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Real-time feedback in video-based motor learning: A pilot study exploring innovative training methods

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Abstract

Video-based training has proven useful for motor learning, particularly when combined with motion feedback. However, the integration of real-time feedback into instructional videos has not been sufficiently explored. This study aimed to develop and explore innovative real-time feedback methods to enhance video-based motor learning. Twenty-seven participants (15 women, 12 men) were assigned to three feedback groups and one control group, who learned a choreography in an initial pilot study. The feedback groups received real-time comparisons of their own motions with those of an instructor. Group A was provided with a proportionally adjusted virtual instructor skeleton superimposed on their movements. Group B's motions were transparently overlaid on the instructor's video. Group C viewed the instructor's demonstration alongside a mirror view displayed of themselves. Group D (control) trained using only the instructor's video, mimicking home-based tutorial formats. Motion tests performed without feedback revealed adaptation across all groups. Temporal motion adaptation was highest in Group A, while spatial motion adaptation was highest in Group B. Findings suggest that motion superimposition is a promising approach for visualizing motion discrepancies. Each method exhibited unique characteristics in the learning process, including different learning curves (e.g., Group A showing adaptation in the second half of the training) and varying levels of adaptation across different exercises and body parts (e.g., Group B experienced arm motion adaptation in squats). While these novel real-time feedback techniques demonstrate potential, further research is required to examine the relationships between feedback modalities and motor learning outcomes, specifically regarding the visualization of motion comparisons.

Keywords: immediate feedback, imitation, movement adaptation, training types

Introduction

To acquire motor skills and to master sport performances in the long term, motor learning is required. Motor learning refers to a lasting change in an individual's ability to perform motor skills, resulting from consistent practice (Coker, 2022). This refers to learning both temporal characteristics of a motion and spatial features in the form of body part positions (Rauter et al., 2015). In addition to the human coach, training materials often play an important role in motor learning. Technologies nowadays have a particularly supportive effect (Pustišek et al., 2021; Raiola et al., 2013; Wang & Parameswaran, 2004). Specifically, videos have been widely applied in sports for the post-training analysis of motor performances. They were found, for instance, to support enhanced riding skills (Kelley & Miltenberger, 2015) and foster motor learning of a front handstand to flat back landing in gymnastics (Potdevin et al., 2018). Furthermore, videos are increasingly used for learning motor tasks in real-time, i.e., learners perform motions while observing those in an instructional video (Quennerstedt et al., 2016; Shen et al., 2019). The latter points to the relevance and motivation for having conducted the present study.

Motor learning through observation with an instructor as a model (McCullagh, 1993) is extended through video usage. Training sessions may be pre-recorded by an instructor and executed asynchronously by learners (Llupar et al., 2022). Furthermore, Extended Reality (XR) enables the visual representation of an avatar that acts as a virtual teacher, thereby supporting the coach (Quennerstedt et al., 2016; Rüth & Kaspar, 2020). One application area of video-based learning is evident in the trend toward home workouts that has been around for several years and is now firmly established in the broad society due to the pandemic (Kim et al., 2022; Sui et al., 2022). Video platforms such as YouTube offer guided training, including learning and executing different motor elements, adapted to individual time and location circumstances. Coaches can create workout videos with different motor training goals (Sui et al., 2022).

One main component of motor learning is not being considered in video-based training, specifically, the provision of feedback to the learner. As there is a lack of direct interaction with the instructor, the learner does not receive any feedback on the discrepancy between one's own motion and that of the instructor. Thus, motor skill acquisition might be accompanied by training errors and become more difficult (Shen et al., 2019; Sui et al., 2022). Through feedback, learners are provided with information about their motions, thereby supporting the learning process (Sharma et al., 2016). In terms of injury prevention, feedback is also useful for making learners aware of incorrect motion executions that might affect their physical health (Harris et al., 2020). Previous research has shown that a common feedback type, called 'knowledge of performance' (KP), has a positive impact on motor learning (Gentile, 1972). Feedback related to KP refers to the provision of information on motion precision, such as limb position and velocity (Oppici et al., 2021). In terms of videos as an analysis tool, KP has been an integral part of delayed feedback provision in sports (Krause, 2017; Rucci & Tomporowski, 2010). However, in addition to delayed feedback for analyzing motor performances, feedback based on KP can also be provided during a motion execution, i.e., in real-time (Oppici et al., 2021; Sharma et al., 2016).

Real-time feedback is essential when learning with pre-recorded videos, e.g., via online video platforms, as coaches are not available to provide any feedback, neither during nor after motor performance. In contrast to face-to-face training, the video serves as the training itself, so all motion-related information must be included. Moreover, real-time feedback has already been shown to be beneficial for motor learning in various application domains (Geisen & Klatt, 2021). Specifically, using XR, virtual elements can be projected into real life training settings for visual feedback during learning (Kaplan et al., 2021). Stroke patients improved spatial motion accuracy and gained temporal efficiency in reach-to-grasp exercises when receiving virtual feedback. They practiced with a multi-joint arm exoskeleton and were provided with the three-dimensional view of their motions via a monitor (Grimm et al. 2016). XR was further used to provide virtual feedback while programming a desk-based robot. In comparison to previous used, i.e., conventional, learning approaches, the innovative XR method led to enhanced learning outcomes (Alrashidi et al., 2017). The effects of real-time XR feedback on sports performance were also investigated. During the execution of squats and Tai Chi pushes, visual feedback was generated as color highlights on the learner's avatar. The researchers found their method to be suitable for learning a sports motor skill (Hülsmann et al., 2018). Besides the possibilities of using XR for motor learning, modern technologies such as motion capture cameras offer the possibility to track human motions for motion analyses. Researchers emphasized the applicability of such cameras in home learning contexts, particularly referring to Microsoft Azure Kinect and its non-invasiveness and low-cost tracking (Antico et al., 2021). Innovative methods such as XR as well as motion capture technology have features that are advantageous for identifying and providing motion-related information in real-time.

In conventional video-based learning methods (e.g., YouTube tutorials), feedback provision is still an issue and has not yet been sufficiently researched and applied in practice. This work focuses on using recent technological developments and visualization methods to provide different options of real-time feedback during the learning process of video-based training. An important role for real-time feedback implementation has been attributed to discrepancy information, which is among the relevant types of extrinsic information in motor learning (Blischke et al., 1999). Discrepancy information refers to the deviation of the momentary motion (actual value) from a targeted motion (criterion value).

Overall, motor learning in video-based training may be particularly enhanced by (1) providing feedback with regard to KP (Gentile, 1972), (2) realizing such feedback provision in real-time using modern technologies, and (3) thereby visualizing discrepancy information (Blischke et al., 1999).

For the purpose of this work, feedback is understood as a comparison of a targeted motion with one's own motion. This form of feedback is indirect, as learners extract performance-related information through the comparison. We refer to real-time feedback as being provided during the task performance/the motion execution, as opposed to, e.g., receiving feedback after completion of the task/motion execution. Thus, learners can compare both motion executions while actually being in motion themselves. This form of feedback is unique because it is intrinsically tied to the learner's motion at that precise moment. For example, at second 12 of a motion choreography, a learner bends their knees to a 45-degree angle in preparation for a squat, while the coach simultaneously performs a squat at a 90-degree angle. Then the real-time feedback pertains to the spatial and temporal execution (knee joint angle position at that time) not matching the coach and thus needing adjustment in the learning process. Both motion aspects are interconnected. Taken together, the visualization of the comparison between the learner's actual motion and the targeted motion serves as a direct source of indirect real-time feedback. On the one hand, we base this on the use of the term 'feedback' from other researchers on similar research topics (Hülsmann et al., 2019; Le Naour et al., 2019). On the other hand, literature on feedback in the learning context notes the following: "[…] the objective of feedback is to move learning forward. Feedback is information, in various forms and from various sources, that is useful for accomplishing this goal. Feedback is effective if it supports learning and ineffective if it does not. Feedback therefore derives its value from the learning it enables" (Brookhart, 2020, p. 63).

Four different learning methods were elaborated to take a step-by-step approach from learning as it is known on online video platforms to learning with a previously unknown innovative strategy with additional virtual information. Each of the tested methods adds an additional new type of motion-relevant feedback into the video. Similar to online video workouts, a conventional method only displayed the instructor, as when motor learning through (video) observation with an instructor as a model (McCullagh, 1993). In the first novel method, feedback was provided in the form of displaying both the instructor and a mirror view of the learner side by side for direct comparison. In a further novel method, feedback on the discrepancy between the actual (learner) and criterion (instructor) value was more clearly visualized than with the previous methods, by transparently superimposing the learner's and the instructor's motions. Previous studies have shown that superimposing motions can be beneficial for motor learning. To learn volleyball pass skills, the executions of an expert and the respective participant were superimposed to make the differences between the two executions more obvious (Barzouka et al., 2015). Participants who used this additional tool significantly improved their pass skills in terms of technical execution and pass skill outcome as opposed to other learning methods. In basketball jump landing, it was found that the feedback method of visually superimposing motion executions of an expert and a learner led to an increased percentage overlap of the learner's motions with that of the expert (Dallinga et al., 2017). However, the described tools were used for providing delayed feedback. In addition to superimposing motions, our final novel method considered different body-proportions of the learner and the instructor. The adaptation and visualization of the instructor’s proportions to the learners’ proportions was enabled through virtual skeleton tracking. An enhanced indication of discrepancy in motions was provided through colored highlights based on the work of Hülsmann et al. (2018).

