IN SEARCH OF INDIVIDUALLY OPTIMAL MOVEMENT SOLUTIONS IN SPORT: LEARNING BETWEEN STABILITY AND FLEXIBILITY

EDITED BY: Ana Filipa Silva, John Komar and Ludovic Seifert

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IN SEARCH OF INDIVIDUALLY OPTIMAL MOVEMENT SOLUTIONS IN SPORT: LEARNING BETWEEN STABILITY AND FLEXIBILITY

Topic Editors:
Ana Filipa Silva, Polytechnic Institute of Maia, Portugal
John Komar, Nanyang Technological University, Singapore
Ludovic Seifert, Université de Rouen, France

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Table of Contents

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Editorial: Search of Individually Optimal Movement Solutions in Sport: Learning Between Stability and Flexibility

Ana F. Silva [1,2]*, *John Komar* [3] *and Ludovic Seifert* [4]

[1] N2i, Polytechnic Institute of Maia, Maia, Portugal, [2] The Research Centre in Sports Sciences, Health Sciences and Human Development (CIDESD), Vila Real, Portugal, [3] National Institute of Education, Nanyang Technological University, Singapore, [4] Cetaps EA3832, Faculty of Sport Sciences, University of Rouen, Normandie, France

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Editorial on the Research Topic

Search of Individually Optimal Movement Solutions in Sport: Learning Between Stability and Flexibility

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Miguel-Angel Gomez-Ruano, Polytechnic University of Madrid, Spain

****Correspondence:***
Ana F. Silva
anafilsilva@gmail.com

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INTRODUCTION

We have always been fascinated by how complex skills are learned and stabilized by experts. Although motor learning has been seen for long merely as a process of stabilization of an optimal solution, it has been recently described that many pathways could be outlined to attain expertise in sports. Recent studies suggested that early specialization could lead to a lack of perceptual-motor adaptability, i.e., difficulties in how performers become attuned to affordances (opportunities for action). Thus, it has been argued that expert performance requires a subtle balance between movement stability and flexibility (Seifert et al., 2013, 2016). The ecological dynamics framework offers a rich, unifying perspective to understand and explain sports performance, providing an innovative perspective on talent development and motor learning, highlighting a nuanced transitioning between specificity and generality of practice and transfer, as needed by each individual (Button et al., 2020). This Research Topic included studies on talent development to achieve sport expertise, motor learning and interventions. It particularly explores the functional role of variability in searching for an individually optimal movement solution. Contributions were classified as: (i) variability as skill adaptation, flexibility, and discuss about adaptability, (ii) variability as individual movement solution, and (iii) variability in interventions, practice, and pedagogy.

VARIABILITY AS SKILL ADAPTATION/ADAPTABILITY/FLEXIBILITY

The challenge in sports performance is to sort what is a "good" (functional) from "bad" (dysfunctional) variability (Latash et al., 2010). To achieve that, not only an expert movement but sports intelligence has been a central concern. Hristovski and Balagué proposed a theory of cooperative-competitive intelligence (CCI) based on: (i) relativity of functional entropy/information in agent (team) environment; (ii) tendency toward the satisficing level of diversity/uncertainty potential; and (iii) tendency toward the non-decreasing potential.

When comparing experts to non-experts, it was showed that all swimming levels were able to change the movement pattern (swim pace), but high-level swimmers exhibited a broader functional adaptation in force parameters (Schnitzler et al.). Also, in karate, it was observed that experts were unable to repeat the kinematics of a front kick movement (Burdack et al.). However, with fatigue, the short-term movement-patterns does not change, only the overall kinematic movement pattern. Indeed, Woods et al., in Australian football, highlighted the relevance to understand affordances to regulate performance behaviors, as they occur according to an ecological approach, being the skilled behavior a functionally adaptable performance solution that arise from the continuous interactions with the environment (Araújo and Davids, 2011). Those sport specific analysis allow coaches to guide learning, understanding the important parameters affecting higher performance levels. Indeed, in baseball it was found that the elevation pitching angle and speed significantly influenced the vertical pitch location, and the azimuth pitching angle significantly influenced the horizontal pitch location (Kusafuka et al.).

VARIABILITY AS INDIVIDUAL MOVEMENT SOLUTION

The existence of individual movement responses has been strongly identified as a hallmark of skilled performance and learning with the growing emphasis of the constraints model from Newell (1986). This aspect has been recently emphasized due to advancements in data analytics that can handle large and multivariate data set and can account for both inter- and intra-individual differences in movement behavior. Using a support vector machine technique, Horst et al. effectively identified a strong individual component in throwing patterns. This is highlighted in various throwing disciplines, although at different degrees depending on the discipline (e.g., stronger individuality in shot put and discus than in javelin). This observation is discussed also by Ranganathan et al. highlighting that different sport skills have dissimilar demands for behavioral flexibility. Athletes with greater flexibility are capable of showing more diverse movement solutions, therefore would be more likely to find his/her own optimal individual solution. However, too much flexibility may impair performance if the task or environmental constraints are less dynamic.

Ranganathan et al. propose to revisit the famous quote from Bernstein (1967) "repetition without repetition" to highlight the key role of movement flexibility in behavioral adaptability but also for learning. In that view, an optimal movement solution can actually refer to an optimal level of movement flexibility (i.e., in addition to the more common consistency and efficiency criteria). This is highlighted by Fernández-Valdés et al. who identified that the increase in performance during a 6 weeks practice appeared during a plateau of variability, somehow during an optimal movement variability, before the task constraints become too predictable therefore not requiring adaptive flexibility anymore. This result precisely highlights a key moment in training and learning when the task constraint may need to evolve to challenge again flexibility of individual movement solutions.

VARIABILITY IN INTERVENTION, PRACTICE, AND PEDAGOGY

Three different forms of variability could be induced during pedagogical intervention: intrinsic, structured and unstructured (Ranganathan and Newell, 2013). During constant practice, variability is intrinsic to motor system, but often insufficient for learners to leave their initial stables states. Thus, structured variability could be used to guide perceptual attunement, so less useful information becomes unreliable during learning (Fajen and Devaney, 2006), resulting in better performances in transfer tasks instead of constant practices (Huet et al., 2011). Schöllhorn et al. (2009) proposed to add unstructured variability to practice at the level of multiple task parameters. To investigate how unstructured variability can enhance motor learning, Tassignon et al. performed a meta-analytic review on the empirical evidence of differential learning. However, given the large amount of heterogeneity, limited number of studies, low sample sizes, low statistical power, possible publication bias, and high risk of bias in general, the authors concluded that inferences about the effectiveness of differential learning would be premature. Even though differential learning shows potential to result in greater average improvements between pre- and post/retention test compared to non-variability-based motor learning methods, more high-quality research is needed before issuing such a statement.

As virtual reality (VR) becomes more popular in cognitive sciences, scientists could be tempted to use it to design variable practice. In the study of Drew et al., VR training showed to impair real-world task performance, suggesting that virtual environments may offer different learning constraints. These results emphasize the need to better understand how some elements of VR environments detract from transfer of an acquired sport skill to the real world.

Otte et al. developed a Periodization of Skill Training (PoST) framework, to propose a model that aims to support practitioners' understanding of the pedagogical constraints of feedback and instruction during practice. In this "hypothesis and theory" article, the PoST framework attempted to guide practitioners on how and when to apply different verbal instruction methodologies and aim to support the design of effective skill learning environments.

In conclusion, it appears from this topic that searching for optimality of movement in sport requires the consideration of the functional role of movement variability, through the lens of flexibility and adaptability. However, looking at movement variability strongly depends on what is considered as a stable movement solution, where stability should be understood at an individual level and therefore an optimal stable movement for one athlete may not be optimal for another athlete. Then, if both reaching expertise requires to develop adaptability to dynamic environments as well as an highly individual stable solution, the path to expertise should also consider this functional role of variability in order to facilitate the search for an individually optimal but adaptable motor solution. Looking at this perspective where functional variability plays a role both in the outcome of learning as well as in the process of learning opens a renewed view on key topics in movement and sport science. For instance, could adaptability of athletes better predict future performance, to inform talent identification. Another key direction relates to injury prevention; Could training methods that promote the infusion of variability better prevent injuries?

AUTHOR CONTRIBUTIONS

All authors contributed in the editing the papers received as well as in the Editorial manuscript, both in conceptualization and in writing.

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Influence of Release Parameters on Pitch Location in Skilled Baseball Pitching

Ayane Kusafuka[1], Hirofumi Kobayashi[1], Takeshi Miki[1], Masumi Kuwata[1], Kazutoshi Kudo[1], Kimitaka Nakazawa[1] and Shinji Wakao[2]*

[1] Department of Life Science, Graduate School of Arts and Sciences, The University of Tokyo, Tokyo, Japan, [2] Department of Science and Engineering, Waseda University, Tokyo, Japan

This study explored the mechanical factors that determine accuracy of a baseball pitching. In particular, we focused on the mechanical parameters at ball release, referred to as release parameters. The aim was to understand which parameter has the most deterministic influence on pitch location by measuring the release parameters during actual pitching and developing a simulation that predicts the pitch location from given release parameters. By comparing the fluctuation of the simulated pitch location when varying each release parameter, it was found that the elevation pitching angle and speed significantly influenced the vertical pitch location, and the azimuth pitching angle significantly influenced the horizontal pitch location. Moreover, a regression model was obtained to predict the pitch location, and it became clear that the significant predictors for the vertical pitch location were the elevation pitching angle, the speed, and spin axis, and those for the horizontal pitch location were the azimuth pitching angle, the spin axis, and horizontal release point. Therefore, it was suggested that the parameter most affecting pitch location weas pitching angle. On the other hand, multiple regression analyses revealed that the relation between release parameters varied between pitchers. The result is expected to contribute to an understanding of the mechanisms underlying accurate ball control skill in baseball pitching.

Keywords: baseball, pitch location, release parameter, accuracy, simulation

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Polytechnic Institute of Maia, Portugal

Reviewed by:
Uday C. H. Hasan,
Al-Kitab University, Iraq
Chiang Liu,
University of Taipei, Taiwan
Tomoyuki Nagami,
Kitasato University, Japan

***Correspondence:**
Ayane Kusafuka
ayane422@g.ecc.u-tokyo.ac.jp

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INTRODUCTION

In various sport-related motor skills, such as throwing, kicking, and hitting, accurately controlling an object (typically a ball) to a target position is one of the most important skills. In this skill, there is a difference in performance, i.e., reproducibility of the ball arrival position, even among experts (Kawamura et al., 2017). The flight trajectory and final arrival position of the ball are physically determined by its state at the time of release or impact. For example, in baseball pitching, these are determined by the combination of nine mechanical ball parameters at release, referred to as release parameters. If the state at the time of release is always the same, the ball will always arrive at the same position. Therefore, the accuracy of final pitch location of the ball can be expected to be improved by increasing the reproducibility of release movements as much as possible. However, it is known that there is always variability in the release parameters, even for skilled players (Faisal et al., 2008).

It is also known that the choice of values of release parameters varies widely between different pitchers, even if the same position is targeted (Jinji and Sakurai, 2006; Nagami et al., 2011). As there are countless combinations of values of release parameters that achieve the same pitch location, i.e., there is redundancy, if a combination satisfies the desired conditions, then the pitcher can select various values of release parameters. However, considering the variability of release parameters, not all combinations can be considered equivalent.

The relationship between parameters influencing the results of movements have been evaluated in previous studies. The relation in which each parameter does not vary independently each time, but fluctuates while maintaining a relationship that compensates for the variability of other parameters has been reported. This is considered to be the best method, which is used by some skilled players, for improving accuracy of the arrival position without increasing reproducibility. The existence of such "compensatory coordination" which contributes to the stability of performance has been reported using many constrained virtual tasks (Müller and Loosch, 1999; Scholz and Schöner, 1999; Cohen and Sternad, 2012) and two-dimensional movements (relatively simple, not including torsion) (Kudo et al., 2000; Nasu et al., 2014).

Some sports skills, such as baseball pitching, involve more parameters for determining the arrival position than the number used in previous studies. In baseball pitching, it has been shown that the spin rate, which is the number of times the ball rotates per unit time, and the spin axis, which is the orientation of the ball rotation, differs between pitchers, and contribute to the ball trajectory in addition to the release position and release velocity vector (Jinji and Sakurai, 2006; Nagami et al., 2011). Considering that there is variability in each parameter and control of all parameters is necessary to realize accurate pitching, a question arises about the weighting; that is, which of the parameters is most dominant in determining pitch location. When more parameters are involved in the pitch location, their contribution to the pitch location may vary depending on their values. However, in previous studies, only a few parameters have been considered in combination, and it is not clear which parameter has the greatest influence on pitch location. Therefore, it is considered necessary to investigate the parameters independently first before considering their combination.

The purpose of this study was to investigate the degrees of influence of each baseball pitching release parameter on pitch location. In addition to the release point and the velocity vector used in the previous studies that performed the throwing task (Kudo et al., 2000; Nasu et al., 2014), the spin rate and the spin axis are important in pitching (Jinji and Sakurai, 2006; Nagami et al., 2011), and were used as release parameters. We created a simulation for pitch location prediction based on the release parameters and calculated the pitch location when each parameter is changed individually in actual examined ranges of baseball pitching. Comparing the magnitude of the fluctuation, it became clear which parameter influences the pitch location most. In previous studies, to find the most important kinematic variables that contribute to achieving a greater throw distance, regression prediction equations were used (Uday, 2019). Therefore, in addition to simulation analysis, in this study a regression model was obtained to predict the pitch location.

MATERIALS AND METHODS

Measuring Data

Seven skilled baseball pitchers participated (sex: male; age: 28.1 ± 9.9 years; height: 175.9 ± 5.1 cm; body mass: 76.5 ± 3.5 kg; 6 right-handed and 1 left-handed), including one former professional pitcher from the NPB (Nippon Professional Baseball; Japan's top baseball league). They pitched 30 fastballs on the mound in an indoor stadium and were instructed to aim at the catcher's mitt, which was 90 cm above the ground, 40 cm outside from the center of home base (outside is defined based on the same side batters, e.g., a right-handed batter in case of a right-handed pitcher), and 50 cm behind home base. The data of 187 pitches were obtained, excluding data in which measurement errors occurred. The release parameters were measured using TrackMan Baseball (TRACKMAN). TrackMan Baseball detected release timing and the release parameters were taken. For the measurement of pitch location, a DV camera (Panasonic HC-V 100 M, Japan) was installed 7–8 m in front of home base, and the moment when the catcher caught the ball was photographed from the front side of the catcher (30 Hz). To obtain the position coordinates, we calibrated 3 points in the horizontal direction (1.5 m intervals) and 5 points in the vertical direction (0.5 m intervals) on the plane, giving a total of 15 calibration points for the catching position. The calibration points were digitized using numerical analysis software (MATLAB, Mathworks, Japan), and the average standard error was set to 1.0 cm or less. The position coordinates of the pitch location were calculated by digitizing the center point of the ball at the moment of catching and by using direct linear transformation. All participants provided informed consent, and the study was performed in accordance with the Declaration of Helsinki and with the approval of the ethics committee of the University of Tokyo.

Simulation Analysis

To create a simulation for pitch location prediction, it was necessary to consider the mechanical elements acting on the ball at release. The three-dimensional orthogonal coordinates were defined as follows; the origin was taken as the center of the pitcher plate on the mound, the orientation of the x axis was in the direction of home base, the y axis was oriented vertically upwards, and the z axis was oriented in the third base direction (**Figure 1A**). Release parameters were defined based on this coordinate system. The pitching angle of the ball was given by the elevation angle $\theta 1$ ($-90°$ to $90°$) and the azimuth angle $\theta 2$ ($-90°$ to $90°$) in polar coordinates, and the rotation axis angle of the ball was given by the elevation angle $\theta 3$ ($-90°$ to $90°$) and azimuth angle $\theta 4$ ($-180°$ to $180°$) (**Figure 1B**). $\theta 1$ was the angle between the projection of the velocity on the x-y plane and the x-axis, and $\theta 2$ was the angle between the projection of the velocity on the x-z plane and the x-axis. $\theta 3$ was the angle between the projection of the spin axis on the y-z plane and the z-axis, and $\theta 4$ was the angle between the projection of the spin axis on the x-z plane and the z-axis. The positive direction of $\theta 1$ and $\theta 3$

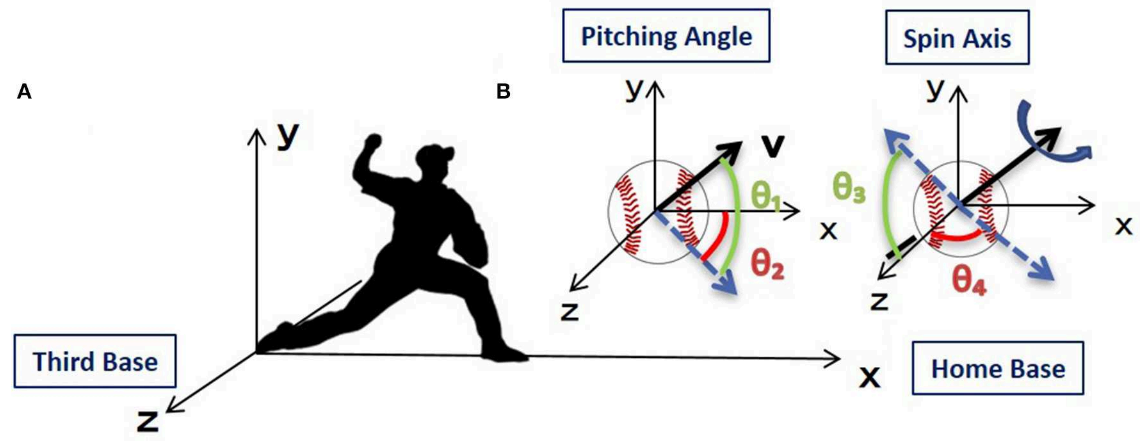

FIGURE 1 | Three-dimensional orthogonal coordinate setup in this study. **(A)** The x axis runs from the mound toward home base, the y axis runs vertically upwards from the ground, and the z axis runs from the first base to the third base. The origin is the center of the plate on the mound. **(B)** The pitching angle is shown by the elevation angle θ_1 (ranging from −90° to 90°) and azimuth angle θ_2 (ranging from −90° to 90°), and the spin axis is shown by the elevation angle θ_3 (ranging from −90° to 90°) and the azimuth angle θ_4 (ranging from −90° to 90°).

was defined as upward direction, the positive direction of θ2 was defined as the direction of third base, and the positive direction of θ4 was defined as forward direction. Speed was defined as the magnitude of velocity vector, and spin rate was defined as the number of times the ball rotates per unit time.

Next, an equation of motion was set based on the coordinate axes, as follows. Generally, drag (F_d) and lift (F_l) are expressed as follows.

$$\begin{cases} F_d = \frac{1}{2}\rho S V^2 C_d \\ F_l = \frac{1}{2}\rho S V^2 C_l \end{cases} \tag{1}$$

where ρ (= 1.2 kg/m^3) represents air density, S (= 4.3 × 10^{-3} m^2) is the sectional area of the ball, and V is the velocity magnitude. C_d (= 0.35) and C_l (= (πS) 0.5 × spin rate/2) are the drag coefficient and lift coefficient, respectively, which are the same as those reported in (Kray et al., 2012).

When the spin axis of the ball is perpendicular to the traveling direction, the drag increases as the speed of the ball increases, and the lift increases as the rotation speed increases. When the spin axis is not perpendicular to the traveling direction, the lift force is perpendicular to both the traveling direction and spin axis, which means the lift force can be represented by the cross product of the traveling direction and spin axis of the ball. From the above discussion, the equation of motion of the ball considering drag and lift can be expressed as follows.

$$m\begin{bmatrix} \frac{d^2x}{dt^2} \\ \frac{d^2y}{dt^2} \\ \frac{d^2z}{dt^2} \end{bmatrix} = \frac{1}{2}\rho SV\left(-Cd\begin{bmatrix} \frac{dx}{dt} \\ \frac{dy}{dt} \\ \frac{dz}{dt} \end{bmatrix} + Cl\frac{H}{V}\begin{bmatrix} \frac{dx}{dt} \\ \frac{dy}{dt} \\ \frac{dz}{dt} \end{bmatrix} \times \begin{bmatrix} ax \\ ay \\ az \end{bmatrix}\right) + \begin{bmatrix} 0 \\ -mg \\ 0 \end{bmatrix} \tag{2}$$

where m (= 0.145 kg) is the mass of the ball, H is the magnitude of the cross product of speed and spin axis, and g (= 9.81 m/s^2) is gravitational acceleration.

a_x, a_y, and a_z are the rotational shaft angles of the ball as follows:

$$\begin{cases} a_x = \cos\theta 3 \sin\theta 4 \\ a_y = \sin\theta 3 \\ a_z = \cos\theta 3 \cos\theta 4 \end{cases} \tag{3}$$

At this time, the equation of motion can be viewed as a second order differential equation with time t as a variable. The pitch location of the ball can be calculated by solving this equation of motion as an initial value problem of a differential equation. However, it is not possible to solve the equation algebraically if specific functions, such as the pitching trajectory, are not determined. Therefore, it is necessary to approximate the pitching trajectory through a numerical analysis. In this study, the Dormand–Prince method (Dormand and Prince, 1986) was applied. The specific calculation formula used in this study was the same as that used in (Kimura, 2009). By using this numerical analysis method, the change in position of the ball was calculated at every moment, and the calculation was repeated until the ball reached the catcher. To summarize the above, the following release parameters are used as initial conditions: release point (x, y, z), ball speed (v), pitching angle (θ1, θ_2), spin rate (n), and spin axis (θ3, θ4). The pitch location (y, z), which was 50 cm behind home base in this study, is calculated based on these parameters and numerical analysis. Due to the limited functionality of TrackMan Baseball, it was not possible to measure the horizontal spin axis (θ4); thus, its simulated value was set to a constant of 30° because several studies (Jinji and Sakurai, 2006; Nagami et al., 2011) have shown that the mean values of the horizontal spin axis are 26–33°.

The variation in pitch location was simulated while varying each parameter individually. Each parameter was varied from its minimum to the maximum value for each pitcher, and the other parameters were fixed to the average for each pitcher. The results indicated that the larger the variation in the pitch location is, the higher the possibility that the pitch location is changed by the parameter.

Multiple Regression Analysis

In addition to simulation analysis, a regression model was obtained to predict the pitch location. By backward-forward stepwise multiple regression analysis, the explanatory rate of the pitch location of each release parameter was calculated. This method finds the optimal combination of explanatory variables by reducing the number of explanatory variables from the most complex model (using all explanatory variables). If there is parameter whose p value is larger than 0.05, the parameter was reduced from the model. The regression was run separately for each pitcher. We used MATLAB to find a regression model with a coefficient of determination as close to 1 as possible.

RESULTS

Variation in Pitch Location When Release Parameters Are Changed

The mean speed of the ball in this study was 32.6 ± 2.2 m/s, whereas it was 33.8 ± 1.7 m/s in Jinji and Sakurai (2006) and 37.7 ± 1.2 m/s in Nagami et al. (2011). The mean spin rate was 29.0 ± 2.8 rps, whereas it was 31.4 ± 2.7 rps in Jinji and Sakurai (2006) and 34.3 ± 3.5 m/s in Nagami et al. (2011). Although these parameters used in this study were slightly less than in those previous studies, they were within standard ranges and this suggests that the participants successfully performed baseball pitching and data was successfully obtained. The mean release parameters for each participant are summarized in **Table 1**. The average error of the measured pitch location and the simulated results using the measured release parameters was 5.8 ± 1.4 cm.

Comparing the variation in the pitch location caused by changing each release parameter, when the elevation pitching angle (θ1) was changed, the fluctuation of the vertical pitch location was the largest. **Figure 2A** shows the magnitude of the variation in vertical pitch location when changing the various mechanical parameters. The pitch location varied by approximately 30 cm each time the elevation pitching angle was changed by 1° and by ∼20 cm each time the speed was changed by 1 m/s (= 3.6 km/h). In addition, the pitch location varied by 1 cm when the vertical release point was changed by 1 cm. The pitch locations for the other parameters only varied by a few centimeters, even when changed from the minimum to maximum value.

When the azimuth pitching angle (θ2) was changed, the fluctuation of the horizontal pitch location was the largest. **Figure 2B** shows the magnitude of variation in the horizontal pitch location when changing various release parameters. The pitch location varied by ∼30 cm each time the azimuth pitching angle changed by 1°. In addition, the pitch location varied by 1 cm when the horizontal release point changed by 1 cm. The pitch locations for the other parameters only varied by a few centimeters, even when changed from the minimum to maximum value.

TABLE 1 | Mean release parameters and pitch location for each pitcher.

Pitcher	V [m/s]	θ1 [deg]	θ_2 [deg]	N [rps]	θ3 [deg]	X [m]	Y [m]	Z [m]	Pitch location Y [m]	Pitch location Z [m]
A	32.2 ± 1.0	1.38 ± 1.1	−3.66 ± 1.09	26.9 ± 2.3	−53.0 ± 3.8	1.72 ± 0.039	1.49 ± 0.025	0.25 ± 0.041	0.63 ± 0.30	−0.23 ± 0.20
B	33.0 ± 0.50	−1.27 ± 0.75	−3.81 ± 0.47	31.3 ± 0.87	−31.3 ± 3.7	1.73 ± 0.047	1.79 ± 0.029	0.50 ± 0.024	0.50 ± 0.25	−0.16 ± 0.11
C	33.4 ± 0.34	−0.72 ± 0.69	−2.70 ± 0.56	31.1 ± 0.64	−21.0 ± 2.9	1.69 ± 0.024	1.62 ± 0.022	0.38 ± 0.020	0.51 ± 0.21	−0.16 ± 0.14
D	33.2 ± 0.72	−0.26 ± 0.83	−4.00 ± 0.55	29.9 ± 1.0	−32.4 ± 5.3	1.73 ± 0.029	1.58 ± 0.012	0.48 ± 0.027	0.62 ± 0.26	−0.27 ± 0.13
E	35.9 ± 0.38	−0.49 ± 1.51	−3.85 ± 0.91	33.4 ± 1.1	−41.3 ± 3.9	1.63 ± 0.030	1.60 ± 0.019	0.58 ± 0.033	0.74 ± 0.43	0.048 ± 0.21
F	32.5 ± 0.49	1.50 ± 0.99	−3.38 ± 1.07	27.3 ± 4.7	−9.47 ± 5.9	1.78 ± 0.049	1.38 ± 0.022	0.81 ± 0.034	0.99 ± 0.26	−0.085 ± 0.35
G	28.0 ± 0.27	1.36 ± 1.64	−1.52 ± 0.61	24.6 ± 0.80	2.39 ± 6.1	1.81 ± 0.021	1.59 ± 0.001	0.15 ± 0.019	0.66 ± 0.44	−0.078 ± 0.21
Mean	32.6 ± 2.2	0.28 ± 0.99	−3.11 ± 0.80	29.0 ± 2.76	−25.2 ± 17.4	1.72 ± 0.06	1.55 ± 0.08	0.43 ± 0.20	0.66 ± 0.15	−0.17 ± 0.11

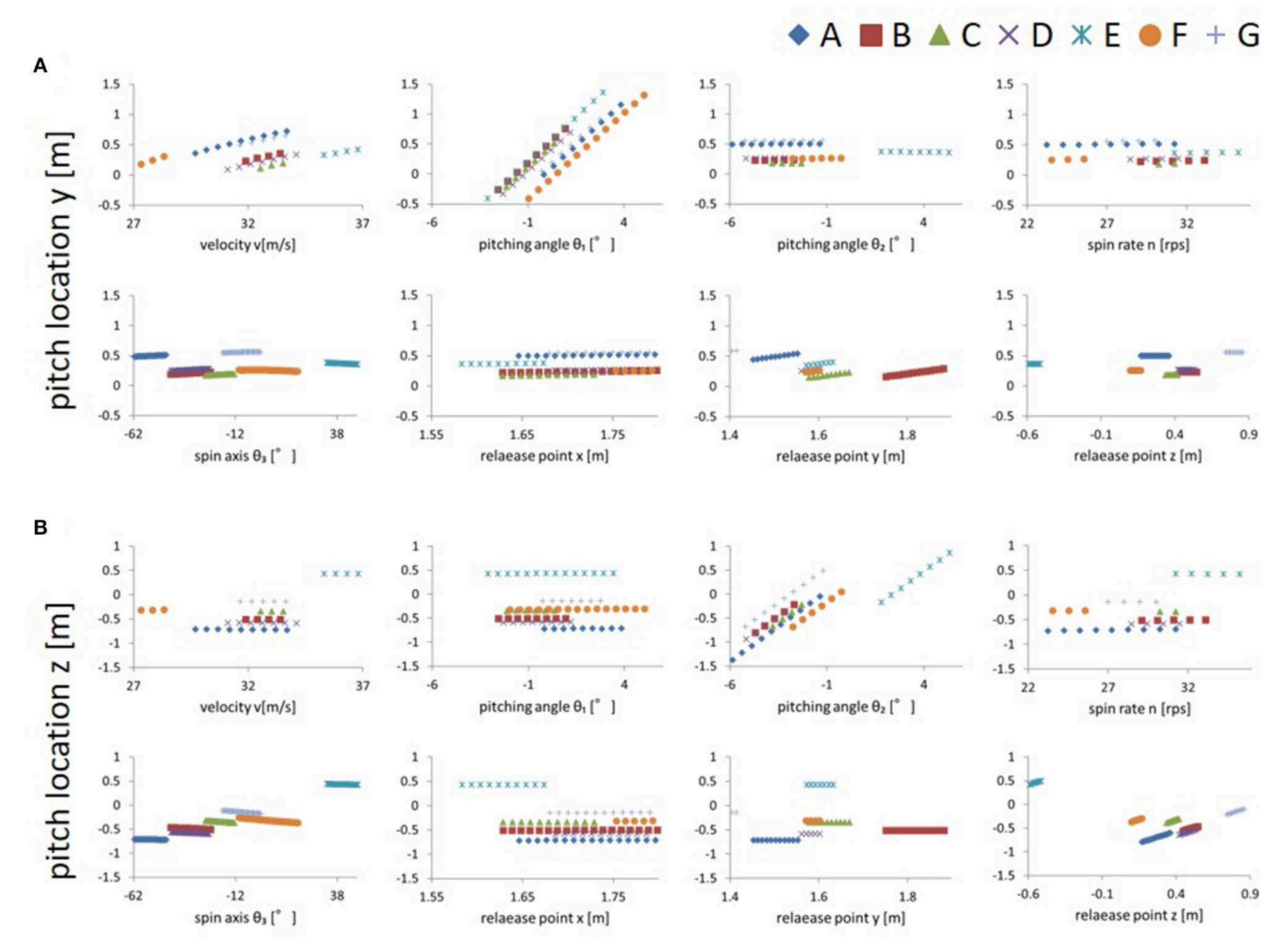

FIGURE 2 | (A) Relationships between each parameter and vertical pitch location. The range of the vertical axis indicates the size of variation of the pitch location when each parameter is varied (other parameters were fixed at their mean values). **(B)** Relationship between each parameter and horizontal pitch location. The range of the vertical axis indicates the amount of variation of pitch location when each parameter is varied (other parameters were fixed at their mean values). Subject E was the only left-handed pitcher.

The fluctuation of the vertical and horizontal pitch location is summarized in **Figure 3** (cf. **Tables S1, S2**). It was shown that the elevation pitching angle (θ1) and speed significantly influenced the vertical pitch location, and the azimuth pitching angle (θ2) significantly influenced the horizontal pitch location. The results had a similar trend among all pitchers.

Regression Model to Predict Pitch Location

Multiple regression was used with the release parameters to independently establish regression equations for each pitcher. The average R^2 values of regression models to predict the vertical pitch and horizontal pitch location for each pitcher were 0.97 ± 0.02 and 0.96 ± 0.04, respectively. **Tables 2A,B** list the regression coefficients of the significant predictors ($p < 0.01$) for each pitcher in vertical and horizontal pitch location, respectively (cf. **Table S3**). The results indicated that the significant predictors among all pitchers are the elevation pitching angle (θ1) for the vertical pitch location and the azimuth pitching angle (θ2) for the horizontal pitch location. For most of the pitchers, the speed and spin axis (θ3) were the significant predictors for the vertical pitch location, and the spin axis (θ3) and horizontal release point were the significant predictors for the horizontal pitch location. The explanatory rate of each parameter was different for each pitcher (**Figure 4**).

DISCUSSION

The present study investigated the extent to which pitch location changes when the release parameters vary within a realistic range. By comparing the fluctuation of the simulated pitch location when varying each release parameter, it was found that the elevation pitching angle and speed significantly influenced the vertical pitch location, and the azimuth pitching angle significantly influenced the horizontal pitch location. Moreover, a regression model was obtained to predict the pitch location,

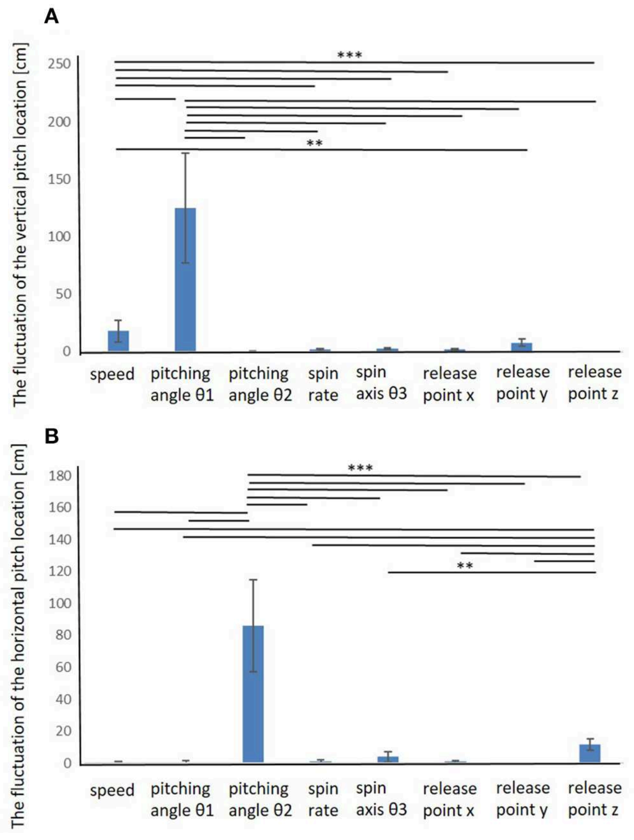

FIGURE 3 | Fluctuation of the vertical and horizontal pitch locations when each release parameter was changed. The elevation pitching angle (θ_1) and speed significantly influenced the vertical pitch location, and the azimuth pitching angle (θ_2) significantly influenced the horizontal pitch location. $^{**}0.01 \leq p < 0.05$, $^{***}p < 0.01$.

and it became clear that the significant predictors for the vertical pitch location were the elevation pitching angle, speed, and spin axis, and those for the horizontal pitch location were the azimuth pitching angle, spin axis, and horizontal release point. Therefore, it was suggested that the parameter most affecting pitch location was pitching angle.

It can be considered that the method used in this study identifies the variability of the pitch location when each release parameter fluctuates from the average value of each pitcher. However, how easily the release parameters themselves vary may be different. Therefore, here, by interpreting the fluctuation range of the measured value of each release parameter as the easiness of variation of each release parameter, the influence of each release parameter on the pitch location was compared as fairly as possible.

Based on the above, it can be considered that the variation in the pitch location is mainly caused by the variation in the pitching angle, suggesting that adjustment of the pitching angle is a crucial factor for accuracy of baseball pitching. By comparing the pitch location when each parameter was varied independently, it was found that the pitching angle and speed, i.e., the velocity vector, significantly affected the pitch location for all pitchers. In particularly, with respect to pitching angle, it was found that a deviation of several degrees produces a deviation of several tens of centimeters. This result was further supported by multiple regression analysis. The reason why such a result was obtained may be that pitching is a task for which the speed of the projectile at the time of release is relatively large compared to the other throwing tasks, and the distance to the target is sufficiently long. It is considered that the variation in the pitching angle, which is the direction of the velocity vector, greatly affected the variation in the pitch location, the distance to which is long. Moreover, how release parameters are defined also the one of the reasons. However, the release parameters used in this study are common in expressing the ball movement. In previous studies, the same way to define the release parameters as this study (ex. Nagami et al., 2011).

Relationship Between Release Parameters and Difference Between Pitchers

Although the fluctuation of the spin axis was very small in the simulation, its explanatory rate for pitch location was high for many pitchers. This result showed that spin axis had little influence when it was fluctuated independently but had a significant explanatory rate when combined with other parameters. Therefore, it was suggested that the spin axis covariated with other parameters to affect pitch location. The release point was conversely shown to cause fluctuation of pitch location in the simulation, but it had no explanatory rate for pitch location. This result suggested that the influence of release point was canceled by changes of other parameters. Thus, the release point may have a cooperative relationship with other parameters. Some parameters, such as spin rate, showed little influence on the variability of pitch location in both the simulation and regression analysis. However, in the previous study, the ratio of the spin rate to ball speed considering the direction of spin axis (i.e., effective spin parameter) would affect the lift coefficient more strongly than the spin rate and the spin axis separately (Nagami et al., 2016). Therefore, it was suggested that even for parameters that did not show a significant effect independently, certain combination of parameters may affect pitch location more strongly than individual parameters. In summary, these results mean that it is important that the influence of each release parameter and the combination of parameters on pitch location are considered separately.

In addition to the similar trend among all pitchers in the simulation analysis, the multiple regression analysis showed that the explanatory rates of each parameter were different for each pitcher. This indicates that the elevation pitching angle and speed are common factors in determining pitch location, but other parameters, such as the spin axis and release point, likely have different relations among the release parameters for each pitcher. One of the reasons for this difference might be that there can be specific combinations of release parameters in individual pitchers, even when targeting the same location (Jinji and Sakurai, 2006; Nagami et al., 2011). Because 9 parameters are related to pitch location in baseball pitching, there are countless combinations of values of release parameters that achieve the

TABLE 2 | Coefficient of regression equation for each patient.

(A)

Pitcher	v	θ1	θ_2	*n*	θ3	*x*	*y*	*z*	R^2
A	–	0.195	–	–	–	–	–	–	0.945
B	0.054	0.318	–	–	0.009	–	–	–	0.988
C	0.060	0.315	–	–	0.008	–	–	–	0.978
D	0.100	0.322	–	–	0.014	–	–	–	0.986
E	0.061	0.300	–	–	−0.009	–	–	–	0.991
F	0.143	0.298	−0.024	–	–	–	0.988	–	0.984
G	–	0.235	–	0.054	–	–	–	–	0.931
Mean									0.97 ± 0.02

(B)

Pitcher	v	θ1	θ_2	*n*	θ3	*x*	*y*	*z*	R^2
A	–	–	0.173	–	−0.009	–	–	–	0.911
B	–	–	0.215	–	−0.007	–	–	0.624	0.988
C	–	–	0.225	–	−0.004	–	–	1.164	0.992
D	–	−0.015	0.223	–	−0.005	–	–	0.626	0.992
E	–	0.015	0.242	–	−0.006	–	–	0.592	0.990
F	–	–	0.310	–	−0.014	–	–	–	0.983
G	–	–	0.318	–	–	–	–	–	0.885
Mean									0.96 ± 0.04

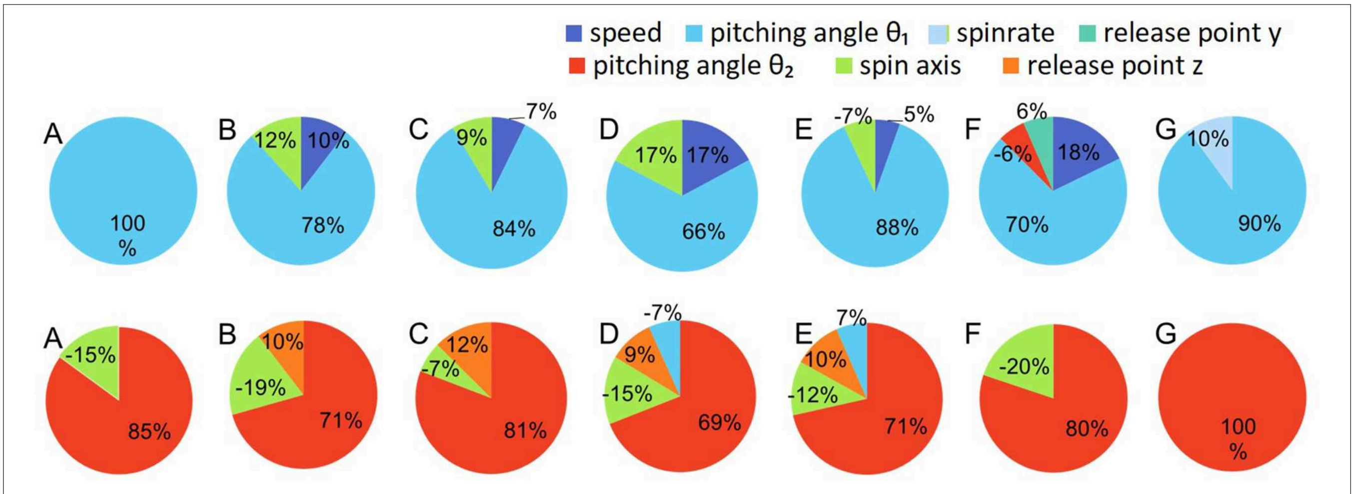

FIGURE 4 | Predictive parameters of vertical (top row) and horizontal (bottom row) pitch locations for each pitcher. The values indicate the *t* value of each parameter. The explanatory rate of each parameter was different for each pitcher.

same pitch location. Therefore, the pitcher can select various values of release parameters. It is clear that the best method for realizing throwing accuracy is not necessarily improving the reproducibility of each parameter, as in previous studies that used two-dimensional motions (Kudo et al., 2000; Cohen and Sternad, 2009; Nasu et al., 2014). The same interpretation could be applied to baseball pitching, which is more dynamic and has more degrees of freedom. Future research will investigate how to control the effect of the parameters, especially pitching angle that was found to have a large effect on the pitch location in this study. If future studies investigate the relationship between parameters and how to adjust them in more detail, it might become possible to better understand the mechanism of accuracy in baseball pitching. The results of this study contribute to understanding accuracy in various sports-related motor skills for which many parameters are complicatedly related in terms of extracting important components.

Limitations of This Study

Some limitations of this study should be noted. The experimental environment in this study was different from that in actual baseball games. The data was measured indoors so as to reduce the effect of wind and air currents on the aerodynamic characteristics of the ball that affect the ball trajectory. The participants always threw at the same target position, and there was no batter. Some release parameters might be influenced by these factors. However, the main results of study are considered not to be different largely by these factors because the release parameters used in this study did not have great difference from the studies have referred before. Moreover, sample size of this study was small. Only seven skilled baseball pitchers participated in the study. Different results may be obtained with more participants with various skill levels. It may need to investigate more participants in more practical settings in the future study.

It should be noted that the result may be specific to the fastball used in this study. The participants threw only 4 seam fastballs in this study, but pitchers throw various types of pitches, such as braking balls, in actual baseball games. Previous studies investigating release parameters for various ball types have shown that, depending on the type of ball, the spin rate and the spin axis can significantly influence on the trajectory of the ball (Jinji and Sakurai, 2006; Nagami et al., 2016). Considering this point, depending on the type of the ball, it is possible that other parameters such as spin rate and spin axis in addition to the pitching angle may affect the pitch location. Moreover, the seams of the ball ware not taken into account in the ball mechanics simulation. The seams may require consideration when breaking balls are investigated.

Application in Actual Fields

This is the first study to investigate the influence of release parameters including spin parameters, on the pitch location. The fluctuation of the pitch location was simulated for variation of each release parameter, and it was revealed that each parameter's contribution to the pitching accuracy varied. In previous studies, the pitch location was found to be related to variability in joint kinematics and ball release timing (Hore, 1996; Timmann et al., 1999; Fleisig et al., 2009), whereas the release parameters have not been studied thoroughly. The flight trajectory and pitch location were finally determined by the dynamical state at the time of release as a result of movements of body. This study furthered our knowledge of release parameters that connect body movements and pitch location and have a deterministic influence on pitching accuracy.

With recent advances in science and technology, measurement equipment, and data analysis technology have made remarkable progress. For example, TrackMan Baseball (TrackMan, Denmark), which was developed in 2003, is generally used as a data analysis system in major league baseball. Because it is possible to easily measure various parameters of the ball with high precision and in real time, practice, and teaching can be aimed at measurable numerical values rather than ambiguous feeling. From this research, we were able to show that the contribution to pitching accuracy varies depending on the parameters. As it is difficult to be conscious of multiple aspects during actual movements, extracting important elements may be useful for practice and teaching. Moreover, understanding the differences of individuals may contribute to performance improvements. Pitching involves multiple skills, such as increasing the ball speed, improving control, and learning breaking balls. Therefore, various styles can coexist even among skilled pitchers. When targeting tasks as pitching, it is important for coaches and players not only to know the tendency seen among skilled players and but to pay attention to cases that deviate from it. The advantage of the approach in this study with the incorporation of theoretical knowledge of body and ball movements, is that the knowledge about what is typical and when it may not be valid is acquired.

CONCLUSION

This study revealed the degree of influence of each release parameter on the pitch location in baseball pitching. The fluctuation of the pitch location was simulated for variation of each release parameter. It was revealed that, the elevation pitching angle and speed significantly influenced the vertical pitch location, and the azimuth pitching angle significantly influenced the horizontal pitch location. Moreover, a regression model was obtained to predict the pitch location, and it became clear that the significant predictors for the vertical pitch location were the elevation pitching angle, speed, and spin axis ($\theta 3$), and those for the horizontal pitch location were the azimuth pitching angle, spin axis, and horizontal release point. Therefore, it was suggested that the parameters most affecting pitch location were pitching angle. In future work, we will consider a relationship of parameters more clearly to further elucidate the factors affecting pitch location.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the ethics committee of the University of Tokyo. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

AK, KK, KN, and SW contributed conception and design of the study. HK, TM, and MK performed experiments. AK performed the analysis and wrote the first draft of the manuscript. KN revised partially the manuscript. All authors contributed to manuscript revision, and read and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fspor.2020.00036/full#supplementary-material

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Sport Practitioners as Sport Ecology Designers: How Ecological Dynamics Has Progressively Changed Perceptions of Skill "Acquisition" in the Sporting Habitat

Carl T. Woods[1,2,3], Ian McKeown[2], Martyn Rothwell[4], Duarte Araújo[5], Sam Robertson[1] and Keith Davids[4]*

[1] Institute for Health and Sport, Victoria University, Melbourne, VIC, Australia, [2] Port Adelaide Football Club, Football Department, Adelaide, SA, Australia, [3] Department of Sport and Exercise Science, James Cook University, Townsville, QLD, Australia, [4] Centre for Sport and Human Performance, Sheffield Hallam University, Sheffield, United Kingdom, [5] CIPER, Faculdade de Motricidade Humana, University de Lisboa, Lisbon, Portugal

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****Correspondence:***
Carl T. Woods
carl.woods@vu.edu.au

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Over two decades ago, Davids et al. (1994) and Handford et al. (1997) raised theoretical concerns associated with traditional, reductionist, and mechanistic perspectives of movement coordination and skill acquisition for sport scientists interested in practical applications for training designs. These seminal papers advocated an emerging consciousness grounded in an ecological approach, signaling the need for sports practitioners to appreciate the constraints-led, deeply entangled, and non-linear reciprocity between the organism (performer), task, and environment subsystems. Over two decades later, the areas of skill acquisition, practice and training design, performance analysis and preparation, and talent development in sport science have never been so vibrant in terms of theoretical modeling, knowledge generation and innovation, and technological deployment. Viewed at an ecological level of analysis, the work of sports practitioners has progressively transitioned toward the facilitation of an evolving relationship between an organism (athlete and team) and its environment (sports competition). This commentary sets out to explore how these original ideas from Davids et al. (1994) and Handford et al. (1997) have been advanced through the theoretical lens of ecological dynamics. Concurrently, we provide case study exemplars, from applied practice in high-performance sports organizations, to illustrate how these contemporary perspectives are shaping the work of sports practitioners (sport ecology designers) in practice and in performance preparation.

