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Real-Time Joint-Torque Feedback in VR Pre-Training for Safe Lifting: A Comparative Study of Visual Encodings

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Abstract— **We present a VR-based pre-training system that estimates user-specific joint torques in real time by coupling a VR interaction environment (SIGVerse) with a biomechanics simulator (DhaibaWorks). The system visualizes internal load together with postural information using four encodings (color map, bar graph, exemplar posture, and exemplar+self posture) and enables rehearsal of lifting posture without handling real weight. In a within-subject study (11 participants), a simulated box-lifting task was evaluated using (i) time-integrated lumbar torque normalized by body mass and (ii) two 7-point Likert ratings (perceived comprehension and perceived load reduction). Across conditions, we did not observe a reliable reduction in normalized torque after training. Perceived load reduction showed a significant overall condition effect, whereas perceived comprehension showed no clear between-condition differences. These findings indicate that visualizing internal load can influence users' perception of effort, although the present short session did not yield measurable torque changes. The proposed platform provides a safe pre-training route for learning low-strain movement strategies and a foundation for adaptive human–agent interaction that can leverage real-time estimates of human physical state.**

I. INTRODUCTION

Virtual Reality (VR) has emerged as a powerful platform for immersive movement training in domains such as construction [1], industrial safety [2], rehabilitation, and sports [3]. By simulating physically demanding or hazardous tasks in a safe and controllable environment, VR allows users to practice complex motions while receiving real-time feedback. Most existing VR training systems focus on visual or postural feedback—such as alignment with exemplar movements or correction of joint angles—which can help improve observable motion patterns. However, these systems typically overlook the user's internal physical state, including joint torque or muscular exertion. Such internal load factors are critical for ensuring comfort, preventing overexertion, and minimizing the risk of injury, especially in tasks that involve repetitive or heavy physical actions. Without awareness of these hidden loads, users may unknowingly adopt inefficient or harmful movement strategies.

While user interfaces that present physical load in real time have been proposed [4], directing attention to such information and simultaneously correcting one's movement during strenuous actions (e.g., carrying heavy objects) imposes a substantial cognitive burden [5]. This motivates a pre-training paradigm in which users rehearse transport posture without handling actual weight, while the system simulates and feeds back the internal loads that would arise under that posture. Although a small number of system proposals have explored this pre-training paradigm, none have supported fine-grained parameterization tailored to individual anthropometry. Moreover, to our knowledge, prior work has not quantitatively established whether such pre-training transfers to real heavy-object handling.

Motivated by these gaps, this paper pursues the following aims: (i) to establish an implementation methodology for a pre-training paradigm in which users rehearse transport posture without actual load while the system estimates and feeds back the internal loads that would arise; (ii) to experimentally determine whether such pre-training transfers to real heavy-object handling and whether it can improve biomechanical load management; and (iii) to comparatively assess which encodings are easier to understand. By addressing these aims, we seek to broaden the applicability of VR training to injury prevention and to the acquisition of motor skills under high physical load.

As a case study, we apply the system to a lifting task where users must transfer a heavy object while maintaining safe and efficient body mechanics. Four visualization strategies—based on showing feedback by color mapping and bar graphs, and showing exemplar posture and self posture—are implemented to assess the effectiveness of different visualization methods. Our experiments evaluate both objective outcomes (time-integrated, body-weight-normalized lumbar torque) and subjective ratings (perceived comprehension and perceived load reduction) to examine how internal-load information supports movement learning.

The remainder of this paper is organized as follows. Section II reviews related work. Section III details the system architecture and feedback designs. Section IV describes the experimental setup. Section V presents results and statistical analyses. Section VI concludes.

II. RELATED WORK

Virtual Reality (VR) has become a widely adopted platform for physical training across various domains such as construction safety [1], manufacturing ergonomics, sports performance [6], and physical rehabilitation [3]. Numerous studies have proposed VR-based training systems that provide users with visual and postural feedback to correct motions and reduce the risk of injury [7]. However, most of these systems have primarily focused on kinesthetic feedback based on posture and motion trajectories. Few studies have addressed the real-time estimation and feedback of biomechanical load, such as joint torques, during task execution in a VR environment[8].

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In the construction and industrial domains, prior works have utilized real-time posture evaluation indices such as RULA [9] or REBA [10] to assess ergonomic risk during lifting and assembly tasks. For example, Akanmu et al. [11] proposed a cyber-physical VR system for construction workers that visualizes posture risk using wearable sensors and provides visual feedback through a VR interface. Similarly, Barkokebas et al. developed VR-RET [12], a system that provides real-time feedback on high-risk postures using ergonomic scoring and visual warnings. These systems demonstrated reductions in unsafe posture durations and improved user awareness. Nevertheless, they rely on simplified scoring models and do not calculate or visualize the physical load (e.g., joint torques) experienced by the body in a detailed or individualized manner.