Summing up, we aimed to enhance video-based motor learning by combining promising possibilities of real-time feedback provision with already successfully applied visualization methods of discrepancy information. In the framework of an initial user pilot study, the following research question was addressed: What are the effects of different means of visualizing discrepancy information (enabled by innovative real-time feedback methods) on video-based sports motor learning? The variables to be tested were temporal and spatial motion adaptation to the instructor's motions. Consequently, motor learning of a video-based choreography (containing dance, pilates, and yoga motions) was examined. By evaluating descriptive and qualitative data, the impact of the different visualization forms and the extent of discrepancy information (actual-criterion comparison) on the adaptation to a given motion were examined. This referred to temporal and spatial deviations from the instructor's motion before, at half time, and after motor learning. Spatial motion was investigated by capturing positional data of elbow, shoulder, hip, and knee joints of each learner.

Methodological design of an initial user pilot study

Participants

Thirty individuals aged 18 to 40 years were initially recruited, resulting in a total of 180 test trials (two pre-tests, two mid-tests, two post-tests per participant as described in detail later in the article). To ensure a similar level of given age-dependent motor performance skills, we focused on the investigation of younger adults as skillfulness in terms of motor performance seems to be decreasing at around 40 years of age (Hollmann & Hettinger, 1990). One participant discontinued the experiment because of physical overstrain. Data from two participants were not complete due to technical limitations during data collection. The final sample thus comprised 27 participants (26.85 ± 4.17 years old, 15 women, 12 men), all of whom reported being physically and mentally healthy. Participants indicated their primary sport, i.e., running (*n* = 2), ball sports (*n* = 10), gymnastics (*n* = 1), yoga (*n* = 2), racket sports (*n* = 3), strength training (*n* = 2), dancing (*n* = 3), cheerleading (*n* = 1), and martial arts (*n* = 1). Two participants did not indicate a primary sport. Six participants had a lot of experience in dance, pilates, or yoga, five had some experience, eleven had little experience and five had no experience. Six individuals had a lot of experience with video-based motion training, fifteen had some experience, five had little and one participant had no experience. Approval was obtained from the institution's ethics board. All participants provided written informed consent.

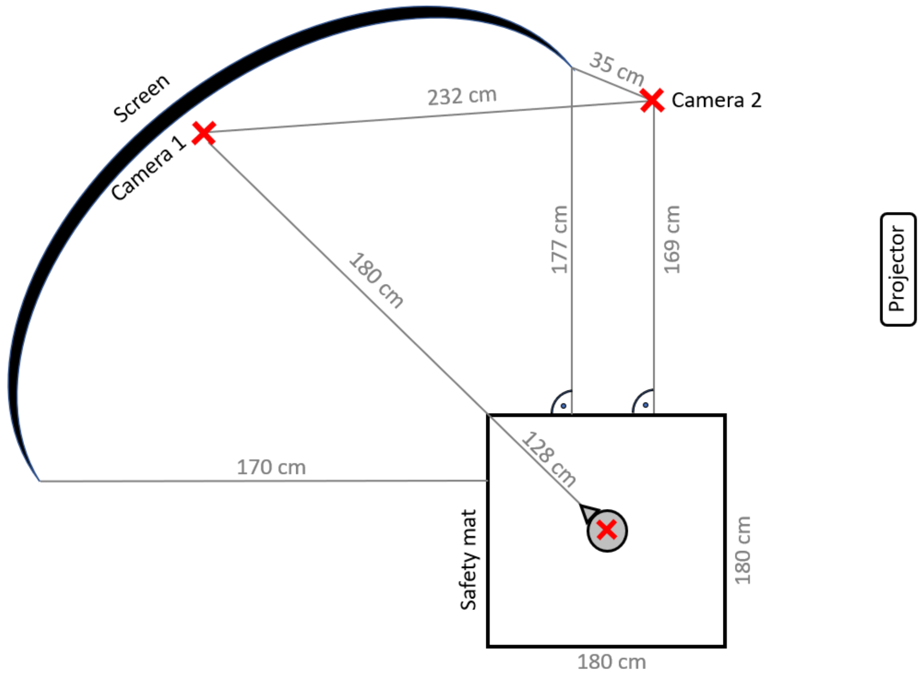
Participants were divided into four groups that differed in terms of the training method and were balanced according to participants' primary sport to avoid confounding effects of previous sports-related experience. The groups had a similar distribution of experience levels in dance, pilates, or yoga (averaging between some and little experience in each group) and video-based motor training (averaging some experience in each group). Group A (*n* = 6), Group B (*n* = 8) and Group C (*n* = 7) were considered as feedback groups and received different visual information on KP. Group D (*n* = 6) served as a control group and was provided with a conventional teaching method. The number of subjects in each group resulted from distributing the 30 subjects as evenly as possible among four groups; however, as mentioned, data from three participants are not included in the present work due to incompleteness.

Materials and design

During the study, participants stood in front of a curved screen (440 cm x 230 cm), with a distance of 335 cm to the screen, and on top of a safety mat (Fig. 1). The starting point for performing the choreography was marked with an X on the floor mat. The respective videos to the groups were presented via a projector on the screen. Motion capture was conducted using two Microsoft Azure Kinect DK cameras, each operating at 30 frames per second (fps) with a resolution of 3840 x 2160 pixels and an estimated system latency of 150-200 milliseconds (according to official online Azure Kinect DK documentation). One camera was positioned in front of the participant and the other to the right side of the mat, enabling both frontal and lateral motion tracking. This setup allowed participants (except those in the control group) to view themselves from both perspectives, improving motion representation and reducing self-occlusion. Additionally, we drew on previous findings on the use of Kinect cameras for motion capture research and the suggestion of its useful transfer to home-learning contexts (Antico et al., 2021). To support the innovative feedback methods implemented in this study, 3D human pose estimation was performed using the Azure Kinect Sensor Development Kit (SDK, Shotton et al., 2011).

Fig. 1

Test set-up



The participant stands on a safety mat, positioned on an X-mark facing the screen. Video material is projected onto the screen by a projector placed diagonally behind the participant. Motion recording is conducted using two Azure Kinect cameras; one positioned low in front of the screen (to avoid blocking the video view) and the other placed to the side. All distances between the participant and equipment are indicated in centimeters.

The motion sequence was choreographed and recorded by an instructor beforehand, using the same two camera views as for data collection. The instructor (25 years old and female) had 20 years of experience as a dancer and was a certified fitness instructor with 12 years of experience of teaching various sports classes at the time of data collection. The one-minute choreography consisted of 25 dance, pilates and yoga exercises, either performed once or a few times in a row before the next exercise followed. In between the exercises, additional motions, e.g., a side step, were incorporated to help moving from one exercise to the next and maintain the motion flow of the choreography. The exercises were given names that contained body parts being involved, e.g., “arms up”, had a similarity to objects, e.g., “airplane”, or were associated with figures, e.g., “pirate”. Next to the respective videos for each group, all participants were shown an information window that listed the names of the exercises one below the other. All exercises were additionally marked with a white dot next to the name and a bright bar moved at the appropriate velocity of the choreography (60 beats per minute) over the names and the dots. Accompanied by a metronome, this provided an indication of the rhythm, i.e., the time point of performing the exercise. Pictures of the instructor performing the exercises were shown as further support next to the exercise names in the information window.

For superimposition of motions as means of feedback for the most innovative learning method in our study, the following procedure was performed: The instructor's skeleton was extracted using a recording of the two cameras and the 3D human pose estimation provided by the Azure Kinect SDK (Shotton et al., 2011). During training, the learner's motion was then extracted in real-time using the same software and compared against the skeleton's motion. The body-proportions of the instructors' skeleton were adapted to those of the respective participant by means of automatic recognition through the cameras. The techniques and software utilized in our study for real-time visual feedback and automatic skeleton adjustments have been developed in C++, leveraging the Microsoft Kinect Azure Software Development Kit (SDK), and OpenCV library functions. In particular, the data processing was conducted using Azure Kinect SDK, enabling seamless integration and real-time data handling. OpenCV functions were used to process the camera input and display the visualizations. A two-step process was implemented to automatically adjust the instructor's skeleton to match the participant's body proportions. First, the Euclidean coordinates of the instructor's joint positions were converted into radial coordinates. This was achieved by expressing the angle of each limb relative to its parent limb, which allowed for a more dynamic comparison between the instructor's and the participant's body proportions. Following this, the instructor's skeleton was reconstructed using these radial coordinates based on the limb lengths of the student. This method enabled automatic recognition and adjustment of the instructor's skeleton to match the participant's physique, contributing to a reliable and confident fitting process.

Upon successfully adapting the instructor's skeleton to the student's body proportions, the rescaled instructor model was meticulously positioned in the virtual 3D scene, ensuring precise alignment of the pelvis locations between the two entities. This alignment laid the foundation for an efficient comparison phase. The evaluation error, a measure of our technique's efficiency, was then calculated as the Euclidean distance between the reconstructed student and the adjusted instructor skeleton. This step allowed us to quantify the discrepancy between the actual objective and predicted skeletal alignments, providing valuable insights into the effectiveness of our method and highlighting potential areas for future enhancement.