Keywords: constraints-led approach, ecological dynamics, self-learning and preparation for performance, practice designs, skill adaptability

INTRODUCTION

> *The gardener cannot actually "grow" tomatoes, squash, or beans – she can only foster an environment in which the plants do so.*
>
> *– Stanley McChrystal*

This is an exciting era for sports practitioners and applied scientists interested in understanding how to help athletes "grow and flourish" in complex performance surroundings. In a high-performance sport environment, the significant aims of coaches, sport scientists, and performance analysts are to develop "athletes of the future" and prepare "athletes of the present" for competitive performance. To foster successful interactions of athletes and teams with competitive performance and practice environments, the areas of skill acquisition, practice and training design, performance analysis, and talent development have never been so vibrant in terms of theoretical modeling, knowledge generation, technological deployment, and the application of innovative ideas in practice, training, and performance preparation. Viewed at an ecological level of analysis, the work of sports practitioners is to facilitate a productive, evolving relationship between an organism (athlete and team) and its environment (sports competition).

Indeed these ideas were originally promoted in sport science over two decades ago in theoretical concerns raised with traditional, mechanistic perspectives of movement coordination (Davids et al., 1994) and skill acquisition (Handford et al., 1997). Those position papers advocated the potential of an ecological approach to sport scientists and scrutinized reductionist information-processing perspectives on human performance dominant at that time. An important insight was that skill "acquisition" was conceptualized to emerge from an *evolving practice ecology*, which necessitated sports practitioners to appreciate the complex, deeply integrated, and non-linear reciprocity of the organism (performer), task, and environment subsystems (Newell, 1986). Such a theoretical conceptualization challenged the traditional perspectives of skill acquisition, having profound implications for understanding the performer–environment relationship and for how sports practitioners viewed their role in the preparation of athletes for performance. Here we seek to examine the progress made on complementing that emergent consciousness through the contemporary theoretical lens of ecological dynamics, exploring how the original ideas have been advanced in the intervening decades. We also examine case studies showing how the key concepts are currently shaping the work of some sports practitioners in practice and in performance preparation.

An ecological dynamics rationale, integrating ecological psychology, dynamical systems theory, the complexity sciences, and evolutionary science, views skilled behavior as the emergence of functionally adaptable performance solutions (i.e., actions, for a detailed review, see Araújo et al., 2020). In this framework, behavior is a self-organizing phenomenon that emerges from the continuously dynamic interplay of an organism's characteristics and the *affordances* (possibilities for action: Gibson, 1979) offered in a specific competitive performance environment (Araújo et al., 2006). Thus, skilled behavior evolves over timescales of performance, learning, and development (Button et al., 2020). These theoretical propositions are grounded in James Gibson's (1979) theory of direct perception in ecological psychology and in Scott Kelso's seminal work on coordination dynamics (e.g., Kelso, 1981a,b, 1984). Specifically, Gibson (1979) proposed how detection of information regulated action (and *vice versa*) and how the realization of affordances underpinned functional behaviors in dynamic performance environments. In a series of laboratory experiments, Kelso observed inherent, spontaneous self-organization tendencies in human movement systems and sudden phase transitions between states of coordination as the participants interacted with informational constraints of the environment (Kelso, 1981b, 1984).

In this commentary, we discuss how the role of a sports practitioner has shifted through the application in sport science of these key ideas in ecological psychology, behavioral neuroscience, and human movement science. Sports practitioners have moved on from an instrumental role of ensuring compliance of performers with "operational standards" or "technical performance templates" defined in coaching and performance manuals toward the designer of a learning ecosystem, working in multidisciplinary teams, to promote emergent, self-organized athlete–environment interactions. We highlight how this role perspective focuses more attention on the adaptability of athletes in performance, predicated on being excellent learners. The aims of this commentary are to: (1) provide an appreciation of advances in key concepts in ecological dynamics made in the past two decades and (2) provide (brief) practical insights from case studies in high-performance sport describing how this ongoing conceptualization is facilitating the implementation of practice designs inviting effective behaviors.

PART 1: SKILL ACQUISITION AS AN EVOLVING PRACTICE ECOLOGY – AN UPDATE

A Progression Toward Ecological Dynamics

A critical theoretical tenet of the ecological approach to skill acquisition, highlighted by Handford et al. (1997), is the appreciation of the performer–environment mutuality. From an ecological perspective, the "environment" refers to an animal's surroundings within which it can perceive and act, changing the environment and their deeply entwined relationship with it (Gibson, 1979). These relationships can be changed across different timescales (in sport, evolving along the macro-scale of talent development and changing within the micro-structure of practice; see Davids et al., 2017; Balagué et al., 2019). Thus, actions and behaviors should be understood as the result of specialized relationships that emerge between an organism and its environment (Handford et al., 1997). More directly, behaviors and actions do not appear in a vacuum. An athlete's behaviors cannot be understood without sustained reference to the specific environmental context in which they emerge (Renshaw et al., 2009). Specifically, the ecological dynamics approach focuses less on the putative control mechanisms of organisms, like internalized representations and knowledge structures stored in memory, and more on the reciprocal nature of perception and action which supports performance functionality. This was captured elegantly by Beek and Meijer (1988, p. 160) as the appreciation of "phenomena within the organism–environment synergy rather than within the organism *per se*." This more biophysically oriented theoretical conceptualization subsequently rejects the more mechanistic traditions of mental information-processing theories of skill acquisition. Such theories historically view movements as idealized, internalized templates for actions that originate from the mind and which are optimized with practice, rather like a computer programmer "debugs" a piece of software (for an original overview of implications for sports science; see Davids et al., 1994).

Organismic Asymmetry in Human Behavior

This inordinate emphasis on internalized representations somehow acquired in the mind of the athlete is another example in science of a dualism, in this case mind–body, proposed in explanation of natural physical phenomena (Turvey and Shaw, 1995). A prominent example is the confected "nature vs. nurture debate" to discuss exclusive influences on human behaviors such as learning, intelligence, propensity to disease, and expertise. The manifestation of this organism–environment dualism was recognized by Dunwoody (2007) who criticized the inherent bias caused by "organismic asymmetry" in the study of human behavior. Dunwoody (2007) identified one such organismic asymmetry as neglecting the foundational *person–environment relationship* as an interrelated basis for explaining human behavior, in favor of a biased preference for organismic-centered mechanisms such as internal mental models of the world. Brunswik (1955) indicated that, in organism–environment interactions, it was considered that both equally contribute to the organization of behavior. Brunswik (1955) noted a bias in most psychologists for attributing achievement to the internal process of humans, rather neglecting the influence of the environment in co-shaping human behaviors. Typically, much cognitive psychology remains focused on conscious mental life, with little reference to the role of the environment in shaping behavior (Davids and Araújo, 2010).

In 2011, Araújo and Davids highlighted the relevance of organismic asymmetry to sport scientists seeking to understand how athletes self-organized during practice and performance. This theoretical re-positioning offered significant implications for how sports practitioners could learn to rely less on traditional approaches to athlete development and preparation for performance, which emphasized verbal instructions and corrections, constant repetitions to "optimize a movement pattern," and the internalization of rehearsed behavioral reactions and responses in training. Indeed this theoretical re-positioning was in agreement with the empirical work conducted by Schöllhorn and colleagues, who demonstrated both inter-individual (Schöllhorn and Bauer, 1998) and intra-individual (Schöllhorn et al., 2002) variability and differences with regards to movement patterning, highlighting the fallibility of sport pedagogies grounded in the (attempted) acquisition and reproduction of "optimal" movement patterns. To further exemplify, an organismic asymmetry can be detected in some current notions of the concept of self-regulation in human behavior. Traditionally, self-regulation has been defined from a cognitive orientation referring to all the "self-generated thoughts, feelings, and actions that are planned and cyclically adapted to the attainment of personal goals (Zimmerman, 2000, p. 14). The bias toward the internalized regulation of behavior through planned goal achievement is apparent. From an ecological dynamics rationale, self-regulation can be conceptualized in a broader behavioral framework, emphasizing an individual's emergent interactions with the environment rather than referring to behaviors that are guided by internalized plans and goals with little reference to environmental interactions. In ecological dynamics, individuals can learn to self-regulate by developing and exploiting a deeply intertwined relationship between their actions, perceptions, intentions, and emotions to continuously support these emergent interactions. By harnessing this functional relationship with a performance environment, athletes learn to self-regulate by adapting stable action–perception couplings developed in rich and varied practice environments.

Variability and Performance

In their position statement, Handford et al. (1997) suggested that there was an over-emphasis on the measures of performance outcome variability (such as standard deviations and coefficients of variation) in sport and movement science research, which was focused on the magnitude of variability in task outcomes. This is only part of the picture and biased to the view that variability was often equated with "noise" or error in humans, considered as information-processing channels. This conceptualization was due to the linear movement models that were popular in motor behavior theories in the 1960s to the 1970s and that somewhat still prevail in current practice. Contemporary models of movement, such as ecological dynamics, advocate that humans and groups are *complex adaptive systems* with inherent non-linear properties. Variability in such systems needs to be much more carefully interpreted in a nuanced way, which is the challenge for sports practitioners interested in enhancing athlete and team performance.

Complex systems with many degrees of freedom can be seen as a "curse" (of organization, coordination, and control) or "blessing" (adaptability, re-organization, and functionality) as was discussed by Handford et al. (1997). The blessing is that athletes can continuously be encouraged to exploit self-organizing tendencies in their movement systems to form synergies (coordination patterns). This is where the variability can be functional. However, it is important to recognize that variability in movement patterns can be detrimental. Variability does not just exist within coordination and can manifest at different levels within an individual's kinematic profile. One level consists of fluctuations in individual elements such as joints and segments, usually seen in novices and considered less than desirable. Another perhaps is whole system variability, where several coordinated elements combine to produce an overall movement pattern, which manifests itself in *system degeneracy* (Edelman and Gally, 2001). At the first level, there is consistent evidence that variability decreases as skill level increases (Button et al., 2003; Bradshaw et al., 2009; Fleisig et al., 2009; Betzler et al., 2012; Hiley et al., 2013). It could be hypothesized that higher levels of movement variability in the lower skilled athletes at this level are reflective of them searching for effective movement patterns in line with the degrees of freedom and U-shaped curve hypotheses. However, the consistent decrease in individual variability as skill levels increase may be evidence of the need to constrain element variability to facilitate functional coordination and allow multi-element coordination variability to emerge (Button et al., 2020). Understanding the change in variability profile at each level, in particular during any interaction with motor learning and/or adaptation, could provide insight into how any functional role of variability emerges.

One of the functions attributed to movement variability is facilitation of the adaptation of an organism to changing environmental and task constraints (Davids et al., 2003; Glazier and Davids, 2009). In discrete movements, this type of variability is different to the undesired variability in the endpoint or the outcome of the movement (e.g., the number of targets accurately hit). Functional movement variability is now considered to be a characteristic of highly skilled movers (Button et al., 2003; Wilson et al., 2008), and an individual's variability profile is thought to change during task learning. For example, a U-shaped curve has been hypothesized to characterize coordination variability across skills, where the highest and lowest skilled display increased variability while those in intermediate stages have their variance constrained (Wilson et al., 2008).

In summary, the challenge for sports practitioners is to sort what is "good" (functional) variability from "bad" (dysfunctional) variability in an individual athlete's performance [see Scholz and Schöner (1999) and Latash et al. (2010) on the Uncontrolled Manifold Hypothesis]. At this stage, it is worth drawing attention to the influential theoretical insights and experimental data of Bernstein's (1967) which highlighted the need for psychologists, movement scientists, and sport scientists to re-consider how measures of movement variability should be conceptualized for human performance. Movement pattern variability can support the skill adaptations needed as the influence of task constraints on athlete behaviors emerges during practice and performance. The implications for practice and performance were captured in the phrase of "repetition without repetition," indicating how practice designs for trainers and coaches should provide opportunities for athletes to solve performance problems in different ways using a variety of behaviors.

Skill Adaptation

This re-conceptualization of self-regulation and functional variability has important implications for the translation into practice in sports performance preparation, suggesting that the commonly used term skill "acquisition" does not actually involve the *acquisition* of a physically reproducible motor memory stored in the brain. Rather, a more relevant description of the learning process in sport may be considered as "skill adaptation" (Araújo and Davids, 2011). What is developed is a highly functional relationship that evolves between an athlete and a competitive performance environment over extended timescales: a flourishing relationship that is supported by learning, experience, growth, and development (Seifert et al., 2013). Interestingly, this conceptualization of skill acquisition, predicated on continuously growing athlete functionality, was foreshadowed by Bernstein's (1967, p. 134) notion of *dexterity*, which he defined as the *"the ability to find a motor solution for any external situation, that is, to adequately solve any emerging motor problem correctly* (i.e., adequately and accurately), *quickly* (with respect to both decision making and achieving a correct result), *rationally* (i.e., expediently and economically), *and resourcefully* (i.e., quick-wittedly and initiatively)" (italics in the original). Furthermore, according to Bernstein, the "demand for dexterity is not in the movements themselves but in (adapting to) the surrounding conditions" (Bernstein, 1996, p. 23). In this respect, Bernstein's's (1967) insights foreshadowed how dexterity could provide a foundation for skill adaptation, with his definition of dexterous behavior showing the deeply intertwined links between cognition, action, and perception, the interaction of which is continually used to negotiate a dynamic performance environment. His ideas clarified how movement variability and skill adaptation are founded on the self-organization tendencies that can be exploited in dynamic performance contexts (Chow et al., 2011).

These theoretical insights on athlete performance illustrate the fundamental importance of many natural phenomena in the environments studied by ecologists, exemplified by the inherent self-organizing tendencies observed in complex systems formed by shoaling fish, flocking birds, synchronization of insect emission of sound and light as information, and the exploration of growing conditions by plants or mosses (Passos et al., 2013). Self-organization tendencies are ubiquitous in nature. Based on the key principle of "information–action coupling," these tendencies have even been observed in single-cell organisms without a nervous system (Boisseau et al., 2016). The dynamics of self-organization have drawn attention to the fundamentality of the organism–environment relationship, predicated on actions regulated by surrounding information, emphasizing the ecological systems at the heart of these links. It is important to note that the self-organizing tendencies in ecology are rarely expressed in isolation of a context (i.e., what is happening in the environment). For example, the organizing principle in a self-organizing system like a shoal, with each fish functionally co-adapting with each other, concerns their emergent co-movements (remaining within one "fish" length of each other) relative to those of an approaching predator or food source (informational constraints). The emergence of these rich and sophisticated global behavioral patterns in complex neurobiological systems is not pre-programmed within a knowledge structure shared between each single fish in the shoal nor pre-orchestrated by a piscatorial "leader" (acting as a collective system "coach"). Rather, they emerge from the information created by the movements of each complex system component, continually co-adapting to each other.

Implications of These Ideas for Sports Practitioners: Representative Design

Through an ecologist's perspective, an important part of a sports practitioner's role is to identify the critical informational sources or, more technically, the *affordances* (defined as opportunities or invitations for action; Gibson, 1979; Withagen et al., 2012) of a training setting that are likely to impact an athlete's or a teams' behaviors (similar to an ecologist being cognizant of how the presence of a predator or food source shapes the time–space relations underlying the emergent patterns of behavior of each fish within the shoal as a collective). Understanding the relevant affordances used to regulate performance behaviors allows groups of practitioners to carefully coordinate the design of learning activities that *represent*, or closely simulate, the demands of competitive performance contexts. While Handford et al. (1997) addressed the issue of specificity of practice, later work in ecological dynamics precisely located the key issues for sport practitioners as ensuring *representative design* after insights of Brunswik (1955) (see Araújo et al., 2005, 2006, 2007). The ensuing work of Pinder et al. (2011a,b) drew the attention of sport scientists and sport practitioners to the relevance of this concept for ensuring that the task constraints of learning sessions, especially informational constraints, represented (that is faithfully simulated) those of competitive performance environments. It is through the prolonged exposure to representative practice tasks that a performer learns to attune to (or "detect") the information sources that specify the relevant properties of the affordances of their environment using a variety of modalities such as haptic, visual, and auditory sensory systems [i.e., a surfer progressively learning to detect the motion of a wave (using haptic and visual sensory systems) to inform a "cutting" manoeuver used to score points in competition] (Withagen et al., 2017). The ongoing process of attunement to performance opportunities helps athletes and teams to develop a more functional and adaptable relationship with a particular competitive environment. More specifically, if we consider a performance environment as a *rich landscape of affordances* (Rietveld and Kiverstein, 2014), some of them designed by the coach when presenting practice tasks, then such practice tasks are directing or guiding the search of the performers. Moreover, some affordances can attract or invite the athletes to act upon them, especially if they precisely match the current capacities, abilities, and skills [termed "effectivities" by Gibson (1979)] of the athlete and the task constraints channel the athlete toward them (Araújo et al., 2019). From this perspective, affordances have both body-scaled (e.g., limb lengths) and action-scaled (e.g., strength output) properties that are perceived relative to the performer's current action capabilities (Fajen et al., 2009). This idea is most important to consider in athlete development programs in high-performance sport.

The current thinking on the affordance landscape notion for practice design suggests that, with experience, skill, and quality of practitioner support, athletes can become increasingly competent at perceiving and utilizing the most *soliciting* of affordances. This process is predicated on strong coupling tendencies between the presented affordance landscape and the skill of the athletes' perception and action in specific environmental designs (Withagen et al., 2017). Thus, through the landscape design, the practitioner can "nudge" or guide the athlete to use specific affordances while ignoring other less relevant ones. This ecologist's perspective leads to another important tenet of ecological dynamics for sports practitioners, that of *synergy formation* and *self-organi*zation *under constraints*.

Synergy Formation in Athletes and Sports Teams Exploits Self-Organization

To assist with the understanding and subsequent explanation of synergy formation, it is important to, firstly, appreciate the theoretical roots of ecological dynamics. Ecological dynamics is grounded in theoretical approaches, such as direct perception in ecological psychology, explaining how (detection of) information regulates actions and actions are coupled to perception of affordances (Gibson, 1979). At its core, it provides scientists with a framework for describing the emergence of complex, non-linear, and self-organized behaviors shaped by task, organismic and environmental constraints (Newell, 1986), and the order parameter–control parameter relations underpinning the dynamics of coordination in nature (Kelso, 1981a,b, 1984). Newell (1986) modeled how nested, interacting task and organismic and environmental constraints shaped coordination development, later applied to coordination behaviors and their acquisition in sport performance (Davids et al., 1994; Handford et al., 1997; Renshaw and Davids, 2004). Kelso (1981a,b, 1984, 1995) produced data showing how the coordination dynamics of brain and behavior shaped perceptions, intentions, and actions, during performance and learning, not as separated entities stored in the brain but as self-organizing patterns of behavior formed through the interaction of system components (order parameters) and the critical informational constraints of the environment (control parameters) (Kelso, 1995). In the central nervous system, the functioning of "system components" is observed at a macroscopic level, such as the stimulation of neurons simultaneously firing. In human movement, muscles of different limb segments synergistically interact to form multi-articular actions (Kelso, 1992, 1995). The interaction of system components with critical informational or environmental constraints results in the emergence of coordinated, self-organized behaviors (Kelso, 1981b; Kugler and Turvey, 1987). Ecological dynamics, therefore, fundamentally blends key concepts and insights specific to ecological psychology and dynamical systems theory in the explanation of synergy formation and coordination of action in complex neurobiological systems (for further insights, see Araújo et al., 2006; Warren, 2006).

The initial implications of these theoretical ideas for sport practitioners were raised by Handford et al. (1997) in a discussion of coordination and its acquisition. Gradually over the years, several lines of research began to reveal how these applied scientific insights had radical implications for the work of sport practitioners interested in how athletes coordinated their actions in sport collectives at a mesoscopic level, for example, in synchronized swimming and diving, cycling in a group, and especially in team sports (e.g., Passos et al., 2009; Duarte et al., 2012, 2013; Vilar et al., 2012; Silva et al., 2014; Passos and Davids, 2015; Ric et al., 2016). Over the following two decades, key insights on processes of co-adaptation were raised for understanding the functioning of 1v1 dyadic systems in team sports like basketball (Bourbousson et al., 2010a,b), association football, rugby union, and small sub-groups of athletes in sub-phases of play (e.g., 4v2 in rugby union, 6v6 in association football, 5v5 in futsal) (for empirical examples, see Araújo et al., 2006; Araujo et al., 2014; Passos et al., 2009). These insights now theoretically guide applied scientific work in the fields of performance analytics and biomechanics, sports pedagogy, tactical behaviors in team sports, physiology, skill acquisition, and practice design (Travassos et al., 2013; Araújo and Davids, 2016; Ribeiro et al., 2019a). From an ecological dynamics perspective, the processes of performance and functionality in sport can clearly draw inspiration from biological systems which function in a symbiotic way to flourish together in a specific environment. In sport and other ecological systems, function is predicated on information that reciprocally shapes the ongoing evolution of co-habiting organisms in a particular environment, with each organism shaping the environment while being shaped by its surrounds.

The Coach as the "Designer"

One of the key issues raised by Handford et al. (1997) was that the learner needed to be placed at the center of the learning process, with less of an emphasis of the coach being at the center of the instructional process. Over the past two decades, the ecological dynamics framework has emphasized how the role of the sports practitioner has evolved from an autocratic instructor who leads every sequential step of athlete progression through continuous provision of verbal information and corrective feedback to one of a "learning designer" whose role it is to work with athletes to identify and manipulate the key constraints of practice environments (Davids, 2012, 2015). This co-designing learning activity places the athlete and his/her needs at the heart of the development and performance preparation process. This is likely to augment the design of representative practice tasks as the coach and the athlete work together to co-design critical affordances that the athlete attunes to, thus guiding their behaviors. Traditionally, for example, the role of the coach has been conceived in a hierarchical way, sometimes even autocratically, preparing athletes and teams for performance through a strong emphasis on *global-to-local* synergy formation processes to externally regulate dynamics in performance and learning (Ribeiro et al., 2019b). In team sports, this can be typically exemplified through an external agent (i.e., coach, instructor, and trainer) prescribing strategic patterns of behavior in specific phases of a game. Conversely, an ecological dynamics framework advocates *local-to-global* synergistic tendencies, in which a system's synergy formation tendencies can be exploited in self-organization through interactions with the performance environment designed into representative practice tasks (Ribeiro et al., 2019a,b). Buekers et al. (2019) have re-iterated this point by arguing that the tactical performance of players in sports teams can be understood with respect to the ecological laws governing the perception of information in surrounding energy arrays during performance (aligned with the local-to-global synergy formation tendencies in sports teams). Team sports strategizing, on the other hand, is focused on the adherence to a performance plan prepared in advance (global-to-local synergy formation emphasized, often being led by a coach as Ribeiro et al., 2019b, noted). More recently, this distinction between different pedagogical approaches has been focused on the differences between the more traditional, command-driven practices of "hard education" and eliciting of learning opportunities in practices of "soft education" (van der Kamp et al., 2019).

So, How Does a Sports Practitioner Design a Learning Environment That Places the Athlete at Its Center and Appreciates the Bi-directional Nature of Synergy Formation to Enable the Rich Behavioral Patterns That Self-Organize at Both Intra-individual (Within an Athlete) and Inter-individual (Between Athletes) Levels?

In early recognition of the above question, Handford et al. (1997) paid particular attention to the manipulation of task constraints for sports practitioners, suggesting that it implied a more "hands-off" approach to sport pedagogy. Rather like an ecologist, the practitioner can create conditions for an athlete to exploit and flourish during the development and learning process. The implication is that a practitioner did not need to intervene and "nourish" an athlete continually but instead can work with the individual organism to adapt to the surrounding environment and flourish by getting everything needed from interactions with environmental constraints.

While this descriptor of hands-off coaching to prevent hyperactive verbal interference from coaches has been well understood and heeded over the past decades, there have been some indications that the new role, aligned with an ecologist, has been mis-conceptualized by some in a literal sense. To clarify, *hands-off coaching* signals a shift to a deep understanding of task, personal, and environmental constraints on individual learners and finding ways to co-design learning environments replete with affordances to guide each learner toward active exploration of a range of performance solutions. The role of practitioners, therefore, has become more important than ever, evolving from a prescriptive instructor with complete control over the whole process (hands-on) to a learning designer deeply integrated as a member of a team of sports practitioners focused on athlete performance and development at all stages. An important point to highlight in the hands-off approach is that, instead of offering their pre-programmed task solutions (according to the personal view of the coach), coaches need to work with the athlete to find individualized creative solutions for a performance problem. In this way, coaches are guiding the athletes to find solutions to the unknown problems that they may face in future competitions, not just repeating solutions for the training task problems (Araújo et al., 2009). For example, both tactical and strategical work in contemporary methods for preparation for team sports performance are now predicated on "Big Data" and technology implemented by teams of sports practitioners within the framework of an ecological dynamics rationale for learning designs in practice programs (Woods et al., 2019b; Browne et al., 2019).

A Department of Methodology: A Platform for Integrative Sport Science and Coaching

Although a theoretical and applied move toward practitioners as learning designers is welcome, some practitioners may be locked into traditions of practice and performance that advocate deterministic models of human behavior (e.g., Chow and Knudson, 2011), leading to coach-centric and hands-on approaches (resulting in rather over-dominating performance preparation). Practitioners who are guided by historic traditions of supporting athlete performance and development (a type of "path dependency" or acculturation process) can be subjected to "system capture." System capture occurs when the work of a sport practitioner is not guided by a theoretical framework of athlete development and performance but rather is captured by "operational standards" defined in coach education manuals that promote "optimal" performance templates (Rothwell et al., 2020). System capture of this nature can inhibit the development of innovative methods of athlete support and also disrupt multidisciplinary sport science teams when collaborating to design learning environments. The result is that practice and performance dissonance amongst practitioners could lead to "silo" working (Springham et al., 2018) and disjointed athlete preparation practices. One way for practitioners to avoid system capture and operate effectively as learning designers is to work collaboratively in a department of methodology (DoM) (Rothwell et al., 2020).

A DoM in an applied sport habitat should be composed of a group of practitioners and applied scientists who share integrative tendencies based on a rich mix of empirical and experiential knowledge. The aim of a DoM would be for group members to work within a unified theoretical framework (i.e., ecological dynamics) to: (i) coordinate activity through shared principles and language to avoid working in "silos," (ii) provide an integrative platform to communicate coherent ideas, (iii) collaboratively design practice landscapes rich in information (i.e., visual, acoustic, proprioceptive and haptic), and (iv) guide the emergence of multi-dimensional behaviors in athlete performance (Chow et al., 2011). In addition, as foreshadowed by Davids et al. (1994) a DoM can support practitioners and applied scientists to bridge the gap between theory and practice to enable the design of highly integrated and representative learning tasks. Since Newell's (1986) model focused on the integrated interacting constraints related to the individual, task, and environment, the nested relationship between them advocates the need for practitioners to collaborate together in a DoM to prevent sport practitioners from treating each constraint in isolation (Rothwell et al., 2020). As recently discussed by Woods et al. (2019b), the contemporary practice design of this nature requires an effective multidisciplinary approach, where a team of practitioners such as performance analysts, coaches, sport psychologists, sport scientists, and skill acquisition specialists, can work collaboratively in a DoM to analyze, sample, integrate, and manipulate nested practice task constraints on each individual athlete based on evidence from large sets of competitive performance data. This contemporary multidisciplinary approach would likely resolve behaviors that are perceived to be desirable for team and/or athlete success (product) in addition to the resolution of the interacting constraints that shape their emergence (process). Such information creates the basis for representative learning designs in practice and training. Further, this approach would likely lead to innovation in practice design as sport practitioners would not simply follow sequential steps advocated in coaching manuals as a result of path dependency. Rather, sports practitioners would identify critical sources of information within a competitive environment perceived to impact an individual athlete's performance behaviors and create an ecosystem that augments an athlete's perceptual attunement (i.e., detection) to relevant affordances in the landscape. In this respect, practitioners and applied sport scientists should focus the learning and practice design on a deeply intertwined relationship between value (affordances) and meaning (information) to support the development of highly attuned athletes. Affordances immediately (directly) indicate their value of use in an environment where structured patterns of (visual, acoustic, haptic, and proprioceptive) information (energy) reveal what objects and surfaces are (i.e., their meaning; Withagen et al., 2012). Accordingly, from an ecological dynamics' perspective, an athlete would not "acquire" an idealized skill. Rather, over time, he/she would develop a deeply functional and adaptive relationship with the performance environment (Araújo and Davids, 2011).

In the remainder of this evaluation of the research progress made since the appearance of the paper of Handford et al. (1997) depicting how coaching of athletes at all levels of performance could advance, we will refer to two case studies as examples of the practical application of the conceptualization of ecological dynamics in modern professional sport, namely, Australian football (AF). Importantly, these case studies do not intend to offer a comprehensive empirical examination into the application of ecological dynamics. They provide readers with an initial "how to" perspective when attempting to integrate aspects of its theoretical propositions as discussed in the first part of this paper. We encourage other "practitioner-scientists" to continue to provide rich exemplars of its integration for performance preparation in the continued support of sport practitioners interested in how to apply its key concepts within their ecosystems.

PART 2: IMPLICATIONS FOR THE WORK OF SPORT PRACTITIONERS

Practitioners as Learning Environment Designers

This section offers two case studies of ongoing practice to exemplify how sporting practitioners have integrated the key components of ecological dynamics in their preparation for performance in elite AF. These examples should provide the reader with thought provocation, affording the opportunity to adapt the practice designs presented to suit the need of their ecosystem. Central to these examples, however, is the philosophical shift in how a sports practitioner perceives his role in preparation for performance, viewing themselves as learning environment designers rather than as prescribers of pre-programmed "optimal" movement solutions. It is hoped that these examples will demonstrate that viewing sporting practitioners as *sporting ecology designers* is not as provocative of a thought as perhaps initially perceived.

To instantiate these examples, we will (briefly) discuss the ontological shift that is required for sports practitioners evolving toward learning environment designers. For example, the integration of a "contemporary" approach to preparation for performance may challenge socio-cultural norms that have been engrained from generational traditions (Hodges and Baron, 1992). It is these socio-cultural norms that can subsequently constrain the emergence of new epistemologies (Hodges and Baron, 1992). Accordingly, practitioners are encouraged to theoretically anchor values or principles that shape their practice ecology, which may require a deep introspection of their role in preparation for performance. In these presented examples, sports practitioners were challenged to conceptualize themselves as the designer of an ecosystem that provides a rich landscape of affordances in the achievement of a task goal. In this broad ecosystem, the athletes were free to explore and inhabit certain regions of their landscape. The central tenet of the ecosystem, however, was predication on the notion of representative learning design (Pinder et al., 2011a). Put simply, the practice designs were to consist of a clear task goal predicated on informational constraints sampled from the competitive performance environment. The sporting practitioners subsequently built these informational sources into the ecosystem ("hands-on") and then observed ("hands-off") the emergent interactions that unfolded between the athlete and their environment. It was globally acknowledged that, through this interaction, athletes progressively attuned to the informational sources within their workspace, developing fine-grained relationships with their performance environment – described as developing *knowledge of* their environment rather than *knowledge about* their environment (Gibson, 1966; Araújo et al., 2009; Silva et al., 2013).

CASE STUDY 1: INFORMATIONAL CONSTRAINT MANIPULATION SHAPES BALL PASSING INTERACTIONS BETWEEN PLAYERS

Introduction

Match-play within AF is contested between two teams of 18 (fielded) players, with the primary intention being to have outscored their opponents at the conclusion of the match. Thus, "match score" could be considered as a critical performance indicator (environmental constraint) that guides the players' perceptions, intentions, and actions as they attempt to "manage a game" (i.e., either maintain or obtain the lead over the opposition team). The aim of this example was to demonstrate how the manipulation of key informational constraints (score) within a player's performance environment can result in the emergence of self-organized behaviors as they exploit their environment to achieve a task goal. It is through careful practice design that players can develop a deeply integrated relationship with their performance environment, learning how to co-adapt to and direct the self-organization of their behaviors in response to emergent problems (thus, developing their *knowledge of* the AF performance environment).

Methodology

Procedures

In this example, data were collected from seven match simulations performed during a preseason training phase within an elite Australian Football League (AFL) team. Each match simulation was performed in accordance with the regulation rulings imposed by the AFL (premier AF competition) and officiated by registered umpires. The two competing teams of 18 players were quasi-randomized across each of the seven match simulations, ensuring that neither team had a playing experience bias. Each match simulation was performed for a minimum of 20 min on separate training days across a 4-week period.

All match simulations were scored as in competitive AFL games (six points awarded for a "goal" and one point awarded for a "behind"). Prior to each match simulation, all players were instructed to play for their team to win. To enhance competitiveness, the players were informed of a penalty for the losing team. the players were informed that with ˜3 min left to play within the match simulation, the scores would be manipulated to place one team in front by less than six points (a goal) irrespective of the current score. The scoreboard was visible to the players at all times throughout the match simulation. In addition to this information, the players in the separate teams were given 60 s prior to the start of each match simulation to postulate tactical actions that they perceived could exploit the constraint manipulation to achieve the task goal (winning the match simulation) pending the score (either being in front or behind by less than six points). The practitioners facilitated this process via the use of questioning (Chow et al., 2007), which directed the attention of the players to key affordances enabling possible solutions to the impending constraint manipulation (defined as the tactical problem). The important point to note here is that questioning from an ecological dynamics rationale does not involve the athletes providing verbalized reasoning and responses, which would emphasize the acquisition of what Gibson (1979) terms "*knowledge about*" the environment, framed by verbal descriptions. Rather, the aim of questioning is to direct the athletes' attention to relevant affordances of the performance landscape so that they can respond to verbalized questions with "*knowledge of*" the performance environment (Gibson, 1966) expressed through actions, perceptions, and skilled intentionality (Button et al., 2020).

Data Collection

To observe the emergent responses to the informational constraint manipulation, a multidisciplinary approach was used, which consisted of a team of sports practitioners with expertise in different sub-disciplines of sport science. Each match simulation was filmed using three two-dimensional cameras positioned from behind the goals (frontal/posterior) and broadcast (sagittal) perspective. The augmented visual information was subsequently stacked such that each perspective was concurrently observable during video analysis, with the periods of the match simulations in which the informational constraint manipulation occurred being time-stamped to the vision.

To study emergent ball passing tendencies between players following the score manipulation, notational analysis was performed on all disposal types (kicks and handballs). In accordance with the constraint-led framework (Davids et al., 2008), performer, environmental, and task constraints were heuristically selected, being informed by prior work in AF (Woods et al., 2019a) and recommendations from an expert AF practitioner (defined by holding a senior coaching position within the AFL for more than 5 years) and skill acquisition specialist. These constraints are presented elsewhere (Woods et al., 2019a,b), but a brief description is provided here and in **Table 1**: possession time (task constraint) was defined as the time between the player first obtaining ball possession to the time of ball disposal. This was then split into two components – a possession in general play and a possession from a mark or stoppage (e.g., free kick) – and then into four temporal epochs. The environmental constraints were defined by the number of opposition players within a 3-m radius of the ball carrier at the point of ball disposal (carrier density) and the intended receiver of the passed ball at ball reception (receiver density). Performer constraints were defined relative to the locomotive characteristics of the player at the point of ball disposal – stationary (standing still or walking) or dynamic (jogging or running). The same performance analyst quantified these constraints across each of the seven match simulations using specific notational software (Sportscode version 11.2.18, Sportstec Inc., Warriewood, NSW, Australia).

Descriptive Analysis

All data were transformed to represent a percent of total disposals performed within each constraint class. The data were split into two categories: "pre-informational constraint manipulation" (i.e., before the score-imposed change) and "post-informational constraints manipulation" (i.e., after the score-imposed change), with descriptive statistics (mean) being calculated for each condition. A radar plot was used to visualize the distribution of the disposal percentage within each constraint category across both conditions (Woods et al., 2019a). This analytical approach was chosen as it afforded a relatively simple yet informative means of quantifying the emergent co-adaptability that ensued from the informational constraint manipulation.

Results

As shown in **Figure 1A**, the team that was in front following the constraint manipulation possessed: (i) considerably fewer disposals performed within the 0–1 temporal epoch across both general play and stoppage constraint categories, (ii) a greater percent of total disposals performed from a stoppage in the > 3-s temporal epoch, (iii) a greater percent of total disposals to uncontested and superiorly numbered targets, and iv) fewer total disposals performed to inferiorly numbered targets relative to conditions prior to the score manipulation. Interestingly, this was in contrast to the team who was behind at the point of constraint manipulation (**Figure 1B**), exhibiting (i) fewer disposals to uncontested targets, (ii) fewer disposals performed with <1 opponent within a 3-m radius, (iii) greater disposals

TABLE 1 | The constraint matrix used within this example.

Constraint class	Constraint	Description	Sub-category label
Task	Possession time (general play)	Time between a player obtaining and disposing of the ball while in general play (i.e., not from a "mark" or "free kick")	0–1 s 1–2 s 2–3 s >3 s
	Possession time (stoppage)	Time between a player obtaining and disposing the ball from a stoppage in play ("mark" or "free kick")	0–1 s 1–2 s 2–3 s >3 s
Environmental	Target density	Number of opposition players within a 3-m radius of the intended disposal target	Uncontested Even (e.g., 1 vs. 1) Superior (e.g., 2 vs. 1) Inferior (e.g., 1 vs. 2)
	Ball carrier density	Number of opposition players within a 3 m radius of the ball carrier at ball disposal	<1 opposition player (unpressured) 1 opposition player 2 opposition players 3 opposition players >3 opposition players
Individual	Disposal movement	Locomotive state at point of ball disposal	Stationary (e.g., walking) Dynamic (e.g., running)

s, seconds; m, meters.

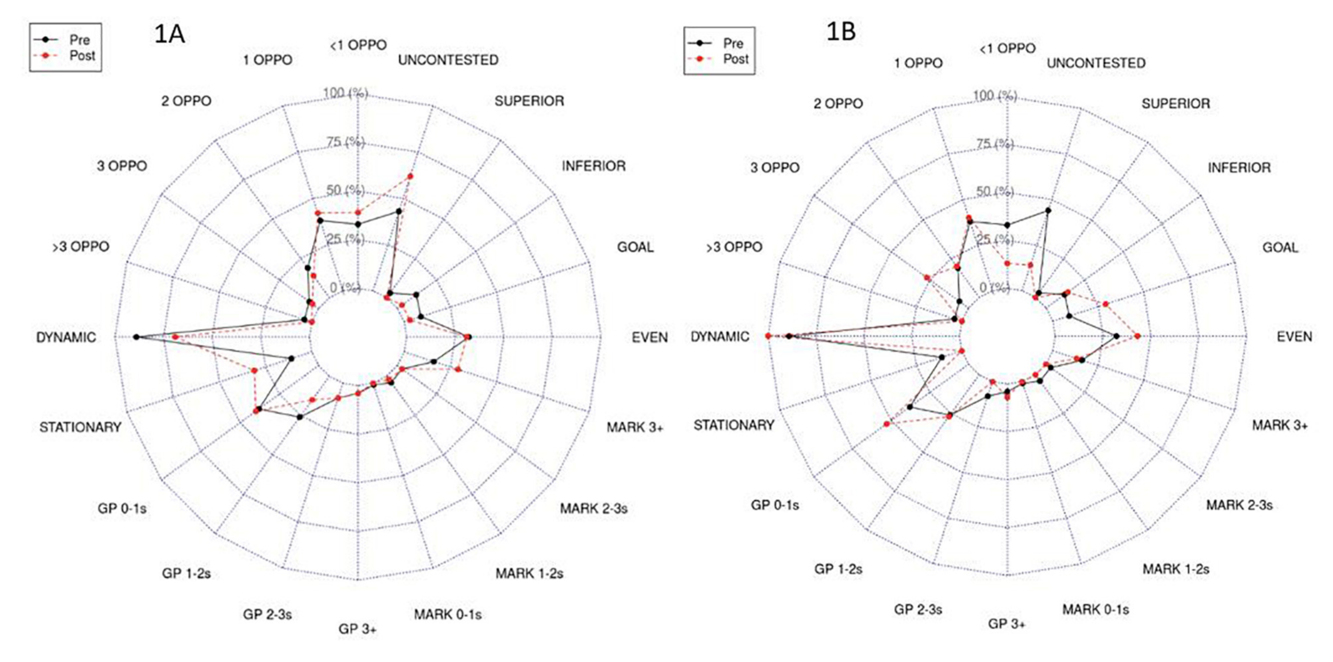

FIGURE 1 | Radar plots demonstrating the mean differences between "pre" and "post" informational constraint manipulation for the team in front **(A)** and behind **(B)** following constraint manipulation.

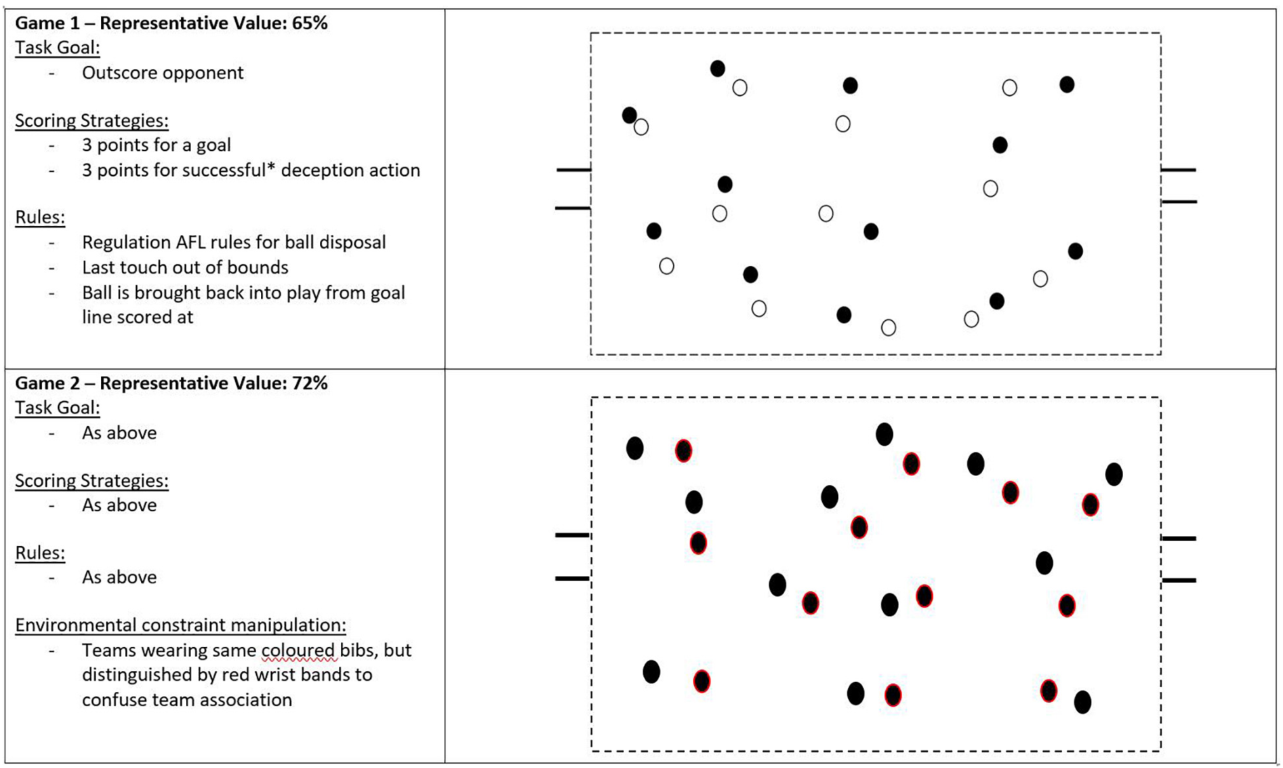

FIGURE 2 | Practice design for two activities that are designed to offer deceptive action opportunities – note the representative values that have been calculated using the methodology described by Farrow and Robertson (2017) and applied by Woods et al. (2019b); *A successful deceptive action was defined as one that coerced an opponent into a movement pattern that was exploited. The dots denote players.

performed with >3 opponents within a 3-m radius, (iv) greater disposals in the 0–1 temporal epoch in general play, and (v) a greater percent of total disposals performed while running.

Discussion

Collectively, the results of this case study indicated that the informational constraint manipulation (i.e., induced score change) led to the emergence of two distinct passing strategies utilized by players on either team: (i) one in which the players searched their workspaces for opportunities to slow their ball speed down and take lesser-risk disposal options when passing the ball to a teammate (1A) and (ii) another in which players searched their workspaces for opportunities to speed up their ball movement at the expense of seeming to take riskier disposal options when passing the ball to a teammate (1B). Specifically, the strategy demonstrated in 1A appeared to reflect a team who was "resting with the ball" in a somewhat conservative attempt to preserve their lead following the informational constraint manipulation. Conversely, the strategy demonstrated in 1B appeared to be one in which the players "threw caution to the wind" in an attempt to optimize their perceived likelihood to score. To further these insights, practitioners could consider the use of more advanced machine learning techniques such as rule association (Browne et al., 2019). Such an approach extends the descriptive analysis described here through the appreciation of the interaction between nested task constraints, offering greater insight into the combination of constraints that are likely to shape the disposal characteristics in response to an emergent "tactical problem" experienced within the competition.

Beyond these nuanced findings, this example demonstrates the utility of a practice design conceptualized through ecological dynamics. Specifically, this practice design afforded opportunities for players to build deeper relationships with their competitive environment, exhibiting *skilled intentionality* (Rietveld and Kiverstein, 2014) through the collective co-adaptability shown in their passing strategy relative to the informational constraint manipulation. This observation echoes our sentiment discussed earlier in this commentary that "behaviors" do not occur in a vacuum but, rather, through the ecological dynamics lens; "skilled behaviors" are functionally adaptable performance solutions that arise from the continuous interactions that an organism shares with their environment (referred to as skill adaptability; Araújo and Davids, 2011).

CASE STUDY 2: INVITING DECEPTIVE BEHAVIOR THROUGH INFORMATIONAL CONSTRAINT MANIPULATION

Introduction

An important design feature of practice tasks in AF is the presentation of affordances where time and space are manipulated to channel successful ball disposal actions between teammates (Robertson et al., 2016). Thus, providing opportunities for players to explore behaviors that could successfully deceive their opponents in the search for time and space should be included within preparation for performance models. The intention of this second case study is to offer the reader insights into how sports practitioners may design a practice activity that solicits deceptive behaviors. Specifically, this example presents a practice task that intends to provide a rich landscape that promotes the exploration of deceptive behavior in AF.