In the manufacturing field, VR and motion capture technologies have been used to monitor workers' postures and provide real-time guidance to improve ergonomic compliance. Systems like the WEM-Platform [13] compute multiple ergonomic indices in real time and display results via visual overlays. These systems however lack high-fidelity biomechanical modeling and do not support dynamic feedback based on internal physical load. In this domain, where manual material handling carries a substantial risk of injury, feedback-driven pre-training in a virtual environment—without handling real loads—is particularly valuable. To our knowledge, however, VR training systems that implement such functionality have not yet been proposed.

In the domain of physical rehabilitation, VR has been used to provide motion feedback to patients during therapy tasks [14]. Many systems offer real-time visual [15] or auditory cues [16] to reduce compensatory movements or guide motion trajectories. Valdés et al. [17], for instance, demonstrated that both visual and haptic feedback could significantly reduce trunk compensation during upper-limb rehabilitation. However, most rehabilitation VR systems rely on kinematic data only and do not provide quantitative feedback on the internal physical load of the joints.

In the field of sports, VR has been used to support motion learning [6], timing control [18], and tactical decision-making [19]. These systems use visualizations such as ghost avatars or trajectory overlays for the training [20]. While a few studies explored muscle stimulation or power output visualization [8], feedback on actual joint load during sports actions remains rare due to the difficulty of force estimation in VR environments.

In summary, prior VR training systems have focused primarily on kinematics-oriented posture training, with comparatively few addressing biomechanical loads. Moreover, for injury-prone tasks such as heavy-object handling, we find no prior VR systems that implement feedback-driven pre-training in a virtual environment without handling real loads. Furthermore, to our knowledge there are no systems that flexibly vary users' height and body mass while feeding back the predicted internal loads during pre-training.

The next section describes a system architecture that realizes these capabilities.

III. VR-based Movement Pre-training System with Physical load feedback

A. System Configuration

Guided by the considerations in the previous section, this section details the system architecture for a virtual pre-training paradigm that teaches safe lifting and transport strategies without exposing users to real physical loads.

Our system integrates SIGVerse [21], a VR interaction platform that captures full-body motion in immersive environments, with DhaibaWorks [22], a biomechanics simulation framework that enables joint-level torque estimation based on user-specific body models and motion data, as shown in Fig. 1. SIGVerse is a Unity-based platform that allows users in the real space to log into a 3D model (avatar) in virtual space using a VR device. It also enables them to record and replay the movements of avatars and objects in the virtual space. The avatar size in this system can be adjusted according to the user's height. DhaibaWorks is a platform that enables the creation of 3D models reflecting individual physical characteristics and estimating joint torque. DhaibaWorks provides 3D human models based on pre-existing templates, which adapt to physical characteristics such as height and body mass. In addition, the torque of each joint is calculated using inverse dynamics analysis, according to the position and posture of the human body and the position and posture of the objects in contact with the human body. As shown in Fig. 1, the model comprises 18 links representing major body segments. The position and posture of the user's logged-in avatar are sent from SIGVerse to DhaibaWorks. By linking these platforms through a real-time communication architecture, we enable users to receive immediate, personalized feedback on how much physical load they are experiencing during task execution.

To establish a real-time communication between SIGVerse and DhaibaWorks, DhaibaConnect, which is based on the eProsima Fast-DDS[1] communication module was used. Regarding data communication flow, the avatar's position and posture are first transmitted from SIGVerse to DhaibaWorks. When the user grasps a virtual object using a VR device, its position, posture, and mass, along with the grasping state (right hand/left hand/both hands), are also transmitted from SIGVerse to DhaibaWorks. Subsequently, DhaibaWorks calculates the torque of all joints and transmits the values to SIGVerse, where it is used for user feedback.

