Investigating Gait Imitation in VR: Impact of Visual Feedback and Avatar Design

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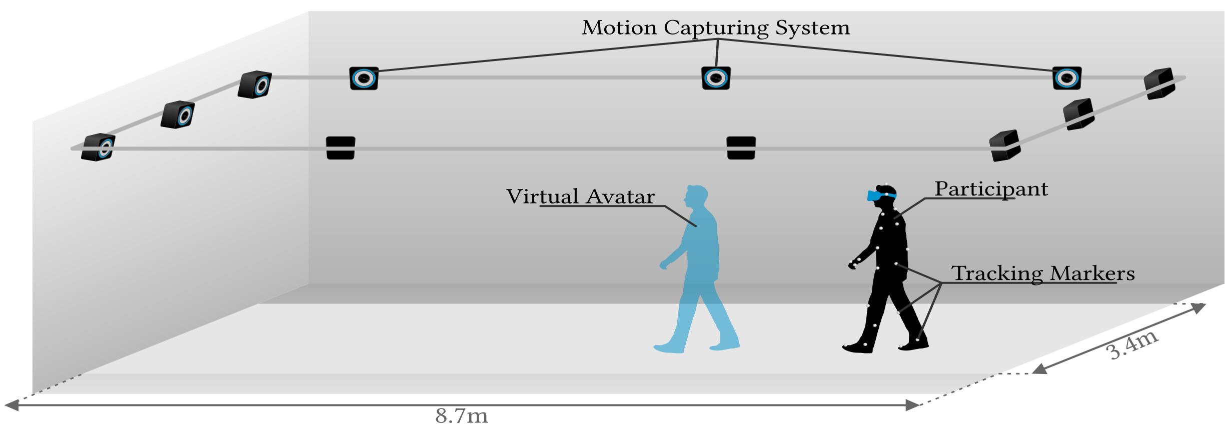

Figure 1: Study setup showing a controlled environment with 11 cameras for full-body tracking. The subject walks wearing a headset and an Optitrack suit with markers behind the virtual avatar, aiming to imitate their movements.

Abstract

Gait is a distinctive behavioral trait, yet its vulnerability against imitation remains underexplored in immersive environments. We present a study investigating how real-time visual feedback in virtual reality (VR) influences a person's ability to mimic another's gait. Through two experiments, we first identify the most usable feedback design (N=8), then evaluate its impact on imitation performance compared to a baseline without feedback (N=18). We analyze positional and rotational similarity between participants and target avatars, examining the influence of avatar–user gender matching and repeated practice. Our findings reveal that visual feedback significantly improves rotational alignment and that practice leads to measurable improvements in mimicry accuracy. We discuss implications for avatar embodiment, personalization in VR applications, and potential considerations for behavioral biometric systems. We also contribute a publicly available dataset of gait mimicry in VR, supporting further research on motion learning and imitation.

All references are last accessed on October 21, 2025

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CCS Concepts

• **Human-centered computing** → *User studies*; **Virtual reality**; Interaction techniques; • **Security and privacy** → Social aspects of security and privacy; • **Computing methodologies** → **Motion capture**.

Keywords

Gait imitation, Virtual Reality, Motion Capture, Embodied Interaction

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1 Introduction

Gait, the characteristic pattern of how a person walks, is a fundamental human movement that is both distinctive and adaptable [36]. People subconsciously change how they walk depending on terrain, footwear, health, or social context [31]. Understanding how gait can be adapted and imitated is valuable for domains such as rehabilitation [39], sports training [7], and interactive entertainment [19], while also exposing vulnerabilities in gait-based biometric systems [22]. These vulnerabilities are amplified when individuals intentionally attempt to imitate another's gait, i.e., gait mimicry, which raises critical questions about the robustness of gait-based identification and motivates our investigation [23]. Therefore, studying gait imitation is relevant across a wide range of applications, offering opportunities for rehabilitation and learning while also highlighting challenges and risks to gait-based biometric identification methods.

Virtual Reality (VR) offers a controlled and immersive environment for investigating these adaptations [18]. Unlike real-world studies, VR enables precise manipulation of variables such as avatar appearance, visual overlays, and viewing perspective, while providing consistent target movements across repeated trials [17]. Prior work shows that users often unconsciously align their movements with their virtual avatars, the "follower effect" [5, 10], and that embodiment in VR can support motor learning in areas such as sports, rehabilitation, and skill acquisition [25, 28].

We focus on gait mimicry, the deliberate imitation of another person's walking pattern. Unlike rehabilitation or sports training, which aim to improve one's own movement [39], gait mimicry requires aligning with an external model, introducing distinct perceptual and cognitive challenges [22]. While gait has been examined in rehabilitation and sports contexts, it remains underexplored in VR, particularly in terms of how different visual feedback designs affect mimicry performance. By leveraging VR, we can create controlled, repeatable scenarios that isolate specific variables and capture detailed motion data. This not only informs the design of VR-based training and personalization systems but also provides insight into whether and how gait mimicry could be leveraged in other contexts, such as impersonating an avatar or, in more speculative scenarios, influencing gait-based recognition systems.

We present two user studies exploring how real-time visual feedback affects gait mimicry in VR. In a formative study (N=8), we compared four visualization techniques for showing differences between a target avatar's gait and a participant's own movements, identifying a semi-transparent body overlay as the most usable. In a follow-up study (N=18), we evaluated this visualization against a no-feedback baseline, examining its effect on gait similarity and the role of avatar–user gender matching. While visual feedback did not significantly improve overall positional mimicry, we observed effects on rotational alignment and a clear influence of avatar appearance on mimicry performance. We also contribute a publicly available dataset of gait mimicry in VR, supporting further research on motor adaptation, avatar embodiment, and movement personalization.