Methodology

Procedures

The same population as described in the first case study was used here. The two practice tasks designed to invite deceptive behaviors are presented in **Figure 2**. Both practice tasks were performed once (14 min in duration) during a pre-season phase of performance preparation. First, the subtle scoring system used within both games is worth noting (**Figure 2**). Given that the task goal of both games was to outscore their opposition, the points awarded for a successful deceptive action immediately led to the emergence of a landscape where deceptive actions were afforded and solicited. Further, it is important to note the environmental constraint manipulation in the second game. Specifically, team association was convoluted through the use of the same colored bibs for both teams, with the players being distinguishable only through the use of a colored wristband. This constraints manipulation methodology was used to encourage the players to explore unique ways to achieve the task goal relative to the first game. Additionally, the utility of such a constraint manipulation was informed from prior work describing the development of expertise in soccer, where team convolution was discussed as a common strategy that promoted scanning and deceptive behaviors (Uehara et al., 2018). To direct the attention to key informational sources of the task for the exploration of deceptive behaviors, the players discussed for 60 s prior to the start of each game about task configurations and possible behaviors that they perceived could be performed to deceive their opponent. As was done in the first case study, the practitioners facilitated this process via the use of questioning to elicit knowledge of the performance environment (Chow et al., 2007).

TABLE 2 | Deception categories and subsequent descriptions.

Deception category	Description
Faked disposal	An action of ball disposal that led an opponent to move in a different direction to where the ball was subsequently disposed
Creative disposal	An "unconventional" means of ball disposal that successfully reached its intended target (e.g., handballing between the legs of one's direct opponent)
Calling for the ball in defense	An act of calling for and receiving the ball from an opponent while in defense
Teammate blocking an opponent	An act of physically blocking an opponent from a teammate who is in possession of the ball
Other	Any emergent deceptive action that was undefined in the above

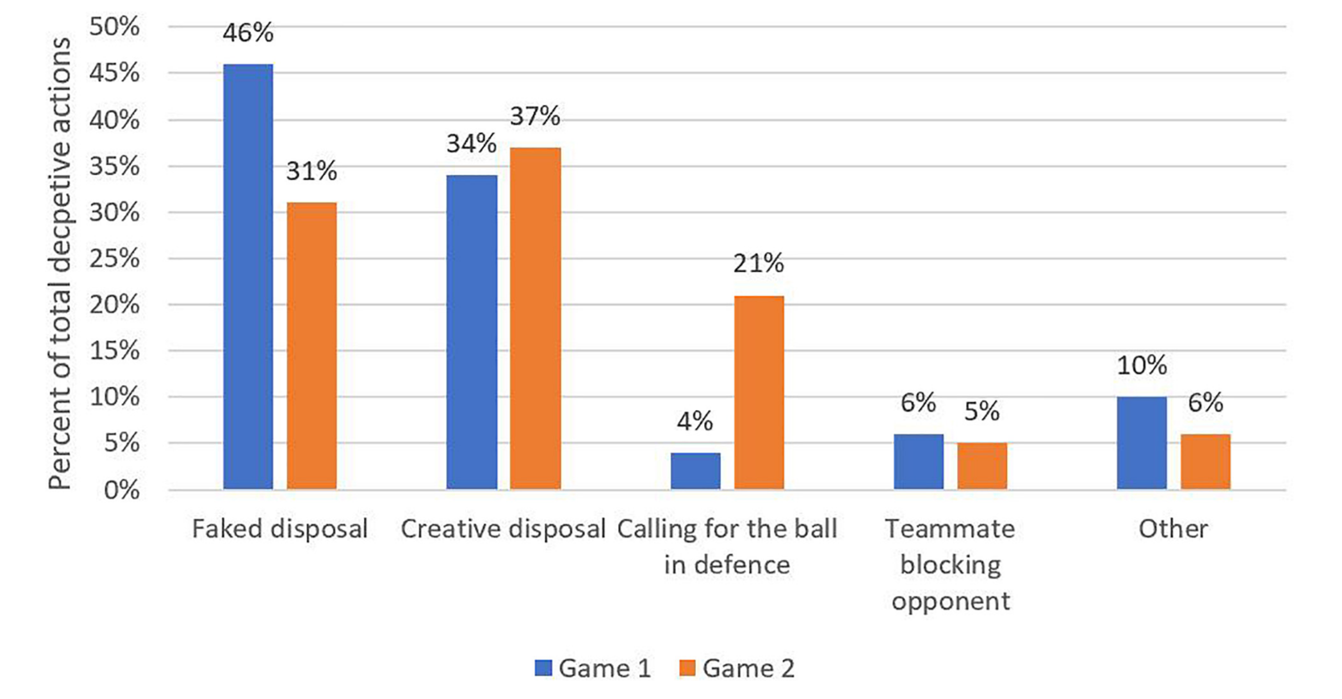

FIGURE 3 | The percentage of total deceptive actions observed in both games 1 and 2.

Data Collection

As was done in the first example, a multidisciplinary approach was used to observe the emergent deceptive behaviors. Both games were filmed using three two-dimensional cameras positioned from a behind the goals (frontal/posterior) and broadcast (sagittal) perspective. The augmented visual information was subsequently stacked such that each perspective was concurrently observable during video analysis. To quantify emergent deceptive actions, notational analysis was used (Sportscode version 11.2.18, Sportstec Inc., Warriewood, NSW, Australia). Specifically, "successful deceptions" were coded and categorized into one of five categories, with a description of each category being provided in **Table 2**. These deception categories were chosen and defined in accordance with the sports practitioner's experiential knowledge.

Descriptive Analysis

All data were transformed to represent a percent of total deceptive behaviors performed within each category, enabling a simple comparison relative to the constraint manipulation. Following this, a bar graph was used to visualize the distribution of the deceptive behaviors across both games.

Results

The most commonly observed deceptive behavior in the first game was the "faked disposal," followed by the "creative disposal" (**Figure 3**). This observation indicates that the most common solicitations for deceptive actions afforded in the first game involved movement adaptability relative to an opponent for the player in possession of the ball. Interestingly, however, while both "faked disposals" and "creative disposals" still remained as primary deceptive behaviors in the second game, "calling for the ball in defense" emerged as a prominent strategy for deceptive actions relative to the first game (**Figure 3**). It was likely that the augmentation for this was the additional environmental constraint manipulation that convoluted team association. Specifically, the players appeared to exploit this environmental constraint while in defense by hiding their wristband and calling for the ball from their opponent. This indicates that the additional environmental constraint manipulation invited more exploratory deceptive actions for the players when they were not in possession of the ball, relative to the first game.

Discussion

Collectively, this example demonstrates the utility of practice design framed through ecological dynamics where the sports practitioner designs a rich landscape that affords opportunities for a specific action to emerge. In this rich affordance landscape, the players were free to accept or reject invitations for action. From this perspective, the use of constraint manipulations directed, or guided, the players' attention toward the exploration and the exploitation of performance invitations (affordances) within their environment relative to their current action capabilities. For example, given that a specific performance solution was not prescribed in this practice task, the players were free to undertake any form of deceptive manoeuver that they felt could exploit their opponent based on the constraints designed in (e.g., score system and team convolution). It is presumed that through this design, the players would progressively learn to couple their movements to the opportunities presented and detected within their environment, progressively "acquiring" a deeper *knowledge of* (Gibson, 1966) their environment through the development of their perception–action coupling. Thus, in this case study, "hands-on coaching" occurred through the practice design rather than through the provision of prescriptive instructions of how to deceive an immediate opponent (i.e., how to perform a "football action").

This more ecological perspective of practice task design draws a stark contrast to the more traditional, linear approach. Specifically, framed through a more traditional perspective, it is likely that the target football action (in this case, a deceptive movement) would have been practised in a de-contextualized manner in isolated, unopposed practice based around the reproduction of a putative gold-standard movement template. Contrastingly, the practice task design framed through ecological dynamics offers the practitioners with a different perspective of skill "acquisition," being the development or "acquisition" of the performers' functionally adaptable relationship to their performance environment, which can be fostered through targeted and careful constraint manipulation, not the repetition of an uncoupled and physically reproducible "technique."

CONCLUDING REMARKS

As poignantly highlighted by McChrystal et al. (2015) in the opening quotation, gardeners do not actually grow a plant; rather, they facilitate an environment to which vegetation adapts and in which plant growth emerges. This commentary and set of case studies sought to foster reflection in readers on the alignment of key ideas in this framework and the fundamentals of preparation for performance models in sport. Pertinently, this practice ecology was originally discussed over two decades ago by Davids et al. (1994) and Handford et al. (1997), who proposed the notion of an ecological approach to skill "acquisition." In their propositions, sports practitioners were urged to appreciate the complex and deeply integrated reciprocity of the organism (performer), task, and environment subsystems, which signaled a change in how their role was conceptualized in preparation for sport performance. Over two decades later, we have seen the continued evolution of this rationale through the contemporary theoretical lens of ecological dynamics. Through this theoretical rationale, sports practitioners are now afforded a guiding framework that fosters many areas of sport science, such as skill "acquisition," practice and training design, performance analysis and preparation, and talent development. We proposed how the framework of ecological dynamics could support the integrated work of an extensive group of sport practitioners in a DoM in sports organizations dedicated to athlete development and preparation for performance.

Indeed this is an exciting era for sports practitioners and applied scientists interested in augmenting athlete performance. We now find ourselves on the cusp of the next "frontier" of ecological dynamics, one which sees the offering of rich exemplars as to how teams of sports practitioners have successfully integrated its propositions into preparation for performance models. To continue to aid this progress, we propose that sports practitioners should conceptualize themselves through a different light, one which sees them appreciating the non-linearities of human behavior, and design ecosystems that have the athlete–environment interaction at its core. It is perhaps through this conceptualization that sporting practitioners may actually see that viewing themselves as *sport ecology designers* is not as farfetched as initially thought.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by James Cook University Human Ethics Committee. The organization provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

CW and KD conceptualized the paper, while CW and IM established the case studies. CW, KD, SR, MR, and DA each contributed to and drafted the first section of the paper, while CW, KD, SR, DA, and IM wrote and drafted the second section of the paper. All authors contributed to the manuscript revisions based on a reviewer's commentary.

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The Trade-Off of Virtual Reality Training for Dart Throwing: A Facilitation of Perceptual-Motor Learning With a Detriment to Performance

Stefanie A. Drew[1], Madeline F. Awad[1], Jazlyn A. Armendariz[1], Bar Gabay[1], Isaiah J. Lachica[2] and Jacob W. Hinkel-Lipsker[2]*

[1] Visual Information Sciences and Neuroscience Laboratory, Department of Psychology, California State University, Northridge, CA, United States, [2] Move-Learn Laboratory, Department of Kinesiology, California State University, Northridge, CA, United States

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***Correspondence:**
Jacob W. Hinkel-Lipsker
jhlipsker@csun.edu

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Advancements in virtual reality (VR) technology now allow for the creation of highly immersive virtual environments and for systems to be commercially available at an affordable price. Despite increased availability, this access does not ensure that VR is appropriate for training for all motor skills. Before the implementation of VR for training sport-related skills takes place, it must first be established whether VR utilization is appropriate. To this end, it is crucial to better understand the mechanisms that drive learning in these new environments which will allow for optimization of VR to best facilitate transfer of learned skills to the real world. In this study we sought to examine how a skill acquired in VR compares to one acquired in the real world (RW), utilizing training to complete a dart-throwing task in either a virtual or real environment. We adopted a perceptual-motor approach in this study, employing measures of task performance (i.e., accuracy), as well as of perception (i.e., visual symptoms and oculomotor behavior) and motor behaviors (i.e., throwing kinematics and coordination). Critically, the VR-trained group performed significantly worse in terms of throwing accuracy compared to both the RW-trained group and their own baseline performance. In terms of perception, the VR-trained group reported greater acute visual symptoms compared to the RW-trained group, though oculomotor behaviors were largely the same across groups. In terms of motor behaviors, the VR-trained group exhibited different dart-throwing kinematics during training, but in the follow-up test adapted their throwing pattern to one similar to the RW-trained group. In total, VR training impaired real-world task performance, suggesting that virtual environments may offer different learning constraints compared to the real world. These results thus emphasize the need to better understand how some elements of virtual learning environments detract from transfer of an acquired sport skill to the real world. Additional work is warranted to further understand how perceptual-motor behaviors are acquired differently in virtual spaces.

Keywords: virtual reality, ocular health, biomechanics, skill acquisition, sports, motor learning

INTRODUCTION

Virtual reality (VR) systems have been under development for over 50 years, but the technology has only recently reached a point where it not only creates a high resolution, highly immersive experience, but is available on the commercial market at a relatively reasonable price (Slater and Sanchez-Vives, 2016; Arnaldi et al., 2018). Given these advancements, a wide range of industries are racing to embrace the new technology for training purposes before fully considering all implications. Integrations across the sporting domain are numerous and widespread (Düking et al., 2018), and recent work has examined its applicability to training skills such as soccer goalkeeping (Stinson and Bowman, 2014), rowing (Ruffaldi and Filippeschi, 2013), surfing (Farley et al., 2020), and marksmanship (Rao et al., 2018), to name a few. The expanding use of VR technology for acquisition or enhancement of sport skills has great promise, as a virtual world makes it possible to create training environments in which learning can take place that would otherwise be too costly, risky, or difficult to produce (Champney et al., 2014; Carruth, 2017). With these explorations, industries are becoming more interested in the basic science involved (Scarfe and Glennerster, 2015) and the physiological and psychological aspects of skill transfer from virtual to real-world environments still need to be thoroughly explored (Düking et al., 2018).

To date, there is some literature focused on the newest commercially available systems that demonstrates the promise of transfer of skills trained in virtual reality (Tirp et al., 2015). These reports have focused on single modalities during their examinations, such as task performance (e.g., Tirp et al., 2015), visual mechanisms (e.g., Mohamed Elias et al., 2019), or movement strategies (e.g., Nisky et al., 2014). Herein lies a critical weakness; Slater recently indicated that we should consider VR conceptually as a system that can alter a person's sensory input and thereby affect their motor output through effective environment design, and thus the perceptual and motor systems are not separable (Slater, 2014). To this end, a more comprehensive examination of VR in the context of both sensory input and motor output is warranted in order to better understand how to maximize sport skill acquisition in these environments.

The notion of the examination of a behavior in terms of perception and action is by no means a novel idea and has been investigated thoroughly across many disciplines (e.g., Gibson, 1979; Wagman and Blau, 2019). Over the years, researchers utilizing this approach have noticed that a change in perception ultimately affects resulting action (e.g., Stoffregen et al., 2004). Further, this approach has been carried over into the realm of virtual reality research where sensory stimuli typically differ from the real world, such as Gray's examination of training in a virtual environment for real-world baseball batting performance (Gray, 2017). However, the literature is sparse and more work is needed to examine skill acquisition across varying tasks and populations before a comprehensive understanding of perceptual motor learning in VR can be established.

Newell's Model of Constraints for skill acquisition is a well-established and widely accepted model (Newell, 1986) that describes how performance of a motor skill is determined by the interaction between perceptual and motor systems. In light of this model, a full understanding of skilled performance requires consideration of the underlying perceptual-motor mechanisms driving task performance. In turn, one's sensory perception of the environment and the way in which they coordinate movement are directly influenced by constraints related to the individual (e.g., the structure and function of body systems), the environment (e.g., characteristics of the physical performance space and sociocultural norms), and the task itself (e.g., rules or guidelines which dictate how the skill is performed). Therefore, it is not unreasonable to think that the individual, environmental, and task constraints offered by a virtual learning environment may differ from that of a real-world environment, thus idiosyncratically affecting task performance. In the context of Newell's Model, the different constraints imposed by a virtual learning environment would affect how that environment is perceived and, subsequently, how movement is coordinated to carry out a task. To truly examine virtual reality as an effective means for motor learning, one must consider how the combination of perceptual input and motor output of a learned task differs between virtual and real-world environments.

Previous work has also discussed how certain factors related to design of the virtual environment may either facilitate or detract from one's ability to transfer a learned skill to the real world. One factor, fidelity, refers to the degree to which a virtual environment resembles that of the real world (e.g., the resolution of graphics; Alexander et al., 2005; Bhargava et al., 2018). Another factor, immersion, describes aspects of the virtual environment that work to make the user feel more present in that world (as opposed to being in the real world; Rose and Chen, 2018; Slater, 2018). Some immersive elements of a virtual environment could include objects that have similar weight and shape as the same ones in the real world, or limiting outside sensory information coming from the real world (such as auditory stimuli). Therefore, when using a VR system for training of sports skills, it is important to maximize fidelity and immersion in order to ensure that environmental and task constraints overlap between environments as much as possible. However, the lay population does not often have access to the skills and resources required to design a custom environment, and thus may be reliant on commercially available platforms. All participants provided written informed consent, and all study protocols were approved by the university Institutional Review Board. It can be expected that there are discrepancies in environmental and task constraints between learning a new sport-specific skill using a commercially-available VR platform and performing that skill in the real world, possibly due to differences in fidelity and immersion. However, to date there is a lack of literature describing transfer of skills from VR to the real world using these environments, and whether the discrepancies between environments promote or detract from one's ability to acquire a new skill. Such work would help to better inform athletes and coaches of whether using a common VR platform for learning or enhancing sport skills is suitable, or if aspects of the environment such as fidelity or immersion need to be optimized to best facilitate transfer.

VIRTUAL REALITY AND PERCEPTUAL INPUT

In the natural world, two oculomotor systems work together to produce clear binocular viewing of an object. The accommodation system is responsible for keeping an object in focus by adjusting the focal power of the lens in the eye and the vergence system is responsible for maintaining binocular fixation on an object, with both eyes rotating in opposite directions to keep the object image on the fovea of each eye (Kim et al., 2014). In the real world, an object's distance to which the eyes must accommodate and converge are generally the same, so the demands to the vergence and accommodative systems are equal (Kim et al., 2014; Hoffman et al., 2015). However, modern technological advancements in stereoscopic displays and virtual reality provide novel environments in which these two systems no longer necessarily operate in synchrony. While wearing a VR head-mounted display (HMD), a user views a display that is positioned at a fixed location in front of their eyes, while focusing on a virtual object with varied binocular disparities and thus varied depths, creating a disassociation between accommodation and vergence cues (Kramida, 2015; Wilson and Soranzo, 2015). The resulting incongruity between these two ocular systems that occurs when viewing virtual reality displays has warranted some attention.

Discrepancies between the vergence and accommodation systems, also known as vergence-accommodation conflict (VAC), have been postulated by many to be a contributing factor of experienced visual discomfort when viewing stereoscopic displays (Wann and Mon-Williams, 2002; Emoto et al., 2005; Lambooij et al., 2009) and Hoffman et al. (2015) provide one of the first experimental demonstrations of the conflict causing visual fatigue and discomfort which have been extensively reported in the literature following stereoscopic display viewing. Investigation into these symptoms experienced by users led to the identification of a set of symptoms specific to VR experiences, coined "virtual reality-induced symptoms and effects" (VRISE; Cobb et al., 1999; Sharples et al., 2008). Symptoms reported after virtual reality usage include nausea, sickness, eyestrain, oculomotor effects, postural instability, and visual acuity (see also Nichols and Patel, 2002; Stoffregen et al., 2017). Ames et al. (2005) developed a symptom questionnaire to assess symptoms, the Virtual Reality Symptom Questionnaire (VRSQ), though this has not been applied to more advanced versions of VR technology.

Despite many advancements made in VR technology since the identification of VRISE, the symptoms experienced by VR users have continued to plague users of this new technology (Wilson and Soranzo, 2015). As previously reported, with the rapid increase in VR usage for training paradigms, it is critical that the impact and understanding of visual discomfort systems on the perceptual component of training be considered. Recently, Mohamed Elias et al. (2019) reported effects on oculomotor behaviors (observed increase in accommodative response and decrease in convergence) and symptoms after VR exposure; understanding these effects will help clarify impact on transfer. Their study provides a preliminary examination of oculomotor contributions to VR training, though the authors concluded that more examination is needed. Further, Mohamed Elias et al. (2019) focused on the oculomotor and task components of VR skill training but did not address the resulting kinematic outcomes involved, a critical piece that must be included to draw comprehensive conclusions about motor skill development in virtual environments.

VIRTUAL REALITY AND ACQUISITION OF KINEMATIC STRATEGIES

These changes in oculomotor behaviors, in the context of Newell's Model of Constraints, should have a direct effect on how movement is coordinated. While a wealth of literature exists describing how perception and action are coupled in the real world across a variety of motor skills and levels of expertise (Warren, 1990; Bertenthal et al., 1997; Kelso and Kay, 2016; Mallek et al., 2017), the way a virtual learning environment influences this relationship between sensorimotor body systems is largely unknown. While a multitude of studies report positive performance outcomes as a result of VR training (Adamovich et al., 2009), very few investigate the underlying kinematics of the performed movement and even fewer utilize a real-world-trained control group as a comparison of learning strategies. Of those that do, reports of positive kinematic transfer from virtual to real performance environments are mixed. For example, some recent work has cited similarities between virtual and real-world-trained individuals on kinematic movement strategies during a real-world performance test on sport-specific tasks such as handball goalkeeping (Bideau et al., 2004) and golf putting (Pataky and Lamb, 2018). On the other hand, another set of studies have described diverging real-world kinematic strategies between those trained in virtual and real environments on tasks such as reaching and grasping (Levin et al., 2015; Thomas et al., 2016). From these mixed results, it is apparent that multiple factors inherent in the virtual learning environment influence transfer of kinematic strategies from virtual to real worlds. For sport skills where utilization of the correct movement pattern is essential, it is important to investigate transfer at the kinematic level as a means to understand whether coordination strategies acquired in a virtual environment are applicable in the real world.

Further, beyond determining whether learning environments affect movement kinematics, it is also important to assess whether the kinematic strategies acquired during a learned skill actually promote successful completion of the task. Previous work has discussed that while individuals tend to demonstrate movement variability from trial-to-trial during performance of any motor task, those who are more proficient at a given skill can utilize that variability to their advantage through what is known as motor redundancy, as there are multiple movement patterns that can promote successful task performance (Cohen and Sternad, 2009). The coordination patterns that do not ultimately affect task performance are considered beneficial in that variance within this set of patterns allows for exploration of movement solutions—essentially, individuals are utilizing variance in a way that promotes learning (Cohen and Sternad, 2009; Sternad, 2018). Experts tend to make greater use of this set of movement solutions, previously termed the uncontrolled manifold (UCM), as they can explore new movement patterns without influencing task success (Scholz and Schöner, 1999). Conversely, novices tend to utilize movement variability outside of the UCM, indicating that they use coordination strategies that may detract from task performance (Rein et al., 2013; Nisky et al., 2014; Komar et al., 2015). Taking Newell's Model of Constraints into account, if the individual, environmental, and task constraints presented by a virtual learning environment differ greatly from that of the real world, the movement solutions within the UCM (or those that allow for exploration of strategies to find the optimal movement pattern through leaving task-related variables unaffected) may differ from virtual to real worlds—ultimately impacting task performance. To date, such an analysis has not been performed as a way to assess transfer of movement coordination from virtual to real worlds. Taken together with the perceptual elements of skill acquisition in VR, it is evident that a greater foundational understanding of how perceptual-motor systems are impacted by VR usage is needed to optimize how well-sport skills can transfer from virtual to real worlds.

THE PRESENT STUDY

The purpose of this study was to determine how a single session of virtual reality training on a dart-throwing task, considered in the context of task performance and involved perceptual-motor mechanisms, compares to how those trained in the real world perform the skill. To this end, a secondary purpose was to evaluate how well a commonly-used virtual platform for dart throwing can be used in place of learning the skill in the real world, despite sub-optimal levels of fidelity and immersion. We formulated hypotheses for the (1) task performance as well as (2) the associated perception and (3) subsequent motor components of learning said task. As such, we hypothesized that overall, (1) those trained in VR would perform worse on a real-world follow-up test compared to those trained in the real world, as measured through a greater radial distance from the bullseye. We also anticipated that (2a) relative to real-world trained participants, virtual reality trained participants would experience a decrease in accommodative and vergence facility measures. Furthermore, we hypothesized that (2b) those trained in virtual reality would report greater number of visual discomfort symptoms post-training compared to those trained in the real world. Finally, we hypothesized that, compared to real-world-trained participants on a real-world follow-up test, VR-trained participants would exhibit (3a) different throwing arm joint angles at the time of dart release and (3b) have a lesser utilization of motor redundancy, as demonstrated through greater use of variability outside of the UCM.

METHODS

Participants

Fifty participants were recruited to participate in this study through flyers and word-of-mouth. All participants provided written informed consent, and all study protocols were approved by the university Institutional Review Board. Eligibility criteria included consenting adults with a minimum age of 18, with normal or corrected to normal vision. Those with corrected to normal vision wore contacts during the study. Participants were screened via a questionnaire for conditions that cause visual discomfort (specifically; epilepsy, migraines, or head trauma), medications that can impact accommodative function (i.e., anti-anxiety agents, anti-arrhythmic agents, anticholinergics, and tricyclic anti-depressants) and participants with a history with any of these components were excluded from the study as they affect accommodative function. Participants were also screened for a history of epilepsy, seizures, loss of awareness, and for symptoms resembling an epileptic condition. Individuals with these conditions were excluded as VR systems may trigger seizures or other symptoms. In addition, individuals with high levels of dart-throwing experience (e.g., playing darts more than one time per month) or any chronic or acute upper-extremity injuries in the 6 months prior to enrollment in the study were excluded.

The data of nine participants were excluded due to poor stereopsis (see Instrumentation), administrative, or technological issues resulting in a total of 41 participants (22 male, 19 female) in the study. Participants were randomly assigned to either a virtual reality (VR) training condition or a real-world (RW) training condition. The VR group consisted of 22 (12 male, 10 female) participants while the RW group had 19 (10 male, 9 female).

Instrumentation

Several standard optometric assessments were used prior to training. To assess stereoacuity (ability to detect differences in depth) and fine depth perception, participants completed the Circle Patterns of the standard Stereo Fly Test. Fixation disparity (misalignment of eyes when viewing with both eyes) was assessed with a Saladin Near Point Balance Card. Facility tests were performed to assess abilities of the accommodation and vergence systems to adjust to changing demands over time. Accommodation facility testing was performed with a +/− 2.00 D lens flipper over 2 min (and then calculated for 1 min duration). Vergence facility was measured with a flip prism 3 PD BI/12 PD BO over 2 min (and calculated for 1 min).

During the baseline, training, and follow-up trials three-dimensional marker coordinate data were recorded for the first five throws of each set at 150 Hz using an 8-camera motion capture system (Motion Analysis Corp., Santa Rosa, CA). 11 retro-reflective markers were placed on the following anatomical landmarks of participants' trunk and throwing arm: spinous processes of C7 and T10 vertebrae, jugular notch and xiphoid process of the sternum, left and right acromion processes, lateral and medial humeral epicondyles, radial and ulnar styloid processes, and the 3rd metacarpal of the hand.

For the dart-throwing task, a standard dartboard was set at regulation height and darts were used, participants were instructed to stand behind a line marking off a distance of 7 feet 9 ¼ inches (as what is listed as standard distance by the World Dart Federation) from the target. For participants assigned to train in a virtual environment, an HTC Vive CPO Education Edition (HTC, Taoyuan, TW) was used. The commercially available game, VR Darts Zone (Reality Busters Co, 2017), that simulates a bar with a standard dartboard available in it was pre-loaded onto the system. The VR space was calibrated as a 4 × 3 m rectangle using SteamVR (Valve, Bellevue, WA) and two lighthouses on opposing corners of the rectangle ∼5 m above the floor tracked three-dimensional movement through the space.

There are a number of elements in this environment that reduced fidelity and immersion, and thereby affected the degree to which task and environmental constraints overlap between the virtual and real-world spaces. For one, in the real world the dart board was set to a single height for all participants regardless of their own height, while in VR the entire environment scaled to the height of the participants' HMD while it is being worn. This could affect the fidelity of the environment as dartboard heights are not consistent across learning environments. In addition, the participants in VR used a standard HTC hand controller, which involves holding and releasing a trigger instead of releasing a dart and has a different weight, distribution of weight, and shape than the standard real world dart. Moreover, the physics of flight and sense of gravity in the virtual environment may have also differed slightly from the real world. All of these factors may have decreased the levels of immersion in this virtual environment. As previously discussed, this environment was chosen as it was representative of a typical game that the lay population would have access to, where they do not have access to the resources or possess the technical skills to construct a virtual environment that perfectly replicates the real world.

Questionnaires were administered electronically via Qualtrics (Qualtrics, Provo, UT) on a Surface tablet device (Microsoft Corporation, Redmond, WA). These surveys included an acute symptom questionnaire administered before and after training (Drew et al., 2013), as well as the Virtual Reality Symptom Questionnaire (VRSQ) developed by Ames et al. (2005) and the Computer Usage Survey (Hayes et al., 2007) given after training. Participants also answered several demographic questions related to age, sex, height, and weight.

Procedure

After giving informed consent, all participants were asked to complete a short, 4-question acute symptom questionnaire to determine baseline levels of acute symptoms experienced. Next, participants were seated in a side room and measures of stereoacuity, fixation disparity, accommodation facility, and vergence facility were measured. Following these optometric measurements, 11 retro-reflective markers were placed on the participants (see Instrumentation). Next, all participants completed a baseline set of dart throws where they were instructed to stand at the pre-marked location and to throw a set of five darts at their own pace. All throws were continuously recorded through motion capture. Once these throws were completed, researchers measured the radial distance of each dart's position from the center, recorded these distances as a measurement of accuracy, and removed the darts from the board. The participants were then instructed throw another set of five darts with the same data collection procedure repeated.

Participants assigned to the VR training group ($n = 22$) used the HTC Vive with the VR Darts game loaded. Participants were instructed on how to navigate the virtual room and told to spend the first 5 min exploring the virtual space, allowing them to acclimate to the new environment. Participants in the RW training group ($n = 19$) were similarly instructed to spend the first 5 min exploring the experimental space in the real world. After this familiarization period, all participants were instructed to begin throwing darts in their assigned environment for 25 min, over which they threw a total of 100 darts. In VR, throwing the dart involved squeezing a trigger to picking it up, and releasing the trigger during the throw at the point in time where the dart should be leaving the hand. After every set of 10 throws, all participants were instructed to rest for 1 min in order to minimize effects of physical strain. Participants continued in this manner until they had completed 100 dart throws. If participants completed all of their throws before the 25-min mark was reached, they were instructed to explore their environment (either virtual or real-world) for the remaining amount of time. This was done to ensure a consistent duration of VR exposure for the VR-training group and mirrored in the control group.

Following completion of the training session, accommodation facility and vergence facility were measured again for each participant in the same manner as the pre-training assessments. Participants were then instructed to return to the indicated place and to throw two sets of five darts in the same manner as described in the pre-training session, with motion capture data continuously recorded. Throughout baseline, training, and follow-up participants were not directly provided with any feedback in terms of throwing accuracy, though they were able to view the thrown dart's position on the board in both VR and the RW conditions. While the VR platform did provide information regarding their score, this does not correspond with radial distance from the bullseye. Next, participants completed several questionnaires administered via an iPad using Qualtrics software (Qualtrics, XM, Provo, UT). This included a post-training acute symptom survey, the Virtual Reality Symptom Questionnaire (VRSQ), the Computer Usage survey and several demographic questions.

Data Analysis

All three-dimensional marker coordinate data were low-pass filtered using a 4th order Butterworth with a 6 Hz cutoff frequency and used to build a 4-segment model (trunk, upper arm, forearm, hand) in Visual 3D (C-Motion, Germantown, MD). This model was used to extract shoulder, elbow, and wrist joint angles during each throw. Next, using a custom MATLAB (MathWorks, Natick, MA) script, data were trimmed into individual throws. The start of each throw was identified as the time when the marker on the 3rd metacarpal on the throwing hand reached its maximum distance away from the target (i.e., was in a "cocked" position), while the end of the throw

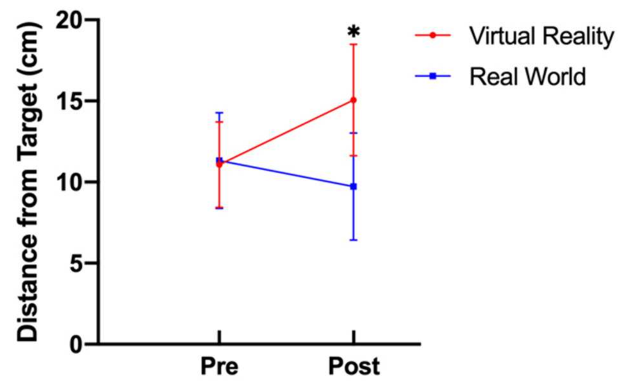

FIGURE 1 | Dart-throwing accuracy before and after training for the virtual reality and real-world training groups (* denotes $p < 0.05$).

was marked as point in time where the angular radial-ulnar deviation velocity of the wrist joint reached a local minimum after achieving its peak angular velocity. Shoulder, elbow, and wrist joint angles were time-normalized from 0 to 100% of the throw and used to form ensemble curves for visualization of throwing kinematics before and after training. In addition, discrete shoulder, elbow, and wrist joint angles were extracted at the time of dart release—which we have termed "end joint configuration"—as a way to quantify whether kinematic strategies differed between groups. These discrete angles were binned into 14 sets of 5 throws: 2 before training (Pre 1 and Pre 2), 10 during training (the first 5 throws in each of the 10 sets of 10 throws, Training 1, Training 2…Training 10), and 2 after training (Post 1 and Post 2).

Additionally, we also sought to determine how participants in each group coordinated motion of the joints of the throwing limb relative to a task-related variable using an uncontrolled manifold (UCM) approach. For this study, we computed a three-dimensional vector from the throwing arm shoulder joint center to the marker on the 3rd metacarpal on the throwing hand. This vector was used as the task-related variable that we anticipated the dart thrower needed to stabilize to promote successful throwing performance, as previous work has shown that variability of hand position at the time of dart release is reduced following practice (Smeets et al., 2002). While the following will briefly outline how the UCM is computed, a more detailed methodology can be found in other works (Scholz and Schöner, 1999; Tseng et al., 2002; Domkin et al., 2005). While the UCM approach has not been used to analyze joint-level coordination for dart-throwing, it has been used to examine similar tasks such as manual tool use (Rein et al., 2013) and Frisbee throwing (Yang and Scholz, 2005).

To determine how changes in arm joint angles affected the throwing arm's hand position at different time points of the throw, we developed a forward kinematic model relating throwing arm segmental lengths and joint angles to the task-related variable. This relationship is represented by a 3x4 Jacobian matrix containing partial derivatives relating small changes in joint angles (degrees of freedom (DF) = 4: shoulder flexion/extension, shoulder ab/adduction, elbow flexion/extension, wrist radial/ulnar deviation) to the three-dimensional vector coordinates of the task-related variable ($n = 3$). The null space of this Jacobian matrix is therefore representative of the joint configurations that do not affect the task-related variable, and the deviations of joint angles from the reference configuration (the mean of each joint angle for each of the 14 sets of 5 throws, 14 total reference configurations) can be projected onto the null space. This component of the deviations from the reference configuration are hence within the UCM (deviations that do not affect the task-related variable), and the orthogonal component is representative of deviations that do affect the task-related variable. From both components, the variances per degree of freedom are then computed, one representative of joint angle variance that is within the UCM (goal equivalent variability; GEV) and the other representative of variance orthogonal to the UCM (non-goal equivalent variability; NGEV).

The normalized difference between GEV and NGEV—termed the index of motor abundance (IMA; Tseng and Scholz, 2005; Auyang et al., 2009) can therefore represent how participants are utilizing variance in joint configurations. An IMA closer to 1 is indicative of much more utilization of GEV than NGEV, therefore revealing that participants coordinated joint angle variability to explore different movement solutions without changing the task variable. On the contrary, an IMA closer to −1 indicates more NGEV than GEV, meaning that participants utilized variance in joint configurations that changed the position of the task-related variable. Finally, an IMA close to 0 indicates no coordination strategy was used. We performed this analysis at five different time slices in the throw: 0% (beginning of dart throw), 25, 50, 75, and 100% (time of dart release). In the context of our study, more skilled dart-throwers should utilize variance to their advantage (i.e., greater GEV than NGEV or an IMA closer to 1), which would imply that they were exploring different throwing motions that allowed for hand position relative to the shoulder to remain relatively constant throughout the throw. Conversely, less skilled throwers should have a lesser IMA than skilled throwers, with the implication being that they utilized more variance in joint configurations that changed the position of the hand. As such, this analysis allows for a more in-depth look beyond discrete kinematic measures at how the throwing motion is coordinated with relation to successful throwing performance, and can help to further understand any differences between practice groups in terms of dart-throwing performance or joint-level kinematics.

Statistical Analyses

To compare throwing performance of each group (hypothesis 1), accuracy on the dart-throwing task was calculated before and after training for both groups. The accuracy measurements were taken by two researchers and these values were averaged between the two to ensure a more robust measurement of accuracy for each throw. Average accuracy was calculated across the first five throws and across the second five throws, and an average accuracy score calculated from these two values. To test for the

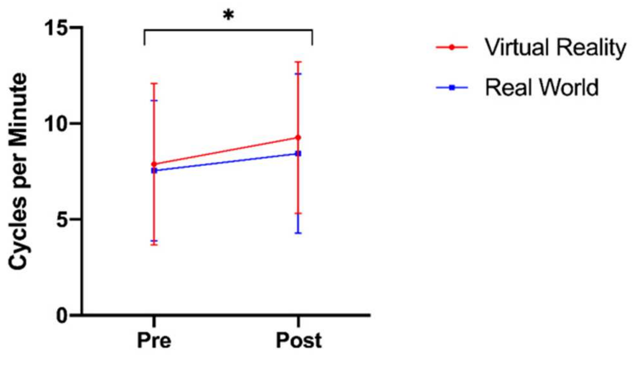

FIGURE 2 | Accommodation facilities before and after training in both virtual-reality and real-world training groups (* denotes $p < 0.05$).

main effects of practice group and time on accuracy, we used a two-factor rANOVA ($\alpha = 0.05$).

Prior to performing any of the aforementioned rANOVAs, we tested for assumptions of homogeneity of variance (Levene's Test of Homogeneity of Variance), homogeneity of covariance (Box's Test of Equality of Covariance), sphericity, and normality (Shapiro-Wilk's test). Greenhouse-Geiser corrections were used when sphericity was violated, and we made square root transformations or ran non-parametric tests if the assumption of normality was violated. When a rANOVA was revealed to be statistically significant, we conducted follow-up Bonferroni-corrected pairwise comparisons.

To address hypothesis 2a, two two-factor repeated-measures analyses of variance (rANOVAs, $\alpha = 0.05$) were performed, testing for the main effects of practice group and time on (1) accommodation facility and (2) vergence facility. Two time points were included, one before training and one after. Similarly, in pursuit of hypothesis 2b, multiple statistical tests were performed to test for the main effects of practice group and time on composite scores for the three symptom questionnaires (acute symptom survey, VRSQ, CUS). First, composite scores for the acute symptom survey were calculated and categorized into one of two possible categories: No Symptoms Reported or Symptomatic. This logic for this organization of the data was 2-fold: (1) the response scale for each of the four questions slightly differed and (2) the scores violated Levene's test of homogeneity. Therefore, binomial proportions were established for both the virtual reality training and the real-world training groups and chi-square tests of homogeneity performed. Next, exploratory factor analysis (EFA) of the VRSQ has found a clear two-factor solution, with factors of General Body Discomfort and Eye Related Symptoms onto which all but one of the questions loaded, therefore composite scores for these two factors were calculated (Del Cid et al., submitted) for further analysis. A Mann-Whitney U test was performed to examine differences between the two training groups on the Eye Related Symptoms and General Body Discomfort factors. Finally, previously performed EFA on the CUS has revealed a four-factor solution onto which the 20 of the 21 survey questions mapped. These factors were Visual Discomfort, Back Discomfort, Vision Difficulties and Extremity Discomfort (Del Cid et al., submitted). Composite scores for each of these factors were calculated and Mann-Whitney U tests were performed for each factor of Visual Discomfort, Back Discomfort, Vision Difficulties, and Extremity Discomfort.

To test for the main effects of practice group and time on throwing arm shoulder, elbow, and wrist joint angles (hypothesis 3a), we performed three repeated-measures, two-factor analyses of variance (rANOVAs; α =0.05). Fourteen time points were included: two bins of five throws before training, ten during training, and two after training. Similarly, to address hypothesis 3b we used five rANOVAs (α =0.05) to test for the main effects of practice group and time on the five IMA time slices (0, 25, 50, 75, 100%), with two time points included—one before training (average IMA for each of the two bins of 5 throws) and one after.

RESULTS

Task Performance

There was a statistically significant interaction between training group and time on dart throw accuracy [$F_{(1,39)} = 35.48$, $p < 0.001$, $\eta p^2 = 0.476$]. Univariate analyses examining the differences between groups revealed that before training, dart throw accuracy was not significantly different in the virtual reality training group compared to the real-world training group ($p > 0.05$). Following training, the accuracy of the virtual reality training group was significantly worse (e.g., further radial distance from the bullseye) than the real-world training group [$F_{(1,39)} = 25.627$, $p < 0.001$, $\eta p^2 = 0.397$]. There was a statistically significant effect of time on accuracy for the VR training group [$F_{(1,21)} = 37.88$, $p < 0.001$ $\eta p^2 = 0.643$] such that participants performed less accurately after training (i.e., further radial distances from the bullseye). There was also a statistically significant effect of time on accuracy for the RW training group [$F_{(1,18)} = 5.61$, p =0.029, $\eta p^2 = 0.238$], such that participants were more accurate (i.e., closer radial distances to the bullseye) after training (**Figure 1**).

Perceptual Measures

There was no significant interaction between time and group on accommodation facility [$F_{(1,39)} = 0.487$, $p = 0.489$, $\eta p^2 = 0.012$]. The main effect of time showed significantly different accommodative facilities before and after training [$F_{(1,39)} = 10.119$, $p < 0.05$, $\eta p^2 = 0.206$]. There was no significant main effect of training group [$F_{(1,39)} = 0.238$, p =0.628, $\eta p^2 = 0.006$; **Figure 2**]. The pre-training vergence facility test was not normally distributed as assessed by Shapiro-Wilk's test ($p < 0.05$), nor was the post-training vergence facility test ($p < 0.05$), therefore a square-root transformation was performed on the data, resulting in a normal distribution ($p > 0.05$). There was no significant interaction between time and group on vergence facility [$F_{(1,39)} = 0.239$, $p = 0.628$, $\eta p^2 = 0.006$]. The main effect of time showed significantly different vergence facilities before and after training [$F_{(1,39)} = 12.174$, $p = 0.001$, $\eta p^2 = 0.238$]. There was no significant main effect of training group [$F_{(1,39)} = 1.278$, $p = 0.265$, $\eta p^2 = 0.032$; **Figure 3**].

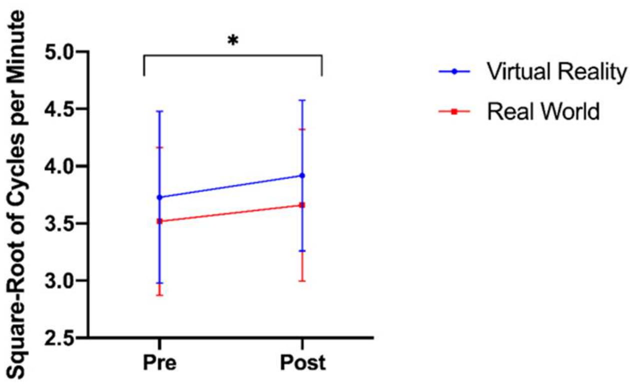

FIGURE 3 | Square-root transformed vergence facilities before and after training (* denotes $p < 0.05$).

In the virtual reality training group, 8 of the 22 participants (36.4%) reported experiencing acute symptoms, while in the real-world training condition, 6 of the 19 participants (31.6%) reported experiencing symptoms prior to training. The difference in proportions of 0.048 was not statistically significant (p = 0.747). Following training, in the virtual reality training group, 15 participants (68.2%) reported symptoms while in the real-world training group, 5 participants (26.3%) reported symptoms, a statistically significant difference in proportion of 0.419 (p = 0.007) (**Figure 4**). Distributions of scores for the VRSQ were similar for the two training groups, as assessed by visual inspection. No statistically significant differences were found between groups for either factor (General Body Discomfort or Eye-Related Symptoms; $p > 0.05$). Distributions of scores for each factor in the CUS were similar, as assessed by visual inspection, and no significant difference was found between the scores of each factor (Visual Discomfort, Back Discomfort, Vision Difficulties and Extremity Discomfort; $p > 0.05$).

Action Measures

A visual examination of shoulder, elbow, and wrist joint ensemble angles qualitatively demonstrated that there were no differences in throwing kinematics between training groups before or after training (**Figures 5A,C,E**). The lack of qualitative differences in joint angles before and after training is corroborated by statistical analyses. For the end shoulder joint configuration, there was no significant main effect of time [$F_{(13,39)} = 1.843$, $p = 0.131$, $\eta p^2 = 0.047$] or for the time × group interaction [$F_{(13,39)} = 2.192$, $p = 0.08$, $\eta p^2 = 0.056$; **Figure 5B**]. For the elbow, there was a significant main effect of time [$F_{(13,39)} = 6.094$, $p < 0.001$, $\eta p^2 = 0.141$] and a significant time × group interaction [$F_{(13,39)} = 5.539$, $p < 0.001$, $\eta p^2 = 0.130$]. Follow-up Bonferroni comparisons reveal that these differences lie solely during training, as the VR training group released the dart with significantly greater elbow flexion compared to the control group for training times 1–5 and 7–10 ($p < 0.05$; **Figure 5D**). There were no significant differences before or after training, however. Finally, for the wrist joint there was no significant main effect of time [$F_{(13,39)} = 2.604$, $p = 0.057$, $\eta p^2 = 0.066$] or a significant time × group interaction [$F_{(13,39)} = 1.226$, $p = 0.304$, $\eta p^2 = 0.032$; **Figure 5F**].

All ANOVAs demonstrated no significant main effect of time [0%—$F_{(1,39)} = 1.725$, $p = 0.197$, $\eta p^2 = 0.045$; 25%–$F_{(1,39)} = 0.092$, $p = 0.764$, $\eta p^2 = 0.002$; 50%–$F_{(1,39)} = 1.771$, $p = 0.191$, $\eta p^2 = 0.046$; 75%–$F_{(1,39)} = 0.036$, $p = 0.850$, $\eta p^2 = 0.001$; 100%–$F_{(1,39)} = 1.4127$, $p = 0.242$, $\eta p^2 = 0.03$] or a time × group interaction [0%–$F_{(1,39)} = 0.723$, $p = 0.401$, $\eta p^2 = 0.019$; 25%–$F_{(1,39)} = 0.120$, $p = 0.731$, $\eta p^2 = 0.003$; 50%–$F_{(1,39)} = 0.326$, $p = 0.572$, $\eta p^2 = 0.009$; 75%–$F_{(1,39)} = 0.023$, $p = 0.880$, $\eta p^2 = 0.001$; 100%–$F_{(1,39)} = 0.528$, $p = 0.109$, $\eta p^2 = 0.014$] on Indices of Motor Abundance (**Figure 6**).