B. Feedback functions

To train users toward an ideal motion, we first recorded an exemplar (ideal) lifting motion $\boldsymbol{\theta}_e(t)$ executed in accordance with the guideline manual issued by Japan's Ministry of Health, Labour and Welfare (MHLW)[2]. Adherence to this guideline has been shown to minimize the mechanical load on the lumbar spine. To provide feedback on users' deviations from this reference, we designed and implemented

[1] eProsima Fast DDS,https://fast-dds.docs.eprosima.com/en/latest/

[2] Low Back Pain Prevention Manual,https://www.mhlw.go.jp/file/06-Seisakujouhou-11200000-Roudoukijunkyoku/0000099336_3.pdf

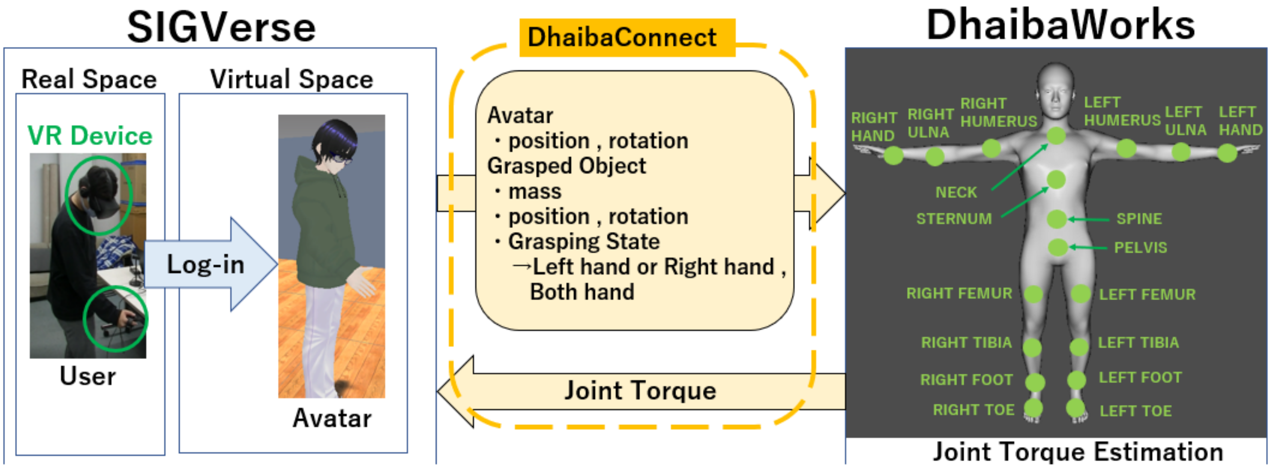
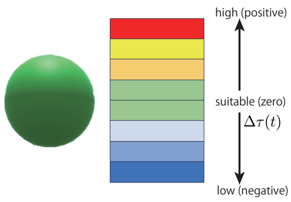
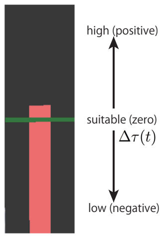


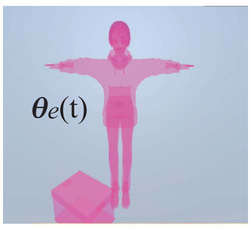
Fig. 1: System configuration of the VR training system



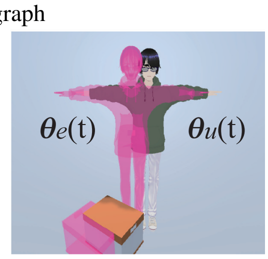
(a) Torque feedback by color



(b) Torque feedback by bar graph



(c) Exemplar posture



(d) Posture feedback by exemplar & self posture

Fig. 2: Four strategies for visualizing physical load and body state

four visualization conditions, as shown in Fig. 2. Before initiating training, we precomputed the expected lumbar load $\tau_e(t)$ during heavy-object lifting by following the exemplar motion $\boldsymbol{\theta}_e(t)$ with each participant's anthropometrics (height and body mass). At this time, the height and body mass of the avatar in DhaibaWorks was set according to the user's actual height and body mass.

During pre-training, the system observes each participant's actual body motion $\boldsymbol{\theta}_{\boldsymbol{u}}(t)$ and examined the associated difficulties of providing two types of feedback: torque-based feedback and posture-based feedback. In the torque-feedback condition, the current physical load $\tau_u(t)$ was estimated in DhaibaWorks from $\boldsymbol{\theta}_u(t)$, using each participant's height and body mass, as well as the precomputation of $\tau_e(t)$.

The difference in torque $\Delta\tau(t)$ is then computed using the following equation:

$$\Delta\tau(t) = \tau_u(t) - \tau_e(t). \tag{1}$$

In the posture-feedback condition, the system either presents only the posture of the exemplar motion, or simultaneously displays both the exemplar motion and the participant's current body posture. The visualization settings for these feedback conditions are summarized below.