Contribution Statement. This work provides an empirical investigation of gait imitation in VR, examining how real-time visual feedback and avatar design shape imitation accuracy. Through two user studies, we show that a semi-transparent overlay is the most usable visualization technique, that avatar gender matching influences rotational alignment, and that imitation skills improve with practice across repeated trials. In addition, we contribute an open dataset containing full-body positional and rotational motion-capture recordings from 16 participants imitating four avatars, creating a resource for future work on motor learning, avatar embodiment, and the robustness of gait-based systems.

2 Related Work

Our work builds on research in gait imitation, avatar embodiment, and the use of immersive technologies to support motor learning and influence user movement.

2.1 Biometric Identification and Vulnerabilities

Biometric systems identify individuals based on unique physiological (e.g., fingerprints, iris) or behavioral traits (e.g., typing patterns, gait). Compared to knowledge- or token-based methods, they offer the advantage of being continuous and harder to lose or forget [8]. However, they are not immune to misuse. Attacks on biometrics range from zero-effort attempts (simply presenting one's own traits) to skilled impersonation, where attackers deliberately mimic or replay another person's characteristics [3, 35].

While spoofing is well studied for static physiological traits such as fingerprints or faces [11, 38], behavioral traits raise distinct challenges. Gait, for instance, is both distinctive and dynamic: it enables continuous recognition without explicit user input but can also be adapted or imitated [22, 36]. This flexibility opens the door for mimicry attacks, where adversaries intentionally adjust their walking style to resemble that of a target. Unlike physiological traits, where liveness detection (e.g., blinking, pulse) is effective [34], behavioral biometrics provide no easy safeguard against such deliberate adaptations.

2.2 Gait Identification and Mimicry

Gait has long been explored as a behavioral biometric because it can be captured unobtrusively and used for continuous recognition.

Vision-based systems typically analyze silhouettes or body models for surveillance [12, 16], while sensor-based approaches rely on wearables or smartphones to capture walking dynamics for mobile authentication [4, 23]. Despite encouraging accuracy, gait recognition is sensitive to external factors such as footwear, flooring, or health conditions [31], which complicates real-world deployment.

More critically, gait is prone to being imitable. Studies have shown that attackers can spoof vision-based systems through deliberate mimicry of silhouettes [6] or by replaying videos of target users [1]. Some research introduced feedback mechanisms, such as treadmills [13] or smartphone prompts [23], to support attackers in aligning their steps. Others leveraged generative models to synthesize target gaits [9]. Yet, these approaches remain limited: most lack real-time, immersive feedback, and few explore how design factors such as avatar appearance shape mimicry performance.

2.3 XR for Motor Learning and Behavior Change

Extended Reality (XR) technologies, including VR and AR, are widely used to support motor learning because they provide immersive environments with real-time feedback. Applications range from physical education and juggling [2, 20] to rehabilitation [30] and sports training [25, 29]. A consistent finding is that visualizing one's own movements, through mirroring, overlays, or cues, enhances learning and coordination [25].

Beyond training, XR also influences behavior. Users often adapt their movements to the appearance or posture of their avatars, a phenomenon known as the follower effect [5, 10]. This embodiment effect has been leveraged to study dance, movement synchronization, and even social interaction [32]. At the same time, XR introduces new privacy concerns: motion trajectories can be linked to identity even when users attempt to disguise themselves [14], and motion matching from video to 3D trajectories has been shown to spoof VR-based systems [21]. Taken together, these findings highlight XR as both a powerful tool for training and analyzing human movement and a potential amplifier of mimicry risks. However, while most prior work in sports and rehabilitation has focused on helping users improve or restore their own gait, our work instead examines the deliberate imitation of another person's gait as an analytical case. This distinction allows us to investigate how specific design factors, such as visualization style or avatar similarity, influence the accuracy of intentional mimicry in immersive environments, rather than the correction of movement patterns for skill acquisition or recovery.

3 Investigating Gait Mimicry in Virtual Reality

Previous studies on gait imitation have largely been conducted in real-world settings without real-time feedback, making it difficult to assess how such guidance shapes mimicry. Virtual Reality offers an ideal testbed by providing consistent replayed movements, precise motion capture, and immediate visual feedback. Beyond security contexts, this approach speaks to broader applications in rehabilitation, motor learning, entertainment, and personalization.

In this work, participants followed a pre-recorded "target" avatar (the *victim*) while their own movements (the *imitator*) were captured in real time using optical motion tracking. By varying the type of visualizations displayed during imitation, we examined how feedback design influences performance and adaptation over repeated trials. To that end, we address three research questions:

- **(RQ1)** which visualization techniques best support gait imitation in VR?
- **(RQ2)** how does real-time visual feedback affect imitation accuracy?
- **(RQ3)** does avatar appearance similarity (e.g., gender matching) play a role?

Our investigation proceeded in two stages. We first conducted a **formative study** comparing four visualization techniques to identify the most intuitive and usable design for gait imitation. In a **controlled study**, we evaluated the top performing *visualization* against a no-feedback *baseline* condition, with additional focus on whether avatar–user gender matching affected imitation accuracy.

3.1 Experimental Setup

Both studies used an optical **motion-capturing system** (Optitrack[0]) with 11 infrared cameras operating at 120 Hz. Participants wore a tracking suit with 34 reflective markers, with three additional markers attached to the head-mounted display (HMD) to ensure accurate full-body tracking. This setup allowed precise reconstruction of joint positions and rotations without requiring cumbersome inertial sensors, and motion data were streamed to Unity[1] in real time to animate avatars and provide immediate visual feedback. Victim gaits were pre-recorded along a straight walking path and replayed as life-sized avatars, while imitator movements were captured simultaneously for comparison. Pilot testing explored several **placement** options for the target avatar; we found that positioning the imitator one meter behind the target provided the clearest perspective for observing gait details while avoiding visual occlusion, consistent with prior work on synchronized walking [15]. To preserve natural variation, avatars were displayed at their real-world body proportions without normalization. The **virtual environment** consisted of a simple corridor with visible start and end markers aligned with the tracking volume, allowing participants to walk back and forth without recalibration. Between studies, we adjusted the path layout: the formative study used a 4 m track with a narrower corridor, while the controlled study employed an extended 8 m path with greater width to give participants more space for natural walking and imitation. The latter setup, which is illustrated in Figure 1, shows the configuration with 11 cameras and an 8 m path used in the user study. This setup ensured consistent, repeatable conditions while allowing fine-grained comparison of gait trajectories under different visual feedback and avatar appearance.