Procedure

Participants completed a single one-hour session. First, a demographics questionnaire was administered and the level of experience in dance, pilates, or yoga as well as with video-based motor training (e.g., YouTube tutorials) was acquired. Two experience-based questions were answered on a four-point scale with 1 = "a lot of experience", 2 = "some experience", 3 = "little experience", and 4 = "no experience". In terms of experience with dance, pilates, or yoga, 1 referred to 'regular training and competitions', 2 to 'occasional participation in classes', 3 to 'at least one of the sports already tried', and 4 to 'none of the sports practiced so far'. With respect to experience with video-based motor training, 1 was related to 'regular training', 2 to 'occasional training', 3 to 'already tried', and 4 to 'not yet exercised'. Participants completed thirteen training trials to learn a motion choreography and six trials of a motion execution test in the following order:

- one observation training trial for familiarization, i.e., participants solely observed the motion sequence,
- two training trials for familiarization, i.e., participants practiced the motion sequence for the first time by following the instructor in the respective video and imitating the movements simultaneously,
- two pre-test trials, i.e., participants were provided with the information window and the sound of the metronome and were supposed to perform the motion sequence without the help of the respective video,
- five training trials, i.e., participants practiced the motion sequence by following the instructor in the respective video and imitating the movements simultaneously,
- two mid-test trials, i.e., participants were provided with the information window and the sound of the metronome and were supposed to perform the motion sequence, without the help of the respective video,
- five training trials, i.e., participants practiced the motion sequence by following the instructor in the respective video and imitating the movements simultaneously,
- two post-test trials, i.e., participants were provided with the information window and the sound of the metronome and were supposed to perform the motion sequence, without the help of the respective video.

The number of training and test trials was verified in advance by means of preliminary tests. It was found that after more than one hour including several practical executions of the motion sequence, physical fatigue occurs in participants. In order to ensure that the post-test results would not be affected by fatigue, the number of training and test trials and the associated duration of the study per subject was determined accordingly.

After training and testing, participants filled in the System Usability Scale (SUS; Brooke, 1996) and answered further questions pertained specifically to the experimental setup. The procedure, data analysis and results of the SUS and further questions are provided in the supplementary material.

Motor learning intervention

Group A received real-time feedback in which the instructor's motion was virtually superimposed and body-proportionally adjusted to the participant's livestream in the form of a skeleton (Fig. 2). Deviations in the participant's motion (actual value) and the skeleton's motion (criterion value) could be identified by participants through superimposition of the two motions as well as yellow dots that visualized the level of deviation, i.e., the dots became larger the more the motions deviated from each other.

Fig. 2

Group A teaching method

The instructor's motion skeleton is body-proportionally adjusted and virtually superimposed on the participant's self-view (both the front view and the side view). Deviations from the instructor's motions are highlighted by yellow dots.

Group B received real-time visual feedback in the form of superimposing the participant's livestream on the instructor's videos, both of which were made transparent to make the motions visible (Fig. 3).

Fig. 3

Group B teaching method

The livestream of the participant's self-view (both the front view and the side view) is virtually superimposed on the instructor's video, both are slightly transparent.

Group C was provided with the instructors' videos and the participant's livestream next to each other. Participants were able to compare the motions in real-time by looking at the instructor's videos on the right-hand side of the screen and the livestream on the left-hand side of the screen.

Group D received only the instructor's videos and did not see themselves. This was comparable to conducting a home workout using an online video platform via a laptop or TV screen with no feedback.

The step-by-step approach is correspondingly reflected in the increasing amount of information from Group D with its most conventional, familiar training environment (no information on one's own motion) to Group A with the most modern training environment that includes previously unknown visual feedback (several virtual additions as real-time information).

Motion execution test

During pre-, mid-, and post-test, participants were presented with only the information window and the accompanying metronome sound. This information was given in order to prevent the motor learning process with its main goal of temporal and spatial motion precision from being compromised by insufficient memory of the choreography. Using Microsoft Azure Kinect, participants' motions were recorded from the front and side view for data collection.

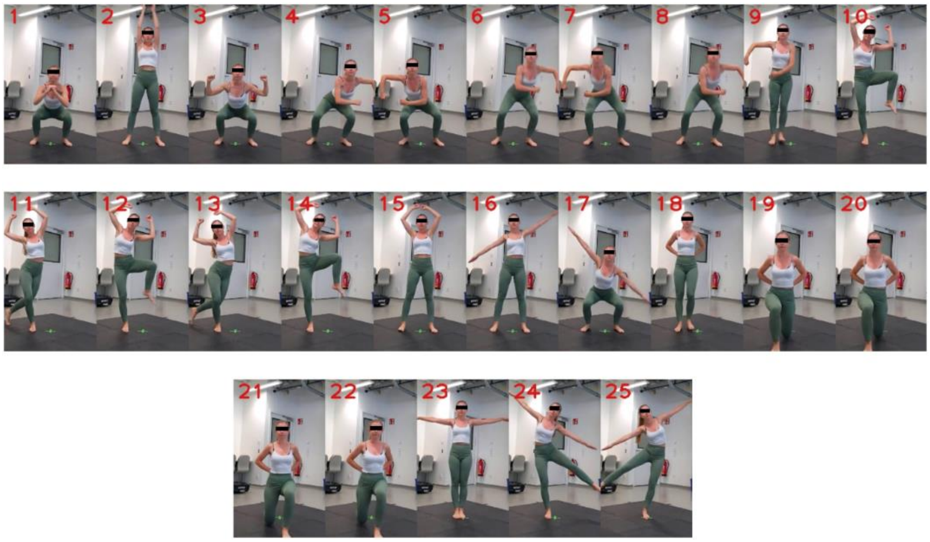
Data analysis

Annotation procedure

Twenty-five distinct poses were determined within the choreography corresponding to the 25 exercises (Fig. 4) for analyzing participants' temporal and spatial motion deviations from the instructors' motions, i.e., the difference between the actual and criterion value. Participants' executions of these poses were identified and annotated manually by two raters independently. Via a frame-by-frame analysis of the video recordings of participants' motions, annotators determined the first frame that showed the participant at the maximum range of motion for the respective exercise, e.g., at the lowest depth of a squat. Six test trials (two pre-, two mid-, and two post-tests) were analyzed this way for each participant. Due to technical issues in one case, data was missing for one of the two pre-, mid-, and post-tests. In this case, only the data from the completed trial was used for the analysis. The raters together analyzed 354 videos, hence making decisions on 354*25 poses, resulting in 8850 decisions in total. Deviations between annotators' ratings across all participants and all trials amounted to an average of 202 ms of temporal deviation and 3.43 degrees of spatial deviation, thus defining the error margin of our combined recording and annotation method. For data analysis the average values (temporal and spatial motion) of the two annotators' ratings were used. Whenever one annotator marked a pose as missing, the value determined by the other annotator was used for data analysis. In case both annotators marked a pose as missing, that pose was not considered for data analysis.

Fig. 4

Twenty-five poses conducted by the instructor



Each photo shows the expert while conducting one exercise, i.e., one pose, of the choreography.

Descriptive analysis and visualization

To determine whether participants learned the motion choreography, that is, to determine whether they adapted their motions to the instructors' motions, and to take a closer look at the motor learning process of the groups, we focused on the temporal motion parameter, i.e., deviations in ms (in the following referred to as *TempDev*) and spatial motion parameter, i.e., deviations in angular degrees (in the following referred to as *SpatDev*). *SpatDev* referred to the averaged angle in a subject's elbow, shoulder, hip, and knee joints. These body joints were deemed by the instructor to be most critical to the performance of the exercises. With respect to the two trials for each pre-, mid-, and post-test, an average score was calculated for each participant. To enable direct comparisons that omitted the difference in body proportions of the instructor and the subjects, the 3D motion representations of the subjects were matched to the segment lengths of the instructor's 3D motion representation, extracting all of the learner's joint angles and applying them to a skeleton of the instructor's proportions. Thus, we were able to analyze the data descriptively and to generate 3D illustrations and graphs representing the results.

For an overall analysis, we averaged each *TempDev* and *SpatDev* across all poses and participants for each group and test. To better depict the progress of motion adaptation of each group from pre-, to mid-, to post-test, graphs were generated for both motion parameters. For a more detailed insight into the results of *SpatDev* (where, in contrast to *TempDev*, a visualization of the results seems particularly useful), a special visualization method was applied. Thus, as with the training methods of Groups A and B, the method of direct comparison in the form of motion superimposition was used for presenting the results.

In this comparison method, unlike for the general evaluation, *SpatDev* refers to the Euclidean distance (in mm) between the instructor's and the learner's segment-length-matched skeleton. Using Figure 4 as a basis, the average *SpatDev* of all subjects in a group was visibly superimposed on the instructor's position for the respective pose. For better visibility of the differences between the subjects' and the instructor's pose, two respective skeletal images were added to each photo. This method was applied to all 25 photos of each test and group (supplementary material, Fig. 1-4). The result of one pose and group is demonstrated in the descriptive results section. This exemplary pose was also used to visualize the course of *SpatDev* (mm) from pre- to mid- to post-test in even greater detail in the form of 3D skeletal representations. Thus, a visualization of the pose was generated for comparison between the instructor, the average of all subjects in each group, and each individual subject in a group, again separately for each of the three tests and separately for each group. This should introduce precise forms of visualization for analysis and allow for result interpretations.

