Influence of Video Instruction on Football Kick Velocity in Young Players

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Abstract

This study aimed to investigate the acute effects of instructional video on kicking performance in young football players. 26 participants were divided into a control group (CG) and an instructional video group (IG). Kicking kinematic variables, including the length of the last step (LLS), distance between the support foot and the ball (DSB), speed of the kicking foot at ball contact (SKF), ball speed (BS), and BS/SKF ratio, were assessed before and after video presentation. The OpenPose was used for marker less pose estimation and data analysis. Statistical analysis revealed a significant increase in LLS in the IG after video presentation (p=0.044), while no significant differences were observed in other variables for both CG and IG. These findings suggest that video demonstrations with instructions can acutely improve the length of the last step in young football players. However, no immediate effects were observed on other analyzed variables. Further studies are warranted to explore the long-term effects of video-based training and assess kinematic variables in a more ecological setting. Overall, video-based instructions can be a valuable tool for enhancing kicking performance and optimizing training in young football players.

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1 Introduction

The action that often determines the outcome of a soccer match is the kick. The lower limbs kinematics are closely related to kicking success, particularly regarding the transfer of speed to the ball [1]. To increase the chances of scoring a goal, players need to achieve the highest possible ball speed, which depends on various variables such as foot speed at impact and the quality of ball striking at foot contact [2, 3, 4, 5]. Furthermore, if the kick is faster, it is less likely for the goalkeeper or opposing player to have enough time to react [6, 7, 8]. Determine indicators that help achieving success in this skill is one of the most important issues when it comes to applied bio-mechanics in soccer [9]. Some of these indicators are related to the lower limb kinematics, which are closely associated with kicking success, especially regarding the transfer of high speed to the ball [1]. The energy transfer is associated, among other things, with the length of the final stride in the kick [10], the distance between the support foot and the ball [11], and the foot speed [12].

Kinematic analysis is usually performed in a laboratory using optical cameras in combination with retro-reflective markers, but this setup was not primarily designed for outdoor use. With the advent of deep neural networks, it is now possible to estimate joint angles needless retro-reflective markers [13]. Thus, marker less motion estimation algorithms publicly available, such as OpenPose [14], appears to be a potential solution in video data analysis and extraction of kicking kinematics in a likely less time-consuming, more cost-effective, and non-invasive manner.

A factor that can affects kicking performance is the set of instructions given to the practitioners. Among the many ways to instruct learners to perform the most proficient movement for the task they are performing is through video demonstration. According to Newell [15], motor learning is a process of exploration under the possibilities of perception-action, those that will best help you to reach the objective of the movement that is being performed. In other words, the novice in kicking task, search the best information's that help to achieve the most proficient kicking.

However, in some cases, the novice does not explore the perception-action possibilities and tends to present the same initial coordination pattern [16]. Instructions (including video instructions) can constraint the available information, directing the beginner to explore new information and, consequently, altering his coordination [17]. For example, Lafe and Newell [18] observed that verbal instruction alters the exploration of coordination patterns in a bi-manual strength task. Therefore, video instruction could present similar results, guiding the individual to another coordination pattern.

Different approaches can be used during video instruction, such as directing attention through video-based information [19], such as, simply show video of a proficient individual performing the task (e.g., Al-Abood [20]) highlighting some specific aspect of the video by a point of light (e.g., Horn [21]), or guiding the individual to attend to different visual information in the video (e.g. the trajectory of the ball in a video of the kick) (e.g., Hodges [22]). A review performed by Pacheco et al. [23] showed that in some cases, only the demonstration video was not enough for the individual to learn a new movement patter, being necessary to add some other variables (e.g. verbal cue, visual cue or feedback).

One way to assess the effect of video instruction on kick coordination is kinematic analysis. Kinematic analysis is usually performed in a laboratory using optical cameras in combination with retro reflective markers, but this setup was not primarily designed for outdoor use. With the advent of deep neural networks, it is now possible to estimate joint angles markreless (e.g., Vieira [24]).

The development of computational sciences such as computer vision and image processing has improved the analysis techniques and measurement systems used in human movement research. These advancements have allowed for a greater understanding of the three-dimensional (3D) kinematic and kinetic characteristics of kicking in soccer [1]. Among the available tools for examining kicking movement performance, video analysis is capable of producing the most objective and sensitive kinematic metrics, which are not always captured solely through visual assessments [25].

Figure 1: Setup for collecting the kick. Where we have the penalty mark, the two cameras (C1 and C2) and where the videos were displayed.

Based on this, the present study aimed to evaluate, ,with in field data collection, if the display of an instructional video can acutely increase ball speed and the length of the final stride, decrease the distance between the support foot and the ball, as well as increase kicking foot speed at the moment of ball contact.