1) Torque feedback by color: Fig.2(a) shows the color feedback mode. Color varies from blue to red according to $\Delta\tau(t)$: hues closer to red indicate larger $\Delta\tau(t)$, whereas hues closer to blue indicate smaller values.

2) Torque feedback by bar graph: Fig.2(b) shows the bar graph feedback mode. The central red bar moves vertically as a function of $\Delta\tau(t)$. A horizontal green line denotes the zero level. When the red bar rises above the green line, $\Delta\tau(t)$ is positive; when it falls below, $\Delta\tau(t)$ is negative.

3) Posture feedback by exemplar motion: Fig.2(c) shows posture visualization of ideal lifting motion $\boldsymbol{\theta}_e(t)$ designed by the manual. The purple avatar performs the exemplar motions, and the user attempts to follow the exemplar motion.

4) Posture feedback by exemplar and self motion: Fig. 2(d) illustrates the posture-feedback condition, in which the exemplar posture and the user's posture are displayed concurrently. The purple avatar reproduces the exemplar motion (as in Fig. 2(c)), whereas the green avatar depicts the user's current motion. Users adjust their motion by comparing the two avatars and minimizing the discrepancy between the exemplar (purple; $\boldsymbol{\theta}_e(t)$) and self (green; $\boldsymbol{\theta}_u(t)$) displays.

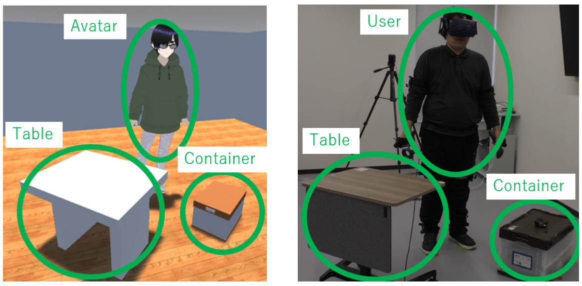
IV. VR Training Experiment

As a case study, we apply the proposed system to a lifting task where users must transfer a heavy object while maintaining safe and efficient body mechanics. In the experiment, we aimed to evaluate feedback effectiveness from two perspectives: (i) changes in physical load and (ii) responses to a subjective questionnaire. First, we measured each participant's normalized lumbar torque before training with

TABLE I: Questionnaire constructs and items. Q1 (Perceived comprehension): self-reported understanding of the visualized information. Q2 (Perceived load reduction): self-reported extent to which the visualized information helped reduce physical load.

ID	Construct	Visualization Condition	Item (question)
Q1a	Perceived comprehension	Color, Bar graph	I understood the visualized *physical load*.
Q1b	Perceived comprehension	Exemplar, Exemplar + self posture	I understood the visualized *posture*.
Q2	Perceived load reduction	All conditions	The feedback helped me reduce my physical load.

7-point Likert scale (1 = low, 7 = high).



(a) VR environment (b) Real environment

Fig. 3: The experimental environment

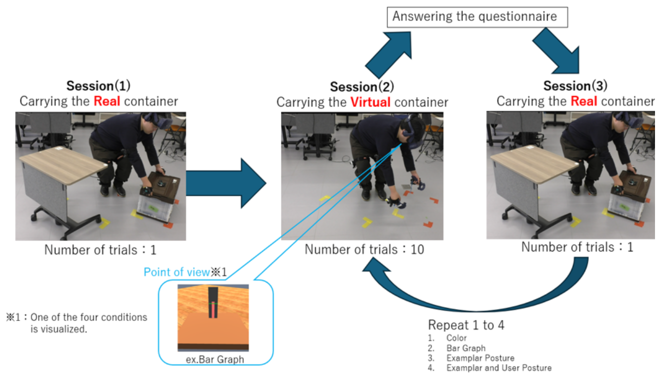


Fig. 4: Flow of the VR training experiment

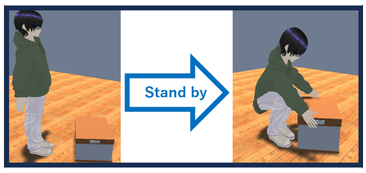
the torque. Next, we examined whether post-training torque differed across the four feedback conditions. In addition, we administered a questionnaire-based subjective evaluation (7-point Likert) to quantify perceived comprehension and perceived load reduction, and we examined how these ratings varied across the four visualization strategies.