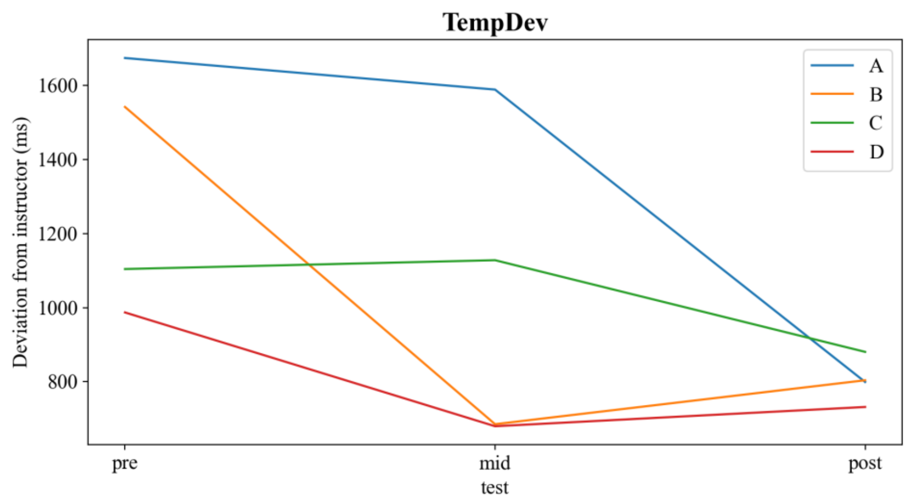
Given the exploratory nature of this initial user pilot study and the relatively small sample size used to test the real-time feedback approaches for the first time, we intentionally refrained from conducting inferential statistical analyses. The primary aim of this study was not to draw generalizable conclusions, but to evaluate the feasibility and practical potential of these innovative methods for video-based motor learning. As such, the reported changes in temporal and spatial motion execution are based solely on descriptive data and are intended to generate initial insights. These preliminary findings provide a foundation for future research with larger samples and formal hypothesis testing.

Descriptive results

All groups improved their temporal motion precision from pre- to post-test. Group A had a temporal motion adaptation of 874.7 ms from pre-test (1674 ± 1455.7 ms) to post-test (799.3 ± 742.7 ms). Group B showed an adaptation in *TempDev* of 738 ms from pre-test (1542 ± 1457.7 ms) to post-test (804 ± 958 ms). Group C adapted with 223.6 ms from pre-test (1104.3 ± 1028.3 ms) to post-test (880.7 ± 1099.7 ms), and Group D was 255.3 ms temporally closer to the instructor's motion from pre-test (987 ± 918 ms) to post-test (731.7 ± 582.7 ms). Figure 5 shows that Group A underwent its greatest temporal motion adaptation starting at mid-test. Group B improved its temporal motion performance from pre- to mid-test, then decreased its adaptation again in post-test. Group C showed a slightly increased *TempDev* in mid-test compared to pre-test and decreased its deviation in post-test. Group D showed a decrease in *TempDev* from pre- to mid-test and a very slight increase from mid- to post-test.

Fig. 5

Deviations in temporal motion execution from the instructor

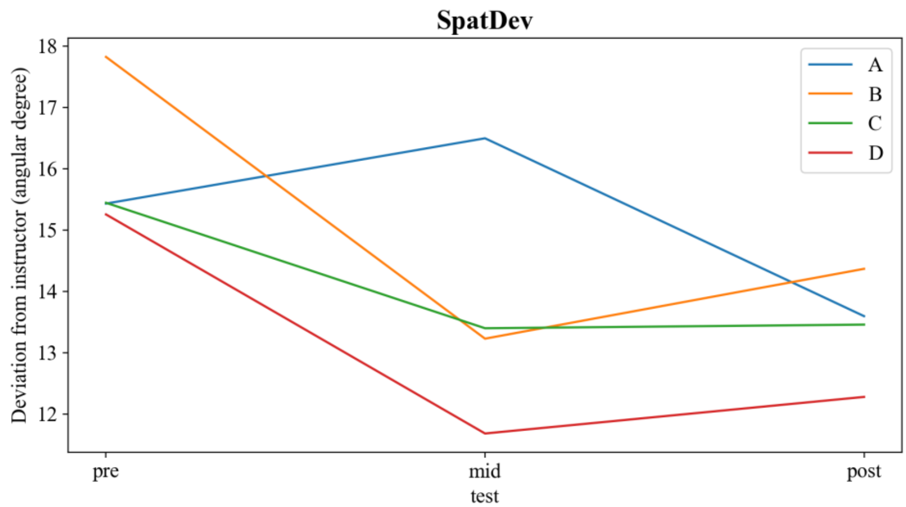


Data are plotted separately for each test and averaged across all exercises/poses and all participants per group.

All groups made progress in spatial motion execution (*SpatDev* averaged across all included joints), whereas Group A showed a spatial motion adaptation of 1.83° from pre-test (15.43 ± 16.18°) to post-test (13.6 ± 14.54°). Group B adapted its spatial motion by 3.45° from pre-test (17.82 ± 18.49°) to post-test (14.37 ± 15.49°). *SpatDev* for Group C resulted in an adaptation of 1.98° from pre-test (15.44 ± 16.13°) to post-test (13.46 ± 14.53°) and Group D adapted its spatial motion by 2.97° from pre-test (15.25 ± 15.44°) to post-test (12.28 ± 12.38°). As illustrated in Figure 6, Group A increased its *SpatDev* in mid-test, then adapting spatial motion to the instructor's motion in post-test. The progress of Group B was similar to *TempDev*, namely an adaptation to the instructor's spatial motion occurred in the first half of the training, followed by an increase in post-test. Group C decreased its *SpatDev* from pre- to mid-test and this average deviation remained consistent. *SpatDev* for Group D was similar to the progress of the same group in terms of *TempDev*, i.e., a decrease from pre- to mid-test and a slight increase from mid- to post-test.

Fig. 6

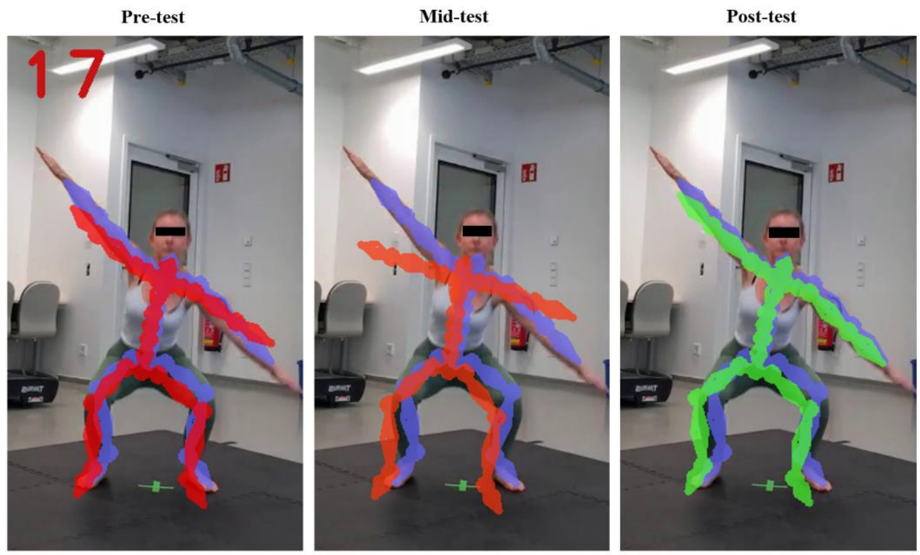
Deviations in spatial motion execution from the instructor



Data are plotted separately for each test and averaged across all exercises/poses and all participants per group.

With respect to the visualization method for data analysis, Figure 7 demonstrates one of the 25 poses, i.e., a variation of a squat exercise, here exemplified for Group A. The course of the motions from pre- to mid- to post-test as well as the average performance of this group (red, orange and green skeleton, respectively) compared to the spatial motion execution of the instructor (real person and blue skeleton) can be seen. The superimposition of the skeletons added to the photo allow direct visible comparison. The lower *SpatDev* is, the more the respective colored skeleton overlaps with the blue skeleton and the photo. Thus, the average result from Figure 6 for Group A can be recognized for this pose, i.e., an increase in the deviation from pre- to mid-test at first (arms, trunk, and legs of the subjects' skeleton deviate from the instructor), followed by an adaptation of the spatial motion execution to the motion of the instructor in post-test (especially arms and trunk are spatially close to the instructor's motion). Based on the results of all 25 images of each test and group (supplementary material), differences in spatial motor learning can be found between the tests (red, orange, and green skeleton), between the exercises (numbered 1-25) and between the body parts involved (visible within each image) within groups as well as between groups.

