LiftVR: A VR-Based Training System for Back-Friendly Lifting

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Abstract

This paper introduces LiftVR, a VR-based training system designed to support back-friendly deadlift practice. The system integrates two feedforward guidance methods: "skeleton," which provides detailed posture replication, and "zone," which offers simplified, symmetrical visualizations to reduce cognitive load. Additionally, post-training feedback visualizations—such as motion replay, joint path analysis, and performance scoring—help users identify and correct movement errors. A user study revealed that the "zone" method reduced cognitive effort and enabled participants to understand movements more quickly, albeit with slightly lower postural accuracy compared to the "skeleton" method. Furthermore, post-training feedback was observed to disrupt muscle memory formation during intensive sessions. Nonetheless, participants' performance across all experimental conditions, regardless of the feedforward method or feedback mode, showed significant improvement compared to their baseline. These findings underscore LiftVR's potential as an effective and safe training tool for back-friendly lifting practices.

Index Terms: Virtual reality, back-friendly lifting, motion guidance.

1 Introduction

Maintaining correct posture during physical exercises is crucial to prevent severe musculoskeletal disorders (MSD), such as herniated lumbar disc, muscle strains, sprains, and tears. In traditional training processes, this is typically achieved through in-person coaching or by following video tutorials. However, the former is highly dependent on the availability of a coach, while the latter lacks in-depth information on movements and does not provide immediate feedback on user performance.

Virtual Reality (VR) has emerged as a promising tool for motion guidance and training by providing interactive feedforward information, such as step-by-step movement demonstrations and spatial posture alignment, within an immersive 3D environment. This allows users to follow and maintain correct postures while receiving real-time feedback for corrections and improvements. However, the impact of VR on training efficiency for physically demanding exercises, such as deadlift, remains underexplored. Two key challenges arise in such contexts: first, physical exertion may compromise users' attention, leading to significant reaction delays [11]; second, the mechanisms of feedforward and feedback in high-effort activities may differ from those in low-intensity, routine tasks.

To fill this gap, we collaborated with sport science experts to develop ***LiftVR***, a VR-based, easily deployable training system for back-friendly lifting. LiftVR offers 3D motion guidance integrating feedforward (to provide guidance before action) and feedback (to provide assessment and corrections about their movements) mechanisms, specifically tailored for deadlift training in VR. For feedforward visualization, we implemented two distinct methods: a conventional skeleton-based approach, which displays the coach's complete skeletal structure to guide users in replicating the demonstrated posture, and a novel zone-based method. The latter leverages the left-right symmetry of the movement by encapsulating the relevant joint areas and their permissible margins of error in capsule shapes, while omitting the visualization of the torso and limbs to minimize visual interference and focus attention on joint alignment. To complement these designs, we introduced textual feedback and motion trajectory playback as post-training feedback mechanisms, enabling users to review their performance and refine their movements effectively.

To evaluate the usability and effectiveness of *LiftVR*, we conducted a between-subject user study in which participants progressed through a structured training program, advancing from discrete posture imitation to continuous movement practice. The results indicated that during the discrete posture training phase, the zone-based feedforward visualization outperformed the skeleton-based visualization in terms of completion time and accuracy. In the continuous movement practice phase, the zone-based method demonstrated a trend of progressively enhancing participants' performance and reducing errors. On the other hand, post-training feedback, however, did not show notable influence on training outcomes. Synthesizing the findings and user experiences from the study, we provide further recommendations and considerations for designing VR guidance systems for physically intensive motions and suggest directions for future research.

Our main contributions can be summarized as follows:

- *LiftVR*, a VR-based, easy-to-deploy deadlift training system adaptable to various body sizes, weights, and age groups, providing 3D lifting motion guidance and real-time feedback.
- A between-subject user study exploring the effects of different types of feedforward and feedback visualizations on training effectiveness in VR-based deadlift guidance system.

2 Related Work

A comprehensive motion guidance system should integrate both feedforward and feedback components [18]. Feedforward mechanisms provide real-time instructions, enabling users to anticipate and execute movements accurately, while feedback mechanisms allow users to reflect on their performance post-training, facilitating continuous improvement. Together, these components create a comprehensive training experience by providing immediate support to users as they perform motions and actionable insights for refining their skills.

Feedforward mechanisms play a crucial role in guiding users through precise, real-time instructions during training. Existing motion guidance systems primarily focus on low-exertion exercises such as Tai Chi [6, 7], physiotherapy [15, 14], and Yoga [3], where postural accuracy is prioritized over speed. While these systems excel in maintaining proper posture, they often fall short in addressing the demands of high-intensity, physically demanding activities that

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require a balance of accuracy and efficiency. This limitation highlights the need for feedforward guidance systems tailored to high-exertion exercises, offering real-time adaptability to such unique challenges.

Feedback mechanisms are equally essential, providing users with opportunities to reflect on and enhance their movements after training. Nabil et al.'s studies have shown that post-training visual feedback significantly improves performance, with even greater benefits when combined with feedforward guidance [13]. Additionally, the use of joint motion trajectories as feedback was found to be effective for precise movement corrections [9]. These findings emphasize the importance of robust feedback mechanisms that complement feedforward guidance to maximize overall training outcomes.

Visual perspectives can further enhance the effectiveness of motion guidance systems, particularly in the context of full-body motion guidance, which has been a focus of extensive research. Hu et al. [8] demonstrated that superimposing an expert's motion onto a learner's avatar significantly enhances performance. They also found that a side view improves retention by reducing errors along the back-front axis, while a front view minimizes errors related to the center of mass. Similarly, Elsayed et al. [5] found that a third-person perspective (3PP) outperforms a first-person perspective (1PP), suggesting that external views provide more effective guidance for full-body movements. These insights highlight the critical role of selecting optimal perspectives in designing effective motion guidance systems.