4 Formative Study: Exploring Visualization Techniques for Gait Imitation

Before running the controlled study, we conducted a formative study to explore different visualization techniques and identify which design best supported gait imitation in VR. The goal was not to measure performance in detail, but to gather qualitative

[0]https://optitrack.com/
[1]https://unity.com/ (version 2020.3.22f1)

and subjective insights on usability, intuitiveness, and perceived effectiveness.

4.1 Visualization Design and Implementation

We selected visualization based on prior research highlighting how real-time visual feedback supports motor learning and movement alignment in VR and related training environments [2, 5, 25, 39]. We aimed to cover a range of feedback types, from predictive cues to direct spatial overlays, to compare how different representations of movement deviation influence imitation behavior. To that end, we implemented four assistive visualization techniques, each emphasizing different aspects of gait alignment, shown in Figure 2. First, the **arrows** indicated the direction of the victim avatar's foot movements. We also considered a **preview** that showed anticipated next steps as ghost footprints, and **threads** that connected the imitator's feet to the victim's, visualizing stride differences. Lastly, we implemented an **overlay** superimposed the imitator's avatar in semi-transparent form onto the victim avatar, providing immediate feedback on alignment. These designs were informed by prior work on motor learning and visual feedback, as well as initial observations highlighting the importance of lower-body movements for gait imitation.

For the overlay, the victim's avatar was rendered semi-transparently and aligned with the participant's tracked body using Unity's humanoid rig, ensuring frame-accurate overlap between both skeletons. The predictive footprints used in the preview condition were generated by extrapolating each foot's trajectory from its previous two positions, fading gradually after contact to visualize step timing. Threads and arrows were dynamically anchored to foot joints and updated each frame to reflect instantaneous positional differences. This setup ensured temporally synchronized, low-latency visualization across all feedback conditions.

4.2 Procedure

Eight participants (6 male, 2 female; aged 24–30) took part, none reporting locomotor impairments. After being fitted with the motion-capture suit and completing a short tutorial, each participant experienced all four visualization techniques in randomized order. Each trial lasted one minute, during which participants followed a pre-recorded victim avatar along the virtual path while attempting to imitate its gait. After each trial, participants rated the visualization on a 7-point Likert scale regarding visibility, intuitiveness, comprehension, and imitability, and provided open-ended feedback on strengths and weaknesses. The questionnaire items were designed around general usability and intuitiveness aspects relevant to evaluating the visualization techniques in the context of gait imitation.

4.3 Findings

The overlay visualization emerged as the most effective design, receiving the highest ratings across all criteria. Participants noted that it offered intuitive real-time feedback, allowing them to easily recognize deviations and correct their movements. Some suggested higher transparency to reduce visual occlusion. The threads visualization was valued for clarity but often perceived as distracting, while arrows and preview were rated as less helpful. In total, six of the eight participants preferred the overlay technique, while one selected preview and one selected arrows. These results (summarized in Table 1) indicate that visualizations which integrate both the imitator's and victim's movements provide more useful guidance than those that isolate only one. Although the study focused on subjective assessments rather than detailed performance metrics, the consistency of these ratings across multiple usability dimensions provides a strong rationale for selecting the overlay visualization for the controlled study that followed.

Table 1: Ratings of the Four Visualization Techniques on the 7-Likert item (1 Strongly Agree - 7 Strongly Disagree). Results show the "Threads" visualization as the most clearly visible, while the "Overlay" visualization is perceived as more intuitive, comprehensible, and easing the imitation.

Visualization	Visibility		Intuition		Comprehensibility		Imitability	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Arrow	4.12	2.17	4.88	2.23	4.12	2.03	3.62	1.77
Overlay	2.00	1.20	1.50	0.76	2.00	0.93	2.62	1.92
Preview	2.62	2.20	1.75	0.89	1.62	0.74	3.00	1.51
Threads	1.88	0.99	4.00	2.56	3.62	2.72	3.38	1.69

5 User Study: Investigating the Impact of Visualization on Gait Mimicry

Building on the formative study, this controlled experiment examined how real-time visual feedback, specifically the overlay visualization, affects gait mimicry performance in VR. We focused on two independent variables: *visual support*, comparing overlay feedback against a baseline without additional feedback, and *avatar appearance*, comparing mimicry performance when the victim's avatar matched or did not match the participant's self-identified gender. This design allowed us to study both the role of feedback and the influence of avatar similarity on imitation accuracy.

5.1 Study Design

The study followed a within-subject design in which each participant experienced all four experimental conditions (Overlay vs. Baseline × Matching vs. Non-Matching). Conditions were counterbalanced using a Latin Square to minimize order effects. Performance was assessed using two motion-capture–based measures. First is the **positional alignment**, calculated via Euclidean and Fréchet distances to quantify the spatial similarity between the imitator and victim. Second, the **rotational alignment**, analyzed with Procrustes analysis to capture angular differences across joints. These measures provided complementary perspectives on gait imitation accuracy and follow established practices in VR motion analysis, where joint positions and rotations are commonly used to evaluate avatar alignment and embodiment fidelity [24, 27]. Lastly, participants completed subjective ratings on perceived success, visualization helpfulness, and task difficulty.