2 Methods

2.1 Participants

26 young football playersfrom 10 to 15 years old participated in the study. The participants were randomly assigned by an online platform Research Randomizer [26] to which video they would watch, with one group as the control group (CG) (n=13; age=12 ± 0.92 years old; mass = 41.2 ± 8.09 kg; height = 1.53 ± 0.11 m; training experience = 6.31 ± 2.74 years) and one group as the instruction group (IG) (n=13; age=13 ± 1.47 years old; mass = 52.69 ± 12.95 kg; height = 1.59 ± 0.11 m; training experience = 6.62 ± 1.65 years). Only one participant among was left-footed for kicking and he was in the CG group. The remaining participants were all right-footed for kicking. The School of Physical Education and Sport of Ribeirão Preto Ethics Committee approved all the experimental procedures (CAAE: 26288119.8.0000.5659). Written consent was obtained from the participants and their legal guardian(s).

2.2 Instruments

The kick and ball kinematics data were collected using two GoPro Hero 10 Black Edition cameras (GoPro® GmbH, Munich, Germany), mounted on tripods, with a resolution of 2720×1530 pixels and a frequency of 120Hz. The cameras were synchronized using the remote control of the GoPro Hero 10 and positioned 2 meters away from the penalty mark, with a distance of 7 meters between them. The lenses were directed towards the penalty mark, forming a 45° angle and providing a diagonal view of the kick. The balls used varied according to age. For individuals aged 10 and 11 years, a ball with a circumference between 63.5 and 66 cm was used. For individuals aged from 12 to 15 years, a ball with a circumference between 68.5 and 69.5 cm was used.

2.3 Videos presented

The participants were randomized into two groups, and each would watch a specified video. The participants in the IG group watched a 30-second video containing four instructions presented in the form of verbal cues with animations created in Unity software (version 2019.4.16f1, USA). The four instructions were (1) The last step is longer; (2) The foot stays beside the ball; (3) Contact with the "instep" of the foot; (4) Don't stop until you kick. The participants in the CG group watched a 30-second video containing information about the importance of physical activity, anatomy, and health, without any specific relation to tips or instructions regarding the kicking technique.

2.4 Experimental procedures

The experimental protocol was conducted on an official field with natural grass (FIFA standard, 100 m × 70 m; goal dimensions, 7.32 m × 2.44 m) located at the Physical Education, Sports, and Recreation Center (CEFER) of the University of São Paulo. Participants were provided with instructions on the procedures and started with a warm-up in which they were instructed to perform five sub-maximal penalty kicks to better understand the task and adapt to the ball. Afterward, participants performed five penalty kicks with instructions to kick as forcefully as they could, aiming to score a goal, with acceleration individualized for each participant, without limitations on running patterns or approach angles. Subsequently, the participants were randomized to determine which video they would watch, either the one from the IG or the CG. The designated video was displayed on a 15-inch monitor of a Eurocom notebook. Immediately after watching the video, each participant performed a new series of five penalty kicks, which were compared to the previous situation.

2.5 Data processing

Each kicking attempt was recorded and considered valid only if it resulted in a goal, while shots hitting the goalpost or going wide were disregarded. To assist in the validation of the kicks during the analysis, a camera was positioned on the edge of the penalty area, with lenses aimed at the goal line. The videos were edited, with the start of the participant's first movement and the end of the evaluation defined as ten frames after the participant's contact with the ball.

To evaluate the kinematic variables of the kick, the video of each kicking attempt was analyzed using the OpenPose artificial intelligence neural network [14]. This network allows for the identification of joints and anatomical points in videos, providing screen coordinates of the recognized points through a skeleton detection algorithm like in Figure 2. In cases where the screen coordinate data obtained by OpenPose were incorrect for the lower limb of the participant, they were manually corrected using the Dvideow software (v. 1.0.0.1) [27, 28].

To evaluate the ball variables, the DeepLabCut toolbox [29, 30] was used. It allows for the utilization of an artificial neural network to estimate marker-less pose of animals performing various tasks. In this case, the network was trained to provide screen coordinates of the estimated center of the ball through a detection algorithm. Similar to the kicking kinematics, if the screen coordinates were incorrect, manual correction was performed by identifying the screen coordinates and estimating the center of the ball.

A total of 230 kicks were evaluated, with each participant performing the same number of kicks divided into 5 kicks before watching the video presentation and 5 kicks after watching the video presentation. The following dependent variables were calculated for each validate kicking attempt:

- Length of the last step (LLS) [11, 10]: defined as the Euclidean distance between the location where the kicking foot's hallux lost contact with the ground and the heel of the support foot