In this work, we developed a VR-based training system specifically for deadlift, a physically demanding sport. This system provide real-time instruction in 3PP during the exercise and offer joint trajectory data and textual feedback during the post-training phase.

3 LiftVR

LiftVR is a VR-based exercise guidance system designed to teach deadlift skills in a back-friendly manner. It immerses users in a virtual fitness studio and provides customizable options to tailor the learning experience to their individual needs.

3.1 Back-Friendly Lifting

Our goal is to teach a lifting exercise that minimizes injury risk while maximizing muscle activation. According to the expert from the sport and movement science, a proper lifting technique involves a wide stance, a natural positioning of the feet, and free-moving knees [4]. During the movement, the student should gaze upwards or forwards to maintain the natural curve of the spine, which helps prevent spinal injuries [16]. Another key characteristic of a healthy lift is the bending of both the knees and hips. The student should not bend forward to pick up an object without simultaneously bending the knees. Conversely, they should not squat and lift without leaning forward, as this can place undue pressure on the spine. Whilst doing so, attention must be payed to maintain natural spine curvature at all times.

3.2 System Overview

The immersive training environment, is primarily composed of a fitness studio purchased from the Unity Asset Store[1]. Within the VR environment, the student is represented by a skeletal avatar, depicted as a white stick-and-ball model. The user interface consists of two dark-hued floating planes: the main menu is positioned to the student's left, while the evaluation menu is situated to the right.

3.3 Guidance Feedforward

During the training phase, the standard target deadlift movements recorded by expert trainer are scaled frame-by-frame (i.e. postures) to match the trainee's body dimensions. These movements are then presented to the students using two different visual encodings: *Skeleton* and *Zone*.

3.3.1 Skeleton

Skeleton guidance is one of the most commonly used approaches in full-body motion guidance systems [5]. It visualizes the target posture recorded from an expert, using a skeleton scaled to match the user's body proportions. As shown in Figure 1, the student's skeleton is rendered in white, while the expert's skeleton is rendered in yellow. To enhance clarity, the expert's current posture is displayed with an opaque yellow skeleton, while a semi-transparent yellow skeleton is used to indicate key positions in the next phase, such as squatting or standing.

To further assist students in aligning their joints with the expert's, spherical indicators are added to the expert skeleton at the neck, elbow, wrist, pelvis, and knee joints. These indicators, each with a diameter of 15 cm, represent the acceptable tolerance range for the corresponding joints. When a student's joint enters the correct sphere, the sphere changes color from red to green, signaling that the correct position has been achieved.

3.3.2 Zone

Offering an alternative to full-body motion guidance via *skeleton* guidance, the *Zone* approach provides an abstract representation of the posture. This method leverages the left-right symmetry of the spine in the deadlift movement. As illustrated in Figure 2, it uses capsule shapes to envelop the expert's shoulders, elbows, wrists, and knees on both sides, while omitting the visualization of other joints and limbs.

When both joints are outside the corresponding capsule but gradually approach it, the capsule's color transitions linearly from red to yellow based on the combined deviation distance. Once a joint is correctly positioned within the capsule, the color changes from yellow to green. Similar to the spherical indicators used in *skeleton* guidance, the capsules have a fixed width of 15 cm, with their length determined by the distance between paired joints. However, unlike the *skeleton* approach, *Zone* does not require the student's joints to be in precise positions within the capsule; it only requires the joints to remain inside the capsule to meet the defined tolerance criteria.

3.3.3 Rubber Bands

To address possible joint deviations from correct posture during the training process, we adopted the "rubber band" method described in [17], which uses lines to connect the user's joints to their corresponding desired positions. In the *Zone* guidance, the rubber bands directly link the student's joints to the corresponding target positions within the capsules. In the *skeleton* guidance, the rubber bands connect the next frame's posture to the subsequent critical position, such as squatting or standing, thereby clearly illustrating the progression of posture changes while minimizing excessive visual distractions around the student.

3.4 Post-Training Feedback

The post-training feedback module is integral to assisting students in reviewing their training process, enabling them to determine whether errors occurred and identify their locations. This module incorporates three core features: last motion replay, textual feedback, and joint path visualizer.

3.4.1 Last Motion Replay

LiftVR enables students to review their most recent performance through motion replay. During the replay, the Expert Skeleton and Student Skeleton are overlapped, and the last recorded motion is played. To gain a comprehensive perspective, students can walk

[1] https://assetstore.unity.com/packages/3d/props/interior/gyminterior-86812

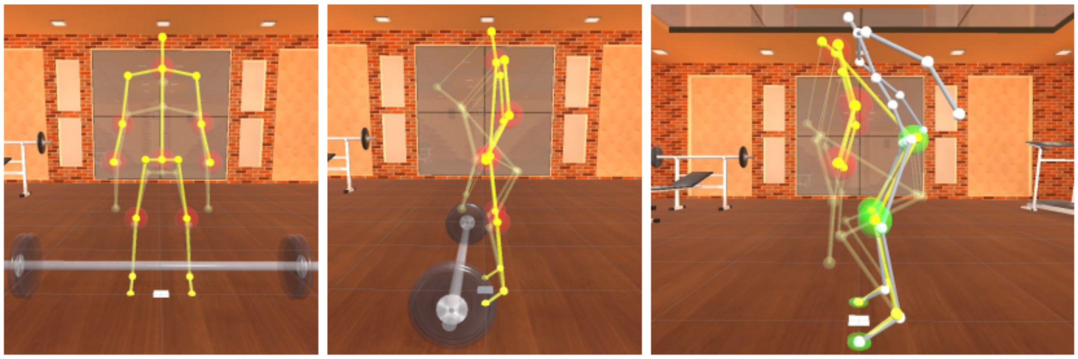

Figure 1: *Skeleton* guidance. The desired posture of next frame is rendered in opaque yellow, while that of the next critical point is rendered in transparent yellow; the yellow rubber bands connect the corresponding joints between these two skeletons. The spherical indicator will turn green from red when the student's joints match the correct positions.