Fig. 7 Skeletal representations of spatial motion executions of one pose

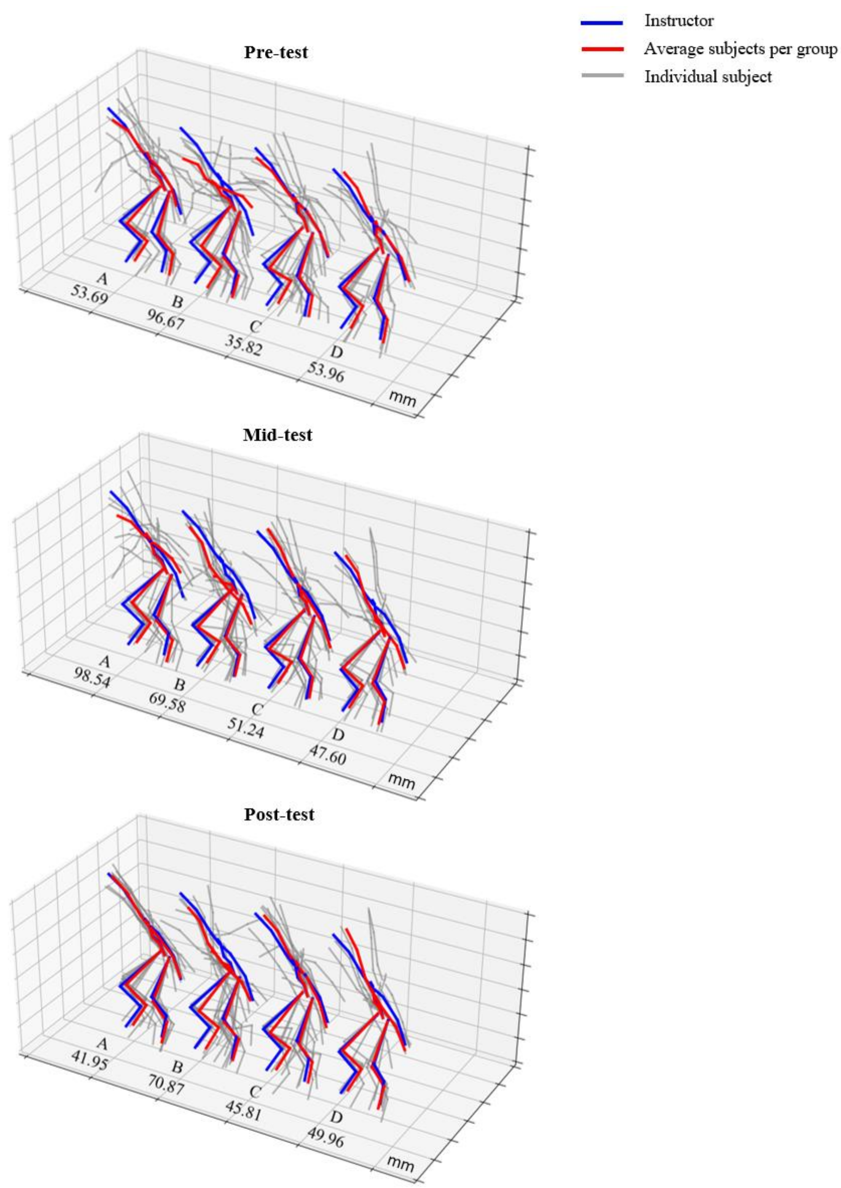


The left figure refers to the visualization of pre-test results, the middle figure is related to mid-test results, and the right figure represents post-test results. All images refer to the same exercise within Group A. The instructor's optimized motion is depicted by the blue skeleton that is the same for all tests. The average of all subjects in each group is shown by the red, orange, and green skeleton, respectively, depending on the test.

Regarding the development of 3D skeletal representations for data analysis, Figure 8 illustrates the same pose as shown in Figure 7, but with additional visual information and results from all groups. There is less insight into the position of the trunk, resulting from the selection of one particular perspective in 3D. Several outliers can be found in the initial status before the respective training sessions (pre-test) in all groups, thus revealing deviations in all joint angle positions investigated. The course of *SpatDev* of Group A as described before can be seen by focusing on the deviations between the instructor (blue skeleton) and the average of all subjects per group (red skeleton). In addition, Figure 8 shows that for a few individual subjects (grey skeletons) in Group A, *SpatDev* refers to deviations of the arm motion from the instructor of up to about 90 degrees in both pre- and mid-test. In post-test, the average subjects' and the instructors' arm position are almost completely superimposed, with a few individuals who deviate slightly from the average values. Deviations of the individual subjects of Group A are noticeable in the knee joint, more frequently in mid- than in pre-test and more frequently in pre- than in post-test. These visualizations are also reflected by the indicated average deviation values in mm. In Group B, average subject performance shows a gradual convergence of arm position to the instructor from pre- to mid- to post-test, accompanied by outliers in all tests. Adjustments towards mid-test are initially evident in the leg position, especially in the right knee joint, again deviating greater in post-test, visible through the average values and outliers. For Group C, Figure 8 shows a greater average deviation of the subjects' shoulder joint towards mid-test, especially in the right shoulder, which decreases again in post-test. An adjustment of the knee joint is visible in mid-test, again deviating greater in post-test. Outliers can be found in all tests. Group D shows few differences between tests. Motion directions of the individual joints are adhered to in the squat exercise. An increased deviation from the instructor can be seen in the shoulder joint in all tests, with a tendency towards a steeper arm position.

Fig. 8

3D skeletal representations of spatial motion executions of one pose



The upper figure refers to the visualization of pre-test results, the middle figure is related to mid-test results, and the bottom figure represents post-test results. All images refer to the same exercise across all groups. The instructor's optimized motion is depicted by the blue skeleton that is the same for all groups and tests. The average of all subjects in each group is shown by the red skeletons, and each individual subject in a group is represented by a grey skeleton. The numbers refer to *SpatDev* (mm), i.e., the deviations of the red skeleton from the blue skeleton, averaged across the joints of the elbows, shoulders, hip, and knees, of all participants in a group.

Discussion

The present work dealt with the development and exploration of innovative real-time feedback methods for video-based motor learning. We made use of existing methods of providing feedback on discrepancy information (Blischke et al., 1999) after a motor performance (Barzouka et al., 2015; Dallinga et al., 2017) and adjusted these for use in real-time, resulting in novel real-time feedback methods. Specifically, we integrated the following factors found to be relevant for motor learning, namely providing feedback on KP, realizing this feedback in real-time using modern technologies, and thereby visualizing discrepancy information for actual-criterion motion comparison. In the framework of an initial user pilot study, we investigated three groups each conducting a training method that differed in regard to the amount and type of visual information, and a control group.

Descriptive findings showed that all groups achieved temporal and spatial motion adaptation to the instructors' motions after training. Temporal motion adaptation was greatest in Group A (followed by Group B) and spatial motion adaptation was greatest in Group B. Thus, a direct actual and criterion comparison via visual superimposition of motions might be beneficial for video-based motor learning. Based on the results, this method could not only serve as a sports training approach for delayed feedback (Barzouka et al., 2015; Dallinga et al., 2017), but might also be used to provide motor feedback in real-time. Our study has shown positive effects of applying the innovative feedback methods on motor learning of this specific sample and the selection of motion tasks. Extended research is needed for specifying the potential for sport-specific application cases.

Motor learning in Group A mainly started in the second half of training. While only minor temporal motion adaptation and increased spatial motion deviation from the instructor occurred in the first half of training, both were greatly adapted in the remaining time of training. Based on Cognitive Load Theory (CLT; Sweller, 2011) studies, this effect might be related to the amount of new visual information that had to be processed during training, i.e., virtual skeleton and additional highlights. Indeed, when learning, the human cognitive architecture has limited capacity to process novel information at any given time (Sweller, 2011). Studies on learning environments with virtual elements have shown that such innovative methods can be associated with information overload during learning tasks (Buchner et al., 2021). Since our specifically developed method was tested for the first time in this particular setting, no specific evidence for a certain amount of information was available. The fact that participants made motor learning progress after a certain training time suggests that they first had to become familiar with the innovative method in order to benefit from it. Further research considering familiarization is needed to confirm this assumption. In addition, future studies may benefit from the inclusion of cognitive load assessments, allowing for more precise insights into the cognitive demands placed on participants during the processing of the new visual information in the training methods. As shown by the data visualization method, major deviations in the squat exercise were primarily related to shoulder joint positions. Accordingly, the impact of this novel method on different body parts and joints might be worth exploring. For this purpose, the method should also be further developed especially with regard to depth information. For instance, solutions should be found for displaying the yellow highlights for exercises in which, from the camera perspective, one body part covers another.

Group B greatly adapted to the instructor in both temporal and spatial motion execution from the beginning of the training until half of the training, followed by a slightly increased deviation for the rest of the training. Thus, superimposition of one's own motion on the instructor's motion (real person) might be beneficial for motor learning. One explanation for the increased deviation from the criterion motion halfway through training could be that motor learning was accompanied by exercise-induced fatigue after previously achieving great learning gains. Indeed, fatigue can occur during prolonged or intense motor exercise leading to a decline in sports performance (Jing et al., 2018). Further research on this phenomenon in the context of our motor learning task is needed, for example, by including self-reported fatigue scales in future studies.

Group C adapted spatial motion to the instructor in the first half of training and temporal motion in the second half of training, i.e., the two motion-related features were not adapted simultaneously. Thus, different features relevant to the successful performance of the choreography might have been learned sequentially (Krakauer et al., 2019). However, a correlation of this phenomenon with the type of feedback provided in the group (livestream and instructor's videos displayed side by side) is not apparent and warrants further investigations. Also, five participants reported focusing visually mainly on the instructor during training, i.e., similar to the training method in Group D. In contrast, only two participants indicated that they paid equal attention to both the instructor and the self-view. Therefore, the attentional focus in this feedback method should be studied more closely to examine the actual usefulness of the livestream. Regarding spatial motor learning, the overall results for this group cannot be considered for each individual exercise. In contrast to the overall improvement by half of the training, Figure 8 shows that the deviation from the instructor (in mm) increased in the first half of training and then decreased until the end of training. Consequently, the benefits of learning spatial motor precision using such a feedback method could vary depending on the motor task and its complexity.