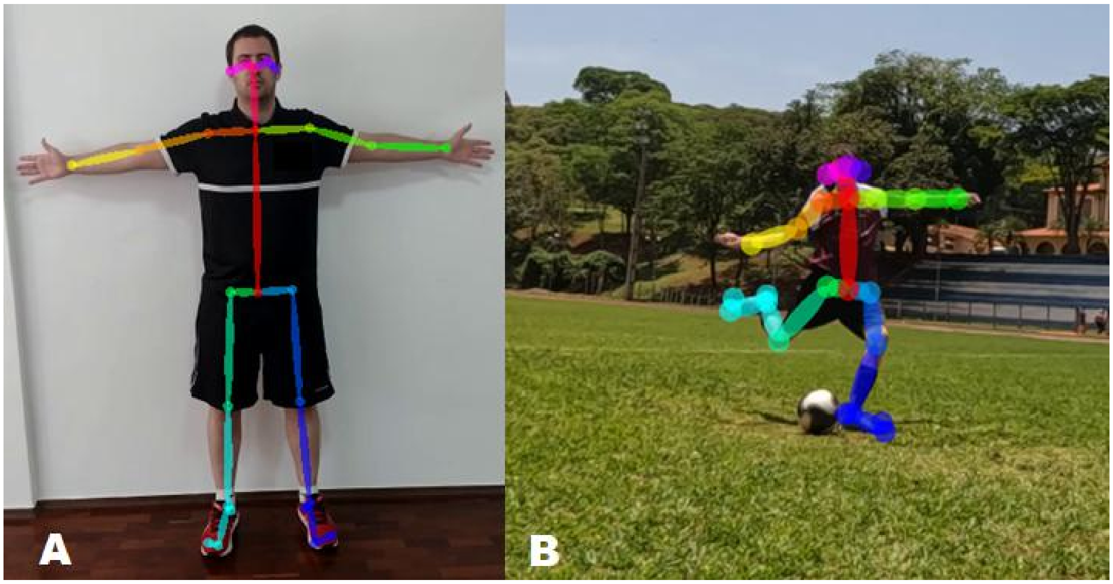

Figure 2: A: OpenPose detection demonstration. B: OpenPose applied to kicking task.

when it landed on the ground during the last step;

- Distance between the support foot and the ball (DSB) [11, 31, 32]: defined as the Euclidean distance between the centroid of the support foot and the estimated center of the ball at the moment of foot-ball contact;

- Speed of the kicking foot at ball contact (SKF) [33, 34]: defined as the instantaneous speed of the dominant foot's centroid at the moment of ball contact;

- Ball speed (BS) [35, 36]: defined as the instantaneous speed of the estimated center of the ball ten frames after foot-ball contact;

- BS / SKF ratio: calculated as a dependent measure [37] and used as an indirect indicator of foot and ball impact quality [38];

The kicking and ball kinematic data were pre-processed, processed, and analyzed using custom routines created in the Python programming language. The screen coordinates from the two cameras were smoothed using the LOWESS method with a delta of 0.1 and alpha of 0.1, and then transformed into 3D global coordinates using the Direct Linear Transformation (DLT) method [39]. Known 3D coordinates of the calibration rigid object were used as a reference for the DLT method.

Subsequently, a Python routine was used to calculate the LLS, DSB, SKF, BS, and BS/SKF kinematic variables for each participant's attempt. The DeepLabCut [29, 30] was used to assist in calculating the error of the DLT method. For this purpose, the detection algorithm was configured to provide screen coordinates for the base and the highest point of a topographic pole. In Figure 3, a detection is shown where ten screen coordinates were marked, with the top of the pole marked in purple and the base of the pole marked in yellow.

The video used to assess the error consisted of recording the topographic pole traversing the entire data collection area. Subsequently, 3D reconstruction was performed using the same DLT method and calibration setup. To measure the measurement error, the Euclidean distance between the top and the base of a topographic pole was calculated. The real distance between the ends of the pole was 1.925 m, and the average of the Euclidean distance between the top and the base of a topographic pole after reconstruction was 1.94 m, demonstrating an average error of approximately 2 cm.

Figure 3: Difference in Euclidean distance of pole length after 3D reconstruction over time.

Table 1: Mean (±Standard Deviation) and p-value (power) of the kicking variables for the Control group in the before and after watching the video moments.

Variables	CG		
	Before	After	p-value (power)
LLS (m)	1.31 (± 0.23)	1.32 (± 0.23)	0.22 (0.06)
DSB (m)	0.32 (± 0.06)	0.32 (± 0.07)	0.69 (0.05)
SKF (m/s)	10.37 (± 1.67)	10.18 (± 1.58)	0.14 (0.08)
BS (m/s)	17.64 (± 4.56)	17.29 (± 4.63)	0.25 (0.08)
BS/SKF	1.69 (± 0.31)	1.69 (± 0.3)	0.83 (0.05)

2.6 Statistical analysis

Statistical analysis was performed using routines developed in the Python language. Mean and standard deviation values were calculated, and to assess the normality of the sample, the Kolmogorov-Smirnov and Shapiro-Wilk tests were applied.

Subsequently, based on the data distribution, the performance in each kicking variable in both groups were compared before and after watching the video kicking variable in the control and instructional video groups were compared. Tests with a p-value less than 0.05 were considered statistically significant. Dependent t-tests and Wilcoxon tests were performed according to the normality of the data. To calculate the sample power was used the G*power software (version 3.1.9.7) [40].

3 Results

The mean (± standard deviation) and p-value (power) of the kicking variables for the CG are present in Table 1, and for the IG are present in Table 2. In Figure 4, a radar plot representation is presented for the mean values of kinematic variables for both groups at before and after moments.

Table 2: Mean (±Standard Deviation) and p-value (power) of the kicking variables for the Intervention group in the before and after watching the video moments.