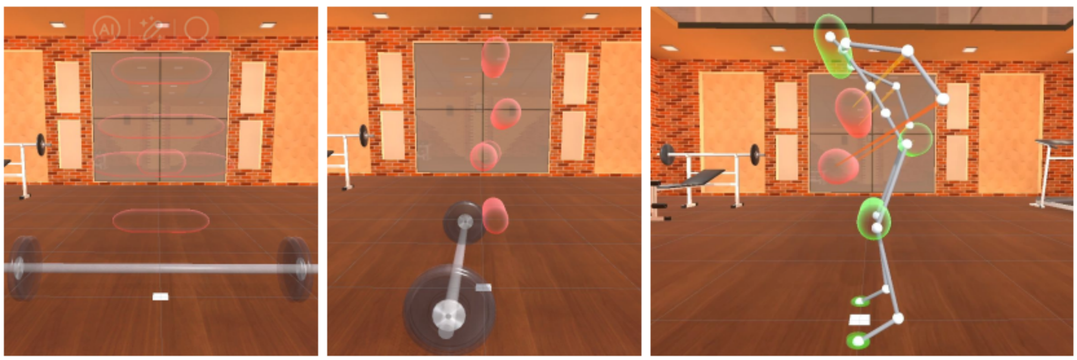

Figure 2: *Zone* guidance. The desired positions of shoulders, elbow, wrists and knees, are paired and enveloped by capsule shapes. The rubber bands connecting between the desired positions of joints inside the capsules and the students' joints.

around the active replay, allowing them to observe their performance from various angles.

3.4.2 Text Feedback

An evaluation function was designed to provide users with a score for their most recent attempt. The function calculates the average distances of the knees, elbows, wrists, pelvis, and neck from their intended positions, i.e. deviation distance, multiplies this value by 100, and then squares the result. Squaring the score amplifies penalties for larger errors, encouraging precise alignment. Figure 3 illustrates the scoring function for distances ranging from 0 to 15 centimeters, with typical scores of 36, 50, and 100 highlighted by black dots. In Figure 4, a student achieved a score of 68, corresponding to an average deviation distance of 0.08239 centimeters.

To enhance feedback, average distances are compared across joints, with the three worst-performing joints highlighted in the Worst Joints Text. This mechanism helps students identify areas requiring improvement when reviewing their replays. For example, in Figure 4, the student's worst-performing joints were the neck, left wrist, and elbow. The combination of wrist and elbow errors suggests that the left arm was misaligned, while the poor neck score indicates difficulty keeping pace with the expert's recording.

3.4.3 Joint Path Visualizer

When students receive feedback on their worst-performing joints, they can watch their replay to identify the source of the problem. However, it can be challenging to determine whether the error occurred over a brief moment or persisted throughout the motion. To address this, we designed Joint Path Visualizer (Figure 5). This

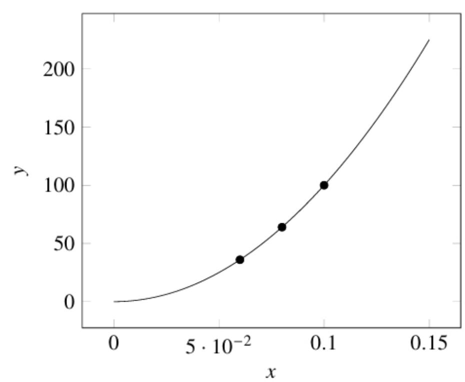

Figure 3: Plot of LiftVR's scoring function with highlights at f(0.06)=36, f(0.08)=64, and f(0.1)=100.

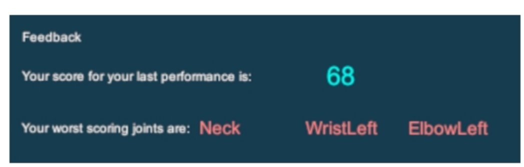

Figure 4: Score text and worst joints text mechanisms shown after training.

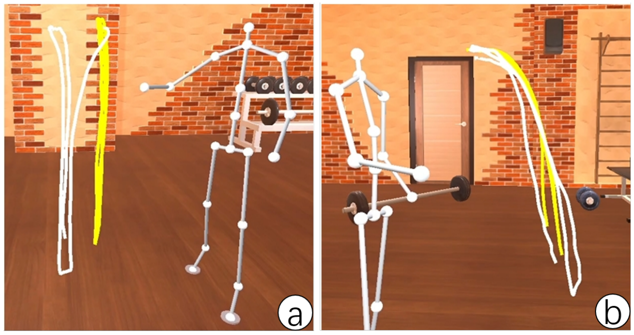

Figure 5: The joint path visualization of the neck joint, where the student's path is visualized in white while the expert's in yellow. The (a) front view shows the horizontal deviation of the student's neck movement compared to the expert's, and the (b) side view indicates that the joints mostly overlapped vertically.

tool draws a line through all joint positions captured during the performance, visualizing the trajectory of each joint throughout the motion. Simultaneously, a reference line is drawn for the expert's corresponding joint positions. The Joint Path Visualizer can remain active during the Last Motion Replay, enabling students to associate specific portions of the path with specific times in the motion and directly compare their movements to those of the expert.

3.4.4 Use The Post-Training Feedback

Together, the post-training feedback modules implemented in *LiftVR* provide students with insights into their most recent performance. A typical workflow begins with the student determining whether they improved by comparing their current score to previous attempts using the Score Text. If their score decreases, they can use the Joint Path Visualizer to examine the paths taken by their worst-performing joints. After reviewing these paths from multiple angles, the student can start the Last Motion Replay to pinpoint when and where deviations occurred during the motion. With a clearer understanding of how, when, and why errors arose, they can make targeted adjustments in subsequent attempts, avoiding previous mistakes and improving overall performance.