Throwing Velocity

After addressing all hypotheses, we performed an additional *post hoc* analysis to further determine the motor mechanism behind the noted group differences in task performance following training. Since previous work has detailed how experts throw darts at a higher velocity than novices (Schorer et al., 2012), we anticipated that the VR training group would throw at a significantly lower velocity following training compared to the real-world group, thereby impacting their throwing accuracy. To pursue this, we computed the peak resultant linear velocity of the marker placed on the 3rd metacarpal of the throwing hand from start to finish of the throw for both groups at the 14 measured time points (2 before training, 10 during training, 2 after training). This analysis revealed a significant main effect of time [$F_{(13,39)} = 90.076$, $p < 0.001$, $\eta 2 = 0.709$] and a significant time × group interaction [$F_{(13,39)} = 102.834$, $p < 0.001$, $\eta^2 = 0.735$]. Follow-up Bonferroni-corrected pairwise comparisons between groups at each time point indicate that the VR training group threw with a significantly lower velocity for all 10 time points during training ($p < 0.001$). However, at the two time points after training there were no significant differences between groups (Post-training 1—$t_{(1,39)} = -1.892$, $p = 0.066$; Post-training 2—$t_{(1,39)} = -1.515$, $p = 0.138$; **Figure 7**).

DISCUSSION

The purpose of this study was to examine the effects of a training session held in virtual reality compared to one held in the real world on a dart-throwing task.

While the VR group seemed to acquire similar perception and action strategies as the real-world group, these strategies did not translate into effective performance in the real world. Moreover, training in VR seemed to be detrimental as this group had significantly worse accuracy compared to how they performed prior to training. These results support hypothesis 1 and indicate that virtual training had a detrimental effect on real-world performance. Because Newell's Model of Constraints describes how performance of skill is dictated by the interaction between perception and action (Newell, 1986), we utilized multiple perceptual-motor measures as an attempt to uncover the mechanisms behind virtual skill acquisition. However, the lack of perceptual-motor differences between training groups on the real-world follow-up tests indicate that participants were behaving similarly in terms of perception and action. Thus, it is possible that some components of fidelity, such as the

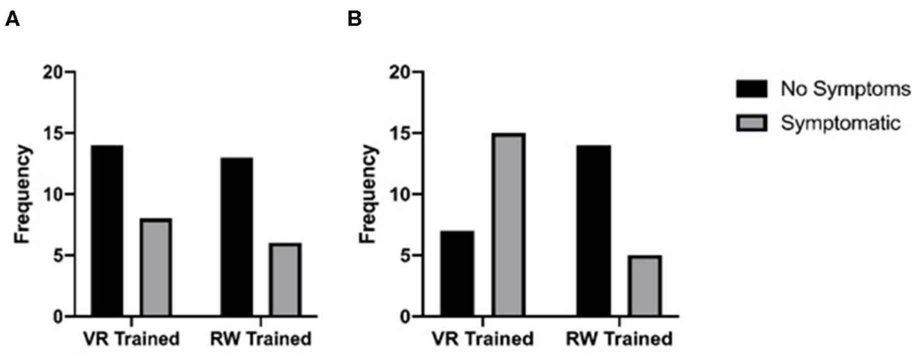

FIGURE 4 | Frequency distributions of symptom reporting **(A)** before training and **(B)** after training.

dartboard height being scaled to the participant in the virtual environment instead of being standard across all participants, may have negatively affected accuracy. To speculate, participants may have acquired a similar dart-throwing form to those in the real world, but were unable to correct that form when adapting their strategy to a slightly different dart board height. Further research should investigate whether scaling a virtual environment to better replicate the real world will in turn impact transfer of learned sport skills.

We hypothesized that (2a) virtual-reality trained participants would experience a decrease in accommodative and vergence facilities compared to real-world trained participants. This hypothesis was not supported by the data, as no group differences were observed, but both groups showed a significant increase in both facilities over time. These data are inconsistent with reports of Mohamed Elias et al. (2019), who reported an increase in accommodation response and a decrease in vergence. There are several possible explanations for this discrepancy between results. One possibility could be virtual reality task differences, as Mohamed Elias et al. (2019) utilized a virtual reality game that simulates continuous motion with content varying in distance on the virtual plane, our task involved remaining relatively stationary while focusing on a far target. As these two tasks had differing oculomotor demands, perhaps it is unsurprising that there were differences observed in the oculomotor behaviors. Furthermore, the oculomotor assessment measures themselves differed between these two studies; we employed accommodative and vergence facilities tests while Mohamed Elias et al. (2019) measured accommodative response and vergence stability. While our differing measures have allowed both Mohamed Elias et al. (2019) and our team to draw general conclusions about accommodative and vergence behaviors, it is likely that differences in the measurements made could account for some of the conflicting results. Arnaldi et al. (2018) have also suggested that while the vergence-accommodation conflict is a problem, perhaps a bigger issue is rapid changes of vergence demands, as reported by Emoto et al. (2005). This assertion would explain discrepancies between the findings of Mohamed Elias et al. (2019) and our own, as their target had changes in the visual plane while ours was at a fixed position; based on these differences, one might expect greater vergence problems reported with the target that varies in depths, as was observed.

Hypothesis 2b, which postulated that participants in the virtual reality training condition would report a greater number of symptoms post-training, was partially supported. There was a significantly greater proportion of symptoms reported on the acute symptom survey, but no significant differences were found between composite scores for the VRSQ or the CUS symptom surveys. The finding that the virtual reality training group experienced greater symptoms is consistent with extensive literature reporting symptoms after VR use (Nichols and Patel, 2002), including reports after using more advanced technology (Wilson and Soranzo, 2015; Mohamed Elias et al., 2019). The lack of significant results on the VRSQ and CUS may have several explanations. One possibility is that these surveys were administered after post-training accommodation and vergence facilities were measured and the final real-world dart-throwing assessment were made, a time of at least 5 min, and symptoms surveys administered subsequently after final dart throw measurements. As literature has reported that some symptoms experienced have a very short duration before being resolved (Mon-Williams et al., 1993; Rushton et al., 1994; Ames et al., 2005), it is possible that symptoms experienced may diminish to a point where subjective reporting did not detect differences; the broad acute symptom survey was administered first, and consisted of only four questions, while it was followed by the 14-question VRSQ and 21-question CUS; the length of these surveys may have resulted in additional time for symptoms to resolve. Furthermore, as with any survey, it is possible that participants were less engaged with the task of reporting for the lengthy 35 questions of the combine VRSQ and CUS. Future studies may want to consider selecting a single measure with a reduced number of items that require less time to complete.

We had also hypothesized that (3a) following training, participants in the virtual reality training group would throw with significantly different arm joint angles in the end configuration compared to real-world-trained participants. The results of this study do not support this hypothesis, as during the real-world follow-up tests there were no differences between groups for shoulder, elbow, or wrist joint angles in the end configuration.

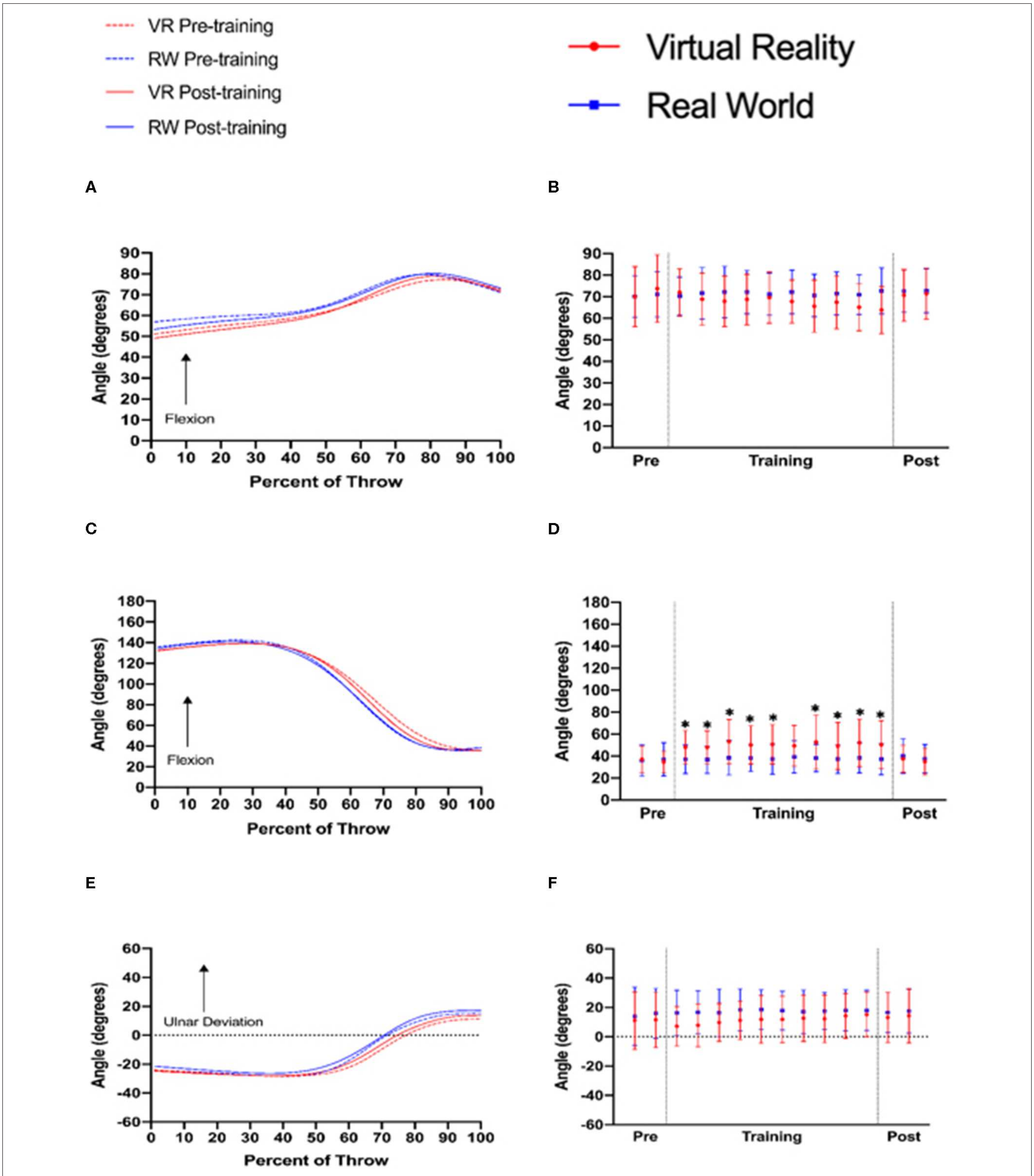

FIGURE 5 | Ensemble curves representing mean joint excursions from start (0%) to finish (100%) of the dart throw (left column) and discrete joint angles (right column) at the time of dart release for participants in the virtual reality and real-world practice groups before (pre) and after (post) training. **(A,B)**—Shoulder flexion/extension, **(C,D)**—elbow flexion/extension, and **(E,F)**—wrist radial/ulnar deviation (* denotes $p < 0.05$).

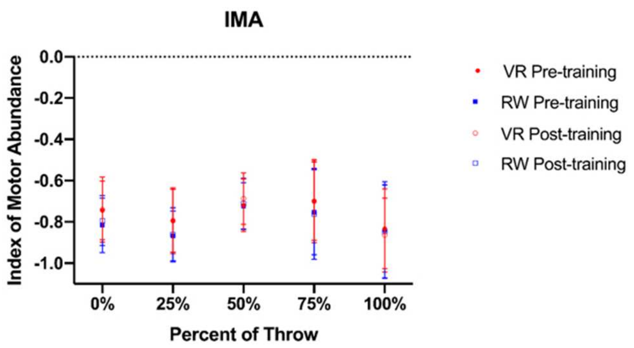

FIGURE 6 | Index of Motor Abundance (IMA) for those trained in virtual reality and the real world before (pre) and after (post) training.

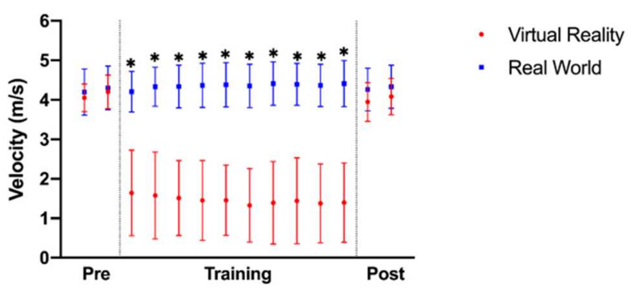

FIGURE 7 | Peak dart-throwing velocity for participants trained in virtual reality (VR) and the real-world (RW) before (Pre), during (Training), and after (Post) training (* denotes $p < 0.05$).

These results are surprising, given that during training the virtual reality training group exhibited significantly greater elbow flexion angles at the point of dart release during training, indicating that they were not extending their arm at the elbow as far as those trained in the real-world. This difference could be due to the fact that during VR training, participants had to hold a controller and release a trigger to throw a dart as opposed to throwing an actual dart. Previous work has discussed how certain physical parameters of objects influence individuals' reaching and grasping behavior (Johansson and Cole, 1992), and therefore the difference in how the virtual dart is manipulated compared to holding a real dart may serve as a task constraint. In turn, throwing kinematics (the motor component of Newell's Model of Constraints) were affected. Despite this unique throwing pattern, those trained in VR were able to rapidly adapt their throwing motion to the real world, as their throwing motion mirrored that of the real-world-trained participants on the follow-up test. Hence, the unique throwing behavior imposed by the constraints of this virtual learning environment does not transfer to the real world, which could indicate that manipulated objects may not need to be fully immersive in terms of weight, weight distribution, shape, and grip orientation if the acquisition of a specific kinematic pattern is the only goal of a virtual learning of sport skills. These results support previous work that has described how individuals who have learned a skill in virtual reality utilize similar kinematic patterns compared to those who learned the skill in the real world (Bideau et al., 2004; Viau et al., 2004; Fluet et al., 2015; Parijat et al., 2015; Pataky and Lamb, 2018). Overall, it seems that use of a standard handheld VR controller in place of a real-world object may be suitable for acquisition of kinematic patterns despite reducing immersion, although more work is needed to ensure that this observation holds true across different skills and sport performance contexts.

This lower level of immersion imposed by the use of a controller instead of a dart in VR and the increased weight of the controller, in combination with lower-fidelity aspects of the virtual environment (e.g., differences in dart projectile motion in VR compared to the real world), may be also be a reason why throwing velocity in VR was slower. However, since participants in the VR group threw at a velocity comparable to the real-world group on the real-world follow-up test, it appears that the VR group acquired a kinematic throwing pattern that is adaptable to different performance contexts. This observation is further supported through the UCM analysis, where participants in both groups utilized movement variability in the same way on the follow-up test, as there was no difference in IMA at 0, 25, 50, 75, or 100% of the throw. These results do not support hypothesis 3b, which predicted that the virtual reality training group would demonstrate lesser utilization of goal equivalent variability on the real-world follow-up test, as evidenced by an IMA closer to -1. Like the discrete joint angles, these results are also surprising given the relatively lower levels of fidelity and immersion in the virtual environment. Interestingly, both groups also exhibited an IMA that was <0 for all time points in the throw, indicating that all participants were utilizing more joint angle variability that affected the task-related variable (NGEV) than variability that did not (GEV). These results may have occurred for one of two reasons. First, the task-related variable (throwing hand position relative to the shoulder) may not be important for an individual to stabilize during a dart throw, and therefore individuals can vary its position while still effectively carrying out the throw. Other work has described how dart-throwing accuracy can be related to other variables such as release point, the angle of the dart, and release velocity (Kudo et al., 2000). Therefore, individuals may be able to compensate for a changing hand position by altering some or all of the other control variables, and thus hand position at the time of dart release may not be an important control variable. Second, as participants only underwent one acute session of training, it is possible that all individuals did not become proficient to the point where they were able to minimize variability of the task-related variable. Third, it should be noted that cognitive processes such as attention may also have had some effect on throwing coordination (Lohse et al., 2014; Sherwood et al., 2014). Regardless of the reason why participants organized variance, these results are noteworthy given that those who trained in VR acquired similar coordination patterns to those in the real world, perhaps lending further credence to the thought that the virtual environment does not need to be perfectly optimized in order to facilitate transfer of motor strategies.

There are other aspects of perception which should be considered by future work to provide a higher-resolution analysis of how performance can be negatively impacted by VR training. For one, the acute symptoms experienced by VR users may have been distracting to the participant or may have influenced their gaze behavior. Research has described how visual symptoms influence gaze behavior during performance of various tasks (van Leeuwen et al., 1999), but greater understanding of the relationship between these symptoms and actual gaze behavior specifically as a result of VR usage would be beneficial to understanding how perception is altered by this medium. A wealth of literature has described how, for far aiming tasks such as darts, experts utilize a "quiet eye," where the eye is stabilized and fixated on a target for a longer duration than novices (e.g., Vickers, 1996; Oppici et al., 2017). Hence, the reported usage symptoms may not have allowed for VR-trained participants to effectively stabilize their gaze during practice. Future work should utilize eye-gaze tracking measures in order to further determine how the use of an HMD for VR usage may affect visual perception of the task.

There are also additional measures of dart-throwing motor behavior that could help to explain performance differences in the future. For example, because VR-trained participants had to use a controller with a trigger to throw the virtual darts, and the controller was heavier (470 g controller vs. 18–24 g darts), their level of immersion in the virtual environment may have been affected. Immersion, an objective factor of a VR system that allows for a person to believe they are present in a virtual space (Slater, 2018), has been previously demonstrated to impact transfer of skills to the real world (Alexander et al., 2005). Future studies investigating VR to real-world transfer for throwing tasks should examine how changing the objects being manipulated in a virtual environment impact transfer of motor behavior and should utilize other projectile motion measures in order to further explain any performance differences compared to those trained in the real world.

LIMITATIONS

In addition to those already described specifically relating to each hypothesis, several additional limitations of our study should be noted. While our design included a real-world training group as a control group to be compared to the virtual reality trained group, perhaps additional information could be gleaned from the inclusion of a third group that would not undergo any training at all. As the target task performance following training declined in the virtual reality training group but improved in the real-world training group, the inclusion of this third group would allow additional comparisons to be made between each training group and no training group at all. A second limitation, as discussed previously, is that several aspects of VR fidelity and immersion (e.g., dartboard height scaling and controller usage) may have limited the degree to which participants in VR were able to transfer their skill to the real world. However, this virtual environment was specifically was chosen as it is free for use and therefore may reflect the quality of common platforms used for training of other sport skills. Additionally, some participants may have had slightly more dart-throwing expertise than others prior to training (though none had extensive experience). This moderate familiarity may have had some impact on the learning curve of those participants on the task. A final limitation to our study was that vergence facilities were always performed after accommodative facilities; it is possible that during the accommodative facility tests, participants' vergence system is able to sufficiently adapt to the real world after VR exposure such that any potential dysfunction could be ameliorated in time for vergence assessment. Future work would benefit from a counterbalancing of measures to avoid this potential confound.

CONCLUSIONS

In summary, the most note-worthy finding is that the virtual reality group performed significantly worse on the throwing task compared to their baseline, while the real-world group improved in performance. This outcome occurred despite the lack of differences between oculomotor behaviors and real-world task throwing strategies; we found that following training, those trained on a task in virtual reality demonstrated greater acute visual symptoms but similar oculomotor behaviors as those trained in the real world. In addition, during training, those in VR utilized a unique kinematic throwing strategy compared to the real-world group as evidenced by less elbow extension during the throw and a slower throwing velocity. However, following training, they adopted throwing strategies that mirrored those of the real-world group, perhaps demonstrating a rapid adaptability of coordinated movement between virtual and real environments. These results are noteworthy given the lower levels of fidelity and immersion of the virtual environment, which thereby limited the amount of overlapping environmental and task constraints between performance contexts. Thus, VR training platforms may not require optimization of fidelity and immersion to mirror real-world training, if acquisition of specific kinematic patterns for sport skills are a training goal. Future work should systematically manipulate aspects of fidelity and immersion in virtual environments to further clarify these results. Thus, it appears that other perceptual-motor factors or design factors may be present that detract from one's ability to transfer skills from virtual to real worlds. Future work should examine these performance differences across other sport skills and using other perceptual-motor measures to further generalize these results. In total, it is critical that those studying acquisition of sport skills in VR adopt an interdisciplinary approach to examining the underlying mechanisms of learning. A better understanding of human interactions with virtual environments will inform athletes, coaches, and the scientific community as to how to best implement a virtual training paradigm for acquisition of sport skills and how to better optimize virtual learning environments to maximize that acquisition. Given the exponential growth in VR utilization across the sporting domain, it is more critical than ever in both research and industry to consider the multiple dimensions through which VR usage can impact users.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Institutional Review Board California State University, Northridge. The patients/participants provided their written informed consent to participate in this study. This study adhered to the principles of the Declaration of Helsinki.

AUTHOR CONTRIBUTIONS

SD, JH-L, MA, and IL contributed to the conception and design of the study. MA, JA, and IL were responsible for all data acquisition. IL completed all data post-processing. SD, JH-L, IL, and BG performed statistical analyses. SD and JH-L wrote the manuscript. All authors contributed to manuscript revision, read and approved the submitted version.

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The Influence of Functional Flywheel Resistance Training on Movement Variability and Movement Velocity in Elite Rugby Players

Bruno Fernández-Valdés[1,2], Jaime Sampaio[3], Juliana Exel[3], Jacob González[4], Julio Tous-Fajardo[1,5], Ben Jones[6,7,8,9,10,11] and Gerard Moras[1]*

[1] National Institute of Physical Education of Catalonia (INEFC), University of Barcelona (UB), Barcelona, Spain, [2] Unió Esportiva Santboiana, División de Honor de Rugby, Sant Boi de Llobregat, Spain, [3] Research Centre in Sports Sciences, Health Sciences and Human Development, CreativeLab Research Community, University of Trás-os-Montes and Alto Douro, Vila Real, Portugal, [4] Futbol Club Barcelona, Barcelona, Spain, [5] FC Internazionale Milano, Milan, Italy, [6] Carnegie Applied Rugby Research Centre, Institute for Sport, Physical Activity and Leisure, Leeds Beckett University, Leeds, United Kingdom, [7] Leeds Rhinos RLFC, Leeds, United Kingdom, [8] Yorkshire Carnegie RUFC, Leeds, United Kingdom, [9] England Performance Unit, The Rugby Football League, Leeds, United Kingdom, [10] School of Science and Technology, University of New England, Armidale, NSW, Australia, [11] Division of Exercise Science and Sports Medicine, Department of Human Biology, Faculty of Health Sciences, University of Cape Town, Sports Science Institute of South Africa, Cape Town, South Africa

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****Correspondence:***
*Gerard Moras
gmoras@gencat.cat;
gmorasfeliu@gmail.com*

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The aim of this study was to identify the changes in movement variability and movement velocity during a six-week training period using a resistance horizontal forward–backward task without (NOBALL) or with (BALL) the constraint of catching and throwing a rugby ball in the forward phase. Eleven elite male rugby union players (mean ± SD: age 25.5 ± 2.0 years, height 1.83 ± 0.06 m, body mass 95 ± 18 kg, rugby practice 14 ± 3 years) performed eight repetitions of NOBALL and BALL conditions once a week in a rotational flywheel device. Velocity was recorded by an attached rotary encoder while acceleration data were used to calculate sample entropy (SampEn), multiscale entropy, and the complexity index. SampEn showed no significant decrease for NOBALL (ES = -0.64 ± 1.02) and significant decrease for BALL (ES = -1.71 ± 1.16; $p < 0.007$) conditions. Additionally, movement velocity showed a significant increase for NOBALL (ES = 1.02 ± 1.05; $p < 0.047$) and significant increase for BALL (ES = 1.25 ± 1.08; $p < 0.025$) between weeks 1 and 6. The complexity index showed higher levels of complexity in the BALL condition, specifically in the first three weeks. Movement velocity and complex dynamics were adapted to the constraints of the task after a four-week training period. Entropy measures seem a promising processing signal technique to identify when these exercise tasks should be changed.

Keywords: entropy, strength training, task constraints, team sports, adaptability

INTRODUCTION

Resistance training is a key determinant of the physical conditioning process in elite rugby (Inness et al., 2016). It has been suggested that traditional resistance training tasks are too static and contradictory to the natural complex open system of team sports, which demands the self-organization of the large amount of degrees of freedom involved in the interaction between the environment and the dynamics of players' decisions and actions (Travassos et al., 2011). Therefore, developing the ability to perform stable actions, i.e., the capacity to accelerate and decelerate (Seitz et al., 2015), under complex scenarios involving attuning interpersonal coordination (Duarte et al., 2012), as well as equipment and pitch space control in decision making (Greihaine et al., 2011), is very challenging but imperative at high levels of competition (Couceiro et al., 2013). In fact, rugby players need to be effective at sprinting while carrying a rugby ball (Pollard et al., 2018), which consequently increases the complexity of running, by altering the natural arm swing performed to counterbalance the hip rotation (Barr et al., 2015).

One of the most important variables to consider when designing an optimal resistance training program is the movement velocity (Bautista et al., 2016), so the training can be transferable to the tasks that require a developed capacity of body acceleration. However, the guidelines available in the current literature lack information on coordination patterns of the neuromuscular control system responses during training (England and Granata, 2007). By describing the effects emergent from different task constraints on such patterns, novel and important information about the players' mechanisms of organic adaptation can be revealed (Mehdizadeh et al., 2015). Indeed, recent research identified motor variability as a key factor to describe the coordination features from the sensorimotor system operations and from the learning processes (Dhawale et al., 2017).

Recent research has found that the use of specific task constraints, such as carrying or passing a rugby ball during the execution of a functional eccentric overload resistance exercise, elicits different structures of variability in players' body acceleration across multiple time scales, particularly toward higher level or systemic scales (Moras et al., 2018). One of the follow-up questions from this first body of evidence is related to the effect of time on the biological complexity responses in resistance training programs that use ball constraints, particularly associated to the acceleration outcomes and their effects on performance.

There are different approaches to analyze human movement and assess variability to identify changes in patterns and spatiotemporal characteristics (Stergiou et al., 2006; Preatoni et al., 2010, 2013; Dhawale et al., 2017; Moras et al., 2018). It has been recognized that linear measurements have several limitations, especially in determining movement degree of complexity and the time-dependent structure of a time series (Lipsitz and Goldberger, 1992). These limitations can be addressed by a non-linear approach, such as measures of entropy, to better describe healthy and pathological conditions (Costa et al., 2002), changes in postural control (Rhea et al., 2011; Lubetzky et al., 2018), assessment of running (Murray et al., 2017), tactical behavior in soccer (Gonçalves et al., 2017), or movement variability in resistance training tasks (Moras et al., 2018).

Entropy quantifies the amount of regularity and unpredictability of point-to-point fluctuations in large sets of time-series data (Richman and Moorman, 2000). Sample entropy (SampEn) and multiscale entropy (MSE) are two of the most popular methods for assessing data regularity in health and sports sciences (Busa and van Emmerik, 2016). Sample entropy measures the probability that similar sequences of points in a time-series remain similar within a tolerance level when a point is added to the sequence, in a single time scale (Richman and Moorman, 2000). On the other hand, MSE analysis has been suggested to be a better method to address the complexity inherent in the biological signals because it considers multiple spatial and temporal scales in a time series, reflecting the multiscale characteristics of the biological system operation (Costa et al., 2002, 2005; Gow et al., 2015). Particularly regarding movement variability, research is still limited to a few examples who suggest that it might be reduced as a function of practice (Newell and Vaillancourt, 2001; Wu et al., 2014) and experience (Ko and Newell, 2015; Williams et al., 2016). However, how movement variability decays over time during resistance training over the course of a training program, thus, how it affects players' adaptive capacity, remains unclear. Therefore, the aim of this study was to identify the changes of movement variability, complexity index, and movement velocity with training in a resistance horizontal forward–backward task without (NOBALL) or with the constraint of catching and throwing a rugby ball in the forward phase (BALL) during a six-week training program.

It was hypothesized that movement variability and complexity index would decrease, and movement velocity would increase, over the course of a six-week training program, especially when using the constraint of catching and throwing a rugby ball. Conversely, the stabilization of movement variability, complexity index, and movement velocity can be used to identify an optimal moment to modify the task.

MATERIALS AND METHODS

Participants

Eleven elite male rugby union players from a professional team in the Spanish league volunteered to participate in this study (mean ± SD: age 25.5 ± 2.0 years, height 1.83 ± 0.06 m, body mass 95 ± 18 kg, rugby practice 14 ± 3 years). All players were asked to avoid strenuous exercise during the study and informed about the procedures and possible risks while giving their informed consent before their admission. No players had any injuries through the study duration and the procedures complied with the Declaration of World Medical Association (2013) and were approved by the local ethics committee (21/20118/CEICEGC).

Design

The study was performed over 6 weeks. A recent meta-analysis about the effects of flywheel training on Strength-Related Variables show that the majority of these studies were carried out on periods of training between 5 and 10 weeks (Petré et al., 2018). However, more concretely, another recent study demonstrated that 4 weeks could be enough time to show muscle adaptation in flywheel resistance training (Illera-Domínguez et al., 2018). Further, in horizontal inertial flywheel training, which has more similarity to our study (de Hoyo et al., 2015; Gonzalo-Skok et al.,

FIGURE 1 | Horizontal movement with an inertial flywheel device with BALL **(below)** and NOBALL **(above)**.

2016), differences in power and functional performance in 6- and 8-week period training were found. So, for these reasons, we hypothesize that 6 weeks could be enough time to find significant differences in both variables, movement velocity and movement variability. Since the players had no previous experience with this device prior to the experiment, participants underwent a familiarization session in which the horizontal movement with an inertial flywheel device was performed at a submaximal intensity in two conditions (BALL and NOBALL). When performing the BALL condition, an expert player made a pass from the right side two meters away. The participant caught the ball over the forward movement, synchronized with the first step (**Figure 1**). Then, during the second step, the participant passed the ball to another expert player standing 2 m away at the other side. Emphasis was placed on the importance of keeping the inertial flywheel rope tight. The training protocol was performed once a week during 6 weeks and included a warm-up, where the players performed 5 min of cycle ergometer, 5 min of general active mobility, two progressive sprints of 10 m, 10 movements at maximum speed forward and backward of 4 m, and five movements of maximum speed with changes of direction of 3 m. Afterward, the participants randomly performed eight repetitions of NOBALL and BALL with 3 min of rest between exercises. In the first two repetitions the intensity was progressively increased, while the last six were performed at maximal voluntary effort. During data collection, participants did not receive any verbal information on the quality of the movement performed or the outcomes of the test. Data collection took place during the competitive season.

Procedures

The inertial flywheel device (Byomedic System SCP, Barcelona, Spain) consists of a metal flywheel (diameter: 0.42 m) with up to 16 weights (0.421 kg each weight), that can be added along the top edge of the flywheel perimeter. The device is comprised of a cone attached above a flywheel, and as the axle spins, a rope winds and unwinds around the cone. The concentric action unwinds the rope and the eccentric action occurs during rewinding. The force applied in the eccentric action to bring the flywheel to a stop will rely on the kinetic energy generated during the concentric action (Vicens-Bordas et al., 2018). To change the resistance to movement, the moment of inertia can be modified by adding any number of the 16 weights to the edge of the flywheel and also by selecting one of the four positions (P1, P2, P3, or P4) by changing the location of the pulley that is close to the cone. Position 1 and 16 weights were selected for this study, because these can generate the highest levels of mean force (Vázquez-Guerrero et al., 2016). The moment of inertia for the flywheel was 0.27 kg m^2. Movement velocity was measure by a rotational encoder (Chronojump, Barcelona, Spain) which measures the spinning velocity of the axis of the flywheel device.

The participants' acceleration performed in both conditions was measured using the inertial measurement unit WIMU (Realtrack Systems, Almeria, Spain), with processing capability consisting of a 3D accelerometer recording at 1000 Hz. The accelerometer was placed on an elastic waist belt close to the sacrum of each player. This position provided the best indication of whole body movement, as the location is close to the player's center of mass (Montgomery et al., 2010).

Four repetitions of the NOBALL and BALL conditions were considered for further analysis. Each sample record contained 13879 $\pm$ 1900 data points for NOBALL and 14703 $\pm$ 1804 for BALL. In addition, the raw signal was obtained from the system specific software (WIMU Software, Realtrack Systems SL, Almería, Spain) to calculate total acceleration (at) based on the summation of vectors in three dimensions: mediolateral (x), anteroposterior (y) and vertical (z) (Moras et al., 2018). The mean velocity was recorded for the same four repetitions, registered with a rotary axis encoder, and analyzed with the software of chronojump (Chronojump, Barcelona, Spain).

The acceleration data were used to calculate entropy measures across a single time scale (SampEn) and across a range of time-scales (MSE), according to Chen et al. (2006) and Costa et al. (2002), using dedicated routines written in Matlab® (The MathWorks, MA, United Sates). Also, the Complexity Index (Gow et al., 2015) was calculated as the area under each of the MSE curves to provide information on the integrated complexity of the system, over the time scales of interest (Busa and van Emmerik, 2016; Hansen et al., 2017). The mean velocity recorded from the encoder was also included in the analysis.

Statistical Analysis

Data normality and homogeneity was assessed using Shapiro–Wilk and Levene tests, respectively. Data analyses were performed using PASW Statistics 21 (SPSS, Inc., Chicago, IL, United States). The level of statistical significance was set at $p < 0.05$. The response variable (SampEn, complexity index, and mean velocity) were analyzed using a repeated measure analysis of variance (ANOVA) to address the main and interactive effects between weeks, comparing the baseline (week 1) with all other weeks.

The comparisons were also assessed via standardized mean differences (Cohen's d) and respective 90% confidence intervals.

Thresholds for effect sizes statistics were <0.20, trivial; 0.20–0.59, small; 0.6–1.19, moderate; 1.20–1.99, large; and >2.0, very large (Hopkins et al., 2009). Movement velocity and Complexity Index values under BALL and NOBALL conditions were also adjusted to a third-degree polynomial for a better visualization of these variables in summarizing the effects of the six-week training protocol.

Finally, Bland–Altman analysis was used to assess biases of the variables (SampEn, complexity index and mean velocity) between conditions (Bland and Altman, 1995).

RESULTS

The individual trends, average, and standard deviation across the 6 weeks for SampEn and movement velocity in BALL and NOBALL conditions are shown in **Figure 2**. SampEn presented higher values in the first four weeks for BALL and in the last two weeks for NOBALL (**Figures 2A,C,E**). However, movement velocity presented higher values across the whole training period for NOBALL, although the values were similar in the last two weeks (**Figures 2B,D,F**).

When SampEn was compared between the baseline (week 1) and the subsequent weeks in the BALL condition, there were no significant changes, but there were moderate effects in the first four weeks, significant changes in the fifth week ($p = 0.015$) with moderate effects, and significant changes in the last week ($p = 0.007$) with a large effect (**Figure 3A**). By contrast, there were no significant differences in NOBALL conditions between weeks (**Figure 3A**). Also, when movement velocity was compared between the baseline (week 1) and the subsequent weeks in the BALL condition, there were significant changes in third ($p = 0.010$), fourth ($p = 0.045$), fifth ($p = 0.029$), and sixth ($p = 0.047$) weeks with moderate and large effects (**Figure 3B**). For the NOBALL condition there were significant changes in third ($p = 0.012$), fourth ($p = 0.048$), fifth ($p = 0.027$), and sixth ($p = 0.025$) weeks with moderate effects (**Figure 3B**).

When complexity indexes were compared between the baseline (week 1) and the subsequent weeks in the BALL condition, there were significant changes for every week ($p \leq 0.05$), except with the fourth week. By contrast, there were no significant differences in NOBALL conditions between the training weeks. The results from the complexity index and movement velocity are presented in **Figure 4**, smoothed using a third-degree polynomial for a better visualization. There were higher levels of complexity in the BALL conditions, specifically in the first three weeks.

Bland-Altman plots are presented in **Figure 5**. The resulting graph is a scatter plot *xy*, in which the *y* axis shows the difference between the conditions (BALL–NOBALL) and the *x* axis represents the average of these measures.

DISCUSSION

This study aimed to identify how movement variability and movement velocity changes during six weeks of training including a resistance horizontal forward–backward task without (NOBALL) or with the constraint of catching and throwing a rugby ball in the forward phase (BALL). In general, the results suggested that movement velocity and movement variability were adapted to the constraints after four weeks of training.

The baseline values at week 1 showed higher movement variability in the BALL when compared to NOBALL condition, supporting results recently reported (Moras et al., 2018). It was also possible to identify that movement variability remained higher until the fifth week of training, showing that using the ball as a constraint during this functional resistance training exercise demands higher levels of coordination patterns, stimulating the beneficial and adaptive aspects of variability in system function (van Emmerik and van Wegen, 2002).

The results also showed that movement variability across the six-week training period had a moderate and large reduction from week 1 to week 6 and a significant decrease in the weeks 5 and 6 for the BALL condition. This decrease might be due to an improved ability to control the coordination of the ball pass through practice (Ko and Newell, 2015; Williams et al., 2016). Based on the principle of optimality, sensory estimation could minimize uncertainty across optimal integration, and minimize variability in motor output through optimal control (Bays and Wolpert, 2007).

After four weeks of training, there was a stabilization on the BALL condition whichh was noted not only in a single temporal scale, as evidenced by SampEn values, but also when different temporal scales are considered, as seen in the complexity index results. The complexity index represents how systems are integrated from its lowest (organic) to highest (systemic) scale levels. When constraints are applied to resistance training, there seems to be changes in the system coordination patterns (Oliveira et al., 2013; Moras et al., 2018), however, the training process seems to regulate movement stability and adaptability (van Emmerik and van Wegen, 2002) to the point where the motor system is adapted to the environmental perturbations. The present study reports evidence that corroborates on the beneficial and adaptive aspects of variability during resistance training (van Emmerik and van Wegen, 2002) but, most importantly, reports details about the time-course of the effects related to the use of these different and unusual constraints. The results showed that four weeks were enough time for the task constraint to become too predictable for the players, therefore, not requiring substantial organic adaptations. Note that, after four weeks of resistance training, the complexity index was similar for both conditions, whereby the application of the constraints loses its effect and exercise tasks should be modified. Although the assessment of movement variability provides information about coordinative adaptations, during resistance training, the velocity at which a given load is displaced determines the strength and power adaptations at the muscular level (Bautista et al., 2016).

As expected in the NOBALL condition, the movement velocity output was higher than BALL, possibly due to the lower level of coordination required to perform the task. However, using match specific constraints during resistance training achieved more improvement between weeks. While NOBALL has a

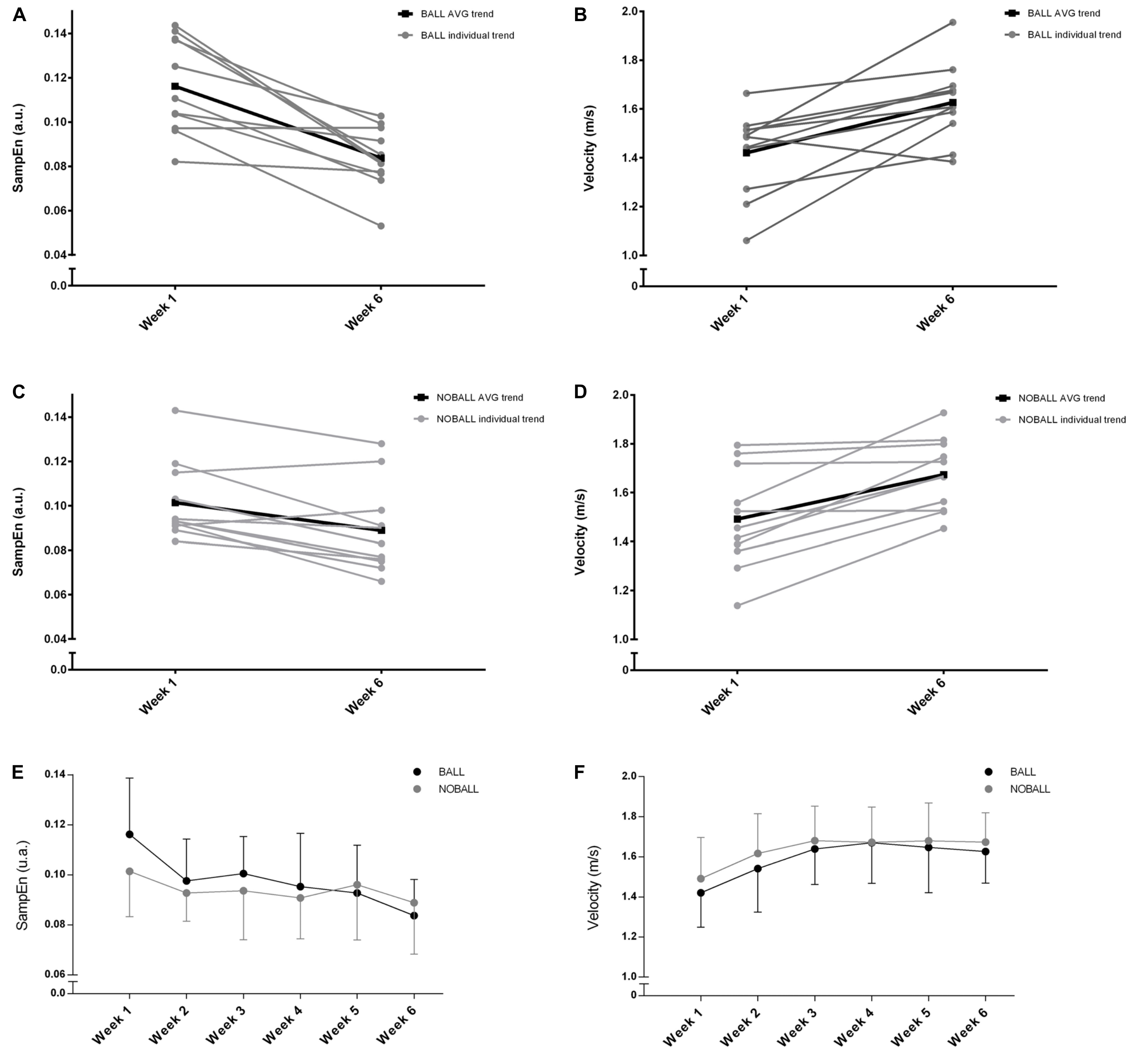

FIGURE 2 | Individual trends, average, and standard deviation. SampEn and velocity in BALL **(A,B)** and NOBALL **(C,D)** compared between the baseline (week 1) and final week (week 6). Group average and standard deviation for SampEn **(E)** and velocity **(F)** in both conditions.

higher dependency on players' capacity of improving force and velocity, BALL demands a higher level of motor skill, because it involves the coordination of carrying a ball while developing rapid accelerations. After three weeks of resistance training there were significant differences in the velocity for both conditions compared with week 1. Nevertheless, from week 4 to the end of the 6-week training period, the movement velocity did not change with training with or without the ball constraint. Thus, the result found in the current study suggests that velocity adaptations are reached before the movement variability, maybe because neuromuscular adaptations to human velocity and human variability are associated with different regulatory mechanisms (Hedayatpour and Falla, 2015). In team sports, the effectiveness of resistance training to improve sport performance depends upon the process of adaptations in terms of temporal structure changes (movement variability) and output performance magnitude (movement velocity). Therefore, the present study provides evidence that might better guide the training process, establishing optimal challenging points for resistance exercises and combining physical and coordinative tasks.

A previous study showed how entropy measures detect increased movement variability in resistance training when the ball is used like a constraint (Moras et al., 2018). The

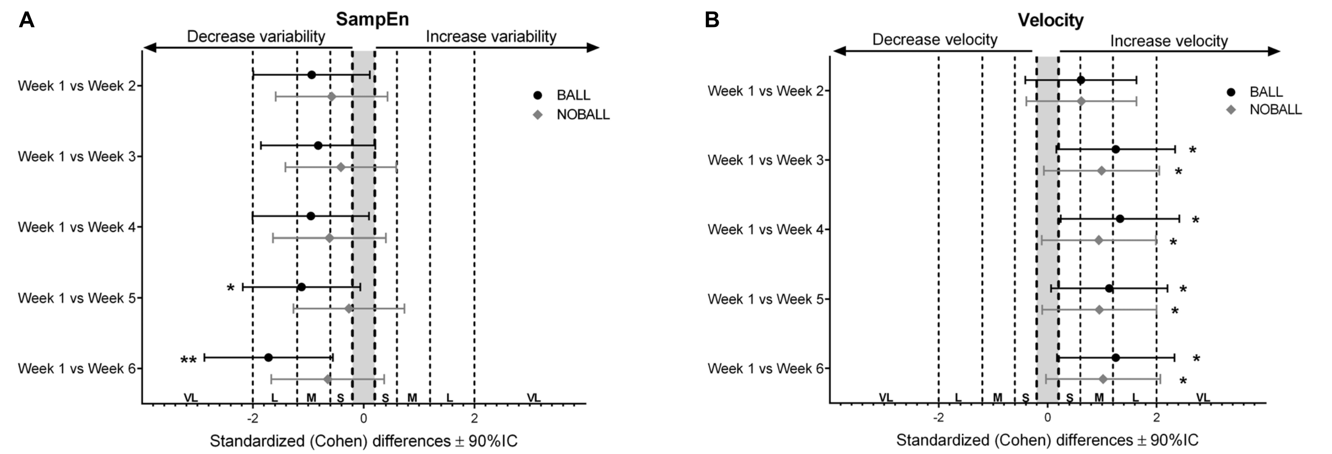

FIGURE 3 | Standardized Cohen's differences between the baseline (week 1) and the subsequent weeks for SampEn **(A)** and velocity **(B)** in both conditions. Error bars indicate uncertainty in true mean changes with 90% confidence intervals. Also, the significant differences were shown as *p < 0.05 and **p < 0.01. VL, very large; L, large; M, moderate; S, small.

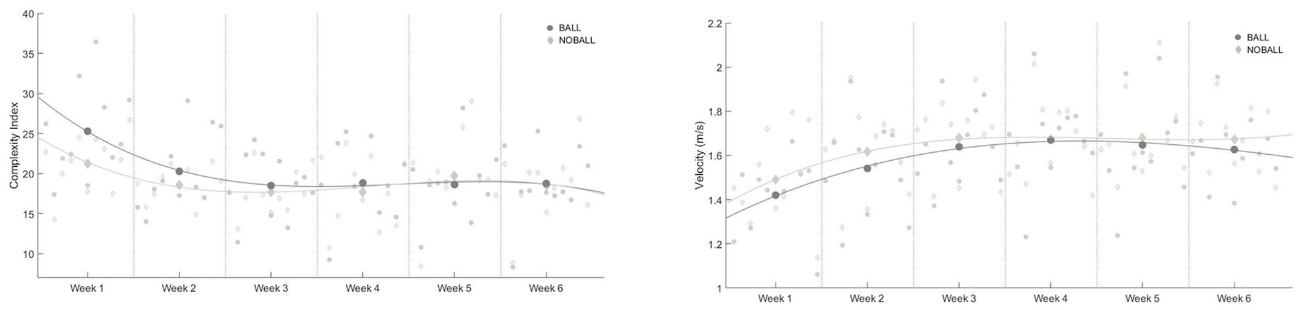

FIGURE 4 | Complexity indexes and movement velocity values. BALL and NOBALL conditions adjusted to a third-degree polynomial.