Variables	IG		
	Before	After	p-value (power)
LLS (m)	1.27 (± 0.26)	1.31 (± 0.21)	0.04* (0.14)
DSB (m)	0.32 (± 0.05)	0.31 (± 0.05)	0.13 (0.09)
SKF (m/s)	10.84 (± 1.36)	10.77 (± 1.38)	0.51 (0.06)
BS (m/s)	18.13 (± 3.30)	18.34 (± 3.34)	0.47 (0.06)
BS/SKF	1.68 (± 0.26)	1.71 (± 0.27)	0.84 (0.06)

* p < 0,05

Regarding the comparison tests of the kicking variables between the before and after moments, a statistically significant difference was found only in the comparison between the before and after moments of the IG for LLS, with a p-value of less than 0.05 (p=0.044). For the other variable comparisons, no statistically significant difference was found when comparing the before and after moments in both groups. However, the sample power found in all comparisons of the kick variables was low, with the highest value equal to 0.14 in the comparison between the before and after moments of the IG of the LLS.

4 Discussion

Considering the importance of kicking in football, the study aimed to evaluate whether the display of a video with instructions could acutely increase ball speed, increase the length of the final stride, decrease the distance between the support foot and the ball, and increase kicking foot speed at the moment of ball contact. A statistically significant difference was found in the variation of LLS between the before and after video presentation moments only in the IG (p=0.044), but the power of this analysis was low. However, no statistically significant differences were observed in the before and after video for both CG and IG for the other variables. No studies were found in the literature that have evaluated the kinematic changes in response to video instruction presentation to improve performance in young soccer players.Nevertheless, there are studies in soccer that use video training focus on game situation perception and decision-making [41, 42, 43, 44, 45].

Considering the method of delivering instructions through videos, Souissi et al. [46] argued that providing only verbal feedback to a participant, without video feedback or video feedback without additional cues, has little effect on skill acquisition. For example, in the study carried out by Nunes et al. [47]. Simple video feedback was not enough for elderly individuals to improve golf putting kinematics performance, however, the group who received video feedback as well as verbal instruction had an improvement in movement kinematics. Therefore, the effects of video and verbal feedback appear to be additive.

Research in motor learning has shown that active participation of the participant in the learning process improves performance [48, 49]. Other studies have focused on strategies for using educational videos for teaching and their effects on participants' understanding of the presented content. These strategies include segmenting the video into smaller units [50] and controlling the pace of the presentation [51]. These strategies seem to have a positive impact on learning compared to continuous viewing of educational videos. They also appear to contribute to a reduction in cognitive load during video

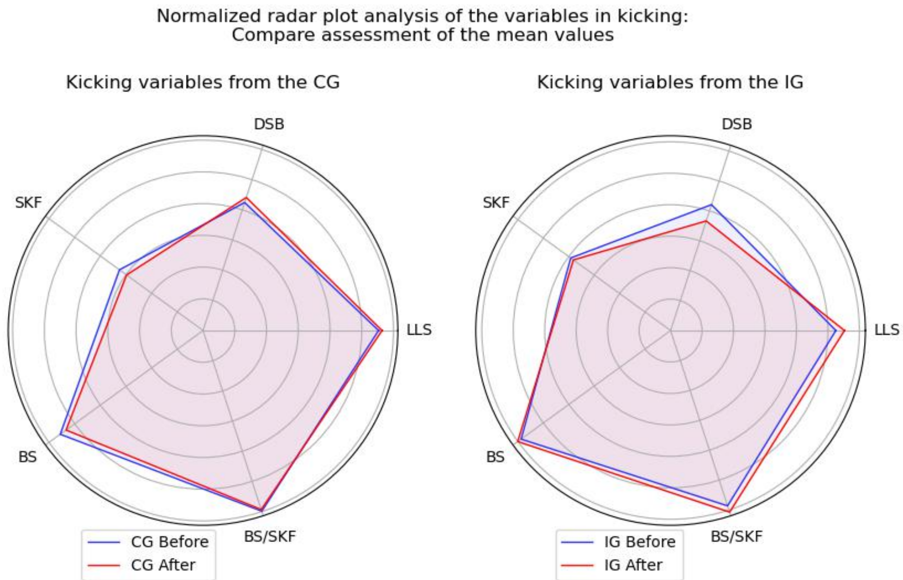

Figure 4: Radar plot with normalized average values of kinematic variables for CG and IG. Before values are shown in blue and after values in red.

viewing [52, 53] and to smoother cognitive processing [51].

To make a comparison with the kinematic variables, a literature search was conducted for results found in similar analyses to those performed in the present study. Regarding BS, the majority of studies evaluated players over 15 years old [38, 34, 54, 55, 32]. The increase in practice time as these young players age is a factor that may contribute to BS improvement [56]. On the other hand, LLS [11, 10, 37] and DSB [11, 54, 32, 37] have been little explored in young players so far.

When analyzing the mean values of the variables, the data for LLS, DSB, and BS in the CG and IG are similar to the values found in the study by Vieira et al. [37], which compared players of over 13 years old, which is the average age of the present study. However, they present lower BS values compared to the studies by Rodríguez-Lorenzo et al. [57], which evaluated players in the U-14 category or younger, and the study by Cerrah et al. [58], which evaluated players with 12 and 13 years old. Additionally, they have lower DAB values compared to those found in the study by Kapidvzic et al. [11].