3.5 Perspective

In *LiftVR*, feedforward guidance is visualized from a third-person perspective, displaying the side view of the user's avatar. This design choice was made because the third-person perspective has been shown to enhance performance in full-body motion guidance [5]. Additionally, the motion in this case, deadlift, involves angle changes at multiple joints and is vertically symmetrical, making this perspective particularly suitable.

3.6 Implementation

LiftVR requires a wide field of view to visualize 6-DOF guidance in three-dimensional space and low latency to ensure accurate and reliable motion guidance for deadlift training. Furthermore, the system requires accurate full-body motion capture without relying on wearable trackers. To fulfill these requirements, the system utilizes Microsoft Azure Kinect for skeletal tracking and HP Reverb as the VR display. The software for *LiftVR* was developed using Unity Engine version 2021.3.22f1.

During development, we observed significant inaccuracies in hand and hand-tip tracking. Similarly, tracking errors were evident for the feet and ankles when students assumed a squatting posture, often causing their legs to drift backward, resulting in a "superman" pose (Figure 6(a)). Overall, low tracker confidence for lower-body joints led to noticeable stuttering of the foot and ankle joints. To address this issue, *LiftVR* implements a mechanism that freezes the feet and ankle joints at the start of each performance (Figure 6(b)).

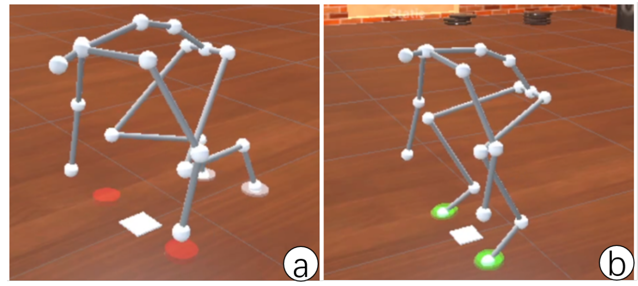

Figure 6: The positions of students' feet for "ready" posture. (a) When the foot-lock is **disabled**, the feet of the student's skeleton will drift away from the feet positions in the real world. (b) When foot-lock is **enabled**, it will prevent foot and ankle backward shift.

4 Evaluation

To evaluate the usability of *LiftVR*, we ran a comparative user study. Our goal was also to explore the effects of different feedforward guidance and feedback modes on the effectiveness of back-friendly lifting training.

4.1 Study Design

We used a between-subject multivariate design with two independent variables Feedforward Guidance (*Skeleton* vs. *Zone*) and Feedback Mode (With vs. Without post-training feedback). Thereby, we had a 2×2 design with 4 distinct groups:

- A: *Skeleton with* feedback
- B: *Zone with* feedback
- C: *Skeleton without* feedback
- D: *Zone without* feedback

4.2 Participants

A total of 24 participants (15 male, 9 female) aged between 18 and 59 years were invited to evaluate *LiftVR*, including 9 students from the local university's Institute for Sport and Movement Science. They were evenly divided into four groups.

4.3 Procedure

We designed the procedure of this study building up on Anderson et al.'s [1], which starts with familiarization, followed by guided and independent practice, a retention test, and concluding with a post-study questionnaire. Each phase was designed to progressively guide participants in learning and mastering back-friendly lifting techniques.

4.3.1 Preparation

First, participants were introduced to the study and provided informed consent. They then entered the *LiftVR* gym environment and familiarized themselves with the controls. Following this, the functionality of the user interface (UI) was explained, and participants were instructed to position their feet correctly. Once a performance began, participants were directed to release the controller and practice squatting to grab the Digital Barbell. This retrieval process was repeated until participants felt confident grabbing the bar without looking downward, relying on its virtual presence.

