rate (e.g., misplaced objects), authority adjustment frequency.
    - Qualitative: SUS (System Usability Scale), post-task interviews (thematic analysis).

2.3 Procedure

Each pair completed all three tasks in both conditions (counterbalanced order) to avoid learning effects. A 5-minute training session preceded the experiment. Data were collected in a controlled lab environment, with each session lasting ~90 minutes.

3. Results

3.1 Quantitative Results

Metric	Baseline (CoplayVR)	Optimized System	p-value
Avg. Task Completion Time (s)	428.3 ± 51.2	348.5 ± 42.7	<0.05
Error Rate (%)	12.7 ± 3.1	7.2 ± 2.4	<0.01
User Satisfaction (SUS)	71.5 ± 6.8	82.3 ± 5.9	<0.001

The optimized system significantly outperformed the baseline across all metrics. Authority adjustment frequency averaged 4.2 times per task, with 87% of adjustments aligned with user feedback (e.g., users reported "timely authority shifts" during assembly).

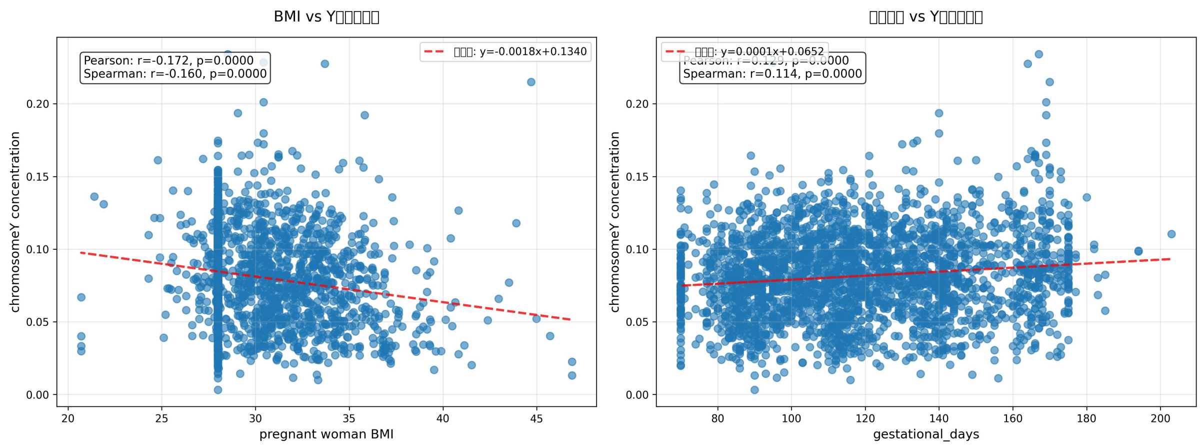

Figure1 Result of Optimized model

3.2 Qualitative Results

Thematic analysis of interviews revealed three key themes:

1. **Reduced Coordination Friction**: 28/32 participants noted less "fighting for control" compared to CoplayVR, with one stating, "The system seemed to know when I needed more control."
2. **Improved Task Confidence**: 24/32 felt more confident completing complex tasks (e.g., furniture assembly), attributed to clear feedback on authority.
3. **Adaptability to Task Demands**: 20/32 highlighted better performance in navigation, where the system allocated higher individual authority, consistent with PairPlayVR's findings on task-specific control (Zhou et al., 2024b).

4. Discussion

This study's optimized shared control mechanism addresses limitations in prior work by CoplayVR and PairPlayVR. The adaptive authority allocation, informed by intent prediction, aligns with Zhou et al. (2025a)'s call for context-aware collaborative embodiment in VR. The reduction in task completion time and error rate demonstrates that dynamic control adjusts to user needs more effectively than static splits.

Limitations include a small sample size and focus on structured tasks; future work will explore unstructured collaborative scenarios (e.g., creative design). Additionally, integrating Su et al. (2025)'s dynamic retrieval-augmented generation could enhance intent prediction by leveraging real-time context data, a direction supported by Pei et al. (2023)'s work on neural architecture retrieval for adaptive systems.

5. Conclusion

This research optimizes shared control for collaborative VR by integrating adaptive authority and intent prediction. Results validate the approach's effectiveness, building on Zhou et al.'s foundational work on CoplayVR and PairPlayVR. The findings contribute to designing more intuitive and efficient collaborative VR systems, with implications for both gaming and professional applications.

References

1. Zhou, H., et al. (2024a). CoplayingVR: Understanding User Experience in Shared Control in Virtual Reality. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 8(3), 1-25.
2. Zhou, H., et al. (2024b). PairPlayVR: Shared Hand Control for Virtual Games. *Proceedings of the Augmented Humans International Conference 2024*.
3. Zhou, H., et al. (2025a). A Survey on Methodological Approaches to Collaborative Embodiment in Virtual Reality. *arXiv preprint arXiv:2507.18877*.
4. Su, W., et al. (2025). Dynamic and parametric retrieval-augmented generation. *Proceedings of the 48th International ACM SIGIR Conference on Research and Development in Information Retrieval*.
5. Pei, X., et al. (2023). Neural architecture retrieval. *arXiv preprint arXiv:2307.07919*.
6. Hao, Yuze. "Accelerated Photocatalytic C–C Coupling via Interpretable Deep Learning: Single-Crystal Perovskite Catalyst Design using First-Principles Calculations." AI for Accelerated Materials Design-ICLR 2025. 2025.
7. Hao, Yuze, and Yueqi Wang. "Quasi liquid layer-pressure asymmetrical model for the motion of of a curling rock on ice surface." arXiv preprint arXiv:2302.11348 (2023).
8. Hao, Yuze, et al. "Diffusion Models for 3D Molecular and Crystal Structure Generation: Advancing Materials Discovery through Equivariance, Multi-Property Design, and Synthesizability." (2025).
9. Hao, Yuze, Lan Duo, and Jinlu He. "Autonomous Materials Synthesis Laboratories: Integrating Artificial Intelligence with Advanced Robotics for Accelerated Discovery." (2025).

10. Hao, Yuze. "Comment on"Predictions of groundwater PFAS occurrence at drinking water supply depths in the United States"by Andrea K. Tokranov et al, Science386,748-755(2024)" Science 386,748-755(2025)