The values of SKF and the BS/SKF ratio were different from those found in the study by Vieira et al. [37], with lower values for SKF and consequently higher values for the BS/SKF ratio observed in the present study. This difference can be explained by the fact that in the study by Vieira et al. [37], participants were required to have started regular practice at 6 years old, which was not adopted as a criterion in the present study. However, it is still possible to observe similarity in some of the kinematic data between groups within the same age range.

The study of Cronin [59] showed that there are some critical distinctions between pose estimation and kinematic analysis. Firstly, strictly speaking pose estimation only involves the detection of body landmarks, which are then used in combination with geometry to compute the angle between any two body segments. Secondly, the accuracy requirements of pose estimation are less strict than those of kinematic analysis. Also the camera settings are another issue relevant to the collection of data, like the frame rate and shutter speed with which the videos are sampled [60], and also image resolution, because very low-resolution images result in pixelated closeup views that can make it difficult to accurately estimate a body part [59]. Given that the current gold standard optical systems and manual digitisation also include inherent limitations (e.g.movement of skin and markers relative to the underlying anatomical landmark), if we reach a state where marker-based and markreless methods yield results within a few millimeters of each other, markreless motion analysis could truly be a feasible option for human movement scientists, both in and outside of the lab [59]. It is important to remember that neural networks do not perform magic tricks, they identify mathematical patterns in data [59].

The present study limitantions are: the data analysis was conducted acutely, which may have minimized the effects of improvement and learning of the task by the participants. Also, four instructions for executing the kick were provided, which may have influenced the results. The amount of information presented can make it difficult for the individual which information to explore. To verify the effect of video instruction on motion kinematics, it may be necessary to extend the training period.

In football, the most important action is the kick, and studies with a more ecological approach to assess kinetic and kinematic variables in the kicking task are of great importance to improve understanding of the task and enhance the performance of young football players. These assessments allow physical education professionals and coaches to better monitor the progress and specific demands of each individual, and the application of video-based instructions and training allows for optimized use of time, reserving part of the training to be conducted at another time.

Therefore, it is suggested that further studies evaluate the long-term effects of this video-based training model with kinematic assessments in the kicking task. Additionally, new studies using OpenPose or other neural networks for human pose detection, with the use of a greater number of cameras to capture images, may be necessary to reduce measurement error and maintaining a more ecological approach to the kicking task.

5 Conclusion

The study concluded that although the demonstration of instructional videos acutely improves the last stride length of young soccer players, it is not possible to modify the ball speed, foot speed and the distance of the foot supporting the ball at the moment. kick sharply. Furthermore, the power of the sample is not sufficient to extrapolate the results to the population.

6 Contributions

Contributed to conception and design: AGC, PRPS; Contributed to acquisition of data: AGC, RLMM, CCAS, AKT; Contributed to analysis and interpretation of data: AGC, RLMM, CCAS, AKT, PRPS; Drafted and/or revised the article: AGC, RLMM, CCAS, AKT, PRPS; Approved the submitted version for publication: AGC, RLMM, CCAS, AKT, PRPS.

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References

[1] Adrian Lees, Takeshi Asai, T Bull Andersen, Hiroyuki Nunome, and Thorsten Sterzing. The biomechanics of kicking in soccer: A review. *Journal of sports sciences*, 28(8):805–817, 2010. doi: 10.1080/02640414.2010.481305.

[2] T Asai, MJ Carré, T Akatsuka, and SJ Haake. The curve kick of a football i: impact with the foot. *Sports Engineering*, 5(4):183–192, 2002. doi: 10.1046/j.1460-2687.2002.00108.x.

[3] T Bull Andersen. Collisions in soccer kicking. *Sports Engineering*, 2(2):121–125, 1999. doi: 10.1046/j.1460-2687.1999.00015.x.

[4] Adrian Lees and Lee Nolan. The biomechanics of soccer: a review. *Journal of sports sciences*, 16 (3):211–234, 1998. doi: 10.1080/026404198366740.

[5] JACOB Levanon and JESÚS Dapena. Comparison of the kinematics of the full-instep and pass kicks in soccer. *Medicine and science in sports and exercise*, 30(6):917–927, 1998. doi: 10.1097/00005768-199806000-00022.

[6] Henrik Carlheim Dörge, T Bull Andersen, Henrik Sørensen, and Erik Bruun Simonsen. Biomechanical differences in soccer kicking with the preferred and the non-preferred leg. *Journal of sports sciences*, 20(4):293–299, 2002. doi: 10.1080/026404102753576062.

[7] G Markovic, D Dizdar, and S Jaric. Evaluation of tests of maximum kicking performance. *Journal of sports medicine and physical fitness*, 46(2):215, 2006.

[8] J Sinclair, D Fewtrell, Paul John Taylor, Stephen Atkins, Lyndsey Bottoms, and Sarah Jane Hobbs. Three-dimensional kinematic differences between the preferred and non-preferred limbs during maximal instep soccer kicking. *Journal of sports sciences*, 32(20):1914–1923, 2014. doi: 10.1080/02640414.2014.965188.