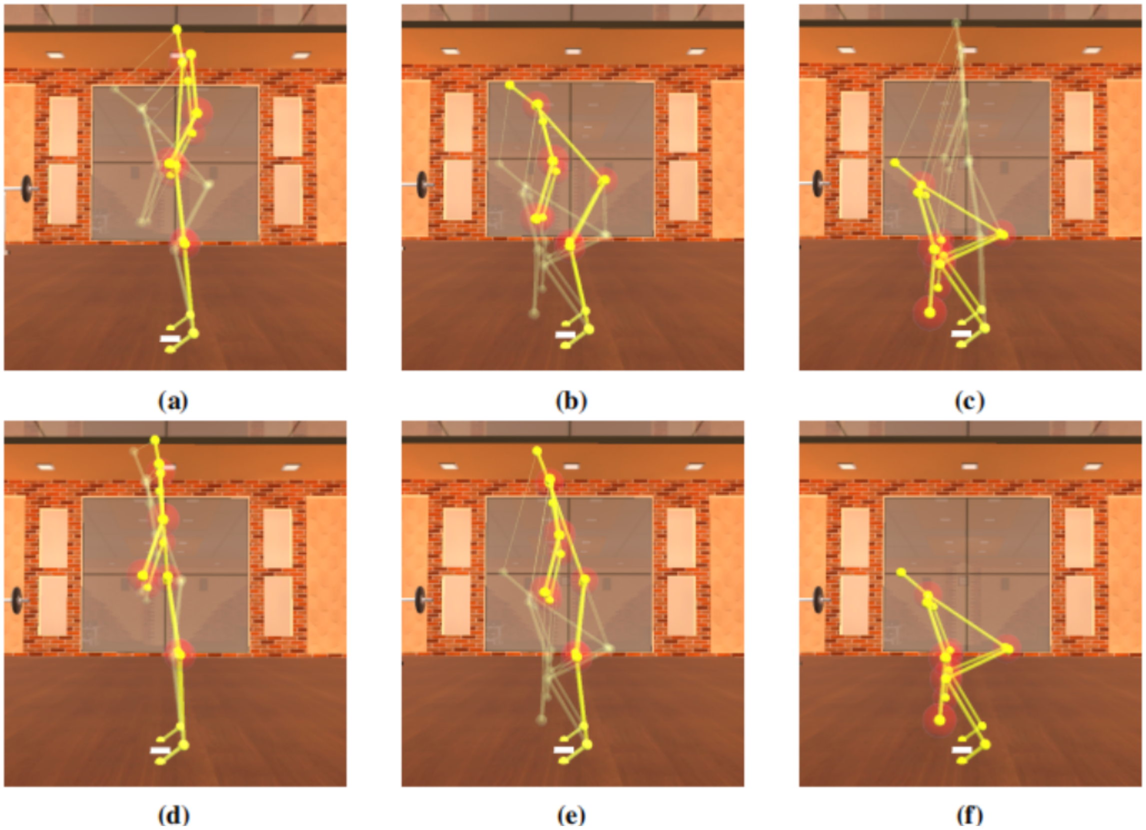

Figure 7: The six key postures in Posture Guide phase.

4.3.2 Baseline

To receive a baseline measurement, participants observed demonstrations performed by an expert *skeleton* and subsequently attempted to replicate the movements unaided after each demonstration. The participants tried three times. To minimize user fatigue from the high number of practice repetitions, a lightweight yet tangible curtain rod was used as a substitute for a loaded barbell, providing a practical alternative for participants to grasp.

4.3.3 Posture Guide

In this phase, the system presents six progressive postures of the deadlift movement, sampled at equal time intervals from the complete motion sequence. Figure 7 illustrates all six postures, starting with a simple standing position by the expert. Figures 7b to 7d depict the descent to grasp the barbell, while Figures 7e and 7f show the barbell being lowered. Posture Guide phase provides participants with the key steps of the deadlift process, including lowering oneself to grasp the barbell, lifting it, and returning to the initial standing position.

Participants completed five repetitions of posture practice using the FEEDFORWARD GUIDANCE associated to their group. For those in the group with post-training feedback enabled, a replay of their last performance was shown. Notably, participants were instructed to disregard the score and joint path feedback options during this phase.

4.3.4 Movement Guide

During the Movement Guide phase, the feedforward system autonomously updates to display the complete deadlift motion, regardless of whether the participant follows it in time. To accommodate participants' preference for self-pacing, we implemented two speed settings in *LiftVR*: Slow Mode, which plays the motion at half speed, and Regular Mode, which plays it at full speed.

Participants were instructed to perform five repetitions using the Slow Movement Guide, followed by an additional five repetitions at Regular speed. In this phase, participants in groups with post-training feedback were granted full access to the feedback modules, including replay, scoring, textual feedback, and the joint path visualizer. They were encouraged to lower their error scores and were provided guidance on effectively utilizing the system to achieve this goal.

4.3.5 Retention

Ten minutes after the Movement Guide phase, participants performed the complete deadlift motion three times without any feedforward or feedback visualizations. This step was designed to assess short-term retention and compare the results to the baseline measurements.

4.4 Measurements

Unlike Anderson et al. [1], during the Posture Guide phase, we measured the time participants took to learn the lifting posture, represented by the number of system frames, to explore differences in the instructional effectiveness of the *Feedforward Guidance* methods. For each repetition in the Movement Guide and Retention phases, we measured the movement error, defined as the average distance between the participant's joints and the expert's joints during the repetition, measured in meters. Based on movement error, we calculated **improvement** as the difference between the participant's performance in various training or retention phases and the baseline.

Following the completion of all training phases, participants were required to complete a demographic survey and a questionnaire to provide subjective feedback on the system. Our question categories are based on the study by Moesgen et al [12]:

- **Understandability** How easy was it to understand how the guidance system works?
- **Mental Effort** During practice, how mentally demanding was it to follow the guidance system?
- **Helpfulness** When in an incorrect position, how helpful was the guidance system in highlighting the discrepancy and correcting the mistake?

Unlike the study on which our questions are based, we opted for a 7-point Likert scale for scoring, citing its advantages over the 5-point version [10]. From the individual categories, we calculated a total score.

4.5 Results

In the following, we present our results including both objective and subjective aspects. When performed outlier identification, we eliminated the data from a participant in the group "*Zone* feedforward *with* feedback".

4.5.1 Objective Results

For the objective results, we analyzed the best performance of the participants (i.e., the minimal frame count in Posture Guide and the minimal movement error in Movement Guide) and conducted statistical analyses based on the mean values of the remaining 23 participants. We used Shapiro-Wilk test to assess the normality of data, and Levene's test to evaluate the homogeneity of variances between groups.

Since the result of the frame count in Posture Guide phase did not follow the normality ($p<0.05$), a Kruskal-Wallis test was conducted to examine the differences between the *Feedforward Guidance*, with the effect size calculated using epsilon-squared (ε^2). The results showed a significantly faster completion with *Zone* compared to *Skeleton* ($\chi^2(1) = 7.67$, p = 0.0056, $\varepsilon^2 = 0.349$), as shown in Figure 8.

Given that the movement error data in the Movement guide and Retention phases satisfied both the assumptions of normality and homogeneity of variances, we then performed one-sample t-tests on the improvements observed in the *Slow*, *Regular*, and *Retention* phases. As presented in Figure 9(a), the results indicated that participants' performance in all three phases—*Slow*, *Regular*, and *Retention*—showed significant improvement compared to the baseline. However, performance in the *Retention* phase was notably reduced relative to the *Slow* and *Regular* movement phases.