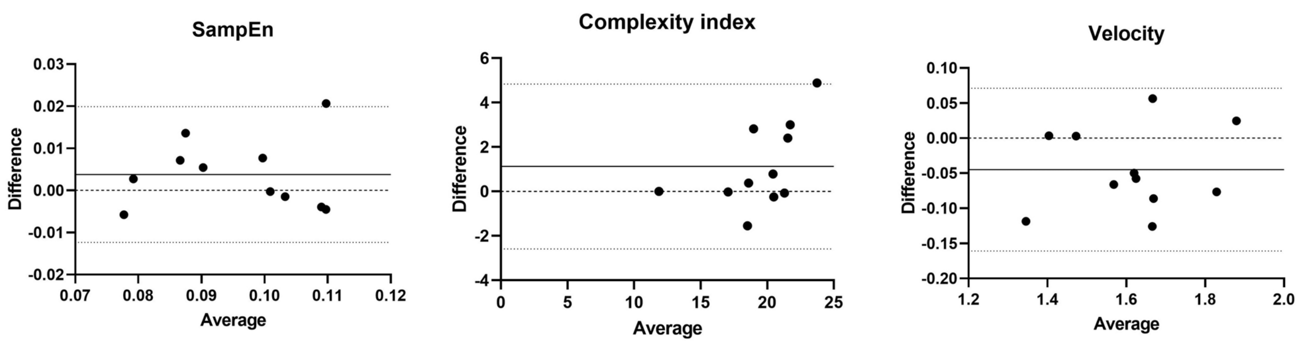

FIGURE 5 | Bland and Altman plots, with the representation of the limits of agreement (dotted line) and bias (line).

present study helps us to understand how the learning process inherent to a period of functional resistance training using a ball constraint changes the variability of the acceleration and affects performance across time. This study shows how entropy serves as an alternative tool to identify not only the changes in movement variability, but its time-course during a training period. This way, the trainers can structure the exercises to enhance players' performance according to the field tasks and match demands required (McLaren et al., 2016) by efficiently combining physical and coordinative capacities in resistance training.

Limitations

One of the main limitations of the current study was the low sample size (n = 11) and all of the players belonging to the same club. Nevertheless, these were expert players at the maximum level of competition in Spain. Rugby Union is a team sport with high levels of injury (Ball et al., 2017), especially at the maximum level (Yeomans et al., 2018), therefore, completing the training protocol during six weeks continuously in the competitive season period with enough healthy players was already an important milestone achieved.

CONCLUSION

Six weeks of resistance training decreases movement variability and increases velocity, especially when catching and throwing a rugby ball. Despite that, the success in the application of tasks constraints might be compromised after four weeks of training. Coaching staffs can consider this moment as the key to decide whether to modify the task.

PRACTICAL IMPLICATIONS

(1) Entropy measures can be used as a way of evaluating the ongoing appropriateness of an exercise stimulus to optimize adaptation. Entropy measures can be used by strength and conditioning coaches to identify when exercise tasks should be modified to trigger further adaptations.
(2) Entropy can help to identify the optimal challenge point, therefore maintaining movement variability and preventing a plateau in exercise adaptations. The use of the ball during a functional resistance training task will result in higher trainability, especially during the first four weeks. This is due to the increased complexity of the exercise.
(3) Strength and conditioning coaches should consider the inclusion of the ball when targeting the development of coordination within a periodized training program.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Catalan Sports Council (Generalitat de Catalunya) ethics committee (21/20118/CEICEGC). The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

BF-V and GM conceived and designed the experiments. BF-V, GM, and JG performed the experiments. BF-V, GM, JS, JE, and JG analyzed the data. BF-V wrote the first draft of the manuscript. BF-V, GM, JS, JE, JT-F, and BJ wrote, reviewed and edited the manuscript. All authors read and approved the submitted version of the manuscript.

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When and How to Provide Feedback and Instructions to Athletes?—How Sport Psychology and Pedagogy Insights Can Improve Coaching Interventions to Enhance Self-Regulation in Training

Fabian W. Otte[1], Keith Davids[2], Sarah-Kate Millar[3] and Stefanie Klatt[1,4]*

[1] Department of Cognitive and Team/Racket Sport Research, Institute of Exercise Training and Sport Informatics, German Sport University Cologne, Cologne, Germany, [2] Sport and Physical Activity Research Centre, Sheffield Hallam University, Sheffield, United Kingdom, [3] Department of Coaching, Health and Physical Education, Faculty of Health and Environmental Sciences, Auckland University of Technology, Auckland, New Zealand, [4] Institute of Sports Science, University of Rostock, Rostock, Germany

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****Correspondence:***
Stefanie Klatt
stefanie.klatt@uni-rostock.de

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In specialist sports coaching, the type and manner of augmented information that the coach chooses to use in communicating and training with individual athletes can have a significant impact on skill development and performance. Informed by insights from psychology, pedagogy, and sport science, this position paper presents a practitioner-based approach in response to the overarching question: When, why, and how could coaches provide information to athletes during coaching interventions? In an ecological dynamics rationale, practice is seen as a search for functional performance solutions, and augmented feedback is outlined as instructional constraints to guide athletes' self-regulation of action in practice. Using the exemplar of team sports, we present a Skill Training Communication Model for practical application in the context of the role of a specialist coach, using a constraints-led approach (CLA). Further based on principles of a non-linear pedagogy and using the recently introduced Periodization of Skill Training (PoST) framework, the proposed model aims to support practitioners' understanding of the pedagogical constraints of feedback and instruction during practice. In detail, the PoST framework's three skill development and training stages work to (1) directly impact constraint manipulations in practice designs and (2) indirectly affect coaches' choices of external (coach-induced) information. In turn, these guide practitioners on how and when to apply different verbal instruction methodologies and aim to support the design of effective skill learning environments. Finally, several practical guidelines in regard to sports coaches' feedback and instruction processes are proposed.

Keywords: specialist role coaching, augmented information, constraints-led approach, ecological dynamics, skill acquisition

INTRODUCTION

Coaches endeavor to engage in behaviors that effectively facilitate each athlete's progress toward achieving particular goals in competition or practice environments. Essential to this progress is athlete learning, and a key tool for coaches is the effective use of verbal instructions and feedback (More and Franks, 1996). Contemporary research has identified verbal instructions are the dominant activity engaged in by coaches at all levels (Potrac et al., 2000; Hodges and Franks, 2002). Different verbal instruction properties, including timing, nature, and intent, have been studied, finding that verbal instruction has important effects on athletes' learning and performance (Davids et al., 2008; Cassidy et al., 2009; Klatt and Noël, 2019). This considered, the provision of constructive augmented information (including verbal instructions, feedback, praise, and criticism) has long been regarded essential psychological and pedagogical competencies of sports coaches designing learning environments (Holding, 1965; for more recent position statements, see Chow, 2013; Button et al., 2020). Particularly, the rationale for type and manner of verbal communication that coaches choose to use (or not use) with individual athletes can support their skill development and discovery of task solutions and can arguably make a difference for each athlete's development and successful performance in sports (Partington et al., 2014; Correia et al., 2019). For the purpose of this article, adopting an ecological rationale, augmented information is considered as an instructional constraint on motor learning (Chow et al., 2016; for original insights, see Newell, 1986). This constraint takes the form of verbal feedback and instructions and is delivered by external agents (such as coaches, trainers, sport scientists, teachers, parents, educators, and peers; Handford et al., 1997). With respect to learning experiences, the main goal of verbal feedback and instructions (often in integration with other sensory modalities, such as vision or proprioception) has been stated as follows: "to help educate the attention of a learner to perceive and utilize relevant information sources" within skill (acquisition and refinement) training environments (Correia et al., 2019, p. 126). In support of this goal during learning, it is paramount that sport coaches and teachers have a viable model of practice design that supports the delivery of verbal feedback and instructions to athletes in coaching interventions (see Newell and Ranganathan, 2010; Chow, 2013, for discussions in a non-linear pedagogy and within a constraints-based framework).

From a non-linear pedagogy perspective, because of augmented verbal information being considered as an instructional constraint, pedagogical expertise in deciding *when*, *how*, and *why* to provide *what* verbal information to athletes is crucial. Thus, coaching behavior needs to be based on a comprehensive theoretical rationale for successful implementation and used as part of the learning design in sports coaching. In this article, we introduce a novel Skill Training Communication Model for use of augmented information as an instructional constraint to guide athlete activities during skill acquisition and in preparation for performance in sport. Here, we focus on the use of verbal feedback and instructions in somewhat unique coaching contexts, such as "specialist coaching" (i.e., coaches in charge of one-on-one or small-group trainings to refine athletes' position-specific skills; Otte et al., 2019a, 2020a).

In order to introduce and underpin the Skill Training Communication Model, this article is structured in three parts. Whereas Parts A and B provide a theoretical foundation for the model in regard of an ecological dynamics rationale for providing augmented verbal feedback during practice (i.e., Part A) and a skill training periodization framework (i.e., Part B), Part C presents the communication model. In particular, this communication model to coaching is further motivated by concerns that traditional coaching strategies and processes often appear to "adhere to established or intuitive instructional methods" (Wulf, 2013, p. 97). Reasons for such concerns include a possible lack of a theoretical framework for providing verbal instructions and feedback in practitioner education programs; this limitation is underlined by the suggestion that there have been "relatively few investigations of coaching" (Partington et al., 2014, p. 404) and that a "body of pedagogically focused coaching research" has only recently begun to emerge (Vinson et al., 2016, p. 54; see also Uehara et al., 2016). Consequently, it is the aim of this article to support coaches in rethinking the role and application of verbal feedback and instructions in a skill training context; this, based on an ecological dynamics rationale to augmented feedback, will be presented in Part A and later be elaborated in Part B [Periodization of Skill Training (PoST) framework] and Part C (Skill Training Communication Model).

PART A: AN ECOLOGICAL DYNAMICS RATIONALE TO AUGMENTED FEEDBACK

Feedback and instructions (whether including sources of verbal information, feedback, and/or other modalities) are considered instructional constraints, form augmented feedback (Annett, 1969; Sigrist et al., 2013), and are commonly provided to a learner from external agents during practice and training (Handford et al., 1997). Instructional constraints such as augmented feedback during learning can be distinguished from intrinsic feedback processes that are ubiquitous and naturally occur within individuals engaged in discovery and externally guided learning experiences in representative training environments (Vereijken and Whiting, 1990). While experience of intrinsic feedback (as sensory afferences) during learning is vital, research has shown that externally provided feedback and instructions, or instructional constraints, carefully applied by coaches, may support, guide, and complement learning (Holding, 1965; Newell et al., 1985; Sigrist et al., 2013).

From an ecological dynamics rationale, information regulates action, and practice has been conceived as a search for functional task solutions and relevant performance behaviors, which can become stabilized with experience and learning (Newell, 1991; Handford et al., 1997). Search activities during practice can support the self-regulation of athletes finding high-quality information sources to coordinate their actions. Functional action solutions exist in a landscape of affordances (opportunities for action; Rietveld and Kiverstein, 2014; Strafford et al., 2020), which surround learners in a performance environment (Button et al., 2020). An important role of sport coaches and teachers is to guide the learner's search of the affordance landscape, and application of instructional constraints is a powerful tool to be carefully used in important search activities (Newell, 1986). Hereby, pedagogical practice is conceived as driving search processes that may be described as "learning to attend to informational variables of the task and modifying actions in terms of informational variables" (Pacheco et al., 2019, p. 3).

The theoretical rationale for using augmented verbal information and feedback to support search activities and guide learners toward functional affordances in the landscape differs considerably from traditional pedagogical models (Davids et al., 2008; Ford et al., 2010). Traditional pedagogies tend to emphasize specific detailed prescription of a movement template for repetitive rehearsal (providing an "optimal" way to perform a specific movement), as well as the application of corrective feedback in repeating a movement technique (Davids et al., 2008). These prescriptive coaching approaches arguably lead to overuse of verbal information and feedback that can impede athlete development by impinging on opportunities for self-regulation (Davids et al., 2008; Partington and Cushion, 2011), which is a major aim of sports training and practice (Handford et al., 1997; Davids, 2015). Therefore, from an ecological dynamics rationale, the careful application or omission of augmented information (i.e., verbally and in integration with other feedback and instruction modes) needs to consider athletes' self-regulated exploration and search activities.

In the current article, our specific focus is the introduction of a novel Skill Training Communication Model (i.e., in Part C). Particularly, the model aims to support provision of instructional constraints in the context of specialist coaching in team sports (e.g., coaching single athletes and subgroups, such as attackers, defenders, goalkeepers), allowing coaches to individually support and communicate with athletes with specific performance needs. Notably, strategic team tactics (e.g., the coach introducing a tactical game plan to the entire team) that traditionally are adopted in performance preparation in team sports, such as soccer, basketball, volleyball, or rugby, are not the focus of the model. Rather, it is the aforementioned specialist coaching context in team sports that places particular emphasis on the objectives of skill acquisition and refinement in practice designs.

PART B: THE POST FRAMEWORK

The proposed Skill Training Communication Model (see Part C) builds upon a recently introduced PoST framework by Otte et al. (2019b). The PoST framework, at its core, is focused on how skills are taught by specialist or individual development coaches working with single athletes and/or subgroups of athletes and is based on the theoretical perspective of the constraints-led approach (CLA; Newell, 1986). The CLA considers emerging task, environment, and individual constraints that can change or be manipulated to lead learners to exploit inherent tendencies to "self-organize in attempts to generate effective movement solutions" (Renshaw and Chow, 2019, p. 104; see also Renshaw et al., 2019, for an overview of CLA, allied to principles of ecological dynamics and non-linear pedagogy). In more detail, the specific context of specialist coaching allows practitioners to design training sessions that support a focus on self-organized movement solutions that emerge in the actions of individual athletes with specialized roles in sports teams. In ecological dynamics, it has been proposed that directions of constraints on self-organizing tendencies of individual athletes and sports teams, during synergy formation, are continuously shaped by local-to-global (exploiting intrinsic dispositions for self-organization) and global-to-local influences (being organized by external agents such as coaches; Ribeiro et al., 2019). Particular emphasis in CLA has been placed on exploiting existing local-to-global self-organization processes, which ultimately aim to develop intelligent, self-regulating, and adaptable performers (see Ribeiro et al., 2019; Guignard et al., 2020, for detailed elaborations of bi-directional self-organization processes in team and individual sports). In order to drive these self-regulatory tendencies, it is a major task of sport practitioners to manipulate task constraints within training session designs to facilitate skill learning (Newell, 1985; Pacheco et al., 2019). For example, by adjusting task constraints, such as field sizes, line markings, or practice game rules, coaches can effectively impact athletes' problem-solving behaviors in finding functional performance solutions themselves; these self-regulating tendencies can emerge, without having to prescribe movement solutions in precise detail for learners. In the constraints-based approach, the coach is not the main problem-solver during practice.

In terms of skill training planning, the PoST framework displays three broad skill development and training stages that are adapted from Newell's (1985) Model of Motor Learning; these stages, as presented below in **Figure 1**, are labeled as Coordination Training, Skill Adaptability Training, and Performance Training (see Otte et al., 2019b, for the detailed theoretical introduction of the framework). The principles of each skill training stage in the PoST framework are a strong guide for the proposed Skill Training Communication Model for specialist coaches to be able to carefully apply various forms of feedback and instruction at each skill training stage. Verbal communication induced by coaches may predominantly be seen as augmented information acting as an instructional constraint to guide learners' search and problem-solving activities (Davids et al., 2008); this is in order to stabilize functional coupling of perception and actions within the specific training environment: the foundation of skilled performance (Newell, 1991; Newell and Ranganathan, 2010; Correia et al., 2019).

Altogether, the CLA presents an emerging and contemporary perspective on skill acquisition and specialist coaching approaches by (implicitly) affecting athletes' goal-directed behavior through the design of training sessions. Constraint manipulation arguably forms the primary coaching approach toward shaping skill learning during practice, and it is particularly important to consider how complementary, augmented verbal feedback and instructional constraints can be used to guide athletes' search for functional solutions. In the following part of this article, we aim to provide guidance for practitioners to consider how and when to apply appropriate feedback and instruction forms within a particular skill training context via the Skill Training Communication Model.

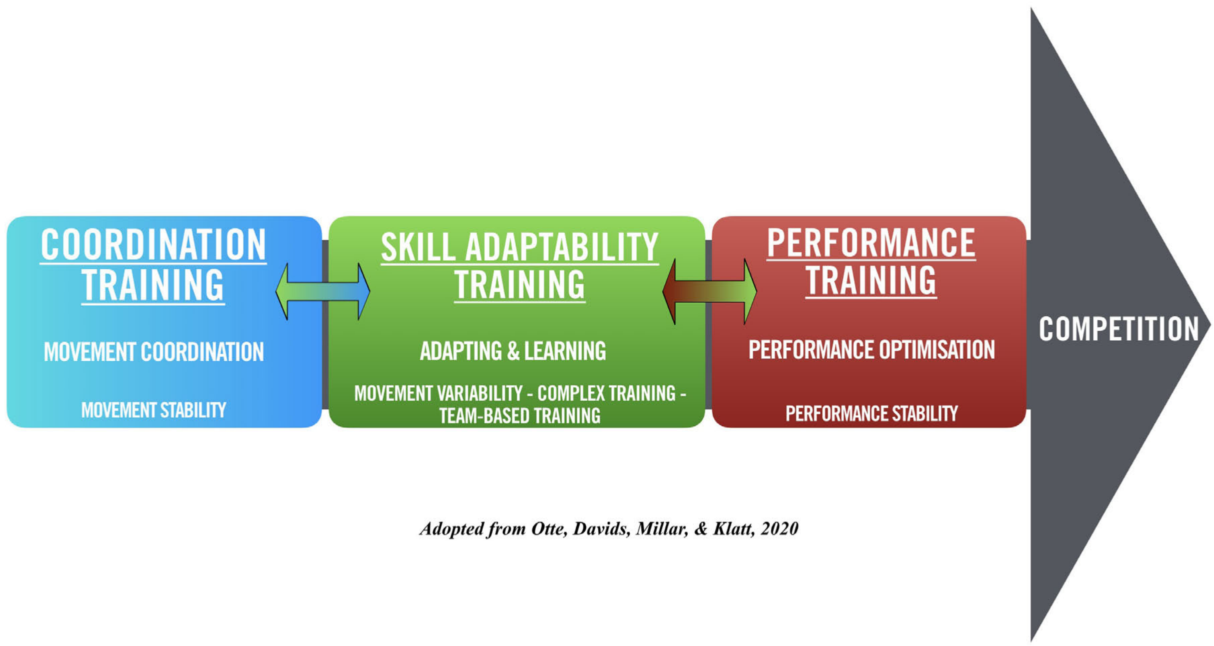

FIGURE 1 | Skill development and training stages according to the Periodization of Skill Training framework.

PART C: THE SKILL TRAINING COMMUNICATION MODEL

As an extension of the PoST framework, **Figure 2** proposes a novel Skill Training Communication Model that presents a multifaceted structural approach to planning effective training session designs (i.e., a core task for sport coaches and displayed by the red box in the center of **Figure 2**). In more detail, the proposed structural approach considers (1) the *athlete's skill training stage* (as displayed by three training stages at the top of the figure); (2) *feedback and instruction methods* [e.g., question-and-answer (Q&A) approach and model learning]; and (3) *information detail* in terms of quality and quantity (i.e., bottom part of **Figure 2**).

According to the Skill Training Communication Model, in order to plan effective training session designs, coaches should follow a stepwise approach. First, coaches would consider the athlete's skill training stages that work to directly impact the manipulation of constraints and the overall training session design (e.g., regarding levels of game-representativeness and task complexity in training; Otte et al., 2019b). In simple terms, the training design is the main pedagogical method for skill learning; for example, athletes in the Coordination Training stage (see below) may be confronted with simplified training tasks that (without verbal feedback and instruction) themselves drive exploration of, and search for, functional movement solutions. Second, coaches' choices of augmented verbal information would be affected by athletes' skill training stages (i.e., athletes in different skill training stages should experience different methods of verbal communication). In turn, the skill training stage and training session design will be complemented by feedback and instruction methods, providing external information. These methods are embedded into the training session and support critical task constraint manipulations; for example, feedback and instructions provided to athletes in the Coordination Training stage complement the training design in that coaches (verbally) guide aforementioned discovery and search processes.

Skill Training Stages

The top section of the Skill Training Communication Model shows how each specialist coach needs to start with an understanding of the athlete's current skill development and training stage for a macrocycle (i.e., multiple training months), a microcycle (i.e., one training week), or a single training session (see Otte et al., 2019b). Starting with the athlete's current training stage affords individualized training sessions, where the individual is coached according to his/her specific needs. In order to place the athlete within a specific skill training stage and, later, to select the most fitting feedback and instruction methods, the framework differentiates between three distinct stages (i.e., the Coordination Training, Skill Adaptability Training, and Performance Training stages).

Coordination Training Stage

Athletes in the Coordination Training stage are at a developmental level, with a primary need to stabilize general coordinative movement patterns during performance within game-representative environments. Here, athletes are encouraged to search and explore movement patterns by (during playful activities and games) learning to exploit intrinsic

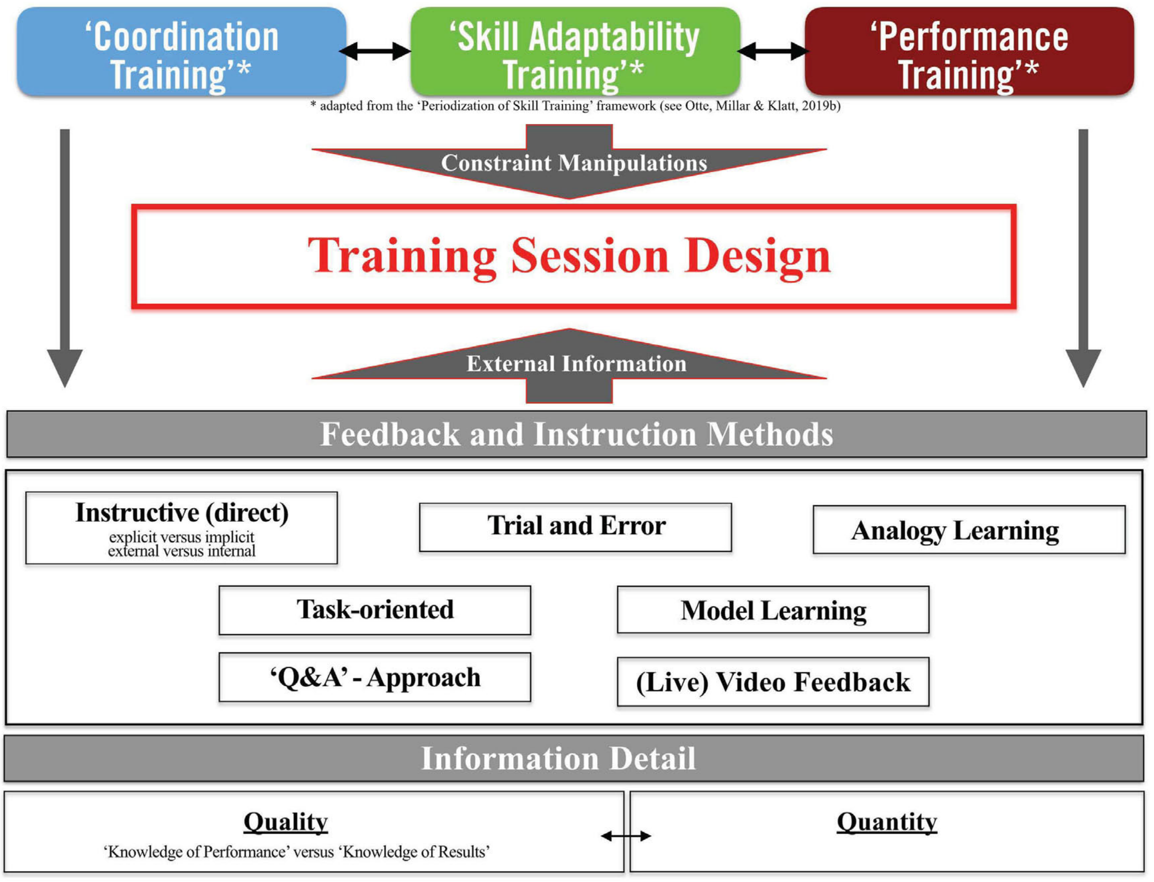

FIGURE 2 | The Skill Training Communication Model in specialist sports coaching.

self-organizing motor system degrees of freedom (e.g., body segments, muscles, and joints; Uehara et al., 2016; Correia et al., 2019). The primary aim at this stage of learning design is exploratory activity by athletes. Exploratory movements are required to perceive relations between system degrees of freedom (roughly, components of the body) and between information and action. Learning experiences at this stage of development should provide opportunities for learners to perceive novel affordances that can be achieved by particular action patterns. With respect to skill development, this idea was elegantly expressed by Adolph and Justin (2019), who harnessed Harlow's (1949) notion during motor development that individuals do not really learn to move, rather they are "learning to learn to move." To encourage exploratory practice in athlete development, the acquisition of functional sport-specific actions, through simplified tasks and coach-supported constraint manipulations, is prominent at this stage (Otte et al., 2019b).

Skill Adaptability Training Stage

During Skill Adaptability Training, the focus lies on perceptual-cognitive regulation of adaptive actions in more complex and varied learning environments. In this regard, the PoST framework proposes three skill training substages termed Movement Variability Training, Complex Training, and Team-Based Training (see Otte et al., 2019b, for practical application of these training stages). Training designs with appropriate levels of game-representativeness and task complexity are used in the (re)organization of functional perception-action couplings, comprised of non-linear and dynamic individual, task, and environment constraint interactions (see Hüttermann et al., 2019; Renshaw et al., 2019). Consequently, the advancement of perceptual-cognitive skills to regulate robust and adaptable movement coordination is the primary goal (Ford et al., 2010; Renshaw et al., 2019).

Performance Training Stage

Performance Training, as the third developmental stage, is focused on preparing athletes to apply the acquired self-regulatory skills (technical-tactical, physical, and psychological) in competitive performance. The main focus is on the preparation of individual athletes through exposure to representative training designs for high-pressure competition. This greater performance-driven focus may highlight the importance of athletes' preparation of perception, cognitions, and actions for competition (e.g., including mental readiness, match fitness, and confidence as important factors for athletes' performance; Ford et al., 2010; Otte et al., 2020b). Notably, this training stage mostly considers competitive environments in professional sports organizations (e.g., performance preparation immediately preceding a major competitive soccer game). While developing athletes (as part of their skill learning and development) need to be exposed to these challenging constraints on carefully considered and limited occasions, it is important not to overdo these experiences. Limited exposure is needed in development because of the high intensity of these practice constraints and to avoid detrimental negative experiences on confidence and to manage expectations at this training stage (Otte et al., 2020a). For example, a young performer may be asked to play up a grade or to sit on the bench as a substitute in a competitive senior game. Limited game time (in the order of minutes) may be provided after careful consideration by the coaching support staff.

Feedback and Instruction Methods

As introduced in the Skill Training Communication Model (i.e., see **Figure 2**), a categorical distinction for verbal feedback and instruction approaches may be made between various methodologies (e.g., task-oriented communication or analogy learning). Depending on the individual athlete's skill training stage and/or the training activities undertaken, different feedback and instruction methods have to be considered by specialist coaches to support effective skill development. Closer descriptions of these communication methods are elaborated in the following sections and displayed in **Figure 3** below. In detail, **Figure 3** presents (1) a description of the *coaching intervention for each feedback/instruction method* (i.e., the third row from the bottom), (2) practical *sports coaching examples* for each communication method (i.e., the second row from the bottom), and (3) the *proposed skill training stages*, which could be predominantly considered by coaches for a coaching intervention (i.e., the bottom row in **Figure 3**). Notably, while major aspects of feedback and instruction are provided verbally, this acoustically based communication approach may direct athletes' perception toward more visual and haptic modalities (e.g., verbal feedback as part of multisensory analogy learning). In turn, there is the notion that for some skill training contexts an integration of different communication methods is inevitable, and furthermore, it could be an effective strategy for providing optimal practice and learning conditions for athletes (e.g., Klatt and Smeeton, 2020; Klein-Soetebier et al., 2020). Consequently, the following sections will present and elaborate on seven feedback and instruction methods of *instructive (direct) verbal communication*; *task-oriented communication*; *Q&A feedback*; *trial and error*; *(live) video feedback*; *model learning*; and *analogy learning.* Notably, presented feedback forms have been selected based on multiple authors' experience of sports coaches commonly applying these instructional constraints to practice environments.

Instructive (Direct) Verbal Communication

The instructive method, whereby the coach gives direct, prescriptive, and corrective verbal instructions to the athlete, is perhaps considered to be the most widely applied, traditional form of instructional constraint used in coaching (Davids et al., 2008; Uehara et al., 2016; Correia et al., 2019). However, verbal information should instead be mainly used as an augmented informational constraint to guide an athlete's search activities. When learning to learn to move, it is the athlete who needs to use information to solve a performance problem and not the coach providing verbal information to solve the problem for an athlete. This pedagogical method is synonymous with an athlete-centered approach to coaching. Consequently, outside the Performance Training stage (where immediate performance is supported under time constraints), directing and prescriptive verbal instructions should be reduced to a minimum (Williams and Hodges, 2005; Ford et al., 2010; Button et al., 2020).

There is a significant body of research that often differentiates augmented verbal information (provided by the coach) into (i) explicit and implicit and (ii) internally focused and externally focused information (Poolton and Zachry, 2007; Lam et al., 2009; Sigrist et al., 2013; Wulf, 2013; Winkelman, 2020). Whereas explicit information constitutes verbal communication containing a lot of detailed information, implicit information describes communication that is associated with implicit learning by athletes, in the absence of detailed (technical) information on movements of specific limb segments and joints of the body (Masters, 2000; Jackson and Farrow, 2005). Notably, both explicit and implicit approaches are highly interdependent and often intertwined in the learning process (Hodges and Franks, 2002; Poolton and Zachry, 2007). Regarding internally focused (or body-focused) augmented information, feedback and instructions directly target the athlete's body parts and specific movements (e.g., coach: "Look at your toes and the angle of 20° at which they should point!"). In contrast, externally focused (or outcome-focused) feedback and instructions focus on effects of movements on the environment (e.g., coach: "Try to flatten the flight curve of the ball in the air and make it spin back after the bounce!").

What does this body of work imply for coaching practice? First, explicit and detailed verbal instructions may constrain and impede performers in attending to and perceiving relevant information and opportunities for action within the learning environment; these information sources would "support the search for functional performance solutions for their specific task goals" (Correia et al., 2019, p. 126). If the main role of instructional constraints and augmented verbal information is to guide athletes' search during practice, providing large amounts of explicit verbal feedback and instructions, especially immediately following skill performance, may curtail and hinder intrinsic feedback system function during self-organized exploration for functional movement solutions.

Second, explicit–internal information and the conscious reinvestment in (technical) movement knowledge that could potentially result from it could hinder the athlete's implicit perceptual–motor regulation during action (see Masters and Maxwell, 2008, for a theoretical overview of the theory). Consciously attending to one's own movements during self-regulated actions may disturb the functioning of perception–action couplings (Masters, 1992; Poolton and Zachry, 2007; Renshaw et al., 2009). In contrast, athletes who receive more

Feedback and Instruction Methods

Method	Instructive (direct)	Task-oriented	Q&A - Approach	Trial and Error	(Live) Video Feedback	Model Learning	Analogy-Learning
Description of coach intervention	The coach provides direct (explicit) and detailed information to the athlete.	The coach provides a challenging task to the athlete.	The coach uses the method of questioning to lead the athlete to a answer.	The athlete tries to execute a movement/ technique and reflects on the outcome.	The coach provides feedback by showing video sequences to the athlete.	The athlete observes a movement/ technique execution together with the coach or demonstrated by the coach.	The coach provides a 'biomechanical' metaphor to encourage visualisation of a movement sequence/technique.
Sports coaching example	*Internally-focused:* "Try both legs to carry equal weight. Then move arms and hands together in one unit, while keeping the wrists solid" *(golf example)* *Externally-focused:* "When the pitcher's front foot plants, look at the arm position and the way the shoulder turns." *(baseball example)*	"Can you pass the ball to the next free player in front of you right after receiving it?" *(soccer example)*	"Show me how you possibly could have kept possession of the ball for our team in the last game situation." *(rugby example)* "Please show me the fastest way to get the ball from here to there when the opponent stands in this position" *(handball example)*	"Try different ways of throwing the ball to pass it to your teammate behind the defender." *(basketball example)*	"Look at how you moved your hockey stick in this video sequence!" *(hockey example)*	"Look at this world-class tennis player's racket movement towards serving the ball!" *(tennis example)* "Watch my run-up and jump before serving the volleyball over the net!" *(volleyball example)*	"Attack the ball by diving into it like superman!" *(soccer goalkeeper example)*
Skill development stage**	'Performance Training'	'Skill Adaptability Training' 'Coordination Training' 'Performance Training'	'Skill Adaptability Training' 'Coordination Training' 'Performance Training'	'Coordination Training' 'Skill Adaptability Training'	'Skill Adaptability Training' 'Performance Training' 'Coordination Training'	'Coordination Training' 'Skill Adaptability Training' 'Performance Training'	'Skill Adaptability Training' 'Coordination Training' 'Performance Training'

* adapted from the 'Periodization of Skill Training' framework (see Otte, Millar & Klatt, 2019b)
** skill development and training stage(s) in which the feedback method(s) may be most appropriate to apply (where top may represent most appropriate)

FIGURE 3 | Description table of feedback and instruction forms and methods in relation to the skill training.

implicit feedback are shown to be demonstrably more effective and efficient in movement regulation (Wulf and Prinz, 2001; Wulf, 2016). Notably, this view has been supported by a large amount of research from multiple sport contexts, such as dribbling tasks in soccer and hockey, putting tasks in golf, batting tasks in baseball, and climbing tasks (e.g., see Masters and Maxwell, 2008).

Third, and in conjunction with the previous points, when under pressure, athletes with detailed declarative movement knowledge rather tend to choke (see Hill et al., 2010, for a review on choking in sport). On the contrary, athletes who had experienced significant amounts of implicit learning were found to be more resistant to perturbations from pressure in their performances (Masters, 2000; Masters and Maxwell, 2008).

Finally, and in order for athletes to use exploratory behaviors in practice and freely self-organize movement solutions, with little consideration of explicit movement details, verbal feedback and instructions should be limited to a minimum in the Coordination Training and Skill Adaptability Training stages. However, in the preparation of athletes for competitive performance, time constraints in the build-up to an event may require more direct and explicit coaching approaches. There is less time for discovery learning and exploratory behaviors at that stage of performance preparation. This is because, in the Performance Training stage, skill learning is not the major objective, but rather prepare athletes to compete in an event or match. At this stage, underpinned by the developmental work already undertaken, coaches may need to communicate verbally in a direct way, implementing a focused, task-oriented coaching method, especially when supporting athletes' adaptation to changing environmental or tactical constraints of a specific competitive event. Nevertheless, it is still important for coaches to use instructional constraints sparingly and avoid overburdening athletes with needless, verbal instructions that are not needed in athletes' decision-making during performance. The use of instructional constraints should still support athletes' self-regulation (i.e., perception, cognition, problem-solving, decision-making, and actions), but in a focused manner related to searching processes within a specific competitive environment or event.

Task-Oriented

With focused task-oriented coaching, the coach initially tries to challenge the athlete by providing a task (e.g., a coach setting a movement task for a hockey player: "Can you open your body toward the full field with your first contact when receiving the ball?"). While this task is delivered verbally by the coach, from an athlete-environment-centered perspective, it demands performers to explore action solutions via visual or haptic senses and thus to directly perceive interactions. Further, this task-oriented approach does not aim at specifying *how* an athlete performs an action (Pacheco et al., 2019). Rather, this approach appears to be more focused, task-orientated, and goal-directed in order to assist athletes in finding more functional task solutions (Pacheco et al., 2019). Especially, in the Coordination Training and Skill Adaptability Training stages, if the athlete is unable to accomplish a task after several training attempts, the integration of further implicit and guiding feedback and instruction forms may be an option to guide the athlete's search activities (Hodges and Franks, 2002; Williams and Hodges, 2005).

Q&A Approach

The Q&A approach or questioning (divergent or convergent in nature) appears to be another suitable method of verbal feedback for reflection and self-learning (Schoön, 1987; Williams and Hodges, 2005; Partington et al., 2014; Vinson et al., 2016). Linked to Mosston (1966, 1992) spectrum of teaching styles (e.g., guided discovery), the Q&A approach may take various forms in which the coach may apply sequences of (systematic) questions to drive athletes' discovery of a (codetermined) target. While there is a need to critically review potential overemphases of teacher-driven decision-making and problem-solving for the learner, a merit of Mosston's proposed teaching styles (Metzler, 1985; Goldberger et al., 2012) is that reciprocal and divergent discovery styles are aligned with the athlete-centered coaching perspective promoted by an ecological dynamics rationale proposed in this article.

It is also of relevance that, in an ecological dynamics rationale, questioning methodology used by a coach needs to be responded to by an athlete's actions, not verbal responses. With respect to this crucial differentiation between emergent actions and verbal descriptions in practice, it is important to note that Gibson (1966) distinguished between "knowledge of" and "knowledge about" the environment. On the one hand, in sport, knowledge of the environment supports functional actions (see Araùjo and Davids, 2011). On the other hand, knowledge about the environment facilitates symbolic representational understanding, which may be exemplified by understanding of shapes and patterns on a tactical white board. The aim of a sport practitioner's attempt to provide questioning should be targeted at developing knowledge of a performance environment, which may stimulate an athlete's self-regulatory activities in practice. In turn, the aim of a sport practitioner's use of questioning should always be to elicit an action, not a verbal response. The coach may try to guide the athlete to the desired answer in an implicit and external way (e.g., a coach guiding a handball player to self-reflect on the past play during practice: "Show me how you could handle the last 1-versus-1 (1v1) situation differently, when you're pressured by an opponent and trying to find your open teammate in space"). Further, a focus on action-scaled affordances, constrained by athletes' action capabilities in emerging environments (see Fajen et al., 2008), may affect coaches' verbal phrasing of questions; for example, a basketball coach asking an athlete to reflect on the possibility of performing an action could say: "How did you time your run toward catching the bounce pass quicker this time, compared to the last pass that went out-of-bounds?"

Predominantly in the Skill Adaptability Training and Coordination Training stages, these latter two approaches of task-oriented coaching and Q&A feedback may be of great value for athlete-environment-centered coaching and the search for and exploration of functional movements and solutions to tactical problems (O'Connor et al., 2017). Particularly, time restrictions in these training stages usually appear to be rather low and the specialist coach (by using "higher order questions," such as why and how; O'Connor et al., 2017) provides an opportunity to reinforce an interactive and detailed exchange with the athlete(s) to guide further exploratory and discovery activities in practice and performance.

Trial and Error

In the perspective of the "trial and error" approach, it is a mixture of verbal, visual, proprioceptive, and haptic information that athletes are facing. While searching for functional solutions by designing training sessions with rich affordance landscapes, players could be further alerted to the presence of key information sources through a limited number of verbal informational constraints (Davids et al., 2008).

First, it is important to note that the training session design aims to be the main stimulus for promoting athletes' search, exploration, and learning behaviors. Particularly, through constraint manipulations and the credo of "repetition without repetition", coaches could follow an implicit and tacit approach toward using instruction and feedback (Bernstein, 1967; see Otte et al., 2020a, for training examples); this approach highlights principles of local self-organization of actions and places a dominant focus on training designs supporting expansive search for, and attunement to (performance-representative), contextual information emergent in competitive environments (Horn et al., 2007; Seifert et al., 2019).

Second, verbal information provides valuable assistance in constraining an athlete's exploratory behaviors, problem-solving, and self-discovery of "the relationships between cues/movement patterns and behavioral outcomes" relatively freely (Jackson and Farrow, 2005, p. 315). For example, a coach encouraging a hockey player to attempt the forehand shot during practice could manipulate task constraints "driving" the shooter toward the forehand side for him/her and providing an instructional constraint by saying, "Just try this shooting movement and see how it feels!". The goal of this approach remains for players to self-organize and explore their own movements and through their experiences to receive intrinsic feedback on the effectiveness of their movement attempts; this feedback on the task outcome may often be based on perceiving intrinsic information through visual, proprioceptive, and haptic systems. Moreover, because this feedback method highlights the importance of discovery, self-monitoring, and the self-organization of movement patterns, the coach adopts the role of a facilitator. Specifically, a facilitator would avoid using direct explicit verbal feedback and follow a "hands-off" strategy in learning (Handford et al., 1997; Chow, 2013; Light and Harvey, 2015; Uehara et al., 2016; Correia et al., 2019).

Altogether, this feedback method appears to be suitable for skill training in the stages of Coordination Training and Skill Adaptability Training; this is due to a focus on athlete self-organization and movement variability in these (de)stabilized training stages.

(Live) Video Feedback

(Live) video feedback, as a technological feedback medium, represents another possible method of feedback that provides an effective (real-time) tool for coaches around a training session or competition (Williams and Hodges, 2005; Davids et al., 2008; Ward, 2011). On the one hand, the visualization of training/game sequences (in the best case recorded from a point-of-view camera shot) can prove helpful in the Coordination Training and Skill Adaptability Training stages. For examples, studies in sports such as gymnastics, swimming, and volleyball found increased skill performance in response to coaching interventions including self-video feedback (e.g., Hazen et al., 1990; Winfrey and Weeks, 1993; Zetou et al., 2002; Boyer et al., 2009). Here, this visual self-feedback may not include additional verbal guidance by coaches. On the other hand, clearly targeted verbal feedback, complemented by video footage of an athlete's exploration and (movement) solutions, can support specific search activities in the Performance Training stage. For example, professional soccer clubs began using large video walls at their training facilities for immediate playback of patterns of play in practice (Bundesliga, 2018); these oversized video screens particularly underline how a global-to-local direction of synergy formation in sports teams can be supported by augmented verbal and visual information in performance preparation. Additionally, this performance-driven use of video feedback may be delivered in various forms, such as (opposition) team, individual skill, or motivational videos, which may further be accompanied with statistical performance data (e.g., pass completion rates or shot percentages; see O'Donoghue, 2006, for an overview).

Model Learning

Model learning or observing holistic movements together with the coach can be considered a building block of visually induced information for guiding athletes' search activities (Scully and Newell, 1985; Scully and Carnegie, 1998; Correia et al., 2019). Scully and Newell (1985) showed how visual informational constraints from models guided the actions of learners in motor learning. By perceiving and imitating a model's relative motion pattern (e.g., the relations between body parts), athletes are afforded with constraining augmented information to facilitate their search for functional task solutions (Newell et al., 1985; Scully and Newell, 1985). In other words, model learning may act as a *rate enhancer*, rather than a rate limiter, in early skill acquisition stages, such as the Coordination Training stage with a focus on athletes' exploration for stable movement coordination (e.g., see Al-Abood et al., 2001a,b). Here, evidence further suggests presenting learners with models of movement patterns of different performers at different performance levels, to showcase a range of movement possibilities in the affordance landscape (Al-Abood et al., 2002). Specifically, strategies regarding (expert) video modeling before and after skill performance have been considered by previous research; for example, studies on video modeling in sports, such as tennis, wall climbing, basketball, and volleyball, showed enhanced movement performance following this video intervention (e.g., Scott et al., 1998; Harle and Vickers, 2001; Boschker and Bakker, 2002; Zetou et al., 2002). Further, active, on-field demonstrations and "freezing strategies" (i.e., freezing skill training exercises or play) by coaches could additionally constrain the perceptual search space and help attune athletes to visual information for functional movement solutions (Pacheco et al., 2019).

Overall, model learning (including demonstrations) appears to be apt for learning and the search of specific movement solutions. In other words, these forms of visual instructional constraints during coaching interventions appear to be particularly effective for athletes acquiring sport-specific and novel movement patterns (i.e., in the Coordination Training stage; Al-Abood et al., 2001a,b) and athletes seeking to attune to relevant information variables (i.e., in Skill Adaptability Stage). Notably, and based on a single athlete's intrinsic dynamics, coaches should highlight the existence of a multitude of reliable and dynamically stable movement patterns and solutions for a task (Newell and Ranganathan, 2010); this approach stands in contrast to traditionally advocated idealized technical movement solutions promoted by coaches (e.g., see Otte et al., 2019a, for findings in the specialist soccer goalkeeper coaching context).

Analogy Learning

In addition to the former communication method of model learning, movement analogies (also termed as "biomechanical metaphors"; i.e., a verbal illustration and visualization of a movement) can provide a valuable feedback alternative for coaches (e.g., Hill et al., 2010; Newell and Ranganathan, 2010; Fasold et al., 2020). For example, the statement "your arms and hands could build a wall from which the ball bounces back into the other team's court" could be one movement analogy for a "blocking" action in volleyball.

Despite analogies representing verbal forms of communication, these augmented informational constraints potentially direct the search activities of an athlete toward an external focus of attention, a previously experienced feeling (e.g., "imagine throwing a frisbee" for a one-handed backhand return in tennis), and contribute an additional, strong visual value; thus, analogies have the potential to be subconscious to the perceiver and/or promote implicit learning, which is more resistant to forgetting or emotional perturbations (Poolton et al., 2006; Poolton and Zachry, 2007; Renshaw et al., 2009; Williams and Ford, 2009; Newell and Ranganathan, 2010). In detail, Winkelman (2020) recently proposed three categories of analogies for providing visual information to support movement performance: (1) scenario-based analogies (i.e., the consideration of an analogous scenario, such as the well-known "reaching for the cookie jar" analogy for a basketball throw); (2) constraint-based analogies (i.e., perturbation or channeling of information on movement performance, such as "you have resistance bands in your knee joints that constantly pull you down slightly" to guide a volleyball player's set position); and (3) object-based analogies (i.e., featuring an inanimate object onto, e.g., a soccer

GK's movements: "make a scoop net with your arms and hands to intercept a low shot rolling toward you"; "make a wide wall with your arms, legs, and trunk to block any shot that may be low or high"). All of these categories establish fruitful arrays for coaches to transfer explicit verbal information into an arguably more relatable and effective form for athletes in various skill training stages. Consequently, athletes in the training stages of Skill Adaptability Training and Coordination Training may particularly benefit from analogy learning.

Information Detail

In the last part of the Skill Training Communication Model (see bottom part of **Figure 2**), the coach selects the degree of information detail to be communicated to athletes. From a more applied coaching perspective, the quality and quantity of information play crucial roles and need to be considered in perspective of the athlete's development stage.

Information Quality

The quality of augmented information could also be related to traditional concepts such as "knowledge of performance" (KP) and "knowledge of results" (KR; see Johnson and Proctor, 2017, for a review on feedback in skill acquisition and training). First, KP provides information on movement performance or processes during the motor skill execution (e.g., kinetic feedback on forces applied during the movement or kinematic feedback on spatial and temporal properties of the movement; Johnson and Proctor, 2017). Notably, this information may not solely be aimed at the past state of the movement dynamic; it may be regarded as *transition information* that focuses on the control of the performance solution that facilitates the transition to a new pattern of coordination (see Newell, 2003). Transition information may target feedback regarding athletes' changes over different timescales in organization and transitions between various movement patterns; these changes form an integral part of emerging sport contexts and non-linear learning (Chow, 2013; Orth et al., 2018a,b). Second, KR provides rather externally focused information on task outcomes (e.g., information provided to athletes on whether the task goal was achieved or the degree of error that led to lack of achievement; Williams and Hodges, 2005; Winkelman, 2020). Based on the athlete's focus to search for functional task and movement solutions, coaches have opportunities to provide informational constraints to athletes through both KP (e.g., through movement-related analogies) and KR (e.g., through the training session design and constraint manipulations). The latter information on KR may be further underlined by extrinsic feedback through external sources that stands in contrast to intrinsic feedback (i.e., the athlete's own attunement to perceptual information emerging from movement performance). Specifically, through (objective) performance analytics data compiled from motion tracking devices or sensors, coaches in high-performance sports increasingly have the opportunity to include extrinsic feedback sources into their coaching. For example, high-quality GPS data on individual players' sprinting speeds and running distances within soccer games may be used by coaches to globally guide synergy formation between teammates. However, a challenge is to avoid athletes becoming overdependent on augmented information rather than becoming highly attuned to information from intrinsic feedback systems to solve movement problems (Handford et al., 1997).