Group D experienced a similar motor learning process as Group B, i.e., temporal and spatial motion adaptation in the first half of training, followed by a slightly increased deviation from the instructor in the second half of training. Accordingly, learning progress took place since the beginning of training, which was then interrupted, possibly by fatigue, from half of the training onwards. As with Group B, this assumption of a decline in performance after fatigue (Jing et al., 2018) needs to be verified by empirical validation for ultimate conclusions. Given that Group D, as the control group without receiving feedback, nevertheless showed improvement may be explained by the fact that it was an active control group that, like the other groups, repeated the choreography multiple times during training. It therefore seems plausible that this group also improved at least slightly. In this context, improvement refers to a partial adaptation of the participants' motions to those of the instructor, compared to the beginning of the training when the exercises were entirely unfamiliar. While Group B and D showed a similar course in motor learning, Group B achieved a noticeably greater adaptation in terms of temporal motion precision and a slightly greater adaptation in terms of spatial motion precision in the first half of training. It could be assumed that the additional transparent superimposition of one's own motion (Group B) might have an advantage over seeing only the instructor (Group D) during motor learning. This could also be confirmed specifically for the spatial motion execution of the squat exercise. Group D implemented the basic idea of the motion task, but as far as the shoulder joint motion is concerned, its average spatial precision was poorer than that of Group B (as well as that of all other groups). Consequently, the provision of real-time feedback in the other groups as well as motion superimposition may have been of particular benefit in the performance of this exercise.

According to the SUS results (supplementary material), Group A achieved the highest score, followed by Group B. This might indicate that superimposing motions for real-time feedback proves to be efficient, effective, and satisfactory (Brooke, 2013), thus being feasible for video-based learning. Moreover, the addition of virtual elements into the real training scenario (training videos) might be considered for the development of new feedback methods. As can be summarized from previous literature, exercising with virtual avatars in the role of a coach, doppelganger of the self, or as a training stimulus triggered motivation and enjoyment in learners (Geisen et al., 2023; Geisen & Klatt, 2022; Geisen & Klatt, 2021). Referring to the virtual skeleton (variant of an avatar) shown in the training of Group A, the high SUS score might be an indicator for the advantages of such an innovative method, specifically concerning psychological factors in motor learning.

Overall, individual group-specific factors for the learning process can be identified based on the descriptive results of the user pilot study rather than clear differences in the motor learning process between the feedback methods and the control condition. Based on previous research findings, we approached some conclusions about the results in connection with the characteristics of the respective training method. It can be assumed that each training method may have its advantages and disadvantages for motor learning. In summary, video-based sports motor learning can be enhanced by real-time feedback, which is in line with previous findings on motor learning settings in other application fields like medicine (Geisen & Klatt, 2021). Motion superimposition can be considered as a useful strategy to visualize discrepancy information that according to Blischke et al. (1999) can be highly relevant for motor learning. Previous studies have already found this to be the case with regard to time-delayed feedback. The novelty of our study relates to the focus on real-time feedback in combination with different visualization methods, which is essential especially for video-based sports motor learning. Appropriate methods have been lacking so far. Particular merits of each method tested in our study, and thus the potentially different relevancies for specific training purposes, ought to be further explored.

The present work explored video-based motor learning in multiple sequential motion executions, i.e., a one-minute motion choreography with 25 exercises, which inherently implies a high degree of variability. This procedure resulted in a large amount of data from a rather smaller sample size per group. Our visualization methods for data analysis indicate that the benefits of a particular training method on spatial motor learning may differ with respect to the exercise and the body parts involved. Future studies should focus on single, possibly sport-specific motion executions and increase the sample size in order to even better isolate the efficacy of the innovative training methods. Moreover, our user study was conducted in a laboratory setting, which allowed for initial standardized pilot testing of the innovative training methods. This setup may not reflect all real-world conditions, such as using smaller screens for home-based workouts. Future research should aim for even more ecologically valid environments, including field studies that integrate varied screen setups, e.g., laptops, tablets, or smaller curved monitors, instead of a big curved screen and a projector.

Beyond their use in learning dance, pilates, and yoga motions, the innovative training methods could be applied across a wide range of additional contexts. For instance, they could be employed in physiotherapy contexts to support patients in independently recognizing and correcting motion deviations during exercises. Public datasets such as TheraPose, which includes 123 physiotherapy exercises, e.g., for shoulder mobility, knee extensions, or balance training (Yalic et al., 2024), could serve as reference material for the innovative video-based feedback in home or clinical settings. In ball sports like soccer, such real-time feedback integrated into video-based learning could be valuable for refining certain motion techniques, for instance, when practicing kicking or goalkeeping in front of a large screen simulator (e.g., Jia et al., 2024). Personalized avatars could be incorporated into the simulation, allowing the learner's motions to be superimposed with a model avatar demonstrating the targeted execution. Yet, the high speed of motion executions such as a soccer kick may constitute a cognitive challenge for sufficient visual perception, especially when learners are expected to identify deviations between their motion and the targeted motion in real-time (CLT; Sweller, 2011). In such cases, slow-motion training may be even more effective, enabling the learner to visually perceive the actual-criterion value comparison at reduced speed. Slow-motion practice is an established technique that can help learners gradually approximate complex targeted motions (Moon, 2022). Future work should investigate more systematically which domains can benefit from the application of the innovative real-time feedback methods and what adaptations may be necessary depending on the task characteristics and application context.

At last, the visualization methods developed specifically for this study represent innovative ways of analyzing data. Adapted from the novel feedback methods, visual motion superimposition is not only intended to support motor learning, but also to serve as optimized visualization of results. This can be important for science, as the human mind is strongly vision oriented, making the development of suitable data visualization methods an essential need (Aparicio & Costa, 2014). While this data visualization of the 25 poses (referring to the 25 exercises) in the present pilot study was based on manually annotated pose estimations, future research could benefit from automated tracking methods. For example, the use of artificial intelligence (AI) may enhance both the efficiency and objectivity of the analysis and visualization process.

Conclusion

The current study demonstrated how real-time feedback can be effectively integrated into video-based motor learning, offering potential for enhancing both temporal and spatial motion precision. However, further research is needed to systematically investigate different visualization techniques and the degree of discrepancy information between criterion and actual motion. The innovative methods developed in this work have broad application potential and warrant further exploration, particularly in the context of performance optimization and injury prevention. Video-based motor learning, especially in sports-related contexts such as YouTube tutorials (Sui et al., 2022), represents a growing field that would greatly benefit from continued research.

Appendix

Visualization of the results of all groups, tests and exercises (user pilot study)

Figures 1 to 4 present the results of all 25 images of each test and group. Differences in spatial motor learning can be found between the tests (red, orange, and green skeleton), between the exercises (numbered 1-25) and between the body parts involved (visible within each image) within groups as well as between groups.