We then conducted a mixed ANOVA with *Feedforward Guidance* and *Feedback Mode* as between-subject factors and Phases as the within-subject factor. Effect sizes were reported using generalized eta squared (η^2_G) [2] for ANOVA and Kendall's W for Friedman tests. The results, including 95% confidence intervals, are presented graphically in Figure 9. No significant effects were found for *Feedforward Guidance* (F(1,18) = 0.335, p = 0.57, η^2 = 0.017) or *Feedback Mode* (F(1,18) = 3.064, p = 0.097, η^2 = 0.138), regardless of whether participants were in the *Slow* (Figure 9(b)) or *Regular* movement guidance phases (Figure 9(c)), or during the *Retention* phase (Figure 9(d)). For *Feedforward Guidance*, the *Skeleton* method tended to provide more efficient guidance than the *Zone* method during the *Slow* and *Regular* Movement phases, regardless of *Feedback Mode*. However, the *Zone* feedforward method *without* feedback showed a tendency to evoke higher retention effects (Figure 9(d)), although this potential interaction effect was not statistically significant (F(1,19) = 0.030, p = 0.86, η^2_G = 0.001). Regarding Feedback Mode, participants in groups *without* post-training feedback tended to perform better than those in groups *with* post-training feedback.

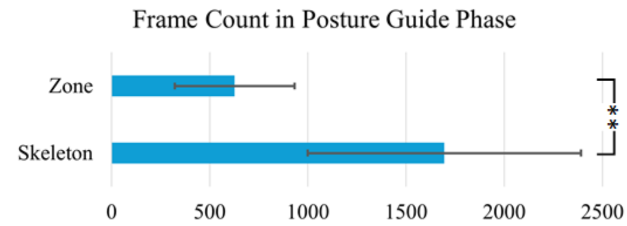

Figure 8: The frame count reflects the time participants spent to complete all six postures in Posture Guide phase: participants using *Zone* guidance spent significantly less time. The significant differences have been marked with stars * (* for p<.05, ** for p<.01, and *** for p<.001). The error bars denote the 95% confidence intervals. Same definitions are used in the other figures.

4.5.2 Subjective Results

We asked *LiftVR* participants to evaluate their guidance system based on three criteria: understandability, mental effort, and helpfulness. Additionally, participants in the *with*-feedback groups were asked to share their opinions on the provided feedback, while those in the *without*-feedback groups were asked to describe how and where they would envision feedback being integrated. For statistical analysis, we conducted Welch two-sample t-tests (effect sizes were reported with Cohen's d), because the data satisfied the assumption of normality but violated the assumption of equal variances.

The results of the training system questionnaire are presented in Figure 10. Overall, participants rated *Zone* more favorably than *Skeleton*. Specifically, *Zone* was reported to require significantly less mental effort compared to *Skeleton* (t = 2.18, p = 0.041, d = 0.910). Additionally, participants tended to find *Zone* more understandable (t = 0.48, p = 0.637, d = 0.199) and helpful (t = 1.53, p = 0.142, d = 0.633).

Participants *with* post-training feedback were asked to evaluate the system in terms of understandability and helpfulness of the feedback visualization. Given that the back-angle indicator was the most novel feature, we separately inquired whether participants found it helpful. The results, as presented in Figure 11, indicated that participants generally found the feedback easy to understand and mostly helpful. However, the back-angle indicator's helpfulness was rated neutrally. Participants *without* feedback were asked whether they preferred feedback during or after the motion, with responses evenly split between the two options.

5 Discussion

Our evaluation revealed that *Skeleton* guidance tended to outperform *Zone* in terms of Feedforward Guidance. However, participants' subjective ratings favored *Zone*, as they found it more helpful, easier to understand, and significantly less mentally demanding. We attribute this preference to the visual encoding of *Zone* guidance, whose symmetrical design eliminated the need for participants to frequently turn their heads to observe both limbs. Instead, they could focus their gaze on the center of the *Zone* capsule. This design reduced the visual attention required compared to *Skeleton* guidance. Furthermore, as shown in Figure 8, the improved visual clarity and leniency in joint positioning enabled participants using *Zone* guidance to complete the posture guide phase of the evaluation significantly faster than those using *Skeleton* guidance. However, the shift of users' attention away from the joints on both sides appeared to hinder the execution of precise movements.