[9] Luiz H Palucci Vieira, Vitor L de Andrade, Rodrigo L Aquino, Renato Moraes, Fabio A Barbieri, Sérgio A Cunha, Bruno L Bedo, and Paulo R Santiago. Construct validity of tests that measure kick performance for young soccer players based on cluster analysis: exploring the relationship between coaches rating and actual measures. *The Journal of sports medicine and physical fitness*, 57(12):1613—1622, December 2017. doi: 10.23736/S0022-4707.16.06863-8.

[10] Adrian Lees, Liam Kershaw, and Felipe Moura. The three-dimensional nature of the maximal instep kick in soccer. In *Reilly T, Cabri J, organizers. Science and football: the proceedings of the Fifth World Congress on Science and Football. London: Routledge*, pages 65–70, 2005.

[11] Alen Kapidžić, Tarik Huremović, and Alija Biberovic. Kinematic analysis of the instep kick in youth soccer players. *Journal of human kinetics*, 42(1):81–90, 2014. doi: 10.2478/hukin-2014-0063.

[12] Ryuji Kawamoto, Osamu Miyagi, Jiro Ohashi, and Senshi Fukashiro. Kinetic comparison of a side-foot soccer kick between experienced and inexperienced players. *Sports Biomechanics*, 6(2): 187–198, 2007. doi: 10.1080/14763140701324966.

[13] Neil J Cronin. Using deep neural networks for kinematic analysis: Challenges and opportunities. *Journal of Biomechanics*, 123:110460, 2021. doi: 10.1016/j.jbiomech.2021.110460.

[14] Zhe Cao, Tomas Simon, Shih-En Wei, and Yaser Sheikh. Realtime multi-person 2d pose estimation using part affinity fields. pages 7291–7299, 2017. doi: 10.48550/arXiv.1611.08050.

[15] Karl M Newell, PN Kugler, Robert EA Van Emmerik, and PV McDonald. Search strategies and the acquisition of coordination. In *Advances in psychology*, volume 61, pages 85–122. Elsevier, 1989.

[16] John Komar, François Potdevin, Didier Chollet, and Ludovic Seifert. Between exploitation and exploration of motor behaviours: unpacking the constraints-led approach to foster nonlinear learning in physical education. *Physical Education and Sport Pedagogy*, 24(2):133–145, 2019. doi: 10.1080/17408989.2018.1557133.

[17] Karl M Newell and Rajiv Ranganathan. Instructions as constraints in motor skill acquisition. In *Motor learning in practice*, pages 37–52. Routledge, 2010.

[18] Charley W Lafe and Karl M Newell. Instructions on task constraints mediate perceptual-motor search and how movement variability relates to performance outcome. *Journal of Motor Behavior*, 54(6):669–685, 2022. doi: 10.1080/00222895.2022.2063787.

[19] N Hagemann and D NIEMMERT. Coaching anticipatory skill, in e3 ad minton: Laboratory versus rield. based perceptual training. *Journal of Human Movement Studies*, 50:381–398, 2006.

[20] Saleh A Al-Abood, Keith Davids, and Simon J Bennett. Specificity of task constraints and effects of visual demonstrations and verbal instructions in directing learners' search during skill acquisition. *Journal of motor behavior*, 33(3):295–305, 2001. doi: 10.1080/00222890109601915.

[21] Robert R Horn, A Mark Williams, and Mark A Scott. Learning from demonstrations: the role of visual search during observational learning from video and point-light models. *Journal of Sports Sciences*, 20(3):253–269, 2002.

[22] Nicola J Hodges, Spencer J Hayes, Daniel L Eaves, Robert R Horn, A Mark Williams, et al. End-point trajectory matching as a method for teaching kicking skills. *International Journal of Sport Psychology*, 37(2/3):230–247, 2006.

[23] Matheus M Pacheco, Luiz MM de Oliveira, Carlos CA dos Santos, José RM Godoi Filho, and Ricardo Drews. Challenging traditions: Systematic review of practice, instruction, and motor skill acquisition in soccer. *International Journal of Sports Science & Coaching*, page 17479541231168930, 2023. doi: 10.1177/17479541231168930.

[24] Luiz H Palucci Vieira, Paulo RP Santiago, Allan Pinto, Rodrigo Aquino, Ricardo da S Torres, and Fabio A Barbieri. Automatic markerless motion detector method against traditional digitisation for 3-dimensional movement kinematic analysis of ball kicking in soccer field context. *International journal of environmental research and public health*, 19(3):1179, 2022. doi: 10.3390/ijerph19031179.

[25] Pascual Marqués-Bruna, Adrian Lees, and Paul Grimshaw. Structural principal components analysis of the kinematics of the soccer kick using different types of rating scales. *International Journal of Sports Science & Coaching*, 3(1):73–85, 2008. doi: 10.1260/174795408784089423.

[26] George C. Urbaniak and Scott Plous. Research randomizer (version 4.0). Computer software, 2013. Retrieved on June 22, 2013, from `http://www.randomizer.org/`.

[27] RML de Barros, René Brenzikofer, NJ Leite, and Pascual J Figueroa. Desenvolvimento e avaliação de um sistema para análise cinemática tridimensional de movimentos humanos. *Research on Biomedical Engineering*, 15(1-2):79–86, 2011.