Fig. 1

Group A

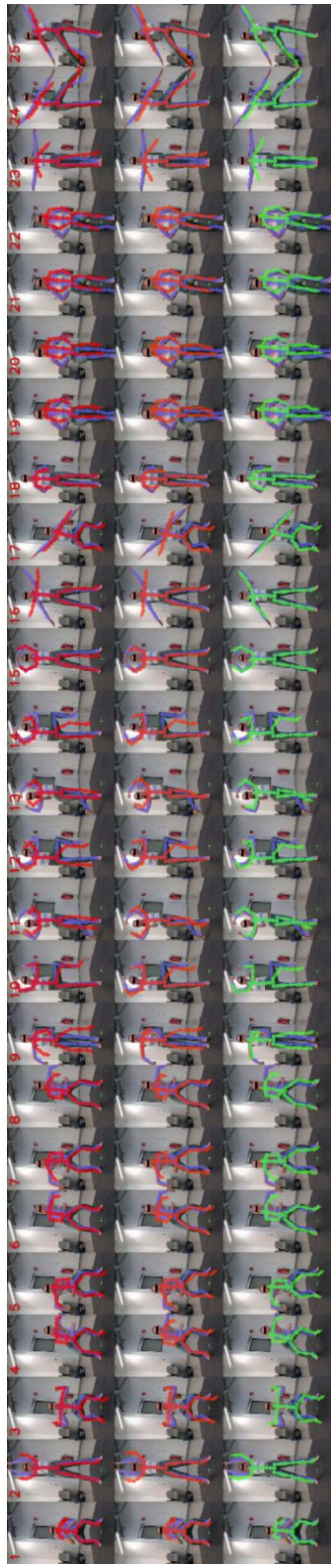


Fig. 2

Group B

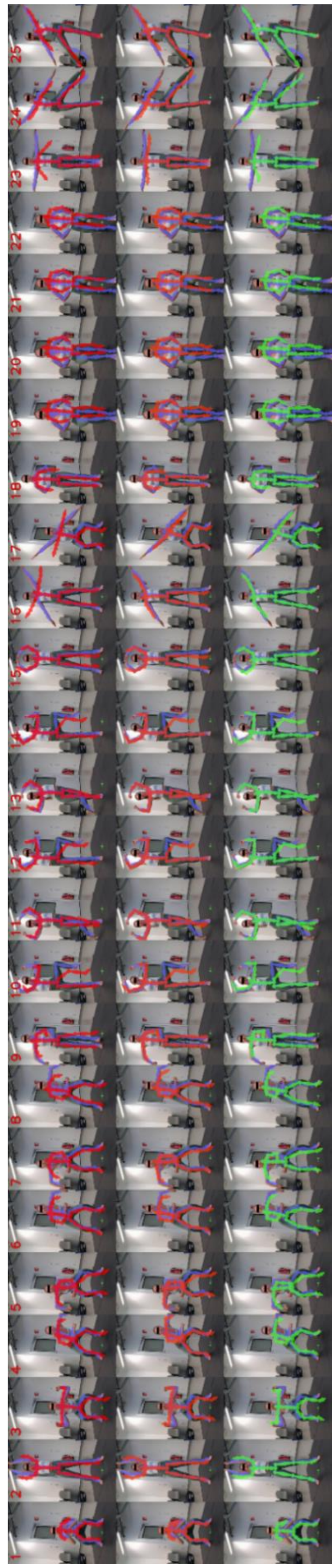


Fig. 3

Group C

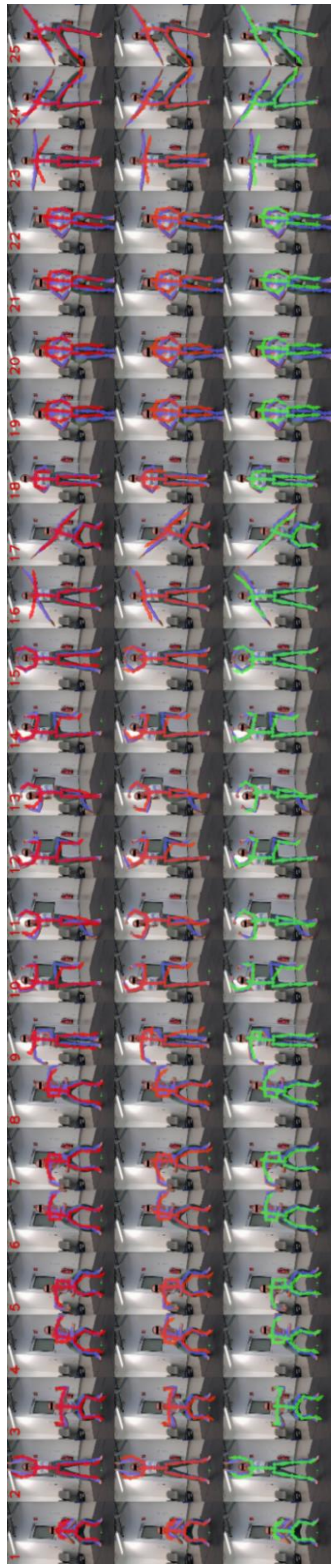
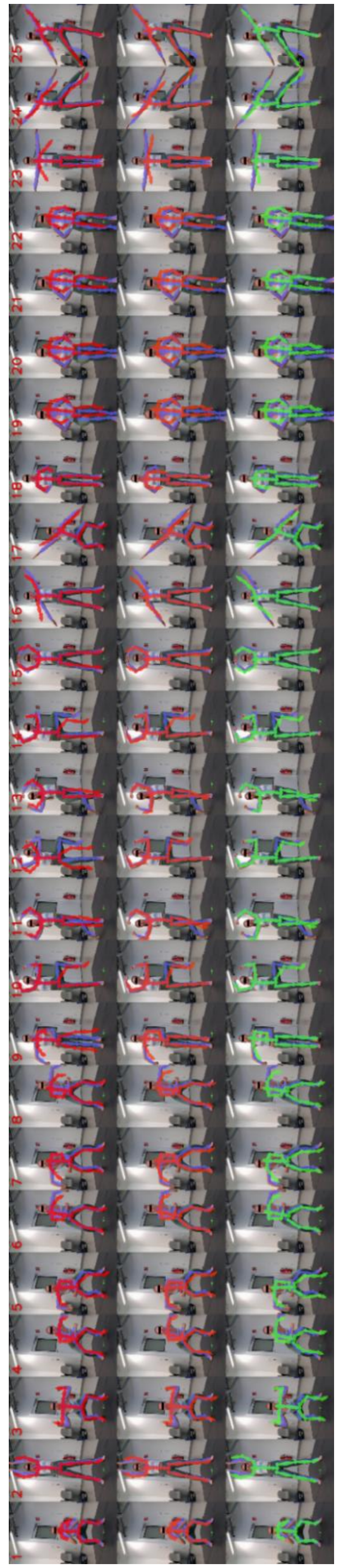


Fig. 4

Group D



SUS and further questionnaire (procedure, analysis and results)

Participants filled out the System Usability Scale (SUS; Brooke, 1996); a questionnaire used to assess the usability of systems in terms of efficiency, effectiveness, and satisfaction (Brooke, 2013). SUS consists of 10 items scored on a 5-point Likert scale (1 = "strongly disagree"; 5 = "strongly agree"). The German version of SUS (Rummel & Ruegenhagen, 2013) was used in the present study. Further questions pertained specifically to the experimental setup: 'During the examination, did you predominantly pay attention to only one of the two video views (front and side view)? If so, which of the two views did you pay more attention to?, and 'During the study, did you mainly pay attention to either yourself or the instructor? If yes, who did you pay more attention to?'. The question 'Did you pay attention to the instructions (information window) during the examination?' had the answer options "never", "rarely", "sometimes", "often" or "always".

Responses on SUS were calculated according to the procedure suggested by Brooke (1996). In this way, a SUS score of each subject could be determined, which in turn, by averaging, allowed the determination of a score for each group. The further questionnaire responses were analyzed manually.

Group A had the highest SUS score with 82.5 ± 9.2 in a range of possible 0-100 scores, followed by Group B with an 80.6 ± 8.8 score. Group D had a score of 80.4 ± 14, and Group C had a 72.1 ± 14.3 score. All but two participants (1xB, 1xC) predominantly paid attention to only one of the two video views and in all but two of those cases (2xC) they focused mainly on the front view. Furthermore, while only two participants (1xB, 1xD) indicated that they paid more attention to themselves during the study, eighteen participants paid more attention to the instructor (5xA, 4xB, 5xC, 4xD). The remaining seven participants (1xA, 3xB, 2xC, 1xD) indicated that they did not pay more attention to either themselves or the instructor. Finally, none of the participants indicated that they "never" paid attention to the instructions (information window) during the examination. Three participants (1xA, 1xB, 1xC) paid attention to the instructions only "rarely", seven (4xA, 2xB, 1xC) said they "sometimes" paid attention, thirteen participants (5xB, 3xC, 5xD) "often" and four participants (1xA, 2xC, 1xD) "always" paid attention to the instructions.

Author's contributions

Mai Geisen, Tobias Baumgartner and Nina Riedl developed the video-based feedback techniques, performed the data analysis, and contributed to the interpretation of the results. Nina Riedl collected data. Stefanie Klatt supervised the experimental procedures and provided critical feedback throughout the study. Mai Geisen took the lead in writing the manuscript, with support from all authors.

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Availability of data and materials

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

Statements on open data and ethics
The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008. Approval was obtained from the institution's ethics board (No. 105/2019). Informed consent was obtained from all individual participants included in the study.

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References

Alrashidi, M., Almohammadi, K., Gardner, M. & Callaghan, V. (2017). *Making the invisible visible: Real-time feedback for embedded computing learning activity using pedagogical virtual machine with augmented reality* [Conference paper]. 4th International Conference on Augmented Reality, Virtual Reality and Computer Graphics, Ugento, Italy. https://doi.org/10.1007/978-3-319-60922-5_27

Antico, M., Balletti, N., Laudato, G., Lazich, A., Notarantonio, M., Oliveto, R., Ricciardi, S., Scalabrino, S., & Simeone, J. (2021). Postural control assessment via Microsoft Azure Kinect DK: An evaluation study. *Computer Methods and Programs in Biomedicine, 209*, 106324. https://doi.org/10.1016/j.cmpb.2021.106324

Aparicio, M., & Costa, C. J. (2014). Data visualization. *Communication Design Quarterly, 3*(1), 7–11. https://doi.org/10.1145/2721882.2721883

Barzouka, K., Sotiropoulos, K., & Kioumourtzoglou, E. (2015). The effect of feedback through an expert model observation on performance and learning the pass skill in volleyball and motivation. *Journal of Physical Education and Sport, 15*(3), 407–416. https://doi.org/10.7752/jpes.2015.03061

Blischke, K., Marschall, F., Müller, H., & Daugs, R. (1999). Augmented Information in Motor Skill Acquisition. In Y. Vanden Auweele, F. Bakker, S. Biddle, M. Durand & R. Seiler (Eds.), *Psychology for Physical Educators* (pp. 257–287). Human Kinetics.

Brooke, J. (1996). SUS: A 'quick and dirty' usability scale. In P. Jordan, B. Thomas, B. Weerdmeester & I. L., McClelland (Eds.) *Usability Evaluation in Industry* (pp. 189–194). Taylor & Francis.

Brooke, J. (2013). SUS: A retrospective. *Journal of Usability Studies*, 29–40.

Brookhart, S. M. (2020). Feedback and Measurement. In S. M. Brookhart & J. H. McMillan (Eds.), *Classroom Assessment and Educational Measurement* (S. 63–78). Routledge.

Buchner, J., Buntins, K., & Kerres, M. (2021). The impact of augmented reality on cognitive load and performance: A systematic review. *Journal of Computer Assisted Learning, 38*(1), 285–303. https://doi.org/10.1111/jcal.12617

Coker, C. A. (2022). *Motor Learning and Control for Practitioners* (5th ed.). Routledge.

Dallinga, J., Benjaminse, A., Gokeler, A., Cortes, N., Otte, E., & Lemmink. K. (2017). Innovative video feedback on jump landing improves landing technique in males. *International Journal of Sports Medicine, 38*(2), 150–158. https://doi.org/10.1055/s-0042-106298

Geisen, M., Fox, A., & Klatt, S. (2023). VR as an innovative learning tool in sports education. *Applied Sciences, 13*, 2239.