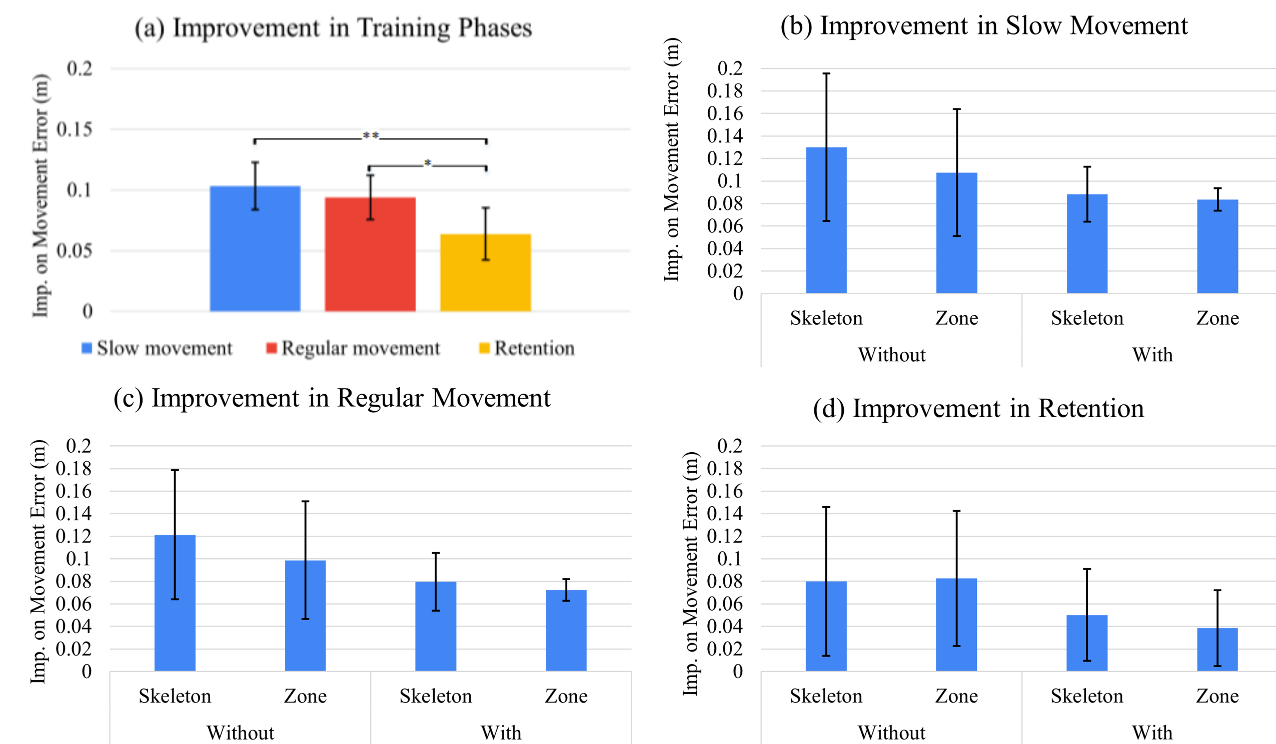

Figure 9: Result of improvements in different training phases and retention. (a) The participants performed better in movement guidance and retention phases compared to baseline. The *Skeleton* method tended to provide more efficient guidance than the *Zone* method during the (b) *Slow* and (c) *Regular* Movement phases. However, the *Zone* feedforward method *without* feedback showed a tendency to evoke higher (d) *Retention* effects.

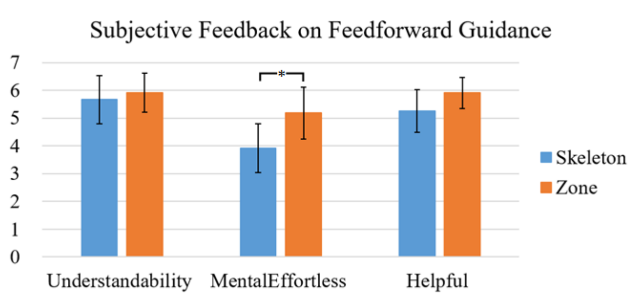

Figure 10: Questionnaire results regarding the Feedforward Guidance.

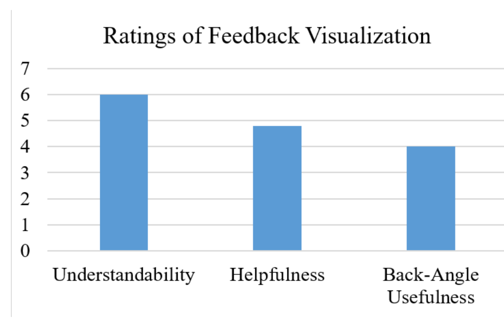

Figure 11: Questionnaire results regarding the Feedback Visualization.

For example, a pair of joints might enter the capsule at an angle (e.g., when holding the barbell, the left hand is positioned at the bottom of the capsule while the right hand is at the top), leading to suboptimal performance with *Zone* guidance compared to *Skeleton*. Nevertheless, the objective results indicate that *Zone* was effective in facilitating training. Combined with the participants' subjective preference for *Zone*, we suggest that *Zone* can serve as a valuable alternative for users seeking a guidance system with lower cognitive demands, without compromising overall training effectiveness.

Groups *without* post-training feedback tended to show greater improvement compared to those *with* feedback. During the Post-Questionnaire phase, participants noted that while the feedback provided a useful review of previous repetitions and identified their mistakes, it was not particularly helpful during training. This was primarily because the feedback was delivered after the training process, when participants were focused on engaging their muscles and maintaining balance, making it difficult to retain and apply the feedback. Furthermore, post-training feedback disrupted the flow of rapid practice and hindered the memorization of movements.

Finally, participants expressed that the training process was well-structured, progressing from learning fixed-point postures to practicing at slow and regular speeds sequentially, and culminating in an "examination". Although participants' performance in the *Retention* phase was noticeably lower than in the *Slow* and *Regular* movement phases, it remained significantly higher than the baseline. This result suggests that *LiftVR* effectively supported users in training correctly, even in the absence of a coach. Furthermore, participants' performance in the *Slow* movement phase was slightly better than in the *Regular* movement phase, likely due to the additional time afforded by the slower pace, allowing them to more closely follow the guidance animation.

6 Limitations

This work is a technical exploration of back-friendly lifting practice and training using VR. As empirical work, our studies come with a set of limitations.

Demographic Factors We observed that demographic factors, such as gender, body weight, and prior exercise experience, had an influence on our user study, particularly during the baseline phase. For instance, female participants tended to demonstrate smaller movement errors at baseline compared to male participants. Additionally, participants with prior deadlift experience completed movements more quickly during the baseline phase and demonstrated a higher initial proficiency. These findings will help us design participant groupings more scientifically in future user studies, enabling a targeted exploration of the impact of demographic factors on such motion training processes, while also refining our study procedures based on kinematics and physiology.

Study Setup First, each group in our study included only six participants, which may have limited the statistical power and reduced the generalizability of the findings. Second, to ensure participants' safety, we neither urged them to complete movements nor measured completion time during the Movement Guide phase. Future studies could incorporate temporal performance metrics, such as dynamic time warping, to better evaluate participants' timing and synchronization. Third, we allocated only a 10-minute break during the Retention phase, which may have been insufficient to effectively evaluate muscle memory or short-term memory effects.

Motion Capture System This study utilized the Azure Kinect for motion capture; however, the system exhibited instability in tracking results. For instance, during the user study, fluctuations were observed in the captured back angle values. Another example can be found in Figure 6 that the user's virtual feet may deviate from their physical counterparts. Future research should consider employing more accurate and stable full-body motion capture systems, such as OptiTrack or Vicon, to ensure reliable data collection and enhance the robustness of the findings.