A. Participants

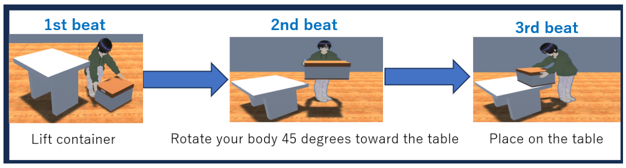
Twelve adults were initially recruited for the study. One male participant was excluded due to data logging errors, leaving eleven participants in the final analysis (7 male, 4 female). All participants were adults in their 20s–30s; no minors or older adults took part in the study. Body mass ranged from 39 to 82 kg (M = 63.1, SD = 13.1 kg). Exact ages and prior lifting experience were not collected, which we acknowledge as a limitation of the present work.

B. Experimental Environment

The experimental environment consists of a table and a 10kg container both for real and virtual environment. as



(a) Countdown guidance for initiating the lifting task posture.



(b) Three-beat audio guidance for standardizing the time duration of the lifting task.

Fig. 5: Audio guidance with countdown and beat sounds used to standardize task timing across participants.

shown in Fig.3. In order to measure the whole body motion, participants wear an HTC Vive Pro Eye[3] head-mounted display and nine Vive trackers on their body. Additionally, a Vive tracker is placed on the container to record the participants' lifeting motion. In the pre-training, participant performs the lifting action without grasping the container, instead they grasp the virtual container using the VR controller. When the participant actually performs the lifting action in the real space, they directly grasp the container with their hands.

C. Experimental Task

The experimental task requires the participant to lift a container and place it on a table either in the virtual space or in the real space. The motivation behind this experimental task is to train the participant to perform a twisting motion of the hips when placing a heavy object from the floor onto the table. As shown in Fig. 4, the participants first performed the task once in the real space (Session 1). Participants then performed the pre-training task 10 times in the virtual space with one of the four feedback conditions (Session 2). One of the four feedback visualization models in Fig.2 is displayed on the container. After the 10 times lifting action the participant answered the questionnaire in Table I. Finally, the participants performed the real lifting task once using the actual container (Session 3). Sessions 1 through 3 were grouped into a single block, and this block was

[3] HTC Vive Pro Eye,https://www.vive.com/jp/product/

TABLE II: Time integral of lumbar joint load per unit body mass [N·m·s/kg]

Participant ID	Body mass [kg]	Before training	Color	Bar Graph	Exemplar posture	Exemplar + self posture
1	50	5.24	5.33	5.1	5.13	5.39
2	73	4.51	5.02	4.19	4.70	5.06
3	58	3.77	4.10	5.99	4.43	4.16
4	39	6.40	5.61	4.93	7.05	5.58
5	75	5.26	3.93	3.77	5.33	4.41
6	51	5.27	4.94	4.42	5.10	4.94
7	63	4.35	3.63	4.23	4.13	4.63
8	69	4.27	4.28	4.11	5.02	5.01
9	75	6.04	4.72	4.66	4.78	6.22
10	59	4.44	4.12	5.16	3.69	4.15
11	82	4.18	4.47	4.60	5.46	4.09

repeated under each of the four visualization conditions. To avoid bias in training effects across feedback conditions, the order of four feedback conditions was randomized for each participant.

Participants performed the lifting task under the following conditions:

- Participants must use both hands when holding the container.
- The position and orientation of the participant's feet are fixed during the lifting motion.
- To standardize both lifting speed and overall task duration, we presented a three-beat auditory metronome and instructed participants to synchronize their movements to these cues. The load had to be lifted off the floor on the first beat, raised to its maximum height on the second beat, and placed on the table on the third beat. Figure 5 shows the synchronization of the motion to the beat sound.

D. Questionnaire Measures

Subjective effects were captured with a brief two-item questionnaire, each answered on a 7-point Likert scale (1 = low, 7 = high). Q1 probed *Perceived comprehension*: "I understood the visualized physical load (or posture)." Q2 probed *Perceived load reduction*: "The feedback helped me reduce my physical load." Detailed question expression for Q1 is shown in Table I. For each feedback mode the two ratings were averaged across participants and used for subsequent statistical analysis.