Geisen, M., & Klatt, S. (2021). Real-time feedback using extended reality: A current overview and further integration into sports. *International Journal of Sports Science & Coaching, 17*(5). https://doi.org/10.1177/1747954121105100 6

Geisen, M., & Klatt, S. (2022). KI im Sport: Wie werden Menschen durch den Einsatz von Avataren im sportlichen Training auf psychologischer Ebene beeinflusst? *Zeitschrift für Sportpsychologie, 29*, 31–32.

Gentile, A. M. (1972). A working model of skill acquisition with application to teaching. *Quest, 17*(1), 3–23.

Grimm, F., Naros, G., & Gharabaghi, A. (2016). Compensation or restoration: Closed-loop feedback of movement quality for assisted reach-to-grasp exercises with a multi-joint arm exoskeleton. *Frontiers in Neuroscience*. https://doi.org/10.3389/fnins.2016.00280

Harris, S. A., Chivers, P., McIntyre, F. L., Piggott, B., Bulsara, M., & Farringdon, F. H. (2020). Exploring the association between recent concussion, subconcussive impacts and depressive symptoms in male Australian football players. *BMJ Open Sport & Exercise Medicine, 6*, e000655. https://doi.org/10.1136/bmjsem-2019-000655

Hollmann, W., & Hettinger, T. (1990*). Sportmedizin. Arbeits- und Trainingsgrundlagen.* Schattauer.

Hülsmann, F., Frank, C., Senna, I., Ernst, M. O., Schack, T., & Botsch, M. (2019). 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. https://doi.org/10.3389/frobt.2019.00043

Hülsmann, F., Göpfert, J. P., Hammer, B., Kopp, S. & Botsch, M. (2018). Classification of motor errors to provide real-time feedback for sports coaching in virtual reality: A case study in squats and Tai Chi pushes. *Computers & Graphics, 76*, 47–59. https://doi.org/10.1016/j.cag.2018.08.003

Jia, T., Sitthiworachart, J., & Morris, J. (2024). Application of simulation technology in football training: A systematic review of empirical studies. *The Open Sports Sciences Journal, 17*, e1875399X277947. https://doi.org/10.2174/011875399X277947231228071109

Jing, M., Huimin, C., Xiaoli, L., Lingtao, Z., & Decai, Q. (2018). Exercise-Induced Fatigue Impairs Bidirectional Corticostriatal Synaptic Plasticity. *Frontiers in Cellular Neuroscience, 12*(14). https://doi.org/10.3389/fncel.2018.00014

Kaplan, A. D., Cruit, J., Endsley, M., Beers, S. M., Sawyer, B. D., & Hancock, P. A. (2021). The effects of virtual reality, augmented reality, and mixed reality as training enhancement methods: A meta-analysis. *Human Factors, 64* (4), 706–726. https://doi.org/10.1177/0018720820904229

Kelley, H., & Miltenberger, R. G. (2015). Using video feedback to improve horseback-riding skills. *Journal of Applied Behavior Analysis, 49*(1), 138–147. https://doi.org/10.1002/jaba.272

Kim, H.-M., Kim, M., & Cho, I. (2022). Home-based workouts in the era of COVID-19 pandemic: The influence of Fitness YouTubers' attributes on intentions to exercise. *Internet Research*. https://doi.org/10.1108/INTR-03-2021-0179

Krakauer, J. W., Hadjiosif, A. M., Xu, J., Wong, A. L., & Haith, A. M. (2019). Motor Learning. *Comprehensive Physiology, 9*, 613–663. https://doi.org/10.1002/cphy.c170043

Krause, D. (2017). Effects of additional knowledge of results on modifying highly practiced acyclic swimming techniques with knowledge of performance. *International Journal of Sports Science & Coaching, 12*(6). https://doi.org/10.1177/1747954117738894

Le Naour, T., Hamon, L., & Bresciani, J.-P. (2019). Superimposing 3D virtual self + expert modeling for motor learning: Application to the throw in American football. *Frontiers in ICT, 6*, 16. https://doi.org/10.3389/fict.2019.00016

Llupar, M. L., Malones, L. J. L., Sombria, A. J. F., Calixtro, V. L. (2022). Development of folk-dance videos for e-learning. *Indonesian Journal of Teaching in Science, 2*(1). https://doi.org/10.17509/ijotis.v2i1.41586

McCullagh, P. (1993). Modelling: Learning, developmental, and social psychologcal considerations. In P. Hirtz & F. Nüske (Eds.), *Bewegungskoordination und sportliche Leistung – integrativ betrachtet* (2. Bernstein-Konferenz). Czwalina.

Moon, J. (2022). Connecting sport coaching, physical education, and motor learning to enhance pedagogical practices. *Journal of Physical Education and Sport, 22*(1), 3–12. https://doi.org/10.7752/jpes.2022.01001

Oppici, L., Dix, A., & Narciss, S. (2021). When is knowledge of performance (KP) superior to knowledge of results (KR) in promoting motor skill learning? A systematic review. *International Review of Sport and Exercise Psychology*, https://doi.org/10.1080/1750984X.2021.1986849

Potdevin, F., Vors, O., Huchez, A., Lamour, M., Davids, K. & Schnitzler, C. (2018). How can video feedback be used in physical education to support novice learning in gymnastics? Effects on motor learning, self-assessment and motivation. *Physical Education and Sport Pedagogy, 23*(6), 559–574. https://doi.org/10.1080/17408989.2018.1485138

Pustišek, M., Wei, Y., Sun, Y., Umek, A., & Kos, A. (2021). The role of technology for accelerated motor learning in sport. *Personal and Ubiquitous Computing, 25*, 969–978. https://doi.org/10.1007/s00779-019-01274-5

Quennerstedt, M., Gibbs, B., Almqvist, J., Nilsson, J., & Winther, H. (2016). Beatrice: Dance Video Games as a Resource For Teaching Dance. In A. Casey, V. A. Goodyear & K. M. Armour (Eds.), *Digital Technologies and Learning in Physical Education* (1st ed.). Routledge.

Raiola, G., Parisi, F., Gugno, Y., & Di tore, P. A. (2013). Video analysis applied to volleyball didactics to improve sport skills. *Journal of Human Sport and Exercise 8*(2), 307–313. https://doi.org/10.4100/jhse.2012.8.Proc2.33

Rauter, G., Sigrist, R., Riener, R., & Wolf, P. (2015). Learning of temporal and spatial movement aspects: A comparison of four types of haptic control and concurrent visual feedback. *IEEE Trans Haptics, 8*(4), 421–433. https://doi.org/10.1109/TOH.2015.2431686

Rucci, J., & Tomporowski, P. (2010). Three types of kinematic feedback and the rxecution of the hang power clean. *Journal of Strength and Conditioning Research, 24*(3), 771–778. https://doi.org/10.1519/JSC.0b013e3181cbab96

Rummel, B., & Ruegenhagen, E. (2013). *Fragebogen zur Systemgebrauchstauglichkeit. System Usability Scale* (Translation into German). http://www.sapdesignguild.org/resources/sus.asp

Rüth, M., & Kaspar, K. (2020). Exergames in formal school teaching: A pre-post longitudinal field study on the effects of a dance game on motor learning, physical enjoyment, and learning motivation. *Entertainment Computing, 35*, 100372. https://doi.org/10.1016/j.entcom.2020.100372

Sharma, D. A., Chevidikunnan, M. F., Khan, F. R., & Gaowgzeh, R. A. (2016). Effectiveness of knowledge of result and knowledge of performance in the learning of a skilled motor activity by healthy young adults. *Journal of physical therapy science, 28*(5), 1482–1486. https://doi.org/10.1589/jpts.28.1482

Shen, C.-C., Yang, C.-C., Mao, T.-Y., Sia, W.-Y., & Line, C.-T. (2019). Do YouTube fitness videos help YouTube user to learn fitness*? International Journal of Innovation, Creativity and Change, 5*(2), 93–104.

Shotton, J., Fitzgibbon, A., Cook, M., Sharp, T., Finocchio, M., Moore, R., Kipman, A., & Blake, A. (2011, June 20–25). *Real-time human pose recognition in parts from single depth images* [Conference paper]. Proceeding of the IEEE Conference on Computer Vision and Pattern Recognition, Providence, United States.

Sui, W., Morava, A., Tsang, J., Sui, A., & Rhodes, R. E. (2022). Describing the use of behavior change techniques among the most popular home workout channels on YouTube: A quantitative content analysis. *Journal of Health Psychology*. https://doi.org/10.1177/13591053221074584

Sui, W., Rush, J., & Rhodes, R. E. (2022). Engagement with web-based fitness videos on YouTube and Instagram during the COVID-19 pandemic: Longitudinal study. *JMIR formative research, 6*(3), e25055. https://doi.org/10.2196/25055

Sweller, J. (2011). CHAPTER TWO - Cognitive Load Theory. *Psychology of Learning and Motivation, 55*, 37–76. https://doi.org/10.1016/B978-0-12-387691-1.00002-8

Wang, J. R., & Parameswaran, N. (2004). *Survey of sports video analysis: Research issues and applications* [Conference paper]. Pan-Sydney Area Workshop on Visual Information Processing, Sydney, Australia.

Yalic, H. Y., Usta, A. E., Atila, Ü., Uçan, A., Yilmaz, A A., & Yiğit, A. Y. (2024, May 30-31). *TheraPose: A large video dataset for physiotherapy exercises* [Conference paper]. Proceedings of 15th Turkish Congress of Medical Informatics, Trabzon, Turkey.

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