5.2 Apparatus and Implementation

The apparatus mirrored the formative study setup but was extended to support longer trials. We used an Optitrack motion capture system with 11 infrared cameras recording at 120 Hz. Each participant

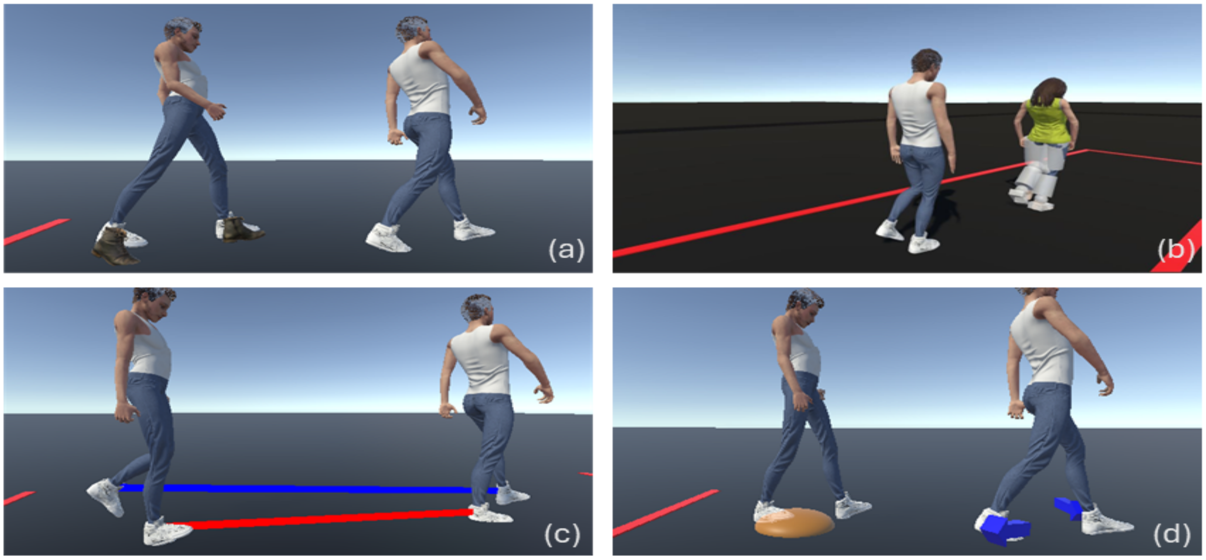

Figure 2: Visualization techniques for gait imitation: (a) preview footprints, (b) overlay (the most effective method, later used in the user study), (c) threads, and (d) arrows. Both male and female avatar appearances were included to study the effect of gender-matching.

wore a tracking suit with 34 reflective markers plus three markers attached to the HMD, enabling accurate full-body tracking. The data was streamed into Unity and applied to a life-sized avatar via Inverse Kinematics, ensuring that body proportions and stride lengths were preserved without normalization.

The virtual environment replicated the physical capture space, with a straight walking path extended from 4 m (formative study) to 8 m based on participant feedback that longer walks were needed for more natural imitation. Start and end points were visually marked in the VR scene, aligned with the capture volume to ensure high tracking fidelity. The imitator's avatar was consistently placed 1 m behind the victim avatar, which preliminary testing showed to provide the clearest observation of gait while avoiding occlusion.

Avatar Gender Representation. To manipulate appearance similarity, we created male and female avatars using the Unity Multipurpose Avatar framework. These were animated using walking data recorded from four volunteers (two male, two female; aged 23–34, $M = 26.8$, $SD = 5.7$; height 163–186 cm, $M = 174.7$, $SD = 12.4$). Recordings with minimal tracking errors were selected to ensure consistent victim animations across participants.

5.3 Participants

We recruited 18 participants (9 male, 9 female) through mailing lists and social connections. Ages ranged from 19–31 years ($M = 24.3$, $SD = 3.3$) and heights from 165–195 cm ($M = 178$, $SD = 8.3$). Seven participants had no prior VR experience, five reported trying VR once, and six reported more frequent use (3 monthly, 2 weekly, 1 daily). None reported locomotor impairments or conditions affecting walking. All provided informed consent, and the study was approved by the university's ethics committee. Participants received 15€ compensation for their time.

5.4 Procedure

Upon arrival, participants completed consent and demographic forms, were fitted with the tracking suit, and had markers adjusted to their body measurements. After calibration, they donned the HMD and explored the VR environment. Participants were instructed on the task: to follow the victim avatar as closely as possible, imitating its gait. Trials were participant-triggered via controller, allowing them to begin when ready and focus entirely on the imitation task.

Each *take* consisted of walking the 8 m path behind the victim avatar until reaching the endpoint, at which point the avatar disappeared. Participants then turned and returned to the start for the next take. Short practice was allowed before recording: most participants required 2–6 training takes, though one required 18 before feeling comfortable. Regardless of the number of training, each participant then completed 20 recorded takes across the four conditions, with condition order counterbalanced. In total, every participant completed at least 22 takes, including training. After each condition, participants rated their perceived imitation success and visualization helpfulness. At the end of the study, they completed the iGroup Presence Questionnaire (IPQ) and provided open-ended feedback.

5.5 Limitations

The study design prioritized internal validity, focusing on straight-line walking tasks common in gait-based identification scenarios (e.g., door entry). As such, it did not account for more complex gait

Table 2: ANOVA results for gait imitation accuracy across visualization (Overlay vs. Baseline) and avatar gender-matching conditions, separated by body region. Reported are F-values and corresponding p-values for three alignment measures: Fréchet Distance, Euclidean Distance, and Procrustes Analysis. Significance levels: $^{*}p < .05$, $^{\dagger}p < .10$.

Similarity Level	Condition	Fréchet Distance		Euclidean Distance		Procrustes Analysis	
		$F(1,67)$	p	$F(1,67)$	p	$F(1,67)$	p
Entire Body	Visual Support	1.84	0.18	1.31	0.26	0.06	0.79
	Gender Matching	0.12	0.73	0.45	0.50	4.06	0.04^{*}
Upper Body	Visual Support	1.23	0.27	1.18	0.28	2.49	0.12
	Gender Matching	0.02	0.89	0.58	0.45	3.13	$0.08^{\dagger}$
Lower Body	Visual Support	1.82	0.18	1.54	0.22	3.18	$0.08^{\dagger}$
	Gender Matching	0.25	0.62	0.24	0.62	0.16	0.69

patterns, such as turning or varying speed, nor for external influences like footwear or surface types. The participant pool, while balanced by gender, was relatively small and age-homogeneous, which may limit generalizability. Nonetheless, the controlled setup offers a robust first step toward understanding gait mimicry under visual feedback in VR. Lastly, given the exploratory nature of the work, we did not perform a formal power analysis. However, the sample size aligns with comparable VR motion studies of similar within-subject complexity [24].