V. Results

A. Result of change in objective physical loads

1) Target parameter for the evaluation: To assess the effectiveness of the VR-based training, we examined changes in the mechanical load acting on the lumbar joint before and after the training. Because the lifting task duration was standardized to approximately 3 seconds, we considered performance using the time-integrated lumbar load. Moreover, since both the container mass and a participant's body mass

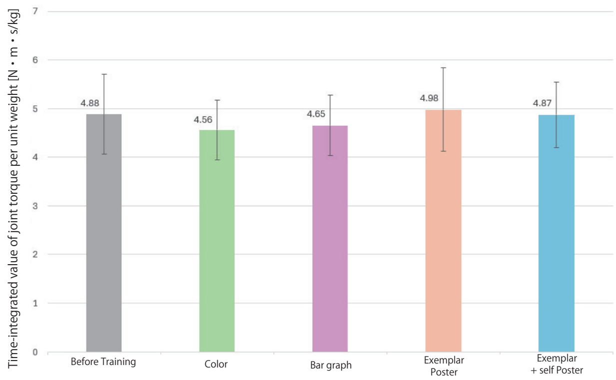


Fig. 6: The average and error bar of the joint torque integral value per unit mass for each visualization condition. Normalized values obtained by dividing by each participant's body mass.

Fig. 7: Boxplot showing the distribution of score differences between each condition and the baseline condition (before training). Each box represents the interquartile range (IQR), with the horizontal line inside indicating the median difference. The whiskers extend to the minimum and maximum values within 1.5 times the IQR. A horizontal gray dashed line at zero represents no change from the baseline.

influence the absolute load, we used the value normalized by each participant's body mass for the evaluation

$$\mathcal{T}_n = \frac{1}{w_n}\int \tau_n(t)dt, \qquad (2)$$

where n is index of the participant, $\tau_n(t)$ is the lumbar joint torque at time t of n-th participant, and w_n is the body mass of the n-th participant. This mass-normalized metric served as the primary outcome for quantifying the training effect.

Table II shows $\mathcal{T}_n$ at baseline and after each feedback condition, calculated by (2).

Fig.7 presents boxplots of the joint torque differences observed at the lower back when participants performed an actual load-lifting task before and after the training intervention. A negative load difference indicates a reduction in joint load, suggesting that the training effectively decreased the physical burden on the lower back during the task.

2) Statistical analysis: To determine whether the dependent measure differed across the four visualization conditions

(Color, Bar, Exemplar, and Exemplar & Self), we treated the study as a one-factor, within-subjects design (11 participants experienced every condition).

The dependent variable was $\Delta\mathcal{T} = \mathcal{T}_{\text{post}} - \mathcal{T}_{\text{base}}$ (time-integrated lumbar torque normalized by body mass). We analyzed within-subject differences in $\Delta\mathcal{T}$ across the four visualization modes. Assumptions for repeated-measures ANOVA were met (Shapiro–Wilk, all $p \geq 0.23$; Mauchly's test of sphericity, $W = 0.72$, $p = 0.32$), so we ran a one-factor ANOVA (two-tailed, $\alpha = 0.05$) and reported partial η^2 with 95% CIs. As a robustness check for ordinal-like distributions and small n, we additionally performed a Friedman test. Where the omnibus test was significant, pairwise differences were examined with Wilcoxon signed-rank tests and Holm-adjusted p-values.

TABLE III: Descriptive statistics for each condition

Condition	Mean	SD	95% CI
Color	0.33	0.65	$[-0.11,\ 0.76]$
Bar	0.23	1.10	$[-0.51,\ 0.98]$
Exemplar	-0.10	0.72	$[-0.59,\ 0.39]$
Exemplar & Self	0.01	0.52	$[-0.34,\ 0.36]$

TABLE IV: One-factor repeated-measures ANOVA

Source	F	df_{num}	df_{den}	p	η_p^2
Condition	1.76	3	30	0.177	0.150

TABLE V: Exploratory paired *t*-tests (Bonferroni-corrected)

Comparison	$p_{\text{uncorrected}}$	$p_{\text{Bonf.}}$
Color vs. Bar	0.713	1.000
Color vs. Exemplar	0.057	0.343
Color vs. Exemplar-Self	0.086	0.518
Bar vs. Exemplar	0.349	1.000
Bar vs. Exemplar-Self	0.459	1.000
Exemplar vs. Exemplar-Self	0.692	1.000

The result of repeated-measures ANOVA is shown in Table IV. The main effect of condition was not statistically significant, $F(3, 30) = 1.76, p = 0.177$, partial $\eta^2 = 0.15$. A confirmatory Friedman test yielded $\chi^2(3) = 6.25, p = 0.10$, supporting the same conclusion.

As pairwise comparisons, no pairwise contrast survived Bonferroni correction; the smallest adjusted p-value (0.343) arose for Color vs Exemplar as shown in Table V.