In order to provide more distinction to the quality of information provided by coaches, the concepts of KP and KR may be further embedded into goal-directed *categorical* (i.e., correct/false), *graded* (i.e., the degree of correctness of a movement solution), and *detailed information* (i.e., degree of correctness along with detail information) (e.g., Luft, 2014; Johnson and Proctor, 2017). In the Coordination Training and the Skill Adaptability Training stages, it may often make sense to (if at all) solely provide brief categorical or graded feedback (e.g., "too slow," "too fast," "too high," "too much spin"). Particularly, aforementioned action-scaled affordances may support key coaching points in these training stages. By directing feedback toward external information (e.g., the sprinting distance and speed needed to receive an air pass in American Football), simple cues provided to athletes could aim to guide athletes' search processes. Moreover, this reduced communication approach should be delayed in order to allow an athlete to provide his/her own performance estimate before directing the athlete's attentional focus toward discovery and self-organization of functional movement patterns and task solutions (Hodges and Franks, 2002; Davids et al., 2008; Sigrist et al., 2013). However, in the Performance Training stage and potentially in later parts of the Skill Adaptability Training stage (e.g., when working with more advanced performers), graded feedback or detailed (extrinsic) feedback on the performance and/or the results may be deemed as more appropriate. For example, a coach providing feedback to a soccer goalkeeper defending the goal could say: "Watch the distance between the approaching attacker and yourself—once the attacker dribbles inside the box, defending a close distance 1v1 situation will be your task" (for evidence of goalkeeper's use of time to contact information with an attacker in 1v1 dyads, see Shafizadeh et al., 2016). Note that there is no specification of precisely how an athlete should solve a performance problem using that exemplar feedback, because the wording is used to stimulate further exploration of a specific affordance (which can be for "good or ill" as noted by Gibson, 1979).

Finally, information quality may be judged in terms of different levels of *emotional value*. For example, feedback for athletes could be positive and supportive, in that it is praising, motivating, and constructive, or rather negative, in that it is critical or scolding (Smith and Cushion, 2006; Ford et al., 2010; Luft, 2014). Notably, supportive feedback and praise for performance outcomes, improvements, and efforts should be prioritized, whereas negative feedback should be limited (Smith and Cushion, 2006; Sigrist et al., 2013).

Information Quantity

Information quantity may be constituted of two components: the *timing of feedback* (e.g., before, during/concurrent or after the action/training/game) and the *feedback frequency* (e.g., during/after each attempt, in regular intervals or randomly) (e.g., Hodges and Franks, 2002; Luft, 2014). First, in terms of *feedback timing* before and during skill execution, practitioners may be cautious of not providing large amounts of movement-related, verbal information to athletes in the Skill Adaptability Training and Coordination Training stages. Because a key aim of practice designs is to facilitate athletes' self-regulation tendencies, provision of verbal feedback should also not occur *immediately after* an action sequence in training. Provision of too much verbal feedback, especially immediately after a movement response, is a form of "overcoaching," as previously stated, and has been shown to negatively restrict movement exploration (Davids et al., 2008), possibly inhibiting players' own decision-making abilities (Smith and Cushion, 2006; Ford et al., 2010). In further support of this notion of delaying verbal feedback, studies have shown expert athletes to judge own performances more accurately than their coaches (e.g., see Millar et al., 2017, for an investigation into athlete–coach agreement on boat speed in rowing). Hence, athletes' intrinsic and self-directed feedback for own performances may provide enough information to drive skill learning in certain skill training stages.

Second, low *feedback frequency* for athletes in the Coordination Training and Skill Adaptability Training stages may be sufficient, mainly due to previously highlighted search and discovery processes for functional movement solutions. Additionally, coaches giving less frequent feedback would be able to spend longer time periods on (silently) observing the athletes, which may be helpful in order for practitioners to monitor athletes' (functional) perception–action couplings and individual capacities and assess the overall quality of the designed training environment (Smith and Cushion, 2006; Correia et al., 2019). Notably, in the Performance Training stage, feedback may be required more frequently than at developmental stages of learning; this, and only if athletes need the verbal intervention information, is due to time constraints and the apparent performance focus under immediate competitive pressure. Here, it still may be argued whether this feedback would need to be given as part of an explicit and internally focused verbal coaching intervention. In order to assist athletes' search and exploration for functional movement solutions, simple prompts, cues, and questions may display verbal alternatives for guiding athletes' search activities (O'Connor, 2012).

CONCLUDING REMARKS

Overall, this article pursues the goal of presenting a conceptual Skill Training Communication Model. In order to follow the call for "more practitioner-based articles in coaching journals [. . .] showing how goal setting and performance feedback procedures can be adopted" (Ward, 2011, p. 109), this position article aims at integrating academic knowledge with practically applicable feedback and instruction forms for various specialist coaching contexts (i.e., coaches focusing on sport-specific skill acquisition and refinement when working individually with single athletes or subgroups of athletes). The presented theoretical and practical insights underline the need for specialist coaches to display great levels of psychological and pedagogical expertise on how and when to (purposely not) provide external feedback and instructions to individual athletes in training and competition environments.

Finally, the Skill Training Communication Model hopes to inspire future research in the field of sports coaching. Additionally, the article aims at supporting sports coaches by providing the following feedback and instruction guidelines:

1. The training design that facilitates athletes' self-regulation in sport performance should always be at the core of all learning and coaching activities. By developing representative training sessions and manipulating relevant task constraints, coaches can most effectively drive athletes' search processes that, in turn, provide highly valuable intrinsic feedback for athletes; this type of feedback is essential for supporting self-organization tendencies for functional movement solutions in response to game-related problems.
2. The coach's understanding of the athlete's particular skill development and training stage is paramount for appropriate selection of feedback and instruction methods. Especially the stages of Coordination Training and Skill Adaptability Training may (if at all) demand more implicit haptic and visual feedback forms (e.g., including methods, such as analogy learning, model learning, and video feedback). This stands in contrast to the Performance Training stage, which due to immediate performance and time pressure may require coaches to apply a more targeted and direct communication style.
3. An increased amount of feedback and instructions (in terms of information quality and quantity) likely is not more beneficial for athletes. In contrast to the common notion, "the more, the better", athletes at particular skill developmental stages actually benefit more from self-regulatory approaches and minimized explicit feedback and instructions used sparingly (Jackson and Farrow, 2005).
4. Related to Point 3, the timing of visual feedback is also important in order for athletes to perceive and use intrinsic information from movements to self-regulate in solving ongoing performance problems. Coaches should delay the provision of augmented feedback in order to provide time for athletes to perceive movement feedback for use in ensuing practice tasks (Button et al., 2020).
5. Augmented verbal information should avoid a specification of precisely how an athlete should solve a performance problem. The wording of feedback and instructions is used to stimulate and elicit further exploration of specific opportunities for action. Consequently, the coach is not the main problem-solver during practice (i.e., by directly verbalizing the performance solution to the athlete) and rather acts as a "moderator" to guide athletes' search and problem-solving for functional (movement) solutions.
6. The feedback and instruction methods that athletes seek and the way that individual athletes respond to these should drive coaches' communication. In this respect, an "understanding of athlete-centered coaching is necessary"

(Côté et al., 2010, p. 64), and thus individualized feedback and instruction approaches should also consider each individual athlete's preferences.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

FO developed the conception of the model and wrote the first draft of the manuscript. KD, S-KM, and SK contributed to re-design and presentation of the model and wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted manuscript.

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Repetition Without Repetition: Challenges in Understanding Behavioral Flexibility in Motor Skill

Rajiv Ranganathan[1], Mei-Hua Lee[1] and Karl M. Newell[2]*

[1]Department of Kinesiology, Michigan State University, East Lansing, MI, United States, [2]Department of Kinesiology, University of Georgia, Athens, GA, United States

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Singapore

***Correspondence:**
Rajiv Ranganathan
rrangana@msu.edu

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A hallmark of skilled motor performance is behavioral flexibility – i.e., experts can not only produce a movement pattern to reliably and efficiently achieve a given task outcome, but also possess the ability to change that movement pattern to fit a new context. In this perspective article, we briefly highlight the factors that are critical to understanding behavioral flexibility, and its connection to movement variability, stability, and learning. We then address how practice strategies should be developed from a motor learning standpoint to enhance behavioral flexibility. Finally, we highlight some important future avenues of work that are needed to advance our understanding of behavioral flexibility. We use examples from sport as a context to highlight these issues, especially in regard to elite performance and development.

Keywords: synergy, variability, motor learning, coordination, skill acquisition

INTRODUCTION

A fundamental hallmark of motor skill is "behavioral flexibility" – i.e., skilled performers are not only consistent and efficient at producing goal-directed behavior, but also have the ability to do so even in altered conditions or environments (Johnson, 1961). For example, the "grand slam" in tennis is considered one of the highest achievements in the sport because it requires winning on vastly different surfaces that require flexibility in playing style. Although the central concept of behavioral flexibility in motor control has been recognized since Bernstein's use of the phrase "repetition without repetition" to describe how even well-learned movements show variation when achieving the task outcome (Bernstein, 1967), there are only a few studies that directly examine this issue in the context of skilled performance (Arutyunyan et al., 1969; Bootsma and van Wieringen, 1990; Cohen and Sternad, 2009). Furthermore, we still have a limited understanding of its relation to other constructs such as learning, development, and operational aspects such as practice strategies. The focus of this perspective article is not to present or examine a specific theoretical position, but instead to highlight open theoretical and practical issues surrounding behavioral flexibility and suggest directions for future work.

CHALLENGE 1: CHARACTERIZING BEHAVIORAL FLEXIBILITY

Behavioral flexibility is a broad term that has been used in several contexts and can often overlap with other terms such as transfer or generalization. In this article, we focus specifically on behavioral flexibility in terms of the ability to achieve the *same task outcome* using different movement solutions (as opposed to transfer/generalization which often refer to achieving *novel task outcomes*). A related term that has been used in this context is "adaptability" – which shares features with flexibility (Seifert et al., 2014), but we will use the term flexibility because adaptability has also been used in a broader sense to indicate better generalization to new environments (Seidler et al., 2015). Given the focus on task outcomes, we will examine flexibility within the same skill domain (e.g., within the same sport) and not across domains. An important condition for such flexibility is the presence of degeneracy (Edelman and Gally, 2001) – sometimes also called redundancy (Bernstein, 1967) or abundance (Latash, 2012; although these terms are not always interchangeable) – where structurally different elements can be coordinated in different ways to produce the same task outcome. For example, if the desired task outcome in tennis to land the ball at a particular point on the court, flexibility refers to the ability to use multiple movement solutions that achieve this task outcome. These multiple solutions include solutions that can be termed variations of the same movement pattern (e.g., using a forehand with different amounts of topspin) and solutions that are distinct enough to be termed "qualitatively" different (e.g., using a backhand or a running volley). Given this definition, we highlight three important factors that can be used to characterize behavioral flexibility in the context of motor skill.

Flexibility Can Occur Over Different Time Scales

The timescale over which the transition(s) between the old and new movement solutions occur is a critical aspect of flexibility (Newell et al., 2001). Flexibility may be observed over relatively short-time scales (of the order of a few seconds) on a trial-to-trial basis, as seen in the classic study of expert blacksmiths (Bernstein, 1967). But flexibility can also be observed over longer time scales requiring relearning of a new movement pattern or implementation of another movement technique or strategy (Wallis et al., 2002; Napier et al., 2015; Gray, 2018). The time scale of change also relates behavioral flexibility to the related construct of "stability" (Schöner and Kelso, 1988). Although formal definitions of stability are not directly related to variability (van Emmerik and van Wegen, 2000; Dingwell and Marin, 2006), the term stability in motor skill has been used to refer to consistency. This stability can be present at two levels – "task-level" stability (measured by variability of the task outcome) and a "movement-level" stability (measured by movement variability). Flexibility at short time scales (e.g., at the level of trial to trial variability) is associated with high task-level stability and (relatively) low movement-level stability so that multiple movement solutions can be used. However, flexibility at longer time scales (e.g., modifying someone's technique) involves *increasing* movement-level stability of the new solution so that the performer does not return to the old solution. For example, an athlete who has changed their throwing technique after injury would not want to return to their "old" movement pattern even if they could achieve the task outcome using the old solution.

Flexibility Can Be Explicit or Implicit

It is important to consider the degree of change involved in generating the new movement solution because this directly ties into how the flexibility is generated – either through explicit "strategy-like" behavior (Taylor and Ivry, 2011; Christensen and Bicknell, 2019; Christensen et al., 2019) or through implicit "synergy-like" behavior. Strategic changes are likely associated with cognitive skills, such as anticipation and decision-making, and involve relatively large modifications to the movement patterns that could be employed in contexts, where there is a distinct change in the environment (e.g., adjusting to different surfaces in tennis). Additionally, strategic changes may also arise when there is a need to surprise an opponent (e.g., a between-the-legs shot in tennis). On the other hand, when the desired change is minimal, flexibility can be achieved by channeling the natural movement variability (i.e., variability observed in the task without any externally imposed perturbations) through "synergies" that constrain the degrees of freedom. For example, there is evidence that expert shooters are able to reduce the variability at the hand by employing a compensatory coordination between the shoulder and wrist movement (Arutyunyan et al., 1969). These synergies are likely created through extensive practice and do not require strategic behavior.

Flexibility Can Arise From Different Constraints

From a dynamical framework, identifying the source of the constraint that induces the need for new movement solutions is important to understand behavioral flexibility. Constraints at the individual (organism), task, and environmental levels can all lead the performer to adopt different movement solutions (Higgins, 1977; Newell, 1986). However, the dynamics of the available solution space and how it is perceived by the performer depends to a large extent on the source of the constraint. Task and environmental constraints (e.g., a change in playing conditions) can change over short time scales and are typically large enough to be apparent to the performer and, therefore, provide a window into strategy-like flexibility. On the other hand, most individual constraints change gradually over relatively long time scales (e.g., fatigue) or very long time scales (e.g., growth; Newell et al., 2001) and, therefore, are a window into more synergy-like flexibility.

CHALLENGE 2: LINKING MOVEMENT VARIABILITY, FLEXIBILITY, AND TASK PERFORMANCE

The amount of movement variability and its relation to task performance is the central focus of behavioral flexibility and is closely related to "stability." By the definition assumed here, an individual with greater flexibility should be able to generate the same task performance with greater changes in the movement pattern relative to an individual with less flexibility. Thus, on a plot of the change in the movement pattern vs. task error, flexibility can be measured by how "shallow" this curve is (**Figure 1A**). However, our view is that this "within-person" measurement alone does not provide the whole picture of flexibility because it ignores the issue of whether this flexibility comes at a cost. For example, when now comparing two individuals (or equivalently two groups) with different degrees of flexibility, greater flexibility may result in higher task error (**Figure 1B**), which would be suggestive of a trade-off between movement-level stability and flexibility. On the other hand, greater flexibility may result in lower task error (**Figure 1C**), which would be consistent with the notion that the variation associated with flexible behaviors may help the performer to find new solutions that optimize task performance even further. Therefore, both within- and between-individual analyses are necessary to gain a full understanding of how flexibility affects task performance.

In addition to the amount of movement variability, it is also important to consider the structure of variability (Newell and Slifkin, 1998). This structure can give insight into "exploration" – both in terms of how multiple degrees of freedom are involved in the movement and how these behaviors evolve over time. This distinction between the amount and structure of variability is critical from the viewpoint of characterizing exploration. For example, it is well-established that children show higher motor variability overall relative to adults in a wide range of tasks (Deutsch and Newell, 2001). However, when the structure of this variability was examined when children learned a novel task, children actually showed less exploration relative to adults because they expressed that variability mostly along a single coordination pattern (Lee et al., 2018). Similarly, sequential analysis of trial-to-trial behavior has emphasized that the variation when exploring is not typically "random" but shows specific patterns of exploration from trial-to-trial depending on the context (Dingwell et al., 2013). Overall, these findings suggest that the relation between movement variability and flexibility is complex and mediated by several factors. This becomes especially relevant during learning when the amount of movement variability, the structure of movement variability, and task performance all change with practice.

CHALLENGE 3: ENHANCING FLEXIBILITY THROUGH PRACTICE STRATEGIES

How can behavioral flexibility be enhanced through practice strategies – i.e., how can we structure practice so that the learner learns to use multiple movement solutions to achieve a given task outcome? We highlight two broad but distinct "routes" to increase flexibility through practice – direct and emergent, each with several theoretical orientations.

Direct Flexibility Elicited During Practice

The first approach to enhance flexibility is to directly practice multiple movement solutions for achieving a given task outcome (Ranganathan and Newell, 2013). From a "specificity of practice" interpretation, if the flexibility to use multiple solutions is desired, then these multiple solutions have to be practiced. Even assuming a certain degree of transfer beyond the practiced solutions, a key aspect of this approach is to introduce variation during practice to elicit new movement solutions. This has been addressed in a number of theoretical frameworks, but is particularly prominent in the dynamical systems framework,

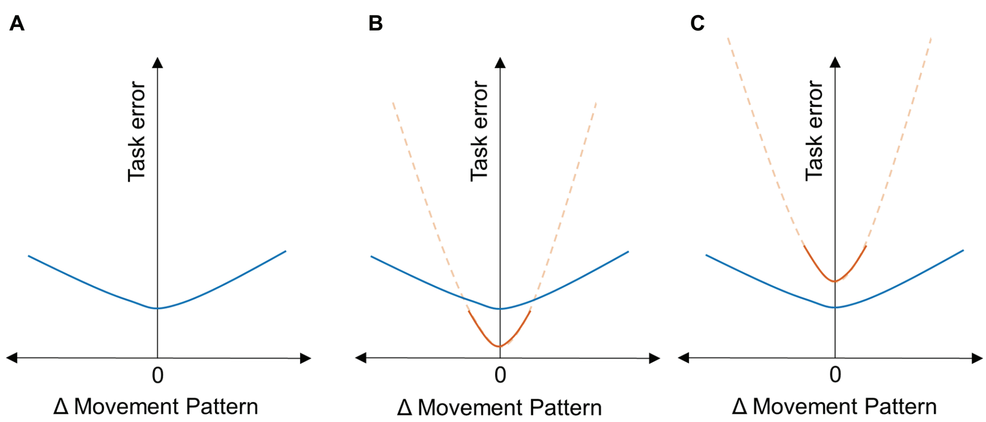

FIGURE 1 | Flexibility, movement variability, and task performance. The plots indicate potential relations between the task error and the change from a preferred movement pattern. **(A)** Flexibility can be measured at an individual level by measuring the "flatness" of this curve (indicated in blue). An individual with greater flexibility will have a flatter curve indicating that they are capable of using multiple movement solutions to achieve (approximately) the same task error. However, comparisons between-individuals provide greater insight into whether this flexibility comes at a cost. An individual with lesser flexibility (indicated in red) is shown with a smaller range of movement variability (solid line) and the extrapolation of this curve to the same range as the more flexible individual (dashed line). The relative positions of these two individuals on the task error axis can reveal the potential cost of flexibility. **(B)** If the more flexible individual has higher task error, then flexibility comes at the cost of lower task performance. **(C)** However, if the more flexible individual has lower task error, then it suggests that greater flexibility can potentially lead to finding solutions with higher task performance.

where these variations are interpreted as fluctuations that can help transition from one solution to another. Two related approaches inspired by this framework have been suggested in the literature – the nonlinear pedagogy approach (Chow et al., 2011), which emphasizes the use of appropriate constraints to facilitate these transitions, and the differential learning approach, which emphasizes the amplification of fluctuations inherent in the learner (Schöllhorn et al., 2012). However, to date, studies using these approaches have focused mainly on improving overall task performance, so it remains to be seen if they also apply to enhancing behavioral flexibility.

Emergent Flexibility After Practice

The second approach takes a somewhat counterintuitive notion that increasing flexibility need not require multiple solutions to be *directly* practiced, but rather flexibility is an "emergent" feature with learning. In other words, flexibility is not the primary goal but rather a *by-product* of training. This is particularly relevant for open skills such as tennis or soccer (Poulton, 1957), where the unpredictable nature of the environment constantly requires coming up with novel solutions in both short and long time scales that cannot be directly practiced.

One such example of emergent flexibility comes from optimal feedback control, where flexible ways of achieving the task outcome can emerge because rather than choose a solution *a priori*, the system constantly looks for a solution that minimizes both error and effort to achieve the task outcome. For example, in an obstacle avoidance task (Nashed et al., 2014), where participants had to navigate around multiple obstacles, flexibility in behavior for reaching the same target (either going between obstacles or going around them) was observed depending both on the magnitude of the perturbation and the estimated position of the hand (i.e., the sensory feedback). Similarly, when examining learning a target interception task with different obstacle positions, we found that participants who practiced without variation but learned the target position well could adapt to different obstacles, even if they had not explicitly practiced with different obstacle positions (Ranganathan and Newell, 2010). These results suggest that flexibility, at least when the degree of variation is small, can emerge without direct practice of different solutions.

This emergent flexibility can also be seen with the ability to perceive the appropriate affordances. A famous example of extreme behavioral flexibility involves Gael Monfils' "spinning jump forehand," where he ran back from the net to return a lob, and then performed a spinning jump to return a forehand winner (Dawson, 2019). It is rather unlikely that he would have practiced this shot to any significant degree during training. Rather it was the ability to pick up the appropriate information (the time to contact with the ball, but also the higher bounce on clay) that enabled a "creative" solution to emerge under novel constraints without direct practice (Orth et al., 2017).

Finally, because perception and action are interrelated (Gibson, 1979), the ability to pick up affordances is also intricately tied with the movement repertoire of the individual. Many of the examples of behavioral flexibility described above are only feasible because of the athlete's characteristics – such as strength, speed, and joint range of motion. Therefore, another possibility to increase behavioral flexibility is to increase this movement repertoire during training. This effectively would increase the degeneracy of the system so that more flexible behaviors are possible.

AVENUES FOR FUTURE RESEARCH

We highlight three avenues to further our knowledge of behavioral flexibility – (i) the measurement of flexibility in motor learning designs, (ii) characterizing behavioral flexibility over development, and (iii) better understanding the constraints on behavioral flexibility at elite (or near-elite) performance levels.

Measurement of Flexibility in Motor Learning Designs

A primary limitation of current motor learning studies in terms of studying behavioral flexibility is the combination of simple laboratory tasks and the exclusive reliance on retention/transfer tests. The use of "richer" tasks, where there are possibilities of multiple solutions either at the individual (multiple DOFs) or the task/environment, is essential to gain insight into flexibility (Newell, 1991; Ranganathan and Scheidt, 2016; Sternad, 2018).

How could behavioral flexibility be measured in such tasks? Two different approaches can be used to provide a complementary understanding of both explicit and implicit flexibility during motor learning. The first approach is to use quantitative methods for analyzing movement variability (Scholz and Schöner, 1999; Cohen and Sternad, 2009). These techniques provide insight into how natural variability is channeled in the task with no external perturbations and, therefore, are a good window into implicit flexibility with small magnitudes of change. However, it is important to note that there is a risk in these techniques of using "observed" variability to infer the flexibility. This is because (i) the relation between observed variability and flexibility is likely non-monotonic (i.e., too much or too little variability can both be "bad"; Stergiou et al., 2006) and (ii) unless measured in a context that requires flexibility, the observed variability tends to typically decrease with practice, even though flexibility may have increased (Ranganathan and Newell, 2010). Therefore, a second approach is to directly change the constraints to challenge the learner's flexibility and observe how well the task outcome is met (Ranganathan and Newell, 2010; Komar et al., 2015; Orth et al., 2019). This approach overcomes the disadvantage of using observed flexibility as a metric, however, because the learner is generally aware of a change in these constraints, it is therefore better suited to study explicit flexibility involving larger changes in the movement pattern.

Flexibility Over Developmental Timescales

Development over the life span provides an opportunity to understand the influence of individual constraints on behavioral flexibility. Development is characterized by both physical changes (e.g., growth during childhood or the loss of muscle mass in old age) and cognitive changes (e.g., working memory and information processing capacity), and there is at least some evidence that flexibility and exploration during motor learning change over the life span (Lee et al., 2018; Lee and Ranganathan, 2019). This gives rise to important questions like – how does behavioral flexibility develop with age and how does it relate to other aspects of development? Moreover, this also has important implications for how practice strategies should be tailored to developmental age and skill level. Currently, the main approach behind tailoring practice strategies relies on setting an appropriate level of task difficulty (Guadagnoli and Lee, 2004). However, understanding how flexibility (and stability) changes with development would have direct real-world relevance to issues such as the emphasis on consistency and variability during practice (Whiteside et al., 2015). More broadly, this issue also relates to the role of early specialization vs. diversification in the development of expertise in sport skills (Côté et al., 2009), specifically related to the issue of when it might be appropriate to start diversification without disrupting the desired skill.

Flexibility at Elite Levels of Performance and Technique Modification

From the viewpoint of elite (or near-elite) performance levels, it is important to recognize that different sports skills have differing demands for behavioral flexibility. For example, in closed skills like gymnastics, behavioral flexibility may not be as critical given the relatively predictable nature of the environment. However, in open skills like tennis or soccer, where the constantly varying environment places high demands on behavioral flexibility, there are two issues that need to be addressed – (i) how flexibility changes with high levels of performance and (ii) how flexibility plays a role in the specific context of technique modification.

First, at high levels of performance, there are two mutually competing demands on flexibility. On the one hand, at elite performance levels, there is *less* room for flexibility because

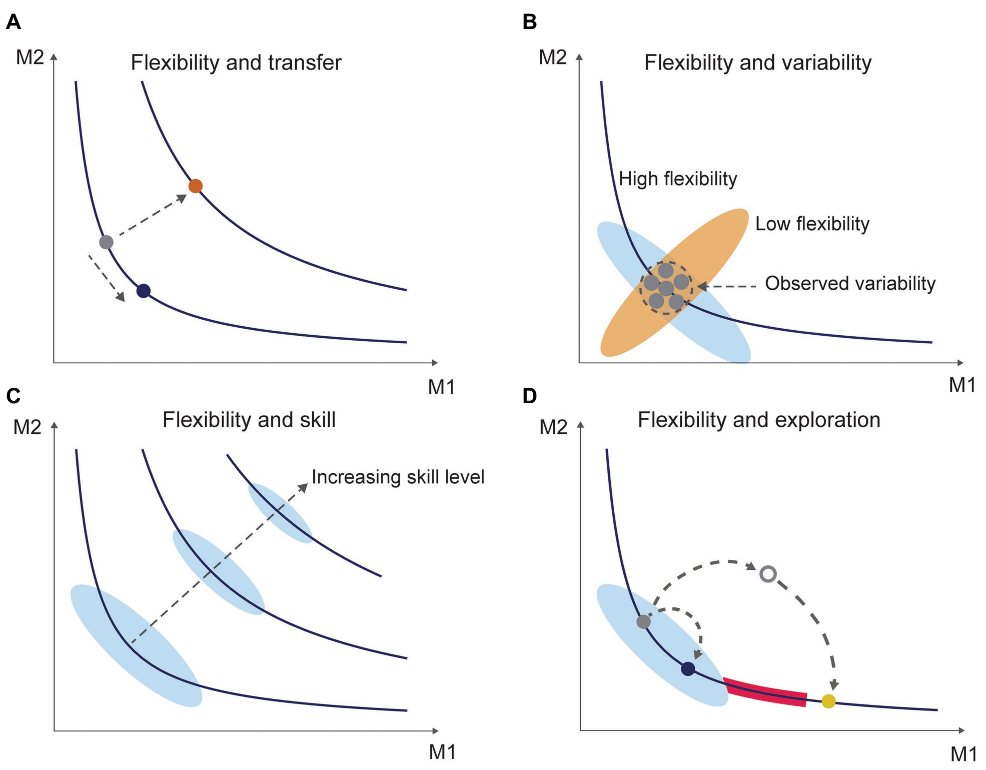

FIGURE 2 | Flexibility and associated constructs of learning. Each plot shows two hypothetical movement parameters (M1 and M2). Contours represent combinations of movement parameters that achieve the same task outcome, and so each point on a given contour represents a "movement solution" to achieve that task outcome (Latash et al., 2002). **(A)** Flexibility and transfer. Flexibility in the current definition refers to moving from a point on the contour to another point on the *same* contour (i.e., same task outcome, indicated in blue). Transfer on the other hand refers to moving from a point on the contour to a *different* contour (i.e., different task outcome, indicated in orange). **(B)** Flexibility and variability. Inferring flexibility directly from the observed movement variability can be difficult because the observed variability in movement patterns (shown inside the circle, with each dot representing a different trial) could either be a part of a movement repertoire with high (blue ellipse) or low flexibility (red ellipse). **(C)** Flexibility and skill. As skill levels and associated task performance levels go up, the degeneracy available in the system (shown by the ellipses) generally goes down. This makes it a challenge to find new solutions to achieve the same task outcome at high skill levels. **(D)** Flexibility and exploration. Exploration refers to the process of finding a new movement solution. Exploration can be quick when solutions are within the same movement pattern (indicated in blue). However, there may be regions on the contour that are unstable (indicated by the red band), which require prolonged exploration and creativity to find a qualitatively different movement solution (indicated in yellow).

the space of possible solutions is considerably narrowed. For example, there are fewer movement patterns to hit a forehand at 80 mph compared to hitting a forehand at 50 mph. On the other hand, at higher levels of performance, there is a need for *more* flexibility because of constraints such as the need to adapt to different surfaces, game strategies, and the need to deceive opponents by being more unpredictable. Therefore, understanding how high-level performers manage these competing demands on flexibility, and the analysis of individual differences at these levels (Dicks et al., 2010; Müller et al., 2015), is an important avenue for future work.

Second, an extremely relevant topic related to elite athletes and flexibility is the issue of "technique modification" – i.e., reorganizing from an existing movement solution to a new movement solution (Napier et al., 2015; Gray, 2018). Although there are plenty of examples of elite players changing their movement pattern to improve performance or reduce injury, there is very little information available on the process of how this reorganization occurs. Anecdotally, evidence during such technique modification is characterized by lower levels of performance for rather sustained periods of time (weeks to months) before reaching pre-modification levels. This pattern is consistent with a dynamical systems view that long-term flexibility does not occur on a blank slate, and that the stability of prior patterns has an influence on how easy it is to be flexible. In particular, finding ways to experimentally address issues of multistability and metastability (Kelso, 2012) in motor learning (Hristovski et al., 2006; Liu et al., 2010; Pinder et al., 2012) may be critical to understanding technique modification and can provide insight into how practice strategies may be developed to accelerate relearning in the presence of prior solutions. This understanding will not only have implications for athletes, but also for movement rehabilitation, where movement patterns have to be modified in the context of a prior pattern to achieve the same goal (Ranganathan, 2017).

CONCLUDING COMMENTS

Classic definitions of motor skill emphasize aspects such as task achievement, consistency, and efficiency (Guthrie, 1952), yet behavioral flexibility is critical to understand how these aspects emerge in dynamically changing contexts. Behavioral flexibility intersects with several central themes in motor behavior such as variability, learning, and practice strategies and provides a fertile ground for future work. The issues raised here (summarized in **Figure 2**) provide a basis for a renewed focus on behavioral flexibility that go beyond Bernstein's (Bernstein, 1967) original observation, and we anticipate that this will lead to theoretical and practical advances in a wide range of domains.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

RR, M-HL, and KN contributed to the conceptualization of the idea. RR and M-HL designed the visualizations. RR wrote the first draft of the manuscript. RR, M-HL, and KN edited and revised the manuscript. All authors contributed to the article and approved the submitted version.

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HYPOTHESIS AND THEORY
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Theory of Cooperative-Competitive Intelligence: Principles, Research Directions, and Applications

*Robert Hristovski[1] and Natàlia Balagué[2]**

[1] Complex Systems in Sport Research Group, Faculty of Physical Education, Sport and Health, Ss. Cyril and Methodius University, Skopje, Macedonia, [2] Complex Systems in Sport Research Group, Institut Nacional d'Educació Física de Catalunya (INEFC), Universitat de Barcelona (UB), Barcelona, Spain

We present a theory of cooperative-competitive intelligence (CCI), its measures, research program, and applications that stem from it. Within the framework of this theory, satisficing sub-optimal behavior is any behavior that does not promote a decrease in the prospective control of the functional action diversity/unpredictability (D/U) potential of the agent or team. This potential is defined as the entropy measure in multiple, context-dependent dimensions. We define the satisficing interval of behaviors as CCI. In order to manifest itself at individual or team level, this capacity harnesses properties such as degeneracy, pleiotropy (pluri-potentiality), synergies, and metastability. Intelligence is embodied because intelligent behavior is deeply dependent on body functionalities, defined as entropy measures. We base our theory on three principles: (a) relativity of functional entropy/information in agent (team)-environment systems, (b) tendency toward the satisficing level of D/U potential, and (c) tendency toward the non-decreasing D/U potential. The conjunction of these three principles provides existence of sub-optimal behaviors associated with CCI. First, we deal with the problem of how to reduce multidimensional behavior to a concept that accounts for the vast set of scenarios in which CCI is manifested. Secondly, we define and discuss the three interacting principles that underpin CCI behavior as well as providing an outline for a future CCI research program supported by agent-based modeling and empirical research. Finally, we provide some preliminary practical issues that stem from the theory.

Keywords: intelligence, cooperative-competitive intelligence, sport intelligence, game intelligence, embodied intelligence, affordances, perception-action, entropy

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Ana Filipa Silva,
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Roberta Frontini,
University of Aveiro, Portugal
Verónica Morales-Sánchez,
Universidad de Málaga, Spain

****Correspondence:***
Natàlia Balagué
nataliabalague@gmail.com

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INTRODUCTION

Concepts such as game intelligence, sport intelligence, or technical/tactical intelligence are common in the scientific literature and in discussions among practitioners but are used vaguely and have rarely been elaborated (e.g., Gould et al., 2002; Blue, 2009; Memmert et al., 2010; Rosslee, 2014; Lennartsson et al., 2015). These concepts have been used primarily in team sports, while their use for individual sports is mostly absent altogether (with the exception of Blue, 2009 for golf-specific intelligence). Sport intelligence has been predominantly considered from the traditional trait theory perspective and from explanatory patterns belonging to and used eminently by the information-processing theory. For example, Gould et al. (2002) defined sport intelligence as a highly developed set of traits, such as decision-making, innovativeness, and quick learning. Memmert et al. (2010) used the traditional, sport-contextualized definition of intelligence as convergent tactical thinking, or more precisely, as the ability to find the best solution (e.g., best positioning). Recently, a thoroughly developed "psychometric trait" model of sport intelligence was suggested (Rosslee, 2014). This model construes sport intelligence as a set of six interacting sub-systems spanning over different levels, starting from the neuro-physiological up to the metaphysical level. On the other hand, psychometric research on collective intelligence traits (e.g., Woolley et al., 2010) have revealed that individual intelligence contributes far less than the properties of interpersonal interactions. This means that a psychometric (or indeed, any other lower level, such as neuro-physiological or genetic) approach to intelligence reveals a high level of dependence in the understanding of intelligence. Hence, a general conceptual framework of intelligence, valid for both the individual and the collective level, seems hard to obtain within these kinds of approaches. This state of affairs clearly points to a need for a more general conceptualization of intelligence in cooperative-competitive environments, which would be valid for the individual as well as the collective level of action. In other words, level-dependent variables, although important for each level, have to be treated as specific rather than general determinants of CCI.

Another aspect of game intelligence was captured by constructing a theoretical game model (Lennartsson et al., 2015). Within the framework of this approach, the fundamental idea is the concept of *potential*, that is, the difference between the probability of the offense scoring the next goal and the probability that the next goal is scored by the defense. Authors have obtained optimal strategies for both offense and defense, and one main result is that the optimal defensive strategy exists when the maximum potential of all offensive strategies is minimized.

Based on the above, it becomes clear that intelligence in competitive-cooperative environments, such as sport, can be conceptualized differently depending on the level at which it is defined (personal or collective), or on some limited behavioral properties that lack generality. This is the main reason why we have adopted a more general approach to intelligence in this paper as the tendency of living systems and their dynamic social structures (e.g., teams) to *evade* and *escape* states of reduced possibilities in what we call functional action diversity/uncertainty (D/U) potential, where the potential is expressed through the entropy concept (Hristovski, 2017). Under D/U potential, we understand action diversity/uncertainty, which consists not only of richness of the functional coordinative patterns (i.e., functional classes of action or movement forms) of the agent and/or among agents but also of the diversity/uncertainty potential in timing resolution, speed, and other skill parameters. For example, larger entropy in the variable of accuracy or acuity means larger resolution of perception-action. A constant space with a finer-grained structure, or higher sensitivity to details, has larger entropy because of greater discriminatory ability (see Gibson and Gibson, 1955; Araújo et al., 2019). In a similar vein, D/U potential may be based on degeneracy, i.e., the capacity of agents and teams to attain a similar outcome by structurally different components, e.g., Edelman and Gally (2001), but can also be based on the capacity to functionally change the intended outcomes. Hence, these concepts are not necessarily reducible to degeneracy.

In the text that follows, we offer a general conceptualization of what we call cooperative-competitive intelligence (CCI) in order to capture current definitions of game intelligence as special cases of CCI. CCI would include a vast set of behaviors that exist in sports science literature under different names, such as: sport intelligence, game intelligence, and technical/tactical intelligence. However, it may also include a wider set of behaviors outside the immediate sports performance realm, such as strategic planning.

The CCI term is chosen because it does not tend to define intelligent behavior solely at the scale of sports performance (e.g., a competition or a match) but also captures the longer-term tendencies of strategic behavior in systems that contain cooperative-competitive interactions in general. Keeping in mind that the systems we plan to discuss are multidimensional complex adaptive systems, the first question that comes to mind is: how can we dimensionally reduce the multidimensional behavior to a concept that can be useful in a principled way in accounting for the vast set of scenarios in which CCI is manifested? Obviously, this problem needs a selection of what can be called a "common conceptual currency."

ENTROPY AS A COMMON CONCEPTUAL CURRENCY

In recent research, entropy as a partial measure of performance has been extensively used either in individual or in collective sports. Researchers have investigated a large set of variables in many sports disciplines (e.g., Hristovski et al., 2006; Passos et al., 2009; Fewell et al., 2012; Vilar et al., 2013; Couceiro et al., 2014; Silva et al., 2016; Castellano et al., 2017; Gonçalves et al., 2017; Neuman et al., 2018; Lopes and Tenreiro Machado, 2019, 2020), showing that behavioral entropy, as measured by different entropy measures, has considerable effect on a number of teams and individual performance indexes. These immensely important results seem to point to a possible unifying explanation of how entropy, as a property of these systems, enters and becomes relevant for performance. We concur with the claim that behavioral entropy is a highly relevant concept for sports performance. In the text that follows, we will explain the relevance of the entropy concept for performance by showing that it underpins the CCI concept *in a specific way*.

The main reason why CCI can be defined in entropy terms is because it sufficiently unifies different measures of variability (e.g., variance, range, etc.), that is, variability can be put under the same measure. Moreover, it is often expressed as a logarithm of a spatial construct, line, surface, volume, and any scale whether physical or formal (i.e., formal scales in psychology or physiology can be cast in spatial terms). In thermodynamics, the dependence of entropy on variability and space variables are given in one of the basic relations between entropy and temperature (i.e., variability) and volume (space) (Balesku, 1975). Hence, an entropy value can be ascribed to any construct that can be expressed as a variability and/or a space. In this way, entropy enables us to work with a "*common currency*" in different dimensions. For example, space creation and occupation, number of possible passes, and agility can be all expressed as entropy.

In the research on perception-action, it has been convincingly argued that the information picked up by agents to control their actions can be cast as a co-variance between the distal properties of environment and the structured energy array that further co-varies with the perceptual systems of agents (Segundo-Ortin et al., 2019). Because of the co-variance relation, the ecological information can be quantified as Shannon information (defined as a reduction of entropy; e.g., de Carvalho and Rolla, 2020).

In the text below, we define and discuss the three interacting principles that underpin CCI behavior. We first discuss the relativity of the information-entropy principle and show what the adaptation of agents and teams to their environment means in terms of the increment of the functional integrative information of the system. The integrative information of the system is seen by the external observer as behavioral D/U potential. The sufficing variability principle then sets a limit to the growth of the D/U potential and is manifested as a dynamic entity dominantly constrained by the richness of environmental perturbations. The tendency toward non-decreasing action D/U potential unifies the manifestations of CCI in different dimensions and some aspects of creative behavior. Finally, we discuss some aesthetic, practical consequences and outline a research program that stems from this conceptualization of CCI. To help the interested reader grasp some of the more abstract ideas, suitable examples are provided in each subheading.

PRINCIPLES OF THE THEORY

Principle 1: The Relativity of Information[1] Entropy. Non-functional and Functional Action Diversity/Uncertainty Potential

The principle of D/U potential (Hristovski, 2017) captures two moments. First, it captures important aspects of the transition from non-functional to functional action, diversity/uncertainty of the system (agent or team). Second, it captures the relativity of the role of functional action diversity/uncertainty potential for the system when seen, on the one hand, from within, and on the other, by an external observer. The term *potential* signifies that the diversity or uncertainty of actions need not be manifested always and everywhere. When the context allows, the system may attain its goals using highly repetitive actions. The term "potential" means a space of individual or collective action properties, which, *when needed*, can be organized in order to attain a certain well-defined goal or chain of sub-goals. It also has a wider meaning than repertoire of movement forms, including perceptual and other psychomotor abilities.

This principle contends that the practice-induced transition from non-functional to functional D/U potential from the perspective of the agent or team (perspective from within) represents gaining integrative information and greater *within-system* certainty. Seen, however, from the external observers' (e.g., opponent's) perspective, it represents gaining functional entropy or functional uncertainty. This is because in a finite configuration space, the sum of the entropy and information is constant (Layzer, 1975). This means that before the occurrence of some event, its entropy (i.e., degree of uncertainty) is equal to the information one obtains after its occurrence. A gain in information is always compensated by loss in entropy and vice versa (Layzer, 1975; Serdyukov, 1987). Hence, according to this, the training process is conceptualized as a conversion of entropy into stable integrative information structured by different psychomotor dimensions (Hristovski, 1989). Integrative information is defined as information that arises from the couplings among goal-directed actions of the system. The behavior of agents in a deterministic and stable environment is then formulated as a variation principle of the least entropy (uncertainty) action. From this, it follows that in highly stable and repetitive (i.e., predictable) environments, adaptive systems will converge to a minimum uncertainty by minimizing the irrelevant action variations. However, even so-called "individual" sport competitions rarely offer highly stable environments. On the contrary, competitions create conditions where the highly demanding non-cooperative behavior of the environment is the rule rather than the exception. In such non-deterministically changing non-cooperative environments, agents (players and teams) must develop high D/U potential to increase their fitness and survival possibilities. This means that the adaptation process on long time scales, such as years, rests on a tendency of permanent increase in the D/U potential which affords the ultimate goal, the survival (winning) of the system in sports environments. In our view, therefore, cooperative intelligence would crucially depend on how the agent or team manages the adequate level of integrative information within its boundaries and the entropy (unanticipatedness or uncertainty) potential for the opponent, while being continually under their (environmental) perturbing influences. Between-team competitive intelligence would depend on the abilities of the agent or team to suppress the opponents' integrative information and increase the non-functional entropy. Importantly, within-team competitive intelligence would be higher, if the intra-team competition brought about larger integrative information and larger entropic (uncertain) behavior potential for the opponents.

The principle is general, but let us cast it in a more familiar form for the reader, in terms of synergies and the process of reducing the bad and increasing the functional (good)

[1]Information as a quantity here should be understood as arising from co-varying variables or processes and as a magnitude of integration or organization (e.g., Haken, 2006) rather than in the sense of capacity of communication channels or codes (Shannon and Weaver, 1949). On the other hand, in the text that follows, ecological information will be named as such.

variability (Latash, 2008). This example is especially important to make a distinction between non-functional and functional D/U potential. The former is present mostly in novices, and the latter, in experts. Synergy has been defined as the capacity of reciprocal compensatory intervention of component variables V_1–V_n in order to maintain the achievement of certain goal or performance variables (Latash, 2008). The co-varying and reciprocally compensating components induce necessarily a dimension reduction of the system. It has mostly been exploited in motor control literature (Schöner, 1995; Scholz and Schöner, 1999; Latash, 2008; Maldonado et al., 2018) and to a lesser degree in interpersonal, social systems literature (Dodel et al., 2010; Riley et al., 2011; Passos et al., 2018).

In the light of the principle of entropy-information relativity, agent or team adaptation may be conceptualized as an increasing disagreement between the external observer and the agent (or team) performing a task on the level of the *functional* uncertainty of the agent's or team's future policy. For simplicity, let us assume that a certain policy has to satisfy a well-defined stable task goal constraint[2]. As depicted in **Figures 1A–C**, the process of adaptation may be portrayed as a sequence A->B->C; that is, as an ongoing condensation of configurations of the component actions given by variables V_1 and V_2 on the manifold (the blue line) signifying the increased frequency of attaining the task goal. One can consider that each red oval represents a task realization (a trial), which was achieved by some configuration of component variables V_1 and V_2. Panel A would represent a case where the agent, dyad, or the team very rarely comes close to attaining the goal. Accordingly, panel C would, therefore, represent an ideal case in which all trials of the agent, dyad, or the team attain the goal (e.g., scoring a point or making a successful pass).

In **Figure 1**, the functional variability spreads along the blue line and the non-functional variability spreads in a direction perpendicular to the blue line. One may understand it as a goodness of fit between the configurations of component values V_1 and V_2 and the blue line which represents the subset of configurations of V_1 and V_2 which satisfy the goal constraints. In other words, it represents how good the co-varying and reciprocally compensating combinations of components fit the goal. If V_1 and V_2 lie anywhere along the blue line, their synergy satisfies the goal constraint. If they lie far from the blue line, there is no functional synergy. The goal is far from being attained. Hence, there may be a large number of combinations of component actions that satisfy the goal constraints, not only one. In multidimensional spaces, more than two independent component variables may also create synergies (Latash et al., 2007). The component variables V_1–V_n may be intrapersonal (e.g., muscle activations, joint angles, moments of inertia, etc.) or interpersonal variables (see Black et al., 2007; Dodel et al., 2010; Riley et al., 2011; Passos et al., 2018).

Concerning the entropy-information relation, the initial state of scarce co-variation between elementary variables corresponds to the case of high entropy H and low integrative information (I) between components V_1 and V_2 of the system (see **Figure 2**, oval A). As the novice learns, the synergy component variables start to co-vary, increasingly satisfying the goal constraints. Increased covariance means increased mutual information (I) among elementary variables. This gain in information is at the expense of the reduced entropy (H) of the system. A goal-attaining synergy contains large mutual (shared) information among the components V_1 and V_2 and low entropy intrinsic to the system (i.e., agent or team; **Figure 2**, ovals B and C). However, since there is a large amount of good variance, for an external observer, the synergistic system has a large uncertainty potential, while simultaneously being able to satisfy the goal constraint. This means that the synergies for an external observer are *functionally* entropic, diverse, and uncertain. "*Functionally*" means that the synergy satisfies the goal constraints. The synergy achieves the goal. For an external observer, the maximally *functional* uncertain behavior in **Figure 2** would be oval C, which corresponds to **Figure 1C**.