6 Results

The results are presented as follows: we first describe the dataset and preprocessing steps, report similarity measures between avatars, analyze improvements across repeated trials, and conclude with participants' subjective feedback.

6.1 Dataset and Preprocessing

The dataset consists of synchronized recordings of both victim and imitator movements captured with the Optitrack system. Positions and rotations of 37 markers were logged in 3D space and translated onto full-body avatars using Inverse Kinematics. Each take represented a walk from start to end in both directions, with attacker and victim movements recorded concurrently and synchronized via a shared time column. Two participants were excluded due to recording errors, leaving 16 valid datasets. For each participant, mimicry attempts were grouped by victim, resulting in four files per participant and 64 files in total. Conditions of visual support and victim gender were counterbalanced using a Latin Square design.

Preprocessing included dropping non-informative values (e.g., spinal markers), trimming initial and final seconds to remove transition movements, and excluding inconsistent hand-tracking data. To reduce incidental tracking errors, we applied a median filter with a window size of 7. Visual inspection confirmed data alignment. The cleaned dataset was then analyzed to compare mimicry performance across conditions.

6.2 Similarity Between Avatars

Mimicry performance was evaluated using positional and rotational similarity. Euclidean and Fréchet distances quantified spatial alignment, while Procrustes analysis assessed rotational differences. These measures were analyzed with a two-way ANOVA on the factors *Visual Support* (baseline vs. overlay) and *Gender Matching* (matching vs. non-matching). We first applied the Aligned Rank Transform (ART) procedure [37] for non-parametric ANOVA and verified ANOVA assumptions; if normality held, we instead reported the corresponding parametric results. The corresponding results are summarized in Table 2.

At the whole-body level, neither visualization nor gender matching significantly influenced Fréchet or Euclidean distances. For example, Fréchet distance showed no significant effects of visualization ($F(1,67) = 1.83, p = 0.18$) or gender matching ($F(1,67) = 0.12, p = 0.73$). Similarly, Euclidean distance showed no effects of visualization ($F(1,67) = 1.31, p = 0.26$) or gender matching ($F(1,67) = 0.45, p = 0.50$). However, rotational analysis revealed a significant effect of gender matching ($F(1,67) = 4.06, p = 0.048$), suggesting that imitators aligned their entire body joints' rotations more closely when the avatar matched their self-identified gender. Gender matching lead to significantly higher procrustes values ($M = 0.671, SD = 0.051$) than no matching gender ($M = 0.646, 0.053$), which is confirmed by a post-hoc test ($t(67) = -2.00, p = 0.049$). On the other hand, we could not find support for an effect imposed by visual support ($F(1,67) = 0.06, p = 0.793$) and the interaction of both effects also showed no significant differences ($p = 0.363$). We validated these results by checking that the residuals followed a normal distribution. A Shapiro–Wilk test provided no indication of deviation from normality ($W = 0.986, p = 0.63$), which was further supported by a visual inspection of the Q–Q plot. In addition, we checked the homogeneity of variances using Levene's test, which did not indicate that our groups had significant differences in variance ($F(3,67) = 0.29, p = 0.83$).

When separating upper and lower body segments, results remained largely consistent. For the upper body, neither visualization nor gender matching significantly influenced positional similarity, though gender matching approached significance for rotational alignment ($F(1,67) = 3.13, p = 0.082$). For the lower body, visualization showed a marginal trend in rotational similarity ($F(1,67) = 3.18, p = 0.079$), but did not reach statistical significance. Overall, while gender matching appeared to facilitate rotational alignment, visualization support did not produce measurable gains in either positional or rotational mimicry.

6.3 Performance Improvement Across Takes

Beyond condition-level effects, participants consistently improved their mimicry over time. Comparing the first and last take across 22 trials showed a significant reduction in Euclidean distance ($M_{first} =$