Numerically, color condition produced the highest mean score (0.33), but the overall effect of condition did not reach significance. The medium partial-$\eta^2(0.15)$ suggests a potentially meaningful effect that may not have been detected with the present sample size (11 participants; estimated power$\approx$ 0.40). These results indicate that, under the current experimental parameters, the four visualization modes elicited comparable performance on the measured outcome.

B. Result of subjective feeling questionnaire

1) Questionnaire analysis: Fig.8 and Table VI show the results of questionnaire scores. Responses were analyzed

TABLE VI: Mean ($\pm$ SD) Likert scores by condition

Condition	**Q1**	**Q2**
Color	6.36 ± 0.67	5.45 ± 0.69
Bar	5.91 ± 1.14	5.00 ± 1.26
Exemplar	5.55 ± 1.63	4.55 ± 1.63
Exemplar & Self	6.00 ± 0.45	5.45 ± 1.04

TABLE VII: Friedman test and Holm-adjusted Wilcoxon contrasts

Metric	**Q1**	**Q2**
Friedman $\chi^2(3)$, p	5.55, 0.136	14.04, 0.0029*
Pairwise p_{Holm} (only Q2 shown)		
Color vs Bar	–	0.307
Color vs Exemplar	–	0.165
Color vs Exemplar & Self	–	1.000
Bar vs Exemplar	–	0.307
Bar vs Exemplar & Self	–	0.127
Exemplar vs Exemplar & Self	–	0.084

* $p < 0.01$

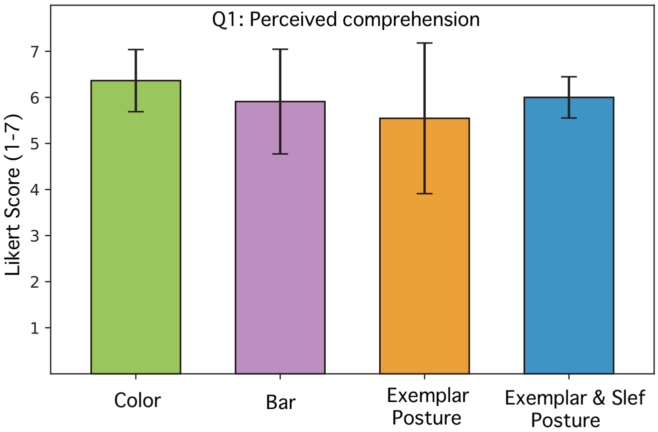
with non-parametric statistics because Likert scores constitute ordinal data and the same eleven participants experienced all four visualization modes. We first applied a Friedman test to detect overall condition effects. Where the omnibus test was significant, Wilcoxon signed-rank tests were conducted for all six pairwise contrasts and p-values were Holm-adjusted.

The Friedman test for Q1 failed to reach significance, $\chi^2(3) = 5.55$, $p = 0.136$, indicating no reliable difference in comprehension across conditions. In contrast, Q2 showed a significant overall effect, $\chi^2(3) = 14.04$, $p = 0.0029$. Pairwise comparisons (Table VII) revealed no individual contrast surviving Holm correction at $\alpha = 0.05$, although the trend *exemplar < exemplar & self* approached significance ($p_{\text{Holm}} = 0.084$). These results suggest that while participants judged certain visualization as more helpful for reducing perceived load, differences in objective understanding were not statistically established with the present sample size.

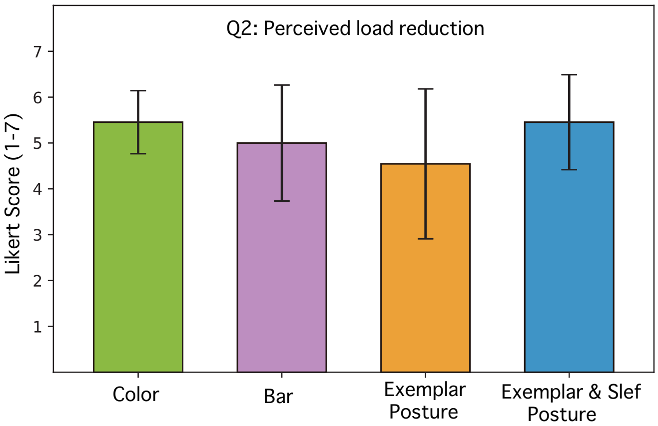
TABLE VIII: Open-ended participant feedback on the training

Participant ID	Impressions
5	I felt that the load on my lower back was reduced when I bent over slightly.
8	When I was referring to the exemplar posture, it was difficult to see the lower body parts, such as the movement of the knees, so it was difficult to refer to.
9	When I actually held the container, I felt that I couldn't move it as I wanted because of the weight of the container. At first, I didn't understand that the exemplar avatar was crouching down in the exemplar condition, but I thought that I could understand it better in the 'exemplar and self posture' condition than in the 'exemplar posture' condition.
10	I think that if you straighten your posture quickly from a bent-over position, the load will be less.