Constant Weight Barbell Our user study used a barbell with a constant weight; however, in real deadlift training, the weight is typically adjusted based on the user's physical characteristics and training progression. Future research will investigate feedforward and feedback mechanisms under varying weight conditions to more accurately simulate real-world deadlift training scenarios.

7 Conclusion

We proposed *LiftVR*, a VR-based motion guidance system for back-friendly lifting practicing and training. The system incorporates two distinct Feedforward Guidance methods, *Skeleton* and *Zone*, to provide users with instructions for correct deadlift motion, alongside post-training feedback to help correct movement errors. To evaluate the usability of *LiftVR*, we conducted a comparative user study consisting of postural training, slow exercise instruction, regular exercise instruction, and a final assessment phase. Our findings revealed that *Zone* guidance required less mental effort and was generally preferred over *Skeleton*. However, it may have caused users to relax their attention to the precise alignment of joints, resulting in less effective training outcomes. Additionally, post-training feedback did not fulfill its intended purpose of error correction. Instead, because it was delivered during intervals of physically intensive training, it appeared to disrupt the formation of muscle memory, potentially diminishing its effectiveness.

Acknowledgments

This work was funded by Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2075 – 390740016.

References

[1] F. Anderson, T. Grossman, J. Matejka, and G. Fitzmaurice. YouMove: enhancing movement training with an augmented reality mirror. In *ACM Symp. User Interface Software and Technology (UIST)*, pp. 311–320, 2013. 4, 5

[2] R. Bakeman. Recommended effect size statistics for repeated measures designs. *Behavior Research Methods*, 37(3):379–384, 2005. 6

[3] P. Caserman, S. Liu, and S. Göbel. Full-body motion recognition in immersive-virtual-reality-based exergame. *IEEE Trans. Games*, 14(2):243–252, 2021. 1

[4] P. Comfort and P. Kasim. Optimizing squat technique. *Strength & Conditioning Journal*, 29(6):10–13, 2007. 2

[5] H. Elsayed, K. Kartono, D. Schön, M. Schmitz, M. Mühlhäuser, and M. Weigel. Understanding perspectives for single-and multi-limb movement guidance in virtual 3d environments. In *ACM Symp. Virtual Reality Software and Technology (VRST)*, pp. 1–10, 2022. 2, 4

[6] P.-H. Han, K.-W. Chen, C.-H. Hsieh, Y.-J. Huang, and Y.-P. Hung. Ar-arm: Augmented visualization for guiding arm movement in the first-person perspective. In *Proc. Augmented Human Int. Conference (AH)*, pp. 1–4, 2016. 1

[7] P.-H. Han, Y.-S. Chen, Y. Zhong, H.-L. Wang, and Y.-P. Hung. My tai-chi coaches: an augmented-learning tool for practicing tai-chi chuan. In *Proc. Augmented Human Int. Conference (AH)*, pp. 1–4, 03 2017. 1

[8] F. Hülsmann, C. Frank, I. Senna, M. O. Ernst, T. Schack, and M. Botsch. Superimposed skilled performance in a virtual mirror improves motor performance and cognitive representation of a full body motor action. *Frontiers in Robotics and AI*, 6:43, 2019. 2

[9] E. Iannucci, Z. Chen, I. Armeni, H. Pfister, and J. Beyer. Arrow: A real-time ar rowing coach. In *ACM Proc. Eurographics*, pp. 1–5, 2023. 2

[10] A. Joshi, S. Kale, S. Chandel, and D. K. Pal. Likert scale: Explored and explained. *British Jour. applied science & technology*, 7(4):396–403, 2015. 6

[11] T. Komiyama, Y. Tanoue, M. Sudo, J. Costello, Y. Uehara, Y. Higaki, and S. Ando. Cognitive impairment during high-intensity exercise: influence of cerebral blood flow. *Medicine and Science in Sports & Exercise*, 52(3):561–568, 2020. 1

[12] T. Moesgen, A. Salovaara, E. Pouta, R. Pyykko, and Y. Xiao. Vibrotactile motion guidance for stroke rehabilitation: A comparative study. In *Proc. the 6th Int. Conf. Medical and Health Informatics*, pp. 147–152, 2022. 6

[13] A. Nabil, H. Hegazy, M. Abdelsalam, M. Hussien, S. Elmosalamy, Y. Hassan, and A. Atia. Usability study of a comprehensive table tennis ar-based training system with the focus on players' strokes. *Jour. Ubiquitous Systems and Pervasive Networks*, 13(1):1–09, 2020. 2

[14] M. Sousa, J. Vieira, D. Medeiros, A. Arsenio, and J. Jorge. Sleevear: Augmented reality for rehabilitation using realtime feedback. In *ACM Int. Conf. Intelligent User Interfaces (IUI)*, pp. 175–185, 2016. 1

[15] R. Tang, X.-D. Yang, S. Bateman, J. Jorge, and A. Tang. Physio@home: Exploring visual guidance and feedback techniques for physiotherapy exercises. In *ACM Conf. Human Factors in Computing Systems (CHI)*, pp. 4123–4132, 2015. 1

[16] T. Tsuji, Y. Matsuyama, K. Sato, Y. Hasegawa, Y. Yimin, and H. Iwata. Epidemiology of low back pain in the elderly: correlation withlumbar lordosis. *Jour. Orthopaedic Science*, 6(4):307–311, 2001. 2

[17] X. Yu, K. Angerbauer, P. Mohr, D. Kalkofen, and M. Sedlmair. Perspective matters: Design implications for motion guidance in mixed reality. In *IEEE Symp. Mixed and Augmented Reality (ISMAR)*, pp. 577–587. IEEE, 2020. 2

[18] X. Yu, B. Lee, and M. Sedlmair. Design space of visual feedforward and corrective feedback in xr-based motion guidance systems. In *ACM Conf. Human Factors in Computing Systems (CHI)*, pp. 1–15, 2024. 1