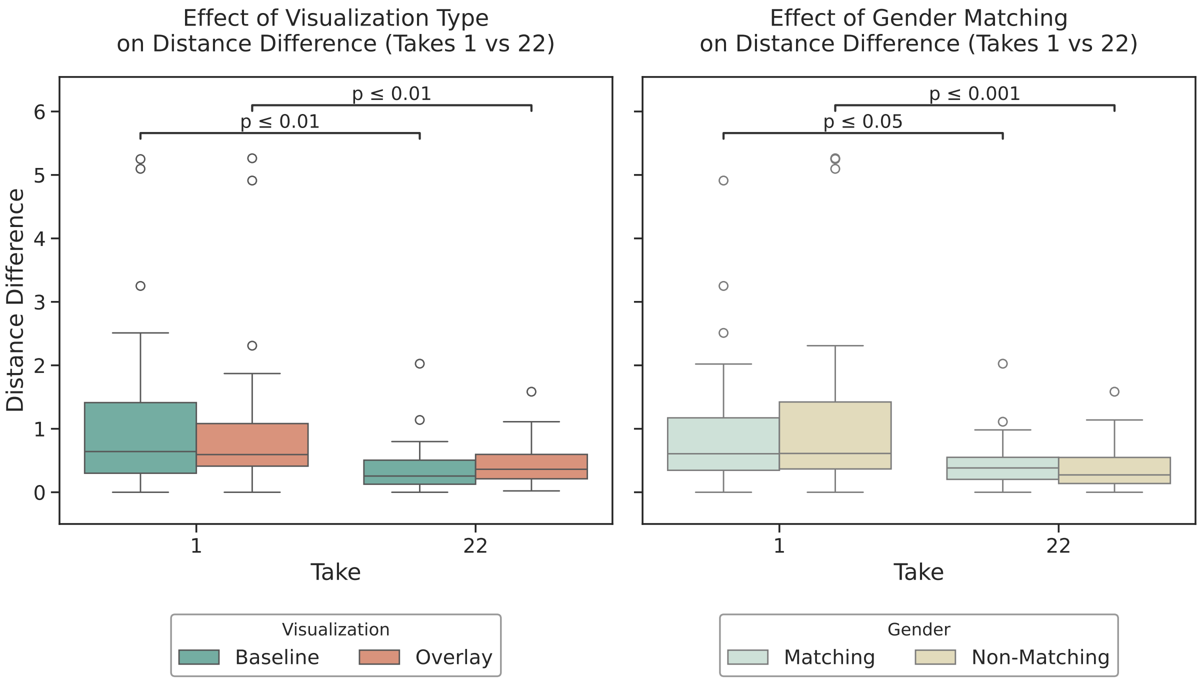

Figure 3: Comparison between takes (1) and (22) in terms of Visualization (left) and Gender Matching (right), showing a significant decrease in distances, regardless of the criteria.

1.123, $SD = 1.242$; $M_{last} = 0.431, SD = 0.365$), with a paired $t(15) = 5.87, p < 0.001$. Linear regression confirmed a gradual improvement with a negative slope (−0.021), which was statistically significant ($R^2 = 0.050$, $F(1, 1406) = 73.70$, $p < 0.005$). Importantly, this learning effect was evident across all conditions. Paired t-tests confirmed significant improvements between the first and last take for gender-matched ($t = 2.65, p = 0.010$) and non-matched pairs ($t = 3.35, p = 0.001$), as well as for baseline ($t = 3.35, p = 0.001$) and overlay visualization ($t = 2.63, p = 0.011$). This indicates that participants improved with practice regardless of visual support or avatar gender. The results are illustrated in Figure 3.

6.4 Subjective Feedback

Following all repetitions per condition, participants reflected on their experience of mimicking each of the four avatars. After completing all recordings, they answered 7-point Likert item questions on their imitation ability, the effect of visualization support, and avatar gender, as well as items from the iGroup Presence Questionnaire (IPQ) [33]. To emphasize a sense of embodiment, items were phrased in the first person (e.g., "I successfully copied the movements of the person in front of me" and "Overall, the added visualization improved my mimicry attempts"). Open-ended questions addressed the walking path, training time, and general comments. As the scope of this work was to evaluate mimicry performance, we did not apply a standardized avatar embodiment questionnaire [26], but followed the same approach of framing questions in a self-reflective manner.

Self-reports complemented the quantitative findings. Participants rated their imitation ability positively, with average scores rising from 4.5 to 5.1 across attempts. However, they were less confident about being misidentified as the victim, giving an average rating of 3.76. Preferences for gender-matching varied: five of eight male participants reported finding male avatars easier to imitate, while only three female participants indicated a preference for female avatars.

Open-ended comments reinforced these patterns. Several participants felt the path length and training time were sufficient ("It was enough to learn how the target walked in that situation," P7, M, 22). Others emphasized gait characteristics over gender: "This has more to do with the gait characteristics than the gender" (P9, F, 28). Some noted specific challenges, such as "Female 2 was especially difficult to imitate" (P14, F, 23). Despite the absence of measurable accuracy gains, participants strongly valued the overlay visualization, describing it as "immensely helpful" (P7, M, 22) and "a big support to understand and mimic the walking pattern of the other person" (P2, M, 31).

7 Discussion

In this work, we presented a novel approach to investigate deliberate gait imitation in VR, combining high-precision motion capture with controlled avatar design and visual feedback. While not all manipulations yielded significant performance differences, the findings reveal important insights into how gait mimicry develops in immersive environments and highlight the potential of VR as a platform for both studying and training this skill.

Assistive Visualization and User Experience. Our first research question (RQ1), *which visualization techniques best support gait imitation in VR?*, examined which visualization technique best supports gait imitation in VR. In the formative study, participants rated the semi-transparent *overlay* as the most usable visualization, leading us to adopt it for the controlled study. However, by addressing (RQ2), *how does real-time visual feedback affect imitation accuracy?*, our results showed that while this real-time feedback did not significantly enhance objective mimicry accuracy, participants consistently reported that it helped them understand and adjust their movements. This distinction between measured accuracy and perceived support suggests that visualizations may play a more motivational and confidence-building role in mimicry tasks rather than serving as a direct performance booster.

Avatar Similarity and Cognitive Alignment. Our third research question (RQ3) addressed *understanding the impact of avatar appearance similarity, such as gender matching, upon the gait mimicry performance.* Although the effect on accuracy was modest, rotational alignment improved when avatar and user gender matched, and participants reported that similarity shaped how approachable or relatable the task felt. These findings suggest that avatar design can lower cognitive barriers and foster closer motor alignment, pointing to new opportunities for tailoring VR systems that guide and possibly alter physical behavior.

Learning Effects and the Potential of VR. While visual support and avatar similarity did not significantly influence overall mimicry accuracy, we observed consistent improvements across repeated trials. Participants' ability to reduce positional differences over time demonstrates that gait imitation is a skill that can be learned and refined in VR. This progression highlights the potential of VR not only as a research tool for studying gait mimicry but also as a training medium for enhancing motor adaptation.

These findings suggest that VR can foster meaningful improvements in gait imitation, even without explicit feedback. Such adaptability points to promising applications where gait practice and modification play a central role, including rehabilitation, sports training, and interactive entertainment. Beyond these domains, understanding how easily gait patterns can be learned or imitated also informs the security community by revealing potential vulnerabilities in gait-based authentication and guiding the design of more robust identification systems. By showing that participants could progressively refine their gait imitation, our study demonstrates the viability of VR as both a controlled environment for investigating gait and a practical platform for developing it as a skill.