2) Analysis of open interview: Table VIII shows some of the impressions of all the participants. Participants 8 and 9



(a) Likert score of Q1: perceived comprehension



(b) Likert score of Q2: perceived load reduction

Fig. 8: Likert score of two questionnaire for each condition

said that the posture of the exemplar was difficult to see in some cases. It might be one of the reasons why the average score for the exemplar posture in Fig.8(a) was low. On the other hand, participants 5 and 10 had opinions about postures that reduced the load on the lower back more than the avatar's posture. It is possible that many of the participants learned postures that were better than the exemplar posture before or during training, which may be why the average score for the exemplar posture in Fig.8(b) was low.

C. Discussion

Beyond training applications, our system contributes to the design of human-centered interactive systems that support safe and efficient body mechanics. The ability to visualize and communicate internal physical effort in real time may also inform the development of intelligent assistive technologies. For instance, in the context of exoskeleton-assisted motion training, force-based feedback could be used not merely to apply assistance, but to teach users the ideal force patterns they should aim to generate. In this way, our approach opens new possibilities for training systems that combine physical support with active motor learning, contributing to the future of adaptive, user-aware interaction design.

D. Limitation

There are several limitations to the present study that should be acknowledged. First, the number of participants was limited. While 12 individuals took part in the experiment, valid data were collected from 11 participants. This sample size restricts the scope of statistical analysis, and we were unable to sufficiently account for diversity factors such as gender, age, or physical characteristics. To enable more robust and generalizable conclusions, additional experiments with a larger and more diverse participant pool are required.

Second, the current system was tested in a context where participants did not physically carry heavy objects, but instead performed simulated lifting tasks in a virtual environment. This setting reflects a practical use case—pre-training in situations where handling real loads is unsafe or impractical—but it does not fully evaluate how physical feedback and training efficacy might change when actual load-bearing is involved. While our system is technically capable of being used in scenarios where real objects are handled in conjunction with VR feedback, further investigation is needed to assess how different feedback modalities perform under actual physical strain, and whether training outcomes differ when real load is experienced during task execution.

Finally, although the proposed system is designed to support dual feedback on both physical load and kinesthetic posture, the initial evaluation experiment implemented only single-modality feedback. This decision was made in consideration of users' cognitive load, to ensure that participants could focus on understanding one type of feedback at a time. However, providing simultaneous feedback on both physical load and posture may lead to synergistic effects in user understanding and movement adaptation. Investigating the effectiveness and usability of such dual feedback configurations remains an important direction for future work.

VI. Conclusions

In this paper, we presented a VR-based training system that provides real-time feedback on physical load and postural alignment using personalized biomechanical modeling. By integrating SIGVerse and DhaibaWorks, our system estimates joint torque dynamically and delivers feedback through multiple visualization modalities, including color mapping, bar graphs, and comparative postures. This design fulfills our primary objectives: (1) constructing a VR platform capable of real-time physical load feedback and multimodal visualization, and (2) evaluating the effectiveness of such feedback in a heavy object lifting task.

Experimental results showed that while no statistically significant reduction in physical load was observed across conditions, participants tended to report higher subjective comprehension under color-based feedback; however, between-condition differences were not statistically significant. These findings suggest that visualizing internal physical states can enhance users' awareness of bodily strain, potentially leading to more ergonomic and efficient task execution over time.

Beyond training applications, this work contributes to the broader field of Human-Robot Interaction by offering a framework for understanding and communicating human physical states in real time. Such capabilities are critical for designing adaptive, human-aware systems that respond not only to what users do, but also to how their bodies are affected during interaction. Importantly, the SIGVerse platform used in our system is not only a tool for immersive avatar-based interaction, but also enables the control of virtual robots using the same software architecture as real robots [21]. This makes it possible to replicate and prototype human-robot interaction scenarios within VR, bridging the gap between simulation and real-world deployment. In future work, we aim to extend this approach to collaborative settings, where robots dynamically adapt their assistance based on users' estimated physical load, further advancing the goal of safe and intuitive human-robot interaction.

Ethics and Consent

The study protocol was approved by the Ethics Committee of Tamagawa University (Approval #TRE23-0031). All procedures complied with the Declaration of Helsinki, and written informed consent was obtained from all participants.

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