Reducing maximally the variability along the blue line (**Figure 1D**), however, maximally increases the information and minimizes the entropy within the system as neither non-functional nor functional variability is present there (**Figure 2**, oval D). This can be a case for behavior in deterministic and cooperative environments in which there is only one way to attain the goal. However, for competitive and non-deterministic environments, this is quite non-adaptive behavior.

Accordingly, establishing functional couplings within the agent, agent-environment, or cooperative agent-agent system is creating integrative information or, equivalently, loss of entropy *within* the system. As the formation of such functional couplings *within* the system proceeds, the D/U potential of the system (agent or team) increases. This means that the team functionality consists of the capacity to satisfy the goal constraints in diverse ways. Because functional diversity is proportional to uncertainty (unanticipatedness), it means that the system, by becoming more diverse, becomes more *functionally* uncertain for the environment or *external observer* (e.g., opponents' team).

It is important to see that this is valid at more levels, not only at the individual level. For example, the diversity of strategically constraining the game (different formations) will reflect the potential diversity of behavior of player dyads and individual players. Conversely, non-expert teams cannot be diversified much at the strategic level due to their lack of competencies on multiple levels. They cannot be sufficiently *functionally* diverse. In experts, in contrast, as the system becomes potentially more functionally diverse, an external observer will be less able to tell the policy, which will be used by the system to satisfy its goal constraints. The adaptive

[2]It may be a dilemma why we use the term uncertainty and not degeneracy, for example. While uncertainty encompasses degeneracy, which is the capacity to attain *similar outcomes* by the spatio-temporal arrangements of structurally different components (e.g., Edelman and Gally, 2001), the D/U potential may also include successful changing of goals and intended outcomes. Also, it can include attaining different outcomes by the same means (see Pol et al., 2020). In this sense, the D/U potential of behavior has a wider meaning than degeneracy alone. Also, importantly, uncertainty is a *relational* variable that exists only at the interface between the performer and the environment (e.g., opponents), while degeneracy is a property of the agent or team.

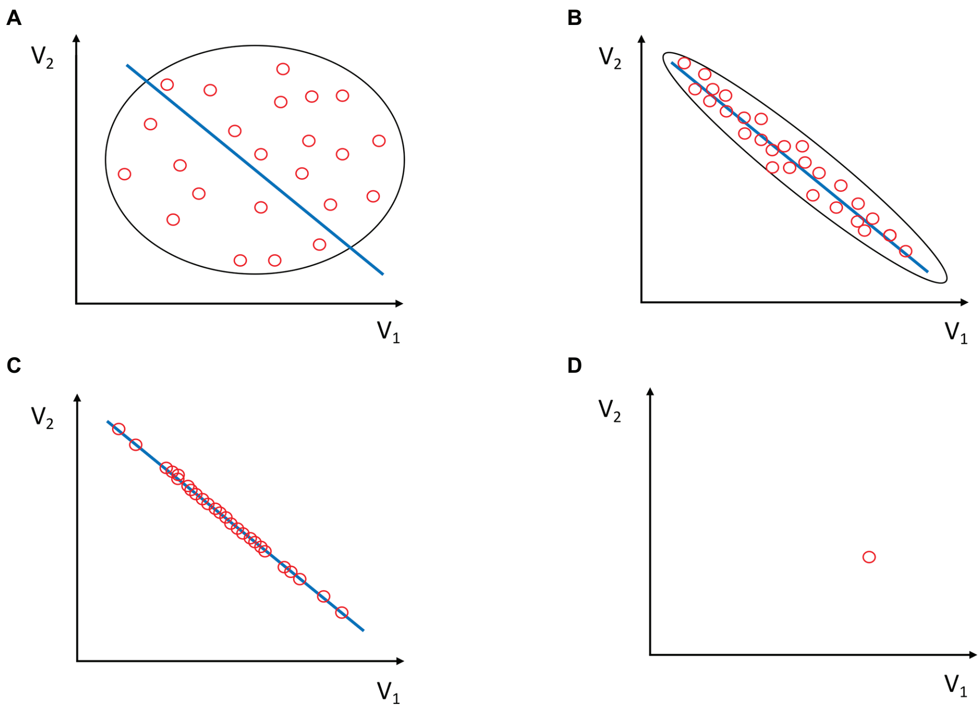

FIGURE 1 | Task solutions (i.e., behaviors) are given as combinations of component variables V_1 and V_2 as red ovals. Task solutions that satisfy goal constraints are given as a blue line. These solutions are functional task solutions. Intuitively, entropy decreases and information increases with the higher condensation of red ovals along the blue line. This is captured by the shape of the oval on the scatterplot. **(A)** Component variables V_1 and V_2 do not efficiently co-vary. They seldom lie along the blue line. Consequently, task solutions rarely satisfy goal constraints. Entropy H is maximal, and hence, common integrative information within the system is minimal. The variability and uncertainty of individual or team behavior are also maximal, but rarely functional (i.e., positioned at the blue line). Thus, the diversity/uncertainty (D/U) potential is small. **(B)** Task solutions fit well with the blue line, which consists of the values of combinations of V_1 and V_2, which satisfy the goal constraints. There is high, although not complete, functional co-variation of component variables V_1 and V_2. The variability along the blue line is larger than the variability perpendicular to it and, therefore, the functional D/U potential is larger than that in panel A. There is lower than maximal entropy in the system and, hence, common integrative information within the system is present. **(C)** All the variability of task solutions lies on the blue line, meaning they all satisfy the goal constraints. Component variables maximally and functionally co-vary. This is the case of maximal functional D/U potential. **(D)** Only one combination of component variables V_1 and V_2 exists and satisfies the goal constraint. All trials are accumulated in the same oval. Neither variability nor functional diversity exists in this case, meaning that D/U potential is zero. This case corresponds to a maximally stable action in a deterministic environment, e.g., automatic robot devices in car factories. The entropy of the system (H) is zero and the integrative information (I) is maximal.

system will become increasingly functionally uncertain for the observer (or the opponent).

Individual Agent-Environment Level of D/U Potential

At the level of agent-environment, consider the following example: the novices' task is to prospectively control the ball in order to drive and allocate it in the goal area. Their behavior may be very volatile and have high entropy/uncertainty within their limited space of possible action configurations. Their coupling with the ball is highly uncertain from both: their perspective and from the observers' perspective (**Figure 1A**).

For example, total beginners, in their degrees-of-freedom exploratory phase of motor learning (Davids et al., 2012), will hardly successfully control the ball prospectively and each time will be surprised by the unexpected bounce of the ball off their leg. The co-ordination between their perception-action systems and the ball can be utterly uncertain from their point of view, but also from the *external observer's* (see **Figure 1A**). However, this uncertainty is not functional. If the novices' actions are uncertain and functional, then novices would be highly competitive, which is a contradiction.

In this case, there is high entropy (uncertainty) within the novice-ball system as well as high uncertainty as observed from the point of view of the external observer. There is low integrative information (I) within the novice-ball-environment system and thus high non-functional entropy (H; see **Figure 2**, oval A). They, the novice and the observer, can concur on the high level of non-functional uncertainty of the novice-ball system.

On the other hand, after some time of practicing, during the solution, stabilization, and especially the degrees-of-freedom exploitation phase (Davids et al., 2012), the novices' space of possible *functional* action configurations has expanded and they can reach the goal area in different ways of controlling the ball (**Figures 1B,C**). Their behaviors will still be diverse and hence uncertain (entropic) from the perspective of an external observer but highly under control (non-entropic and thus

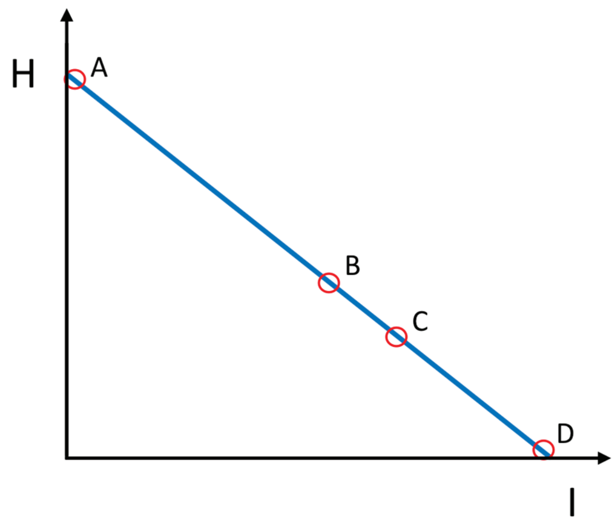

FIGURE 2 | Entropy (H)-Information (I) relation in synergies. Ovals A, B, C, and D refer to respective panels on **Figure 1**. Oval A represents minimal agent or team integrative information (I) and maximal entropy (H). This is also the case of a maximal but non-functional uncertainty (H). Oval B is a case of the system's increased integrative information (I) and lower entropy (H). The increase in integrative information has reduced the entropy (uncertainty), but uncertainty (H) becomes partly functional. Oval C, the integrative information (I) of the agent or team is even more increased and the entropy (H) decreased. Here, entropy (H) comes solely from the functional variability along the blue line in **Figure 1**. This is the ideal case of the functional integration of the agent or team, and its functional D/U potential for the external observer or the opponents is maximal. Oval D represents an excessively (non-flexibly) integrated agent or team, with maximal integrative information (I) and absence of functional D/U potential (H) for the external observer or opponents.

predictable) from their *own* perspective (**Figure 2**, oval B and C). They have attained *functional* diversity and uncertainty, including, but not reduced to, deceptive movements. The ex-novice and the external observer will not concur on the degree of uncertainty or surprise of the ex-novice-ball system. For the ex-novice, ball behavior will be controllable and very predictable [high integrative information (I)], but for the external observer, it will not be predictable [sufficiently high entropy or surprisal (H)][3]. The ex-novice will be able to control and, hence, prospectively anticipate what will happen next to the ball she/he drives (high I), but not so the external observer (sufficiently high H). In individual sports such as gymnastics, the larger D/U potential of performers produces larger surprisal, and in track and field or swimming, a larger potential set of pacing strategies and, hence, larger potential uncertainty for co-competitors (e.g., Thiel et al., 2012; Mytton et al., 2015).

Multi-Agent Level of D/U Potential

Teams have been depicted as superorganisms (Duarte et al., 2012). The relativity of the information-entropy principle offers a way of explaining how a group of agents becomes a team. Consider a group of novices that attempt to keep possession of the ball. Their behavior is highly uncertain, but not *functionally* uncertain. The group is, to a large degree, disorganized. The uncertainty of behavior within the group (as seen by each novice inside the group) is high, as is the uncertainty of the group as seen from outside. They do not form a unit (or units), which is (are) functional (Araújo and Davids, 2016). They do not form a team (see **Figure 1A**).

On the other hand, a team of trained agents is functionally uncertain in the sense that they can realize their goal (e.g., score a point or make a successful pass) in different ways by means of forming temporary task-specific units based on internal, diverse inter-agent functional couplings (**Figures 1B,C**). In skilled agents, affordances are used for prospective (future goal-directed) control, meaning that teammates can coordinate and form synergies more successfully, if they are well attuned to each other's affordances (see Silva et al., 2013). A team, or within-team dyad, as a functional unit, exists to the degree in which its members contribute to the decreasing entropy (increasing integrative information) within the system and the functional uncertainty of the team for external observers (e.g., opponents[4]; **Figures 1, 2**). At this multi-agent level, whenever a team loses a ball due to interception by the opponent or the inaccuracy of a pass, the red oval is out of the blue line, decreasing the integrative team information (I) and increasing the non-functional entropy (H). On the contrary, when there is a successful pass, it is on the blue line and signifies the presence of integrative team information, because the combination of component variables V_1 and V_2 achieves the goal (i.e., satisfies the goal constraints). If the team is able to achieve the goal by passing in many different ways (combinations of V_1 and V_2), then its functional diversity and uncertainty as a superorganism is high. Also, the integrative team information (I) is higher than in the group of novices (**Figure 2**). **Figures 1, 2** help in depicting the opponents' task, which is always to push the team from state C or B toward A. In other words, to decrease the integrative information of the team and to increase internal entropy, while the goal of the team is the opposite.

On the other hand, opposing agents and teams may also co-vary. However, they do not build synergies due to the absence of the same goal, which has to be kept stable. The opponents' goal is different and, therefore, meaningful performance goal variables are different. In the language of synergies, the opponents' co-variance with players tends to

[3]They can concur on the level of functional diversity, though. Both, the observer and the ex-novice will judge the functional diversity as increased.

[4]With respect to this, one can make a distinction between the level of adapted *skills* and *expertise* and the level of cooperative-competitive *intelligent behavior*. An agent can have a high level of skill and expertise but, contextualized by some personal and social constraints, could act in a way that decreases the level of the D/U potential of the team. Some trivial examples are as follows: an expert player that is perseverant in unsuccessful solo actions driven by excessive self-interest or an expert player that commits a fault driven by revenge. In a similar vein, some social and personal constraints may be in conflict with the tendency of non-decreasing diversity of prospective control, e.g., some ethical constraints. This would limit the greedy tendency towards *maximizing* the D/U potential. Hence, because of this, cooperative–competitive intelligent behavior *is not* only, or at least *not dominantly*, based solely on cognitive processes.

increase the non-functionality of the team, that is, to increase the dysfunctional entropy within the opponents' team.

Principle 2: The Satisficing D/U Potential

Satisficing action means sufficiently satisfying behavior where the sufficiency of the outcome may be constrained by some additional criteria (Simon, 1956), for example, criteria such as dribbling past an immediate opponent, dribbling past five immediate opponents in a row, scoring a point, winning at least fifth place in an international tournament, or simply qualifying for some international championship, or winning gold medal in the world championships five times in a row. Note that the fulfillment or not of these criteria cannot be predicted beforehand but can only become clear *after the fact*. Controlling and fulfillment of such criteria would need a full model of agent or team behavior, which is currently not possible (Glazier and Davids, 2009a,b). Since the outcomes of individual movements are context-dependent and there are an infinite number of ever-changing contexts, it becomes impossible to predict the individually globally optimal behavioral pattern.

Sub-optimal behavior, on the other hand, is the one that is *sufficing* in its functionality for the given context (Byron, 1998). When speaking about the D/U potential, Simon's concept of sufficing is close to the concept of requisite variety (Ashby, 1956). This concept describes the principle that states that in order to cope with a variable environment, the system (in our case the agent or team) has to be, at least, as variable as the environment. By joining the two principles, one can speak of *sufficing variability*, that is, variability that suffices for attaining the goal (Hristovski, 2017). For example, players facing an undefended space during a counterattack (i.e., having a large D/U potential) would typically use small behavioral variability (i.e., small D/U behavior), which is sufficient to conquer the space as quickly as possible and try to score a point. On the other hand, if they are approached by one or two defender players, which reduce their D/U potential, they will increase behavioral variability (i.e., the D/U behavior) to some level of sufficing in order to achieve the goal. The achievement or non-achievement of the goal will *post factum* tell whether the level of behavioral variability was sufficing. In general, whereas in stable and cooperative environments the tendency of behavior is to attain low action entropy potential – stabilizing tendency (e.g., walking on flat surfaces such as streets), in uncertain and non-cooperative environments, adaptive behavior is to sufficiently increase the action entropy potential in order to be able to satisfy the goal constraints of the organism. Learning to detect the level to which the D/U potential has to be engaged depending on the opponent is of utmost importance for the success of athlete and team performance. Specific training methodologies may be needed to develop this aspect of abilities. This process is based on permanent co-adaptation of the agent/team-environment/opponent system that sets the asymptotic level of convergence.

Wissner-Gross and Freer (2013) describe intelligence as future entropy maximization tendency. However, in biological systems, global entropy maximization may have limits due to the energy costs of such a behavior. A good example of such restriction in biological systems is the overcompensation phenomenon. It can be detected at cellular, functional, or overt performance level after a suitable amount of perturbation (training impulse) applied to the agent. Overcompensation is the evanescent state of increased functional (integrated information) potential of the organism, which vanishes if the organism is not faced with certain continuity of such perturbations. In the introduction, we defined the functional action potential as a D/U potential. Hence, due to the perturbation, i.e., fatigue, the diversity potential of the organism temporarily decreases, and the cell or organism reacts *prospectively* by a temporary increase in the diversity (integrated information) potential. It most likely anticipates[5], in a sense of strong anticipation (Dubois, 2003; Stepp and Turvey, 2010), the possible incoming perturbations and prepares to negotiate them with enhanced potential. This is a clear example of intelligent behavior. However, the biological system does not continue to increase the potential without limits, although there are immediate available excess resources for it that can be used (e.g., glycogen deposits). The satisficing principle is due in part to the fact that each agent has limited resources of energy for action and for *globally* maximizing the space of future action possibilities, i.e., the D/U potential, would quickly exhaust energy resources. There seems to be a trade-off of energy and entropy/information properties. If perturbations cease, the D/U potential returns to the pre-perturbation level, which it temporarily decreases. This phenomenon has been routinely detected on a macroscopic measurement scale as a daily or monthly (Verkhoshansky and Siff, 2009) time series of ability performances (see **Figure 3**).

Here, it is important to note that the non-decreasing D/U potential is obtained within a certain temporal window, temporal prospect, or horizon. It will continue to increase only if the environment applies a perturbation to the system, by temporarily suppressing the D/U potential. Otherwise, it remains adapted by sufficing the D/U principle to the current environmental demand. The temporary suppressing of the D/U potential, as, for example, getting fatigued during the training session, is made to prospectively increase it, which is the CCI goal within a certain temporal frame. On the contrary, excessive perturbations may cause long-term suppression of the potential, which is not the CCI goal in the said temporal frame.

Thus, it seems plausible to claim that the long-term environmental requirement of sufficing D/U potential in agents and teams *is the reason* for the emergence and evolution of properties such as degeneracy, pluripotentiality (Seifert et al., 2013), metastability (Kelso, 2012), and synergies (Latash, 2008), which, in a circular causality fashion, stabilize the development of the D/U potential. In this light, it seems that the striving toward the non-decreasing action space of possibilities is why biological degeneracy, pleiotropy, and metastability have been

[5]One can hypothesize that overcompensation is an evolutionarily stabilized instantiation of strong anticipation, a purely dynamic effect in which the "slave" system coupled to its "master" system anticipates the behavior of the latter. In this case, the master system would be the environment and the slave, the cell/agent.

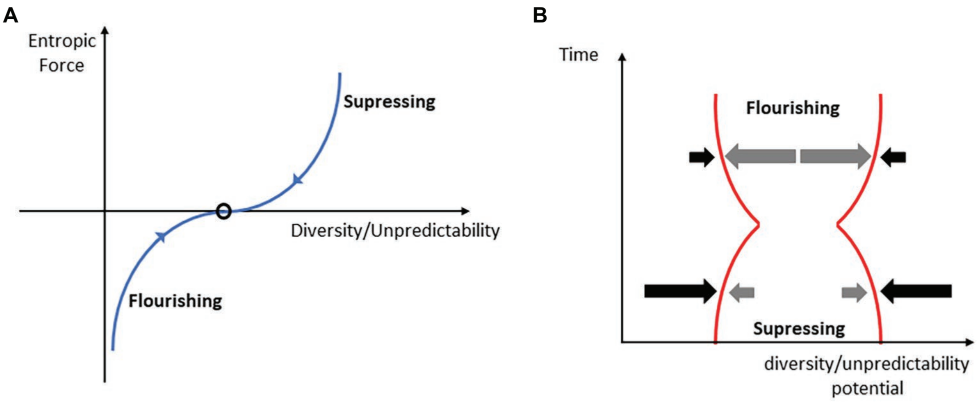

FIGURE 3 | The system is subject to forces that tend to suppress the D/U potential. **(A)**: the balance of suppressing (opponent) and flourishing entropic forces (gradients) determines the D/U potential value (black oval) of the behavior. We hypothesize that the larger the deviation from the average diversity/uncertainty of behavior (the oval), the larger the suppressing or flourishing entropic force will be. **(B)**: cooperative-competitive intelligence (CCI) manifests as the ability to act prospectively. After a narrowing down of the D/U potential as a result of the suppressing forces of opponents, the tendency is to be compensated *at least* to the initial level (*time* = 0). This is a consequence of flourishing forces (see **A**).

evolutionarily stabilized. While degeneracy and pleiotropy (pluripotentiality) form the basis of the repertoire (set of synergies) of individual or team actions (Seifert et al., 2013; Ric et al., 2016), the dynamic mechanism of metastability is responsible for switching among them (Hristovski et al., 2009; Kelso, 2012; Bruineberg and Rietveld, 2014). The net result of the non-decreasing entropy tendency in agents and teams is attaining stability through flexibility and stability of the flexibility (defined as a part of the diversity).

Hence, the satisficing principle as a sub-optimal solution can be expressed as subject to satisfying inequality constraints (e.g., $\Delta H \geq 0$), which means that the satisficing solution for any agent or team is any *average* value of ΔH (change of D/U potential) that is equal to or greater than 0. This means that CCI can be conceptualized as an average behavioral tendency of agents and teams to resist their future actions to be suffocated by the environmental (opponents') perturbations. In this formulation, the upper limit of behavioral diversity/uncertainty H is determined by the satisficing principle. The average here exists because, on some occasions (as in the case of overcompensation), in absence of perturbations, the D/U potential may converge to some arbitrarily given initial value after passing the period of increased potential, which will mean its local decrease. The decrease is, in fact, a re-adaptation to smaller environmental challenges (perturbations). This, however, adds another property to the CCI. In order to grow on average, more often than not, the agent or team must be subject to perturbations that will stimulate the fulfillment of CCI growth conditions. Hence, the satisficing principle puts demands on the system that needs to grow its CCI. Growth of intelligence needs perturbations in the other direction to H growth, to which the system will respond with $\Delta H > 0$ behavior. In other words, this means that the development of CCI is necessarily dependent on environmental dynamic properties. A system coupled to challenging and stimulating environments represents a system of growing CCI. The term "challenging" here means perturbations that are strong enough to provoke the growth and evade the temporary stalemate, which may, on a longer time scale, turn into a decrease in the D/U potential.

Principle 3: The Prospective Non-decreasing Action D/U Potential

This principle claims that a system (agent or team) tends toward non-decreasing D/U potential: the system develops a reactive force in an opposite direction to any perturbation from the environment/opponents, which reduces the previous state of D/U potential (Hristovski, 2017). What the opponent strives to do is to minimize the D/U potential of the opponent or team and simultaneously increase or at least maintain its own satisficing level of potential action entropy.

At the basic level, two forces are molding the behavior: nested goal gradients and the entropy (decrease-increase) force. These forces drive the adaptive response of the system. The nested goals may be keeping the ball in possession, in order to be able to score a point, in order to win (survive) the match. This "nestedness" already assumes a level of D/U potential that can attain these sub-goals in the face of permanent perturbations of the opponent to reduce the chances of attaining the goals by reducing the D/U potential. On the other hand, the force toward non-decreasing D/U potential can in fact be defined as a goal-setting force. The system's general goal is always not to allow the decrease of its opportunities for action. Seen in a certain time frame, this means that, even if the system is temporarily pinned down and has reduced prospective action D/U potential, it always seeks ways to escape from this state. Moreover, in competitive environments, CCI would seek to escape from this state with a sufficing rate, given the constraints. This can be expressed as the sufficing entropy rate or production. For example, a player that has to temporarily dribble-pass one or a few opponent players, through a reduced D/U potential corridor, will negotiate this situation in sufficing rate by having in prospect the perceived free space (larger D/U potential) located further in the field. Otherwise, if the situation affords her/him not to succeed in this action, s/he may decide to pass the ball to a teammate, which sufficiently increases the D/U potential of the team prospectively. This is the same *prospective* adaptive reaction that we described earlier in relation to overcompensation. The reactive force simply acts as a negative feedback, not allowing the initially reduced D/U potential to become even more reduced in the future, so the system becomes pinned down to some minimum, which would most likely bring about non-achievement of the goal (e.g., a stolen ball, receiving a goal, losing the match, etc.). Hence, the larger the *accessible* time scale at which the system non-decreases its entropy, the larger its CCI. Being sensitive to constraints that play a crucial role at these time scales is a part of intelligent behavior. In general, the larger the time frame[6] of the prospective action D/U potential (H), and the quicker one escapes from its reduced state, the larger the CCI behavior.

More generally, the co-adaptivity at multiple time scales and levels may be defined as a competition of two forces: (a) the tendency to decrease the opponent's opportunities of action and increase their informativeness or predictability (suppression) and (b) the tendency to increase one's own D/U potential, i.e., flourishing (see **Figure 3**).

In fact, in the light of the interplay of these forces, opponents and fatigue (on different time scales) play identical positive adaptive roles, temporarily reducing the potential prospective D/U potential, while pushing the agent's organic systems, or the team, to recover or overcompensate. This non-decreasing entropy tendency is basically an *anti-fragility* phenomenon (Kiefer et al., 2018), claimed as a general principle in sociology, psychology, and biology from cell to society (Taleb and Douady, 2013).

Some consequences for the emergence of competitive teams stem from these principles. In general, non-decreasing D/U potential, at the level of agent or group of agents, is often only possible through social cooperation. In sports teams, social cooperation is underpinned by becoming sensitive to affordances. Thus, at performance level, becoming attuned to each other's affordances (Silva et al., 2013) is one of the *means* through which the principle is realized. In other words, the tendency of non-decreasing D/U potential is the *driving force* of the formation and stability of social structures in general and of sports teams in particular. That is, the formation of social structures seems to be a consequence of CCI. As we mentioned above, teams exist to the degree to which their members contribute to their non-decreasing D/U potential. From this perspective, intelligent behaviors, individual, dyadic, and collective, simply emerge as a consequence of satisfying non-decreasing D/U potential constraints.

Within the framework of ecological dynamics, decisions are grounded in actions (Araújo et al., 2006, 2019). Actions are agents' decisions. The actions of living agents are always future-oriented, i.e., prospective (Turvey, 1992), based on perceiving opportunities of action (affordances) that the environment offers and which are not only immediate but also more distant in time (Bruineberg and Rietveld, 2014; Seifert et al., 2014). Hence, CCI at performance level is fully embodied because it is not only crucially dependent on, but also to a degree consists of, bodily capacities (effectivities), which make the usable set of affordances larger, and hence, more flexible. CCI is the capacity of (individual and collective) decision-making to always non-decrease (i.e., maintain or increase) the *prospective* D/U potential. In other words, CCI is a tendency to keep at or grow to, the satisficing level of the prospective control of behavior within some time horizon[7]. Creativity is one of the means to grow the D/U potential.

The game is a permanent exploration of possibilities for satisfying the sub-goal of scoring a point and consequently the main aim of winning the game, i.e., to survive. In this sense, the exploratory phase can be considered as an "incubation" period of the creative process, before the sudden emergence of the satisficing solution that leads to the scoring point (i.e., the satisfaction of the goal constraint). Whenever, the environment (opponent) temporarily suppresses the D/U action potential, the agent (individual or team) is constrained to find/create a solution to the immediate circumstances in order to recover its previous D/U state of possibilities or increase it (Hristovski et al., 2011). After a perturbation that decreases the D/U potential, the system strives to compensate or over compensate the previous potential level of action entropy. Flourishing is a process/state, characterized by an increase in the D/U potential action entropy and is based on creativity. Suppressing habitual action policy and discovering a new mode for attaining the goal is a mode of creativity, (e.g., Torrents et al., 2020). If CCI can be defined as a tendency of non-decreasing the D/U potential, then it follows that there is a tendency of (intrapersonal and inter-personal) positioning in the zone from which a large set of actions are easily achievable (switchable), that is, the zone of optimal grip on the field of affordances (Bruineberg and Rietveld, 2014).

Hence, with respect to the definition of the CCI as "finding the best solution" (Memmert et al., 2010; Memmert, 2015), from the aforementioned, it follows that only if the agent or team is not pinned down (i.e., she/he has a satisficingly large solution space in prospect), can s/he detect the sub-optimal solution (Byron, 1998) in a form of acting on affordances that sufficiently satisfies the task goal constraint. If initially cornered, then a better solution will be the one that will open his/her space of opportunities (enlarging the D/U potential). The non-decreasing D/U potential is, in fact, the *goal* of every CCI system. The game theory definition of game intelligence (Lennartsson et al., 2015) is the probability of the offense

[6]The time frame at the level of performance can be quite short due to the nondeterministic dynamic environment. However, at the level of strategic planning, which includes, for instance, performance analysis of the opponents, it may be much longer. These different timescales, however, cannot be compared with respect to CCI. On the other hand, they are nested and are probably subject to circular causality (Balagué et al., 2019).

[7]The time horizon at the level of performance is orders of magnitude shorter than the one characteristic for the strategic planning of matches, etc. However, the principle is valid for all these temporally nested activities.

scoring the next goal minus the probability that the next goal is scored by the defense. This definition directly follows from the principle we are currently discussing. Only an agent or team with, on average, larger D/U potential can have a larger probability of scoring a point than the opponents. Note that this is valid not only for phases of ball possession but also for phases of defense. For example, a "bunker defense" in football may effectively suppress the opponents' attacking D/U potential (see **Figure 3**) by keeping opponents further from the goal area and lowering the probability of scoring a point. It also increases the undefended opponents' space on the pitch (increased D/U potential for counter-attack). One can see that both definitions of game intelligence can be inferred as special cases of the non-decreasing D/U potential principle.

In fact, the trade-off of suppressing and flourishing (**Figure 3**) signifies the interplay between one type of creativity (see Torrents et al., 2020) and the CCI. Oftentimes, creativity is fostered when the environment does not enhance the opportunities of action of the agent (performer or team), but instead suppresses them (Hristovski et al., 2011). This occurs when the environment (opponent) does not subside to perturbations by the agent or the team. It occurs when there is a *negative feedback* from the environment as a response to the agent's actions. While co-adaptivity within the team strives to produce a *positive feedback* for some initial possibility enhancement, co-adaptivity between opponent teams strives to create a *negative feedback* that tends to suppress the initial enhancement of action entropy in the opponent's team. Hence, CCI may be related to creativity to a degree, which, in fact, has been demonstrated in recent studies (Memmert, 2015).

Biological Intelligence as a Non-decreasing D/U Potential

We have already considered biological overcompensation as a fundamental expression of biological intelligence that satisfies our conceptualization of CCI. However, the suppressing-flourishing dynamics of D/U potential can also be particularly well detected in various forms of reciprocal compensations between psychomotor dimensions during the agent's or team's action. Psychomotor variables such as agility, power, strength, accuracy, speed, endurance, timing resolution, etc., as well as morphological variables (Hristovski and Dukovski, 1996) are self-organizing[8] properties of the agent-environment system (Hristovski et al., 2010; Hristovski, 2017). In ecological psychology, on the one hand affordances and on the other motor abilities and morphological variables (i.e., effectivities) are complementary to each other. Affordances are body- or action-scaled (Fajen et al., 2008). For example, the endurance ability directly enables a larger diversity of immediate or time sequences of affordances, i.e., potential running tactics.

These variables and their interactions are part of what may be called biological intelligence. The larger the volume within the effectivities space, the larger the field of affordances on which it can be acted (Bruineberg and Rietveld, 2014), given the rest of constraints.

Performance in all of these variables depends on the effectivity of coordinative processes at many levels starting from the cellular metabolic to the organism-environment level. Bosch (2015) discusses this from the aspect of intra- and inter-limb coordination. What we understand here as coordination subsumes Bosch's ideas, but also coordination among all levels. For example, the synchronization of motor units is a type of intramuscular coordination. In addition, co-adaptation between cardiorespiratory systems (Balagué et al., 2016; Garcia-Retortillo et al., 2019) is coordination, although measured at the physiological level. This does not mean that the coordination at this level is independent. On the contrary, it is constrained from below and from above (Balagué et al., 2019). Hence, a larger performance in any or all of these abilities means a larger D/U potential of coordinative patterns and, hence, can be measured as entropy variables (Hristovski, 1989; see **Figure 4**). An agent with a larger strength or power has excess potential of coordinative configurations, and hence, a larger D/U potential. Also, his/her integrative information (I) is larger, signifying a larger number and better reciprocal compensatory couplings among the components of the system. Hence, the D/U potential of coordinated components is larger.

It is important to emphasize, however, that all these separate abilities are possibly always contextualized within a certain form of life (Rietveld and Kiverstein, 2014) and molded by each professional environment (e.g., sports discipline).

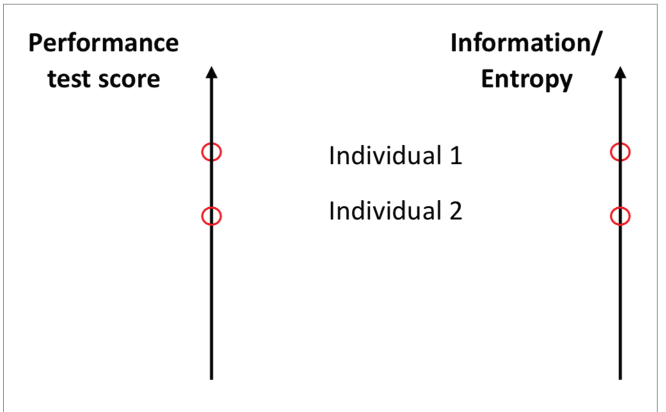

FIGURE 4 | Two interpretations of measurement scales. **Left panel**: the traditional interpretation: individual 1 shows a larger performance or score than individual 2 in certain ability or morphology tests. **Right panel**: individual 1 exhibits larger entropy/information in the same ability test. Here, entropy/integrative information is measured as a logarithm of the length of the scale interval to the position of the oval. One can immediately generalize this definition to n-dimensional space (volume) spanned by n-independent measures of abilities. In a first approximation, the entropy/information will be the sum of all of them.

[8]The existence of performance fluctuations in all these abilities, or in general what is traditionally referred to as "psychomotor traits" (see Delignières et al., 2004), is sufficient evidence of their soft assembly. At each trial, component processes are coordinated (assembled) more or less differently. Performance fluctuations are an inevitable consequence because they are assembled online each time. There is no "ready-to-use", fixed in detail, pre-formed, dormant potential inside the person or team that can be merely "activated" in its unchanged shape. On the contrary, the functionality and reliability of such dormant, "ready-to-use" structures would have near-zero fluctuations similar to the execution of computer programs.

As lab-tested abilities, they are often not representative of their contextualized action manifestations. However, what was said above is valid also for the more contextualized variables once they become measurable. Therefore, we hypothesize that these abilities also form mutually compensatory and co-varying (i.e., dimension reducing) synergetic sets of variables *specific* for each sports discipline and are specific to individual agent-environment systems. These entropy synergies arise as a consequence of the suppressing-flourishing dynamics of D/U potential and would be a part of what we call here biological intelligence.

For example, the possible synergies (reciprocal compensations) between attention focus and body acceleration may be investigated. In certain contexts, the lower acceleration ability of an agent may be compensated by his/her larger attention focus and acuity, or vice versa. Another example on an interpersonal level concerns the interplay between morphological and motor ability compensatory interplay. In order to decrease the D/U potential of the opponent, a boxer with long arms may keep the opponent with shorter arm length at a distance. Here, the length of the arms means larger/smaller potential space control, and hence, larger/smaller entropy, i.e., D/U potential (suppression/flourishing in the morphological/spatial dimension). The latter will have to reciprocally compensate his/her shorter arms disadvantage and his lowered D/U potential by an increased degree of agility performance (flourishing in agility dimension) and attempt with short unanticipated incursions to satisfy her/his goal constraints. The third example concerns the action direction (directional D/U potential) of a player and the free space (D/U) available toward the goal area: a player that has vast space available toward the goal (large D/U potential) typically moves by the shortest path (low D/U). However, when opponent players try to reduce her/his space of action potentialities (i.e., to lower her/his D/U potential) s/he switches to higher entropic (higher D/U) behavior in an attempt to dribble-pass opponents.

An intelligent response of agents to the reduction of the D/U potential in a certain dimension tends to be compensated by a future prospective increase in D/U behavior in the same or another dimension or dimensions. This reciprocal compensatory co-variation of different ability dimension entropies is, hypothetically, an instant of intelligent behavior, present also on a social (team) level. For example, a quick reallocation of the ball can be achieved not only by a very fast player but also by a well-synergized team of moderately fast players.

ARCHETYPICAL MOTIFS OF CCI DYNAMICS

The CCI theory enables not only scientific but also some more qualitative, philosophical research directions. In his paper "Sport as a drama" (Kreft, 2012), the author states that dramatic aspects of sport and sports games are more existentially dense and aesthetically attractive than theater dramatics since the actors are real persons, taking real risks (p. 230). Concurring with Kreft, we would like to briefly comment on how the CCI theory, particularly suppression-flourishing dynamics, captures the dramatics of cooperative-competitive events (e.g., sports, games, and life itself), by containing deeply archetypical aspects of the existential striving of human beings and living forms. In sport, as in any drama, one can readily detect most, if not all, elements of Freytag's dramatic structure (Freytag and MacEwan, 1908) such as exposition, rising action, climax, falling action, and catastrophe. As previously explained, from the aspect of CCI theory, in sports, these elements emerge spontaneously at many time scales as a result of the antagonistic action of two entropic forces, namely, the flourishing and suppressing force. In our view for the philosophy, especially the aesthetics, of sport, it would be important to analyze the content of antagonistic archetypal motifs such as: Eros vs. Thanatos, survival vs. extinction, hope vs. despair, life vs. death, freedom vs. confinement, etc. These qualitative aspects stemming from the CCI theory may be the core of Kreft's existential density that forms the dramatics of sports competition. On the other hand, these possibly pertinent relations between quantitative entropic forces and the qualitative experience of antagonistic motifs may enable a fruitful realm of future mixed-methods research in sports philosophy, sociology, and psychology. An example of this kind of research could be the relationship between the behavioral and archetypal experiential dynamics of athletes and supporters during phases of dominant suppression and flourishing quantified as D/U potential.

AN OUTLINE OF A FURTHER RESEARCH PROGRAM

Theory Predictions and Testing

A desideratum for any scientific theory, aside from its conceptualizing and explanatory power, is to be able to make predictions about the behavior of the system it deals with. At the level of sports performance, the theory of CCI puts forward a general prediction (hypothesis) that can be formulated in the following way: all actions of the system (individual agent or team) emerge from the interplay of two forces subject to specific constraints: the entropic forces as explained above and the general goal of the system. In the text that follows, we offer two interacting strategic approaches in order to test this general prediction. Specific models and predictions (hypotheses) that stem from it can be formulated as behavioral scenarios. We also provide some examples of these scenarios.

Theoretical Modeling Deductive Approach

Sports behavior stems from a multidimensional dynamic system with cooperative and competitive interactions. A suitable deductive approach to understanding CCI would consist of building agent-based models (see Bonabeau, 2002). However, instead of the usual practice of providing each agent with a set of specific rules for each dimension, and scenario-dependent rules of behavior, initially agents can be constrained in fewer dimensions by the principles depicted above. For example, the motivation climate (e.g., Duda and Appleton, 2016) as a slowly changing variable (Balagué et al., 2019) may be applied to an individual agent-environment (Withagen, 2018) and/or at the team level as the entropy parameter. The cascade effects toward quicker processes may then be simulated down to performance level. Entropy principles, which could be applied as a "common currency" among simulated dimensions of behavior, seem more parsimonious due to the substantial reduction of the simulation cost. However, the main advantage and heuristic strength of this approach would be that, in such a scenario, predicted behavioral rules will emerge out of the interaction between the principles and the contextual constraints. For example, we saw previously that space conquering or creation, passing, dribble-passing, or invading actions can be predicted as being a consequence of the tendency of non-decreasing D/U potential. The first step would provide basic behaviors that can be simulated at the level of dyads and increasingly higher-order collectives for different scenarios. These basic predicted emergent behaviors would be the outcome of a small, partial, subset of the full set of dimensions present in real-world behaviors. The level of fidelity of these behaviors can then be validated by comparing the essential variables extracted from the simulated behavior with real-world data from identical scenarios. Based on the detected similarities and differences between simulations and real-world data, the next step would be the parametrization of the model by additional dimensions, i.e., constraints, which can also be cast in the form of satisfaction conditions of the same principles. In this iterative process, we suggest that one can finally reach high-fidelity simulations of cooperative-competitive intelligent behavior and then, by manipulating certain constraints, study the quantitative and qualitative changes of behavior. For example, intelligence defined as a tendency toward non-decreasing D/U potential may be at odds with ethics. In order to maintain or increase its options, the system may not act in coherence with some basic social values. This can be an interesting topic for future research. In this way, one can hope to genuinely understand such cooperative-competitive behaviors based on a few basic principles.

Empirical Inductive Approach

The empirical research could proceed in parallel to the deductive approach outlined above. As we saw in the text above, CCI manifests as a tendency toward non-decreasing D/U potential. Note that it is the "common currency," that is, entropy formulation of D/U potential, which can reveal the compensatory processes of the intelligent coping of systems. As described in the previous text, oftentimes, the suppressed D/U potential in one dimension may be compensated in another dimension and enable flourishing. If we analyze the compensatory processes in their manifest dimensions (space, direction, number of possible passes, agility, etc.), we will hardly be able to detect and formulate the existence of compensatory phenomena in the space of D/U capacity. Some examples of research may include the following elementary scenarios (predictions): (1) If a certain space becomes occupied by opponent players (reducing the behavioral D/U potential of the team), a teammate demarks another spatial position in order to receive the ball (increasing the team's behavioral D/U potential). In this case, the dimension state of numerical imbalance is transferred to a relevant spatial dimension state, and both can be formulated in entropy units. (2) The team synchronously moves into the opponent's half of the field. Synchronization displays low entropy behavior in the direction or relative phase dimensions. However, the D/U potential of passes between teammates increases because of the synchronous movement of the team centroid to the opponents' half. Where there are more teammates, there are more possible passes and, in general, larger D/U potential. In this case, the directional (or relative phase) dimension state is transferred into the connectivity (number of possible passes) state dimension, and both can be formulated in entropy units. (3) Another scenario is when the occupation of space by opponents would correspond to a perturbation that lowers the team's action space and a teammate's demarcation to the recovery compensation corresponding to increasing opportunities for action. In this case, the possibility of spatially defined (or numerical imbalance) lost action transfers into an action possibility gain of the angular dimension, and both can be formulated in entropy units. (4) As a result of conquered space by opponents, the player that possesses the ball compensates his lost space by increasing her/his entropy of actions (attempts to dribble-pass the opponents who have conquered the space). In this case, there is compensatory behavior from the spatial dimension into the individual action dimension. Both can be formulated in entropy units.

Other scenarios of such compensating synergic phenomena may also be predicted as multidimensional, spontaneously emergent, compensatory cooperative-competitive, intelligent behaviors. The results of these and similar studies would have mutually supporting and modifying interactions with results coming from the deductive approach. Big data analytical tools (multilayer neural networks, support vector machines, deep learning, and other current and future analytical techniques) coming from Machine Learning Toolbox, may be used to extract the essential macroscopic, mesoscopic, and microscopic behavioral variables. These variables can then be used in a circular regulative manner for improving the deductive modeling part of the research. In this fashion, an original and fertile research program can emerge in the future.

CONCLUDING REMARKS AND PRACTICAL ASPECTS OF THE THEORY

The full-blown detailed practical consequences of the theory can be assessed after sufficient research with content as described in the previous section. However, some preliminary notes on the practical work of coaches and athletes, or participants in cooperative-competitive activities in general, can be outlined. In the theory, CCI was conceptualized as the capacity of an agent or a team to successfully *evade* or *escape* the state of reduced sufficing D/U potential quickly enough. To successfully evade the reduction in D/U potential, one has to be able to prospectively negotiate environmental perturbations. To successfully escape, one has to develop the multidimensional transfer of D/U potential in the form of multidimensional synergy reorganization. Some examples for practitioners to consider are given below.

The theory of CCI fosters the development of capacity measures for escaping and evading the reduced D/U potential. At the individual CCI level, self-reliant agents (e.g., players) who are not dependent on detailed instructions of coaches may be able to unleash larger D/U potential. Hence, skill acquisition pedagogies, which promote this kind of "hands-off" approach, seem to have a greater potential for accomplishing this task (Davids et al., 2008; Chow et al., 2015; Button et al., 2020).

Pol et al. (2020) argued that the objective of the training process itself should be rethought: instead of excessively focusing on the decontextualized development of the conditional, motor, and psychological attributes or dimensions separately, work should be done on developing the context-dependent D/U potential of athletes/teams. As argued previously, the development of the D/U potential may emphasize, specific to each sport contextualization, the functional reciprocal compensations (i.e., synergies) among different dimensions (e.g., motor, conditional, psycho-affective, collective, and social). For instance, anxiety, injury, or stress in one player, which effectively reduces his/her D/U potential, can be compensated through strategic collective tactical actions prescribed by the coach. However, the work on the skills of athletes/teams to functionally self-reorganize, within the ethical[9] norms, by finding fast multidimensional compensations would be a worthwhile long-term endeavor.

This aim also includes the development of pluripotential (i.e., pleiotropic) players in collective sports (Rangel et al., 2019), that is, players with *sufficiently* overlapping tactical roles. The development of sufficiently pluripotential players and teams involves work on the following sub-tasks: (i) practitioners and researchers should work jointly on determining the degree of skills and competencies overlap in the team, which is satisficing and contextualized for different types and intensities of perturbations by the opponents, (ii) working on the way in which D/U potential-reducing perturbations of different types may be dampened. For example, it can be achieved in the form of task redistribution within sub-groups of players with overlapping competencies, (iii) acquiring skills on negotiating characteristic channels within the team through which D/U-suppressing perturbations are spread by different types of opponents and perturbations, (iv) managing to negotiate the formation of characteristic "hot or task congestion spots" within the team and their characteristics for different types of opponents and perturbations, and (v) learning how to dampen further perturbations across a team in order to eliminate the decreased D/U potential hot spots or to reduce the likelihood of their formation.

[9]Some unethical (or borderline) examples of behavior aimed at reducing the D/U potential of opponents are as follows: losing time feigning injury or holding back the ball under constraints of winning.

In order to develop the athlete/team D/U potential, critical training zones (or *zones of abundance*) may be detected by experienced coaches through the manipulation of constraints (Hristovski et al., 2013). These zones are characterized by the locally maximized D/U potential of the athlete/team. Practicing in this kind of zones may provide a boost to the necessary perception-action skills of athletes.

CCI theory also suggests that working on skills for quick detection and adaptation of the satisficing D/U potential, relative to the opponents, is of key importance during training and competition. In competition, athletes and coaches often make strategic assessment of the requisite use of resources for every opponent. Objectively, more competitive athletes/teams may lose against less competitive ones because the latter often increase their D/U potential when competing against superior opponents. The often-ignored reduced anxiety and increased motivation of inferior athletes/teams when competing with more powerful adversaries should be carefully considered since it increases their D/U potential. In contrast, the lack of motivation when competing against inferior opponents may reduce the D/U of highly competitive teams too much, leading to unexpected results (Clancy et al., 2016).

The CCI theory elaborated in this paper may also prove to have strong integrative capacity since it may be used to channel the practice in relatively disparate domains of human activities. For example, in the domain of well-being, diversification through compensatory activities in different domains (i.e., dimensions) other than stressful professional ones shows an increase in well-being experiences (e.g., Conner et al., 2018). In the realm of health, activities that increase the multidimensional D/U potential and compensatory synergies may prove to be of great importance (Balagué et al., 2020). According to the theory developed in this paper, practical work on these and similar issues supports the growth of CCI in the areas of sports, health, and well-being in physical activities.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

RH conceived and wrote the manuscript. NB reviewed the previous versions. All authors contributed to the article and approved the submitted version.