Implications and Future Work. By releasing our dataset of full-body motion capture recordings, we provide the research community with an additional resource to explore gait mimicry further. This opens opportunities for developing feedback designs, investigating joint-specific contributions to imitation success, and testing long-term training effects across multiple sessions. For the privacy and security community, our findings offer an early benchmark for understanding how attackers could use immersive environments to practice biometric spoofing. For the HCI community, they highlight how subtle factors such as avatar embodiment, appearance similarity, and feedback design shape motor adaptation in VR. These aspects are not only limited to understanding biometric vulnerabilities, but also for designing rehabilitation protocols (e.g., adapting avatar gait to support motor recovery), sports training systems (e.g., teaching movement techniques through tailored feedback), or educational contexts where imitation accelerates skill learning.

Overall, this study provides a first step toward understanding gait mimicry in immersive environments. While our results show that gait imitation is not trivially enhanced by visualization or avatar matching, the consistent improvement across takes demonstrates the great potential of VR as both an investigative tool and a training platform for complex motor behaviors.

8 Conclusion

This study investigated how real-time visual feedback and avatar design in VR shape gait imitation. While direct performance gains from visualization were limited, gender matching between avatars showed measurable effects on rotational alignment, and participants consistently reported greater confidence when supported by visual overlays. Most importantly, imitation performance improved steadily with practice, underscoring the potential of VR not only as an analytic tool for studying gait mimicry but also as a training medium for refining it. To foster continued progress in this area, we contribute a publicly available dataset of full-body motion-capture recordings from 16 participants imitating four avatars,comprising 64 synchronized sessions (over 20 hours of motion data). This resource opens new opportunities for research on movement learning, avatar design, and the resilience of gait-based biometric systems. By demonstrating that gait imitation can be learned and enhanced in VR, this work establishes a foundation for interdisciplinary exploration across security, rehabilitation, sports, and interactive technologies. Even modest improvements in mimicry point to the dual potential of VR: as a platform for exposing vulnerabilities in behavioral biometrics, and as a powerful medium for harnessing gait adaptation in positive, human-centered applications.

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References

[1] Yasmeen Abdrabou, Omar Sherif, Rana Mohamed Eisa, and Amr Elmougy. 2018. Human-based fraudulent attempts on gait based profiles. In *Proceedings of the Second African Conference for Human Computer Interaction: Thriving Communities.* 1–4.

[2] Kuo-En Chang, Jia Zhang, Yang-Sheng Huang, Tzu-Chien Liu, and Yao-Ting Sung. 2020. Applying augmented reality in physical education on motor skills learning. *Interactive Learning Environments* 28, 6 (2020), 685–697.

[3] Stephen J. Elliott. 2009. *Zero Effort Forgery.* Springer US, Boston, MA, 1411–1414. doi:10.1007/978-0-387-73003-5_115

[4] Matteo Gadaleta and Michele Rossi. 2018. Idnet: Smartphone-based gait recognition with convolutional neural networks. *Pattern Recognition* 74 (2018), 25–37.

[5] Mar Gonzalez-Franco, Brian Cohn, Eyal Ofek, Dalila Burin, and Antonella Maselli. 2020. The self-avatar follower effect in virtual reality. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR).* IEEE, 18–25.

[6] Abdenour Hadid, Mohammad Ghahramani, Vili Kellokumpu, Matti Pietikäinen, John Bustard, and Mark Nixon. 2012. Can gait biometrics be spoofed?. In *Proceedings of the 21st international conference on pattern recognition (ICPR2012).* IEEE, 3280–3283.

[7] Liangnan Hu, Changjiang Liu, Wei Jiang, Dai He, Qiang Qu, Zhen Wang, and Chenlin Ying. 2025. Application of gaming robot based on gait recognition algorithm in sports training and assistance system. *Entertainment Computing* 52 (2025), 100763.

[8] Anil Jain, Ruud Bolle, and Sharath Pankanti. 1996. *Introduction to Biometrics*. Springer US, Boston, MA, 1–41. doi:10.1007/0-306-47044-6_1

[9] Meijuan Jia, Hongyu Yang, Di Huang, and Yunhong Wang. 2019. Attacking gait recognition systems via silhouette guided GANs. In *Proceedings of the 27th ACM international conference on multimedia*. 638–646.

[10] Konstantina Kilteni, Jean-Marie Normand, Maria V Sanchez-Vives, and Mel Slater. 2012. Extending body space in immersive virtual reality: a very long arm illusion. *PloS one* 7, 7 (2012), e40867.

[11] Samruddhi S Kulkarni and Hemprasad Y Patil. 2015. Survey on fingerprint spoofing, detection techniques and databases. *International Journal of Computer Applications* 975 (2015), 8887.

[12] Munish Kumar, Navdeep Singh, Ravinder Kumar, Shubham Goel, and Krishan Kumar. 2021. Gait recognition based on vision systems: A systematic survey. *Journal of Visual Communication and Image Representation* 75 (2021), 103052.

[13] Rajesh Kumar, Vir V Phoha, and Anshumali Jain. 2015. Treadmill attack on gait-based authentication systems. In *2015 IEEE 7th international conference on biometrics theory, applications and systems (BTAS)*. IEEE, 1–7.

[14] Dilshani Kumarapeli, Sungchul Jung, and Robert W Lindeman. 2024. Privacy threats of behaviour identity detection in vr. *Frontiers in Virtual Reality* 5 (2024), 1197547.

[15] Jessica Lanini, Alexis Duburcq, Hamed Razavi, Camille G Le Goff, and Auke Jan Ijspeert. 2017. Interactive locomotion: Investigation and modeling of physically-paired humans while walking. *PLoS One* 12, 9 (2017), e0179989.

[16] Tracey KM Lee, Mohammed Belkhatir, and Saeid Sanei. 2014. A comprehensive review of past and present vision-based techniques for gait recognition. *Multimedia tools and applications* 72 (2014), 2833–2869.

[17] Mindy F Levin, Patrice L Weiss, and Emily A Keshner. 2015. Emergence of virtual reality as a tool for upper limb rehabilitation: incorporation of motor control and motor learning principles. *Physical therapy* 95, 3 (2015), 415–425.