[28] Pascual J Figueroa, Neucimar J Leite, and Ricardo ML Barros. A flexible software for tracking of markers used in human motion analysis. *Computer methods and programs in biomedicine*, 72 (2):155–165, 2003. doi: 10.1016/s0169-2607(02)00122-0.

[29] Alexander Mathis, Pranav Mamidanna, Kevin M Cury, Taiga Abe, Venkatesh N Murthy, Mackenzie Weygandt Mathis, and Matthias Bethge. Deeplabcut: markerless pose estimation of user-defined body parts with deep learning. *Nature neuroscience*, 21(9):1281–1289, 2018. doi: 10.1038/s41593-018-0209-y.

[30] Tanmay Nath, Alexander Mathis, An Chi Chen, Amir Patel, Matthias Bethge, and Mackenzie Weygandt Mathis. Using deeplabcut for 3d markerless pose estimation across species and behaviors. *Nature protocols*, 14(7):2152–2176, 2019. doi: 10.1038/s41596-019-0176-0.

[31] B D McLean and D M Tumilty. Left-right asymmetry in two types of soccer kick. *British Journal of Sports Medicine*, 27(4):260–262, 1993. doi: 10.1136/bjsm.27.4.260.

[32] Heidi Orloff, Bryce Sumida, Janna Chow, Lalae Habibi, Aaron Fujino, and Brian Kramer. Ground reaction forces and kinematics of plant leg position during instep kicking in male and female collegiate soccer players. *Sports Biomechanics*, 7(2):238–247, 2008. doi: 10.1080/14763140701841704.

[33] Fabio Augusto Barbieri, Lilian Teresa Bucken Gobbi, Paulo Roberto Pereira Santiago, and Sergio Augusto Cunha. Dominant–non-dominant asymmetry of kicking a stationary and rolling ball in a futsal context. *Journal of sports sciences*, 33(13):1411–1419, 2015. doi: 10.1080/02640414.2014.990490.

[34] Daniel Juárez, Cristina Lopez de Subijana, Javier Mallo, and Enrique Navarro. Acute effects of endurance exercise on jumping and kicking performance in top-class young soccer players. *European Journal of Sport Science*, 11(3):191–196, 2011. doi: 10.1080/17461391.2010.500335.

[35] Athanasios Katis, Eleftherios Kellis, and Adrian Lees. Age and gender differences in kinematics of powerful instep kicks in soccer. *Sports Biomechanics*, 14(3):287–299, 2015. doi: 10.1080/14763141.2015.1056221.

[36] Fabio Milioni, Luiz HP Vieira, Ricardo A Barbieri, Alessandro M Zagatto, Nikolai B Nordsborg, Fabio A Barbieri, Júlio W Dos-Santos, Paulo RP Santiago, and Marcelo Papoti. Futsal match-related fatigue affects running performance and neuromuscular parameters but not finishing kick speed or accuracy. *Frontiers in physiology*, 7:518, 2016. doi: 10.3389/fphys.2016.00518.

[37] Luiz HP Vieira, Sérgio A Cunha, Renato Moraes, Fabio A Barbieri, Rodrigo Aquino, Lucas de P Oliveira, Martina Navarro, Bruno LS Bedo, and Paulo RP Santiago. Kicking performance in young u9 to u20 soccer players: Assessment of velocity and accuracy simultaneously. *Research Quarterly for Exercise and Sport*, 89(2):210–220, 2018. doi: 10.1080/02701367.2018.1439569.

[38] Tommy Apriantono, Hiroyuki Nunome, Yasuo Ikegami, and Shinya Sano. The effect of muscle fatigue on instep kicking kinetics and kinematics in association football. *Journal of sports sciences*, 24(9):951–960, 2006. doi: 10.1080/02640410500386050.

[39] Yousset I Abdel-Aziz, Hauck Michael Karara, and Michael Hauck. Direct linear transformation from comparator coordinates into object space coordinates in close-range photogrammetry. *Photogrammetric engineering & remote sensing*, 81(2):103–107, 2015. doi: 10.14358/PERS.81.2.103.

[40] Franz Faul, Edgar Erdfelder, Albert-Georg Lang, and Axel Buchner. G* power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior research methods*, 39(2):175–191, 2007. doi: 10.3758/bf03193146.

[41] Jie Zhao, Qian Gu, Shuo Zhao, and Jie Mao. Effects of video-based training on anticipation and decision-making in football players: A systematic review. *Frontiers in Human Neuroscience*, page 781, 2022. doi: 10.3389/fnhum.2022.945067.

[42] Felippe da Silva Leite Cardoso, José Afonso, André Roca, and Israel Teoldo. The association between perceptual-cognitive processes and response time in decision making in young soccer players. *Journal of Sports Sciences*, 39(8):926–935, 2021. doi: 10.1080/02640414.2020.1851901.

[43] Leonardo S Fortes, Sebastião S Almeida, Gibson M Praça, José RA Nascimento-Júnior, Dalton Lima-Junior, Bruno Teixeira Barbosa, and Maria EC Ferreira. Virtual reality promotes greater improvements than video-stimulation screen on perceptual-cognitive skills in young soccer athletes. *Human Movement Science*, 79:102856, 2021. doi: 10.1016/j.humov.2021.102856.