[18] Xiaohui Li, Dongfang Fan, Junjie Feng, Yu Lei, Chao Cheng, and Xiangnan Li. 2025. Systematic review of motion capture in virtual reality: Enhancing the precision of sports training. *Journal of Ambient Intelligence and Smart Environments* 17, 1 (2025), 5–27.

[19] Carlos Marín-Lora, Miguel Chover, Micaela Y Martín, and Linda García-Rytman. 2023. Comparative study of interaction methods for mobile gaming while running on a treadmill. *Computers & Graphics* 117 (2023), 164–171.

[20] Benjamin Meyer, Pascal Gruppe, Bastian Cornelsen, Tim Claudius Stratmann, Uwe Gruenefeld, and Susanne Boll. 2018. Juggling 4.0: Learning complex motor skills with augmented reality through the example of juggling. In *Adjunct Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology*. 54–56.

[21] Robert Miller, Natasha Kholgade Banerjee, and Sean Banerjee. 2022. Using external video to attack behavior-based security mechanisms in virtual reality (vr). In *2022 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. IEEE, 684–685.

[22] Bendik B Mjaaland, Patrick Bours, and Danilo Gligoroski. 2011. Walk the walk: Attacking gait biometrics by imitation. In *Information Security: 13th International Conference, ISC 2010, Boca Raton, FL, USA, October 25-28, 2010, Revised Selected Papers 13*. Springer, 361–380.

[23] Muhammad Muaaz and René Mayrhofer. 2017. Smartphone-based gait recognition: From authentication to imitation. *IEEE Transactions on Mobile Computing* 16, 11 (2017), 3209–3221.

[24] Myeongseok Park, Jiwon Lee, Hyeonyong Yang, and Jinmo Kim. 2025. Designing and Analyzing Virtual Avatar Based on Rigid-Body Tracking in Immersive Virtual Environments. *IEEE Access* (2025).

[25] Stefan Pastel, K Petri, CH Chen, Ana Milena Wiegand Cáceres, M Stirnatis, C Nübel, L Schlotter, and K Witte. 2023. Training in virtual reality enables learning of a complex sports movement. *Virtual Reality* 27, 2 (2023), 523–540.

[26] Tabitha C Peck and Mar Gonzalez-Franco. 2021. Avatar embodiment. a standardized questionnaire. *Frontiers in Virtual Reality* 1 (2021), 575943.

[27] Jose Luis Ponton, Haoran Yun, Carlos Andujar, and Nuria Pelechano. 2022. Combining Motion Matching and Orientation Prediction to Animate Avatars for Consumer-Grade VR Devices. In *Computer Graphics Forum*, Vol. 41. Wiley Online Library, 107–118.

[28] Matevž Pustišek, Yu Wei, Yunchuan Sun, Anton Umek, and Anton Kos. 2021. The role of technology for accelerated motor learning in sport. *Personal and Ubiquitous Computing* 25, 6 (2021), 969–978.

[29] Jessica Sharon Putranto, Jonathan Heriyanto, Said Achmad, Aditya Kurniawan, et al. 2023. Implementation of virtual reality technology for sports education and training: Systematic literature review. *Procedia Computer Science* 216 (2023), 293–300.

[30] Sebastian Rutkowski, Pawel Kiper, Luisa Cacciante, Blazej Cieslik, Justyna Mazurek, Andrea Turolla, Joanna Szczepanska-Gieracha, et al. 2020. Use of virtual reality-based training in different fields of rehabilitation: A systematic review and meta-analysis. *Journal of Rehabilitation Medicine* 52, 11 (2020), 1–16.

[31] Alia Saad, Nick Wittig, Uwe Gruenefeld, and Stefan Schneegass. 2022. A Systematic Analysis of External Factors Affecting Gait Identification. In *2022 IEEE International Joint Conference on Biometrics (IJCB)*. IEEE, 1–9.

[32] Bhuvaneswari Sarupuri, Richard Kulpa, Andreas Aristidou, and Franck Multon. 2024. Dancing in virtual reality as an inclusive platform for social and physical fitness activities: a survey. *The Visual Computer* 40, 6 (2024), 4055–4070.

[33] Thomas Schubert, Frank Friedmann, and Holger Regenbrecht. 2001. The experience of presence: Factor analytic insights. *Presence: Teleoperators & Virtual Environments* 10, 3 (2001), 266–281.

[34] Abdulkadir Şengür, Zahid Akhtar, Yaman Akbulut, Sami Ekici, and Ümit Budak. 2018. Deep feature extraction for face liveness detection. In *2018 International Conference on Artificial Intelligence and Data Processing (IDAP)*. Ieee, 1–4.

[35] Ruben Tolosana, Ruben Vera-Rodriguez, Julian Fierrez, and Javier Ortega-Garcia. 2019. Presentation attacks in signature biometrics: types and introduction to attack detection. In *Handbook of Biometric Anti-Spoofing*. Springer, 439–453.

[36] Changsheng Wan, Li Wang, and Vir V Phoha. 2018. A survey on gait recognition. *ACM Computing Surveys (CSUR)* 51, 5 (2018), 1–35.

[37] Jacob O Wobbrock, Leah Findlater, Darren Gergle, and James J Higgins. 2011. The aligned rank transform for nonparametric factorial analyses using only anova procedures. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 143–146.

[38] Xiao Yang, Wenhan Luo, Linchao Bao, Yuan Gao, Dihong Gong, Shibao Zheng, Zhifeng Li, and Wei Liu. 2019. Face anti-spoofing: Model matters, so does data. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 3507–3516.

[39] Junyi Zhu, Yuxuan Lei, Aashini Shah, Gila Schein, Hamid Ghaednia, Joseph Schwab, Casper Harteveld, and Stefanie Mueller. 2022. MuscleRehab: Improving unsupervised physical rehabilitation by monitoring and visualizing muscle engagement. In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology*. 1–14.