[44] João Vítor de Assis, Varley Costa, Filipe Casanova, Felippe Cardoso, and Israel Teoldo. Visual search strategy and anticipation in tactical behavior of young soccer players. *Science and Medicine in Football*, 5(2):158–164, 2021. doi: 10.1080/24733938.2020.1823462.

[45] Ruud JR Den Hartigh, Steffie Van Der Steen, Bas Hakvoort, Wouter GP Frencken, and Koen APM Lemmink. Differences in game reading between selected and non-selected youth soccer players. *Journal of sports sciences*, 36(4):422–428, 2018. doi: 10.1080/02640414.2017.1313442.

[46] Mohamed A Souissi, Yousri Elghoul, Hichem Souissi, Liwa Masmoudi, Achraf Ammar, Nizar Souissi, et al. The effects of three correction strategies of errors on the snatch technique in 10–12-year-old children: A randomized controlled trial. *The Journal of Strength & Conditioning Research*, 2022. doi: 10.1519/JSC.0000000000003707.

[47] Marcelo Eduardo de Souza Nunes, Umberto Cesar Correa, Marina Gusman Thomazi Xavier de Souza, and Suely Santos. Descriptive versus prescriptive feedback in the learning of golf putting by older persons. *International Journal of Sport and Exercise Psychology*, 19(4):709–721, 2021. doi: 10.1080/1612197X.2020.1717579.

[48] Joao AC Barros, Zachary D Yantha, Michael J Carter, Julia Hussien, and Diane M Ste-Marie. Examining the impact of error estimation on the effects of self-controlled feedback. *Human movement science*, 63:182–198, 2019. doi: 10.1016/j.humov.2018.12.002.

[49] Marjan Kok, Annet Komen, Laurien van Capelleveen, and John van der Kamp. The effects of self-controlled video feedback on motor learning and self-efficacy in a physical education setting: an exploratory study on the shot-put. *Physical Education and Sport Pedagogy*, 25(1):49–66, 2020. doi: 10.1080/17408989.2019.1688773.

[50] Mohamed Ibrahim, Pavlo D Antonenko, Carmen M Greenwood, and Denna Wheeler. Effects of segmenting, signalling, and weeding on learning from educational video. *Learning, media and technology*, 37(3):220–235, 2012. doi: 10.1080/17439884.2011.585993.

[51] Stephan Schwan and Roland Riempp. The cognitive benefits of interactive videos: Learning to tie nautical knots. *Learning and instruction*, 14(3):293–305, 2004. doi: 10.1016/j.learninstruc.2004.06.005.

[52] Wayne Leahy and John Sweller. Cognitive load theory, modality of presentation and the transient information effect. *Applied cognitive psychology*, 25(6):943–951, 2011. doi: 10.1002/acp.1787.

[53] Richard E Mayer and Roxana Moreno. Nine ways to reduce cognitive load in multimedia learning. *Educational psychologist*, 38(1):43–52, 2003. doi: 10.1207/S15326985EP3801_6.

[54] BD McLean and DM Tumilty. Left-right asymmetry in two types of soccer kick. *British Journal of Sports Medicine*, 27(4):260–262, 1993. doi: 10.1136/bjsm.27.4.260.

[55] Martina Navarro, John van der Kamp, Ronald Ranvaud, and Geert JP Savelsbergh. The mere presence of a goalkeeper affects the accuracy of penalty kicks. *Journal of sports sciences*, 31(9): 921–929, 2013. doi: 10.1080/02640414.2012.762602.

[56] David L Anderson and Ben Sidaway. Coordination changes associated with practice of a soccer kick. *Research quarterly for exercise and sport*, 65(2):93–99, 1994. doi: 10.1080/02701367.1994.10607603.

[57] Lois Rodríguez-Lorenzo, Miguel Fernández-Del Olmo, José Andrés Sánchez-Molina, and Rafael Martín-Acero. Kicking ability and kicking deficit in young elite soccer players. *Kinesiology*, 50 (2):194–203, 2018. doi: 10.26582/k.50.2.2.

[58] Ali Onur Cerrah, Deniz Şimsek, Abdullah Ruhi Soylu, Hiroyuki Nunome, and Hayri Ertan. Developmental differences of kinematic and muscular activation patterns in instep soccer kick. *Sports Biomechanics*, pages 1–16, 2020. doi: 10.1080/14763141.2020.1815827.

[59] Neil J Cronin, Timo Rantalainen, Juha P Ahtiainen, Esa Hynynen, and Ben Waller. Markerless 2d kinematic analysis of underwater running: A deep learning approach. *Journal of biomechanics*, 87:75–82, 2019. doi: 10.1016/j.jbiomech.2019.02.021.

[60] Alexander Mathis, Steffen Schneider, Jessy Lauer, and Mackenzie Weygandt Mathis. A primer on motion capture with deep learning: principles, pitfalls, and perspectives. *Neuron*, 108(1):44–65, 2020. doi: 10.1016/j.neuron.2020.09.017.