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Can Individual Movement Characteristics Across Different Throwing Disciplines Be Identified in High-Performance Decathletes?

*Fabian Horst[1], Daniel Janssen[2], Hendrik Beckmann[1] and Wolfgang I. Schöllhorn[1]**

[1] Department of Training and Movement Science, Institute of Sport Science, Johannes Gutenberg-University Mainz, Mainz, Germany, [2] Gymnasium Dionysianum, Rheine, Germany

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Edited by:
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***Correspondence:**
Wolfgang I. Schöllhorn
schoellw@uni-mainz.de

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Although the individuality of whole-body movements has been suspected for years, the scientific proof and systematic investigation that individuals possess unique movement patterns did not manifest until the introduction of the criteria of uniqueness and persistence from the field of forensic science. Applying the criteria of uniqueness and persistence to the individuality of motor learning processes requires complex strategies due to the problem of persistence in the learning processes. One approach is to examine the learning process of different movements. For this purpose, it is necessary to differentiate between two components of movement patterns: the individual-specific component and the discipline-specific component. To this end, a kinematic analysis of the shot put, discus, and javelin throwing movements of seven high-performance decathletes during a qualification competition was conducted. In total, joint angle waveforms of 57 throws formed the basis for the recognition task of individual- and discipline-specific throwing patterns using a support vector machine. The results reveal that the kinematic throwing patterns of the three disciplines could be distinguished across athletes with a prediction accuracy of up to 100% (57 of 57 throws). In addition, athlete-specific throwing characteristics could also be identified across the three disciplines. Prediction accuracies of up to 52.6% indicated that up to 10 out of 19 throws of a discipline could be assigned to the correct athletes, based on only knowing these athletes from the kinematic throwing patterns in the other two disciplines. The results further suggest that individual throwing characteristics across disciplines are more pronounced in shot put and discus throwing than in javelin throwing. Applications for training and learning practice in sports and therapy are discussed. In summary, the chosen approach offers a broad field of application related to the search of individualized optimal movement solutions in sports.

Keywords: motor learning, pattern recognition, high-performance sports, machine learning, support vector machine, individuality, transdisciplinary individuality

INTRODUCTION

Most of us are familiar with the experience of identifying friends or colleagues by their walk (Cutting and Kozlowski, 1977), even from a distance and with limited visibility (Stevenage et al., 1999). Practitioners in the field of sports science and physical therapy often report the same experience of identifying individual athletes or patients based on their movement characteristics (e.g., a characteristic forehand stroke in tennis or a unique hand movement). Additionally, most of us have observed people mastering certain tasks easily, while struggling to become proficient in others. Both experiences serve as evidence of the individuality of human movements, though they may hold various meanings and act epistemologically on different time scales (Newell et al., 2001). The tacit, universal acceptance of movement as a method of identifying individuals suggests that most of us understand individualized movement, yet the perfunctory nature of this acceptance has inhibited a deeper investigation of the concept's essential aspects and consequences.

In human movement science, anecdotal evidence has made claims of "individuality" for years (Bernstein, 1967; Marteniuk, 1974). Although the importance of individuality in sports training has been recognized since the origins of sports science (Matveev, 1970), the phenomenon has been mostly regarded as a negligible side effect or as an exception in the search for universal scientific laws (Harre, 1969, 2013; Matveev, 1970; Huber, 1977; Schmidt and Young, 1991; Nitsch et al., 1997; Schnabel et al., 1997). In most cases, individuality appeared in the context of reliability studies that compared intra- and inter-individual variance (Bates et al., 1983). These reliability studies led to the standard requirement that an average of 10 to 25 movement trials be conducted for each individual participant to achieve an appropriate level of reliability or reproducibility (Bates et al., 1983; DeVita and Bates, 1988; Gollhofer et al., 1990). The extent to which the inter-individual variance distributions overlap to discriminate individuals from one another was not investigated.

In the past, the term individuality most often has been normatively applied in three ways: (1) when no classification criteria could be found (Brüggemann et al., 1991; Schöner et al., 1992; Button et al., 2000; Hecksteden et al., 2015; Barth et al., 2019), (2) to explicitly circumvent "the difficulty of achieving statistical significance" by creating smaller standard deviations and by describing several single cases (Davids et al., 1999; Button et al., 2000; Nuzzo, 2014), and (3) when individuality was predetermined in the form of case studies (Mendoza and Schöllhorn, 1990; Schöllhorn, 1993, Schöllhorn, 1998; Wallace et al., 1994; Bauer and Schöllhorn, 1997; Button et al., 2006; Chow et al., 2006). Frequently, all three interpretations were used in combination and reflected a rougher approximation of the phenomenon than scientific evidence would suggest.

While movement and sports science still struggle to balance the demands of group-oriented science and individual athlete- and patient-oriented practice, forensic science remains primarily concerned with individual cases that must lend legal validity. Therefore, the field of forensic science has developed specific methods and criteria for the identification of individuals (disjunct separation) (Kaye, 2010). In this context, Jain et al. (2006) suggested that before individuality can be assumed, one must test the probability of uniqueness (indicating that no two persons have identical characteristics) and the persistence/permanence of a physiological or behavioral characteristic (meaning that the characteristic should be invariant with time).

The first steps toward such criteria took place in the analysis of everyday and sports movements and revealed the identification of individual people based on gait (Schöllhorn et al., 1999, 2002; Nixon et al., 2006), running (Simon and Schöllhorn, 1995), pole vaulting (Jaitner and Schöllhorn, 1995), discus (Bauer and Schöllhorn, 1997), and javelin throwing (Schöllhorn and Bauer, 1998). The proposed approaches used self-organizing Kohonen maps, in combination with cluster analysis, as early representatives for machine learning classification in human movement science. The results indicated the structural application of a statistical approach that is, similar to forensic proceedings, oriented toward a generic understanding of probability. As follows, the probability of an event occurring is equal to the number of ways of achieving success relative to the possible number of outcomes. For example, Schöllhorn and Bauer (1998) recorded 10 javelin throws by a single athlete at different competitions over 5 years. Subsequently, the kinematic patterns of these 10 throws were clustered together out of 51 kinematic patterns of throws from several other athletes. The probability of achieving this classification by chance is extremely low ($<1 \times 10^{-17}$). This outcome is far below the magnitude of common probabilities used, first, in the statistical model based on the work of Fisher and Mackenzie (1923) or Neyman and Pearson (1928) and, second, in the magnitude of becoming legally relevant.

Meanwhile, the uniqueness and persistence of individual movement patterns could be validated for versatile whole-body movements such as walking (Horst et al., 2017b, 2019), pedaling (Hug et al., 2019), basketball throwing (Schmidt, 2012), horse riding (Schöllhorn et al., 2006), or playing a musical instrument (Albrecht et al., 2014). Up to this point, one might still be tempted to argue that a single movement pattern is optimal for an individual athlete. Initial doubts were raised, however, when it was remembered that none of the aforementioned studies could demonstrate identical repetitions of movement patterns, and thus strong indications were provided for the intuitively assumed (Bernstein, 1967) and previously biomechanically derived (Hatze, 1986) extremely low probability of identical repetitions. Theoretically, however, the continuous fluctuations that were observed during the proof of persistence could have been due to limitations in the biomechanical measurement resolutions or could have simply been random, unstructured noise. More detailed investigations of fluctuations between repeated movement executions within individual persons surprisingly revealed strong evidence of fine structures within a class of movement patterns. These finer structures showed a dependence on fluctuations in emotion (Janssen et al., 2008; Janssen, 2017), on fatigue (Jäger et al., 2003; Janssen et al., 2011), or on time (Bauer and Schöllhorn, 1997; Schöllhorn et al., 2002; Rein et al., 2010) with different time scales (Horst et al., 2016, 2017a). The individuality of movement patterns in connection with their fine structures thus indicate that individual movement patterns continuously change and adapt over time.

In practice, the identification of athletes based on their individual movement patterns and their corresponding fine structure does not require individually tailored learning or training methods. If we assume that individual differences exist from birth, then theoretically, the same learning and training content could have led to individually distinguishable movement patterns at a later age. However, this awareness is subject to the assumption that everyone responds in the same way to intervention measures. To shed more light on these questions, further studies on individual learning behavior should be conducted.

Indications for individual responses on a similar intervention came from physiological (Bouchard and Rankinen, 2001) and biomechanical studies (Cole et al., 1995; Schöllhorn et al., 2001, 2002). In the meantime, an increasing number of studies have observed phenomena that indicate the individuality of adaptations and learning (Schöllhorn et al., 2006; Kostrubiec et al., 2012; Caballero et al., 2017). References to the advantages of learning with individual role models also began to question learning approaches based on average-oriented group role models (Brisson and Alain, 1996). Despite these initial signs, scientific evidence of individual learning processes according to the criteria of uniqueness and persistence is still missing (Fisher et al., 2018). Because of the normative nature of these studies, a criteria-driven analysis, as proposed by Jain et al. (2006), is suggested. Applying the same criteria of uniqueness and persistence to motor learning and adaptation processes requires, first, that each athlete/patient (e.g., in terms of changes in movement patterns or performance outcomes) respond differently to a particular intervention (uniqueness) and, second, that individual responses to multiple interventions can be repeatedly demonstrated (persistence).

While the first criterion could be tested indirectly via the degree of learning progress each participant achieves, testing the criterion of persistence is more complicated. The simplest way to prove the persistence of individual learning characteristics would be to allow athletes to learn the same skill several times after wash-out phases. However, a limitation with this approach has been raised by re-learning studies (Newell et al., 2001; Liu et al., 2003). Once a movement is acquired and forgotten, it is re-learned more quickly (Malone et al., 2011). In consequence, initial learning conditions cannot be reproduced exactly when a skill is re-learned several times, even with adequate wash-out phases. This fact makes it almost impossible to compare the persistence of learning processes adequately. Alternatively, individual characteristics of learning processes should be observable in the acquisition of different skills. Therefore, finding approaches that can detach the individual-specific characteristics from the task-specific characteristics in various movements would be helpful. Interestingly, previous studies on the uniqueness and persistence of movement patterns have only been carried out within a single movement task.

This pilot study aims to analyze the three throwing disciplines in the decathlon (shot put, discus throw, and javelin throw) and to search for athlete- and discipline-specific similarities in the kinematic throwing patterns of these disciplines using automatic classification by means of machine learning. Instead of merely testing the individuality of athletes in a single throwing discipline, the present classifications are used to test whether the kinematic throwing patterns will be assigned to the correct throwing discipline and whether the knowledge of, for example, an individual athlete's shot put movement patterns predicts the individual's discus or javelin movement patterns. For this objective, high-performance athletes competing in a national decathlon qualification competition were selected. This high performance level served to guarantee sufficient stability for all three throwing movements. A competition was selected for this study because it is a setting in which athletes often demonstrate their best performances, which we assume can increase the expression of the individuality in their movement patterns (Schöllhorn et al., 2002).

TABLE 1 | Number of throwing trials per athlete and discipline.

Athlete	Age (years)	Shot put	Discus	Javelin
A1	18–21	3	3	3
A2	18–21	3	3	2
A3	18–21	1	3	3
A4	18–21	3	1	3
A5	18–21	3	3	2
A6	18–21	3	3	3
A7	18–21	3	3	3
Sum (disciplines)		19	19	19

MATERIALS AND METHODS

Seven right-handed, male decathletes (18.9 ± 0.4 years), who were members of the German junior national team with at least 5 years of experience in the decathlon, were recorded during a national decathlon qualifying competition. The final throwing phases of 19 shot puts, 19 discus, and 19 javelin throws were analyzed (**Table 1**). For right-handed athletes, the final throwing phases all begin when the left foot touches down and end when the throwing object is released from the hand. Most of the increase in velocity of throwing object is produced during this phase (Hay, 1993; Bauersfeld and Schröter, 1998). The throwing performances ranged from 11.70 to 15.06 m (shot put), 33.66 to 43.74 m (discus), and 40.08 to 58.03 m (javelin).

The recordings were taken using two high-frequency video cameras (Weinberger MiniVis Eco-2; frequency: 200 fps; resolution: 1280 × 1024 pixel), which were positioned orthogonal to each other, one facing toward the flight direction of the throwing object. A space of 3 × 3 × 3 m^3 was covered for the analysis using a calibration cube with 25 marker points. Due to the official competition rules, no marker points were allowed on the athletes. Data of both cameras were synchronized using an electric impulse transmitted from the master camera to the slave camera during each throw. Neither the athletes nor the experienced digitizers were informed about the aim of the study. The following anatomical body landmarks were digitized: the manubrium sterni, the left and right acromion, the epicondylus lateralis, the processus steyloidus ulnae, the spina illiaca anterior superior, the trochanter major, the lateral end of the femur (knee), the patella, the articulatio tibo fibulare talare, the calcaneus, the phalanx distalis, and the hallux.

The digitization of these points allowed the estimation of three-dimensional joint angles of the right and left shoulder, elbow, hand, hip, knee, and ankle. All videos were manually digitized with SIMI Motion Software 5.0 (SIMI Reality Motion Systems, Germany). Data were filtered using a recursive, second-order Butterworth filter with a cutoff frequency of 14 Hz. All trials were digitized for an additional 10 video frames at both phase boundary ends because of filter effects at the beginning and end of each signal.

For javelin, the duration of the final throwing phase lasts about 130 ms; for discus throwing, about 400 ms; and for shot put, about 200 ms (Ballreich and Kuhlow, 1986; Ballreich et al., 1989). Despite the variable duration of these final throwing phases, commonalities between all three throwing disciplines are assumed and used to economize training in combined events (Hay, 1993). The trials were time normalized to 26 intervals to compare the kinematic patterns of three disciplines. After time normalization, the amplitudes were normalized over all trials and all athletes into the interval [0;1].

Time- and amplitude-normalized data formed the input vectors for the classifications using a support vector machine (SVM) (Cortes and Vapnik, 1995). The classification of the kinematic throwing patterns based on SVM represents a supervised learning approach for pattern recognition in data sets. The ability to distinguish kinematic throwing patterns was investigated in multi-class classifications using a "one-vs.-all" algorithm. The L2-regularized, L2-loss, support-vector classification of the Liblinear Toolbox 1.4.1 (Fan et al., 2008) was applied with a linear kernel function within the software environment Scilab 6.0.2 (Scilab Enterprises, France). A grid search within the range of $C = 2^{-5}, 2^{-4.75}, \ldots, 2^{15}$ was conducted to determine C experimentally before the training and testing of the SVM models. An athlete-classification using a leave-discipline-out cross-validation and a discipline-classification using a leave-athlete-out cross-validation were performed. This processing means that data from one discipline (in the case of the athlete-classification) or from one athlete (in the case of the discipline-classification) were used either as training or as test data during the cross-validation of the SVM models. A schematic overview of the entire approach with data acquisition, processing, and classification is depicted in **Figure 1**.

In the case of athlete-classification, the kinematic data of one discipline were used in the cross-validation, either as training or as test data (cf., athlete-classification in **Figure 1**). This use of data means that the classification model did not "see" the throwing patterns of the athletes in the tested discipline during the training process. In the first cross-validation split, the classification model was first trained to distinguish the athletes based on the normalized kinematic patterns of all shot puts and javelin throws. Then, the performance of the classification model was tested using the normalized kinematic patterns of all discus throws.

In the case of the discipline-classification, the SVMs were trained with the corresponding partitions of variable waveforms of all athletes (except one) in all three throwing disciplines. The remaining waveforms of the one athlete were used to test the performance of the SVM models for classification into one of the three possible throwing disciplines.

RESULTS

The results of the athlete-classification are shown in **Table 2**. When the classification models were tested with data from the discus throws, the results showed the highest prediction accuracy of 52.6% for athletes when the SVM considered all kinematic variables except the variables of the throwing arm. The lowest predictive accuracy of 21.1% was obtained when only the kinematic data of the lower-body joint angles were considered.

Similar results were found when the performance of SVM models was determined using the kinematic patterns of shot puts as test data. While the prediction accuracy is slightly lower when all variables are considered, the lowest prediction accuracy of 31.6% is larger than for the discus split and is achieved when all variables and only the lower-body variables are used as test data.

The lowest prediction accuracies are generally found when the SVM models are tested based on javelin throwing patterns (15.8–31.6%). When the SVM models for athlete-classification are trained on discus and shot put data, it seems to be more difficult to assign the movement patterns of javelin throwing to the individuals. Similar results can be observed in the pairwise cross-validations, which are also shown in **Table 2**.

In **Table 3**, the results of the discipline-classification are listed with the same variable partitions as in **Table 2**. When all variables were included in the discipline-classification, the respective disciplines could be predicted with an accuracy of 100%, based on the kinematic throwing patterns.

DISCUSSION

The results of this study reveal that the kinematic patterns of the three throwing disciplines in the decathlon (shot put, discus throw, and javelin throw) could be distinguished independently of the athlete with a prediction accuracy of up to 100% (57 of 57 throws) using an automatic classification using machine learning (i.e., SVMs). In addition, prediction accuracies of up to 52.6% (10 of 19 throws) also indicate the persistence of individual throwing characteristics of athletes across different throwing disciplines. The results further suggest that individual throwing characteristics across disciplines are more pronounced in shot put and discus throwing than in javelin throwing. This finding demonstrates that the approach of classifying movement patterns using machine learning methods allows for the identification of athlete- and discipline-specific similarities in throwing patterns across different disciplines in high-performance athletes and suggests new ways to explore sports training in different disciplines.

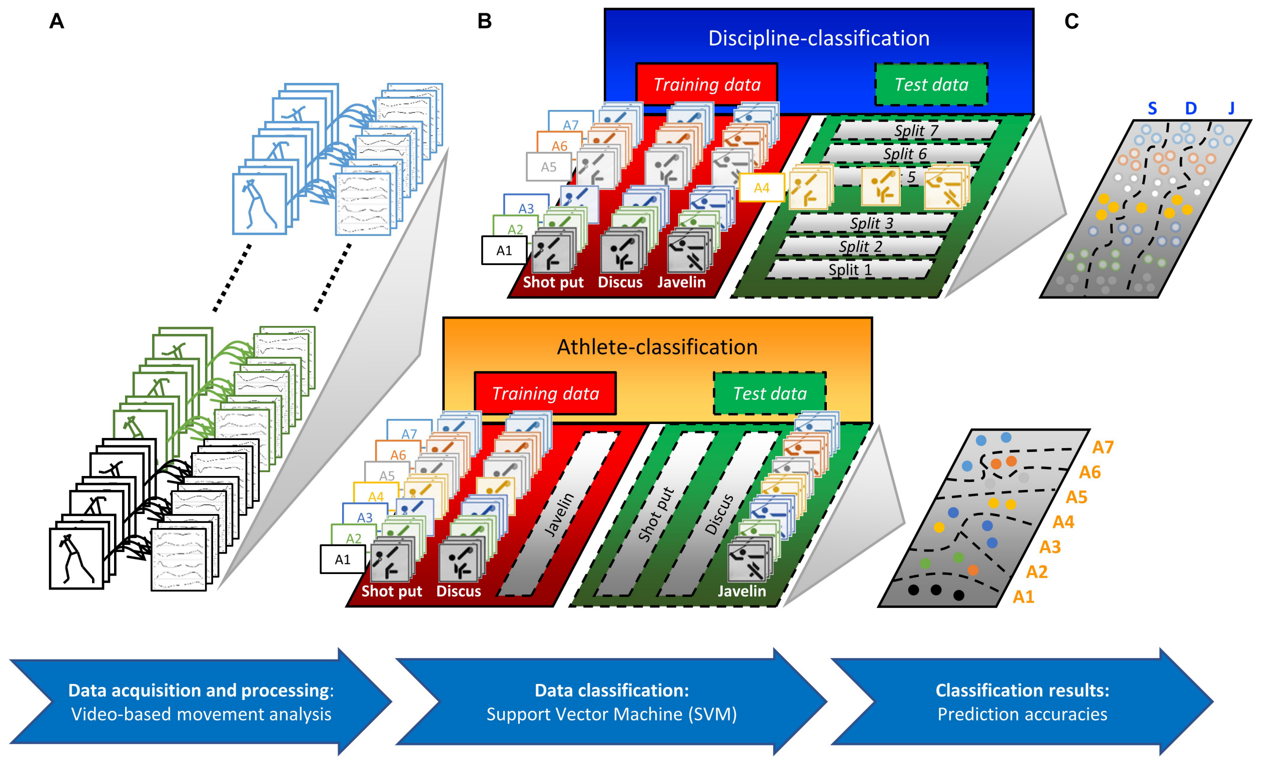

FIGURE 1 | Schematic overview of our approach to data acquisition, processing, and classification. **(A)** Seven right-handed athletes (A1–A7), who were members of the German junior national team with at least 5 years of experience in the decathlon, were recorded during a national decathlon qualifying competition. The kinematic analysis included all valid trials of the competition in the three throwing disciplines: S, shot put; D, discus throw; J, javelin throw. The final throwing phases of 19 shot puts, 19 discus, and 19 javelin throws were analyzed using two orthogonally positioned high-frequency video cameras. After the digitization of 23 anatomical body landmarks, the three-dimensional joint angles of the right and left shoulder, elbow, hand, hip, knee, and ankle were estimated. **(B)** Time- and amplitude-normalized joint angle waveforms formed the input vectors for the classifications using a support vector machine (SVM). An athlete-classification using a leave-discipline-out cross-validation and a discipline-classification using a leave-athlete-out cross-validation were performed. **(C)** The performance of the classification models was assessed based on the prediction accuracy.

TABLE 2 | Prediction accuracy of the athlete-classification with leave-discipline-out cross-validation for different data partitions.

Test data	Training Data	Random baseline	All variables	All variables (without throwing arm)	Only upper-body variables (without throwing arm)	Only lower-body variables
Discus	Shot put and Javelin	14.3% (1/7 athletes)	42.1% (8/19 test trials)	52.6% (10/19 test trials)	47.4% (9/19 test trials)	21.1% (4/19 test trials)
Shot put	Discus and Javelin	14.3% (1/7 athletes)	31.6% (6/19 test trials)	52.6% (10/19 test trials)	47.4% (9/19 test trials)	31.6% (6/19 test trials)
Javelin	Discus and Shot put	14.3% (1/7 athletes)	15.8% (3/19 test trials)	21.6% (4/19 test trials)	31.6% (6/19 test trials)	31.6% (6/19 test trials)
Discus	Shot put	14.3% (1/7 athletes)	36.8% (7/19 test trials)	52.6% (10/19 test trials)	52.6% (10/19 test trials)	42.1% (8/19 test trials)
Discus	Javelin	14.3% (1/7 athletes)	26.3% (5/19 test trials)	36.8% (7/19 test trials)	21.1% (4/19 test trials)	26.8% (5/19 test trials)
Shot put	Discus	14.3% (1/7 athletes)	47.4% (9/19 test trials)	57.9% (11/19 test trials)	47.4% (9/19 test trials)	31.6% (6/19 test trials)
Shot put	Javelin	14.3% (1/7 athletes)	42.1% (8/19 test trials)	47.4% (9/19 test trials)	47.4% (9/19 test trials)	36.8% (7/19 test trials)
Javelin	Discus	14.3% (1/7 athletes)	52.6% (10/19 test trials)	36.8% (7/19 test trials)	21.1% (4/19 test trials)	36.8% (7/19 test trials)
Javelin	Shot put	14.3% (1/7 athletes)	10.5% (2/19 test trials)	15.8% (3/19 test trials)	26.3% (5/19 test trials)	26.3% (5/19 test trials)

In the following sections, we discuss the results in more detail. In the athlete-classification, the highest prediction accuracies by SVM models based on all variables except the throwing arm variables mean that every second shot put kinematic pattern was correctly assigned to the corresponding individual athlete when the SVM model was trained on the kinematic throwing patterns of all athletes in javelin and discus throw. Prediction accuracies over ∼50%, which are well above the random baseline of 14.3%, provide a strong indication that individual movement signatures can be detected in different movements (e.g., different throwing disciplines). The present findings reinforce previous studies that showed the uniqueness and persistence of individual movement patterns within various movements and support the call for a stronger focus on individual athletes or patients in sports and movement science (e.g., Horst et al., 2017b).

TABLE 3 | Prediction accuracy of the discipline-classification with leave-athlete-out cross-validation for different data partitions.

Test data	Training Data	Random baseline	All variables	All variables (without throwing arm)	Only upper-body variables (without throwing arm)	Only lower-body variables
A1	A2–A7	33.3% (1/3 disciplines)	100.0% (9/9 test trials)	100.0% (9/9 test trials)	100.0 (9/9 test trials)	100.0% (9/9 test trials)
A2	A1 and A2–A7	33.3% (1/3 disciplines)	100.0% (8/8 test trials)	100.0% (8/8 test trials)	100.0% (8/8 test trials)	100.0% (8/8 test trials)
A3	A1–A2 and A4–A7	33.3% (1/3 disciplines)	100.0% (7/7 test trials)	100.0% (7/7 test trials)	85.7% (6/7 test trials)	100.0% (7/7 test trials)
A4	A1–A3 and A5–A7	33.3% (1/3 disciplines)	100.0% (7/7 test trials)	100.0% (7/7 test trials)	100.0% (7/7 test trials)	100.0% (7/7 test trials)
A5	A1–A4 and A6–A7	33.3% (1/3 disciplines)	100.0% (8/8 test trials)	100.0% (8/8 test trials)	100.0% (8/8 test trials)	100.0% (8/8 test trials)
A6	A1–A5 and A7	33.3% (1/3 disciplines)	100.0% (9/9 test trials)	100.0% (9/9 test trials)	77.8% (7/9 test trials)	100.0% (9/9 test trials)
A7	A1–A6	33.3% (1/3 disciplines)	100.0% (9/9 test trials)	88.9% (8/9 test trials)	88.9% (8/9 test trials)	88.9% (8/9 test trials)

Note that the highest prediction accuracy is achieved using SVM models that consider all joint angle waveforms except the angles of the throwing arm. Comparatively lower prediction accuracies using SVM models that take into account all joint angle waveforms (including the ones of the throwing arm) might be traced to a slightly reduced individuality and a predominant expression of the discipline specificity in the throwing-arm, joint-angle waveforms. However, further research is needed to determine whether this lower prediction accuracy is due to the specificity of the disciplines or due to the variability in throwing arm movements. In this regard, a joint angle-wise classification and determination of movement variability could provide further clarification.

Higher prediction accuracies for SVM models based on the joint angles waveforms of the upper body without the throwing arm in shot put and discus throwing provide evidence for increased individuality of the movement of the left arm, trunk, and head in comparison to the waveforms of the lower-body joint angles, which are more restricted by their contact to the ground. Whether lower prediction accuracies of the SVM models based on lower-body joint angles are only due to the comparably coarse biomechanical data acquisition without anatomical markers or due to the small geometric differences in the leg movements cannot be resolved satisfactorily here.

Considerably lower prediction accuracies of SVM models for athlete-classification that were trained with the kinematic patterns of shot put and discus throw and tested with javelin throws are in line with findings of national (Kunz, 1980) and international (Pavlović and Idrizović, 2017) decathletes, who showed a high correlation between performances in shot put and discus throwing, but no linear correlation with performance in javelin throwing. The finding that the individual throwing characteristics across the disciplines are more pronounced in shot put and discus throwing than in javelin throwing gives rise to the speculation about a more individual coupling of the joint angles of the trunk and lower body with the left arm and head in shot put and discus throwing. Future research is necessary to investigate whether cross-disciplinary individual characteristics in shot put and discus throwing also foster a positive transfer from training in one discipline to the other. An analysis of individual muscle activation signatures (Hug et al., 2019) during shot putting, discus, and javelin throwing could provide interesting insights in this context.

In discipline classification, a prediction accuracy of 100% for most cross-validation splits and combinations of considered variables implies an automatic and differentiated recognition of shot put, discus, and javelin throwing movement patterns. The results provide promising evidence for the ability of pattern recognition approaches using machine learning methods to distinguish between different qualities of whole-body movements (Schöllhorn and Bauer, 1997; Schorer et al., 2007).

Finally, some specificities of this pilot study should be kept in mind. The chosen pattern recognition approach based on probabilities relative to the number of choices is distinguished from null-hypothesis-testing approaches. No claims for generalization are made. In addition, the demand for a relatively high level of performance in different sports disciplines limited the possibilities for empirical data collection enormously. Some limitations arise from selecting decathletes on their way from juvenile to adult competition classes as the object for this pilot study. The athletes' age suggests that some may not have completed puberty, and ongoing physical growth could have an additional influence on the consistency of their movement patterns. To what extent incomplete physical growth influences throwing patterns and throwing consistency requires further research.

CONCLUSION

The results offer evidence for the possibility of automatic recognition of kinematic movement patterns originating from different sports disciplines and confirm the assumption of a strong and cross-disciplinary importance of individuality in at least two of the throwing disciplines investigated. That certain individual movement characteristics can be identified in the kinematic patterns of both shot put and discus throwing is intriguing. This finding must be distinguished from the recognition of an individual athlete within a single discipline, as shown for discus (Bauer and Schöllhorn, 1997) and javelin throwing (Schöllhorn and Bauer, 1998). An extension of this approach to the kinematic movement patterns in other sports disciplines such as the tennis serve, handball throw, or volleyball smash is reasonable. Exploring the respective proportion of individual characteristics in movement patterns in more detail, even for dissimilar movement classes, will be a challenge for future research. This exploration can be compared with the search for analogies between different biometric characteristics.

A further criterion for individuality, which could be summarized by homomorphism, could be added to the necessary criteria of uniqueness and persistence. Different from static biometric measures such as fingerprints, facial characteristics, or ear shapes, which are frequently directly related to static genetics, movement-based biometry is subject to dynamic changes and uncertain associations to the genome. While it is difficult to find a common underlying basis for the biometrics of finger, face, or ear apart from genetics, the comprehension of individual commonalities in different movements (e.g., throwing disciplines) could provide access to the underlying individuality of central nervous physiology and structure. Future applications of this approach could investigate the extent to which the central nervous system or the muscle physiology are modifiable beyond an individual's range.

Against this backdrop, the probability of finding a single (time-independent) optimal movement pattern for an individual athlete is more than challenging. Instead, rethinking the understanding of an optimal movement pattern is promising. An extension of the term "optimal" by situation-optimal, as the currently optimal solution for an individual athlete, may be initially tempting. However, an optimal solution would only serve as a theoretical model and could never be realistically achieved. Because the motor system of an individual is constantly changing and adapting, the model of a situation-optimal movement pattern would also have to constantly change and adapt. Alternatively, the assumption of a situation-optimal model that is constantly changing could be more advantageous for motor learning than for the pursuit of an insurmountable goal.

The study showed that an applied pattern recognition approach based on a machine learning classification provides an alternative and holistic approach for the analysis of biomechanical movement data. This approach is closely connected to a statistical method based on the original concept of probabilities and may help to circumvent some of the limitations connected with the Fisher and Mackenzie (1923) and Neyman and Pearson (1928) statistics.

Taken together, the findings of human movement science regarding the uniqueness and persistence of individual movement patterns based on machine learning methods and the insights into the influencing factors indicated in this study suggested that we are still at the beginning of understanding the individuality of moving and learning human beings.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation, to any qualified researcher.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

AUTHOR CONTRIBUTIONS

All authors contributed to the article, critically revised the manuscript, and approved the final version. WIS designed the experiment. DJ, HB, and WIS conducted the acquisition and processing of the data. FH, DJ, and HB analyzed the data. FH, DJ, and WIS designed the figure. FH and WIS interpreted the data and wrote the manuscript.

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Fatigue-Related and Timescale-Dependent Changes in Individual Movement Patterns Identified Using Support Vector Machine

Johannes Burdack[1], Fabian Horst[1], Daniel Aragonés[1], Alexander Eekhoff[1] and Wolfgang Immanuel Schöllhorn[1,2]*

[1] Department of Training and Movement Science, Institute of Sports Science, Johannes Gutenberg University Mainz, Mainz, Germany, [2] Department of Wushu, School of Martial Arts, Shanghai University of Sport, Shanghai, China

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***Correspondence:**
Fabian Horst
horst@uni-mainz.de

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The scientific and practical fields—especially high-performance sports—increasingly request a stronger focus be placed on individual athletes in human movement science research. Machine learning methods have shown efficacy in this context by identifying the unique movement patterns of individuals and distinguishing their intra-individual changes over time. The objective of this investigation is to analyze biomechanically described movement patterns during the fatigue-related accumulation process within a single training session of a high number of repeated executions of a ballistic sports movement—specifically, the frontal foot kick (*mae-geri*) in karate—in expert athletes. The two leading research questions presented for consideration are (1) Can characteristics of individual movement patterns be observed throughout the entire training session despite continuous changes, i.e., even as fatigue-related processes increase? and (2) How do intra-individual movement patterns change as fatigue-related processes increase throughout a training session? Sixteen expert karatekas performed 606 frontal foot kicks directed toward an imaginary target. The kicks were performed in nine sets at 80% (*K*-80) of the self-experienced maximal intensity. In addition, six kicks at maximal intensity (*K*-100) were performed after each of the nine sets. Between the sets, the participants took a 90-s break. Three-dimensional full-body kinematic data of all kicks were recorded with 10 infrared cameras. The normalized waveforms of nine upper- and lower-body joint angles were classified using a supervised machine learning method (support vector machine). The results of the classification revealed a disjunct distinction between the kinematic movement patterns of individual athletes. The identification of unique movement patterns of individual athletes was independent of the intensity and the degree of fatigue-related processes. In other words, even with the accumulation of fatigue-related processes, the unique movement patterns of an individual athlete can be clearly identified. During the training session, changes in intra-individual movement patterns could also be detected, indicating the occurrence of adaptations in individual movement patterns throughout the fatigue-related accumulation process. The results suggest that these adaptations can be modeled in terms of changes in patterns rather than increasing variance. Practical consequences are critically discussed.

Keywords: situatedness, individuality, kinematic data, optimal movement, fatigue, support vector machine, machine learning, movement classification

INTRODUCTION

Since the beginnings of sports science in the eastern and western hemispheres, quantitative analyses of the athletes' momentary performance have been performed, targeted toward attaining future improvements and optimization (Matwejew, 1972; Hay, 1978). Following the quantification trend in biomechanics and learning psychology since the 1960s, versatile attempts were made to continuously approach previously established target values by applying control loop models (Anochin, 1935; Miller et al., 1960). Typically for this purpose, group averages of the world's best athletes were chosen to serve as target values and, thus, as a collective orientation for sports training. Medically (Hollmann and Hettinger, 2000; Kjaer et al., 2003) and biomechanically (Hay, 1978) based conditioning and coordination profiles were drawn up, which had to be copied by athletes with extensive numbers of executions of the movement tasks and correction processes (Harre, 1969; Matwejew, 1972; Letzelter, 1978; Martin et al., 1991). Driven by the idea to improve the monitoring and control of sports training, increasingly precise measurement methods for describing human movements were developed. Consequently, fluctuations in movement data also became more obvious. Although anecdotal evidence (Bernstein, 1967) and theoretical considerations (Hatze, 1986) presented early on pointed to the non-repeatability of movements, fluctuations between and within individuals were, for a long time, mostly regarded as measurement errors or as destructive noise. Changes in sports training philosophies were rarely observed.

Over time, however, increasing doubts (Nubar and Contini, 1961; Beckett and Chang, 1968; Hatze, 1973, 1984, 1986) about the orientation of collective (person-independent) profiles eventually led to the development of more group-specific profiles as a basis for orientation for sports training—for example, profiles established according to age, gender, or anthropometry. Later, the availability of more powerful computers enabled the biomechanical simulation of coordination profiles optimized for individual athletes, including those based on person-specific anthropometric characteristics and/or isometric force values (Winter, 1980; Gutewort and Sust, 1989; Liu, 1992; van Soest et al., 1993; Nigg, 1994). The effort to orientate sports training more toward assisting individual athletes rather than toward benefiting the collective (person-independent) average profiles was supported by findings that allowed researchers to distinguish world-class athletes based on their metabolic adaptation behavior (Bouchard and Rankinen, 2001), their muscle-related strength abilities (Sust and Jung, 1990; Weiss et al., 1995), and their movement patterns (Bauer and Schöllhorn, 1997; Schöllhorn and Bauer, 1997, 1998). However, two challenges that were considered to help maintain a persistent gap between theory and practice were not resolved: one concerned the question of whether and how athletes are able to perform according to profiles that were theoretically predicted as being optimal for them, while the other related to the enormous adaptability of the human movement system and the permanent fluctuations of human movement behavior.

An integrated approach was suggested to address these challenges by linking two previously largely separated fields of research, sports biomechanics (Nigg, 1994; Winter, 2009) and system dynamics (Schöner et al., 1986). This involved, on the one hand, parallel observation of fluctuations of various biomechanical variables that describe the behavior of individual athletes in longitudinal studies (Schöllhorn, 1993; Schöllhorn and Bauer, 1997; Schöllhorn et al., 2001), and, on the other hand, fluctuations as an essential feature of dissipative systems in adaptation processes (Schöner et al., 1986). Another contributing issue was related to a principle of biomechanically supported training control (Farfel, 1977; Ballreich et al., 1986), according to which the effect of a variable identified as influencing the overall performance is estimated by its systematic variation. Two major consequences were connected to this linking of sports biomechanics and system dynamics. On the one hand, fluctuations in biomechanically controlled training became reinterpreted and were used for initiating a self-organizing process through their amplification (Schöllhorn, 2000). Variable exercises and deviations caused by internal (e.g., fatigue, emotion, and kinematics), external (e.g., ball weight, field size, and number of team mates), and entangled (e.g., gravitational forces and perception) influencing factors were no more considered as independent or destructive but rather as tools for modifying the athlete's or learner's potential. On the other hand, increased efforts were observed toward realizing the application of pattern recognition methods for a more detailed analysis of the interdependence of individual movement patterns and its fluctuations. Based on methods gleaned from the research areas of artificial intelligence and machine learning, "patterns" should be identified in the fluctuations of time-continuous waveforms of biomechanical variables.

First applications of machine learning methods in the field of sports and everyday movements resulted in the identification of individuals based on their disjunct movement patterns during gait (Nixon et al., 1999; Schöllhorn et al., 1999, 2002), running (Simon and Schöllhorn, 1995), pole-vaulting (Jaitner and Schöllhorn, 1995), discus-throwing (Bauer and Schöllhorn, 1997), and javelin-throwing (Schöllhorn and Bauer, 1998). Besides the identification of individual movement patterns even within world-class athletes, who have already experienced thousands of executions in their sports discipline and formerly served as collective profiles for sports training, permanent fluctuations in the biomechanical movement patterns, no matter whether time-discrete or time-continuous, supported earlier evidence of an extremely low probability of identical movement patterns existing between multiple executions of a movement task (Bauer and Schöllhorn, 1997; Schöllhorn and Bauer, 1997, 1998).

Following the differentiation of individual movement patterns, emotion-specific (Janssen et al., 2008) or fatigue-specific (Jäger et al., 2003; Janssen et al., 2011) subpatterns could be identified within individual movement patterns. However, classifications were made based on pre- and post measurements, while the actual process of becoming fatigued or the actual process of changes trending toward a specific emotional state was not investigated. A further step toward an even more differentiated analysis of fluctuations in biomechanical variables can be assigned to recent findings of highly time-dependent movement patterns. Disjunct changes in individual movement patterns without any intervention (Horst et al., 2016, 2017a) indicate permanent adaptations of the movement system. For example, kinematic gait patterns of the same person could be distinguished within 1 day after a 30-min break with a classification accuracy of 91% (Horst et al., 2017a), while the classification accuracy between days was 98% (Horst et al., 2016). Despite permanent disjunct changes in individual movement patterns over time (Horst et al., 2016, 2017a) and the "non-repeatability" of movement patterns overall (Bernstein, 1967; Hatze, 1986; Newell and Corcos, 1993), unique movement patterns of individual people could be identified even 1 year later (Horst et al., 2017b).

Overall, the pattern-recognition approach introduced for differentiated movement analysis using machine learning methods provides promising insights not only regarding individuals and whole-body movements on a rather coarse scale of observation but, also, the analysis of fluctuations within individuals on a finer scale. Neither emotion-specific nor daily changes of movement patterns have found equivalents in biomechanical simulation modeling so far (Glazier and Mehdizadeh, 2019a,b).

To what extent and at what kind of timescale do the fluctuations of movement patterns change or shift by means of fatiguing training in such a way that the identification of individuality is disturbed by a disjunct separation of the variance-related distributions is the subject of this work. Considering a typical karate training session (Funakoshi, 1973), we conducted a biomechanical movement analysis of a large number of executions of a frontal kick task during a fatiguing process. Fatigue is a naturally occurring influence of movement adjustments inherent in any training session or competition. While the influence of fatigue on performance measures has been well-described (Enoka and Stuart, 1992; Gandevia, 2001), the detailed effects of fatigue on movement execution are only partially elucidated. Most studies to date on the influence of fatigue on movements have been conducted focusing on basic cyclic movements (e.g., walking and cycling), while only a few have focused on ballistic movements and considering just a small number of actions. In these studies, the occurrence of spontaneous movement adjustments under fatigue as a result of multiple executions in various disciplines was reported, including rope-skipping (Bruce et al., 2017), running (Mizrahi et al., 2000), water polo (Oliveira et al., 2016), football (Amiri-Khorasani et al., 2011), and karate (Quinzi et al., 2016).

Aragonés et al. (2018) investigated fatigue-related changes of kinematics at different timescales during a karate training session consisting of many frontal foot kicks. The resulting data contained evidence of timescale-dependent adjustments in kicking patterns occurring, particularly during the first 20 executions on a timescale of some tens of seconds (Quinzi et al., 2016; Aragonés et al., 2018). On the same timescale, mainly variables related to the speed of the movement and their relative maxima changed, while variables related to the form of the kicking movement were hardly affected. However, when using the timescale of tens of minutes, exactly the opposite was noticeable. Understanding fatigue-related movement changes according to different timescales is of great relevance in applied biomechanics since exercise-related fatigue is a source of temporary change that introduces its own timescale into performance dynamics (Newell et al., 2009). In sum, a clear and current deficit in the understanding of timescale-dependent changes in movements can be stated. Previous studies have mostly considered discrete biomechanical variables at discrete time points. To our knowledge, an analysis of sports movement patterns based on time-continuous biomechanical variables over many executions of the same movement task has not been conducted so far.

In this study, the karate front kick is used exemplarily to examine a ballistic whole-body movement by means of pattern recognition procedures (i.e., support vector machine) on the one hand with regard to its individuality and on the other hand with regard to its situatedness over a fatiguing process. Situatedness here refers to spatiotemporal contingency as the momentary being that not only results from environmental, but also from—for example—sociocultural, geographical, historical, and biographical conditions as has been introduced in phenomenology (Heidegger, 1927; Merleau-Ponty, 1945). Thereby, the leading research questions of this investigation are (1) can characteristics of individual movement patterns be observed throughout the entire training session despite continuous changes, i.e., even as fatigue-related processes increase? and (2) how do intra-individual movement patterns change as fatigue-related processes increase throughout a single training session?

MATERIALS AND METHODS

The present analysis was conducted on data collected by Aragonés et al. (2018). The application of machine learning methods for classification offers an extended perspective on the data and provides a more differentiated insight into the development of the foot-kick kinematics of individual athletes over two distinguishable timescales.

Participants and Ethics Statement

The study participants were 16 Caucasian healthy adults (11 men and five women) who practiced karate at least twice a week (the group characteristics are shown in **Table 1**). All were right-footed and were expert karatekas with brown and black belts from the first to the fifth dan. The participants were recruited from local karate clubs, and all were practicing karate at the time of the examination for recreational and health purposes. Before participating in the study, the participants signed informed consent forms. All experimental procedures were conducted in accordance with the Declaration of Helsinki and were approved by the ethical committee of the medical association Rhineland-Palatinate in Mainz. Each participant visited the biomechanics laboratory once, where all kinematic measurements took place.

Experimental Protocol

The karate front kick (i.e., *mae-geri-keage*; see **Figure 1**) was the movement to be performed before returning immediately to the starting position. The kick was directed without impact at a reference target (0.1 m × 0.1 m) supported by a plastic rod placed 3 m in front of the participant and adjusted to the participant's abdominal height. Using a metronome, the actions were prompted acoustically at a frequency corresponding to a kick every 2 s (the participants changed from the orthodox to the southpaw stance and vice versa for 2 s). The starting stance was *zenkutsu-dachi* (**Figure 1**), that is, standing with one foot in front of the other without lifting the heels from the mat. One front and one rear martial arts mat (size: 0.9 m × 0.6 m; height: 0.02 m; material: foam rubber; surface: rice straw pattern) had previously been attached to the floor in such a way that each foot was placed on one of the mats. The participants were asked to keep the angle between the thigh and lower leg segments of the front leg at around 135°, and to keep the rear leg extended as far as possible. The lateral distance between both feet corresponded to the width of the pelvis.

The test protocol was developed in the style of a common karate training protocol (Funakoshi, 1973), where participants are often asked to perform dozens of executions at submaximal intensity before finally performing a few executions at maximal intensity. Such bouts alternate with short intervals of inactivity, during which time, the teacher gives corrections. As shown in a schematic presentation of the test protocol in **Figure 2**, the participants were asked to perform nine sets of kicks, each consisting of 60 kicks with 80% of their self-perceived maximal intensity (K-80) (three blocks of 10 kicks alternately with each leg, starting with the right leg), followed by one set of six kicks at maximal intensity (K-100) (three with the right leg, then three with the left leg). Before set 1 and after set 9, participants were asked to perform a pre-set and a post-set of six kicks at maximal intensity (K-100) (three with the right leg, then three with the left leg). Between the sets, the participants rested for 90 s, except between set 9 and the post-set, when they rested for 10 min. The break of 90 s corresponds on the one hand to the typical break length of karate training, and on the other hand, it was needed to collect the physiological and psychological variables as well as to readjust any markers that might have become loose during prior sets.

After the participants arrived at the laboratory and before the test was initiated, passive optical markers for the purpose of biomechanical analysis were attached at anatomical landmarks. In addition, discrete measurements of heart rate (HR), blood lactate concentration, and the rating of perceived exertion (RPE) were performed to collect baseline values. The participants were then introduced to the test protocol and encouraged to warm up by performing (1) 5 min of self-directed warm-up and (2) one set of kicks while reporting the RPE (they were already familiar with the appropriate scale) to become accustomed to the protocol.

TABLE 1 | Participant characteristics.

	M	SD
Age (years)	39.69	12.81
Height (m)	1.75	0.08
Body mass (kg)	73.14	12.33
BMI (kg/m^2)	24.54	3.11
Experience in karate (years)	16.00	6.60
Left leg length (m)	0.81	0.05
Right leg length (m)	0.81	0.05

Data are presented as mean (M) and standard deviation (SD), BMI, body mass index.

Data Acquisition

Physiological: Heart Rate and Blood Lactate Concentration

A heart rate (HR) monitor attached to a chest strap (HRM2-SS; Garmin, Schaffhausen, Switzerland) and a blood lactate concentration analyzer (h/p/cosmos sirius; SensLab, Leipzig, Germany) were used.

Psychological: Borg's Rating of Perceived Exertion

Borg's rating of perceived exertion (RPE) on a scale of six to 20 points and corresponding instructions (Borg, 1998) was adopted.

Kinematics

Kinematic data were recorded with 10 infrared cameras (Oqus 310; Qualisys, Gothenburg, Sweden), which recorded at a frequency of 333 Hz. Forty-two retroreflective markers were attached to anatomical landmarks (**Figure 1**), including the left and right anterior superior iliac spine, the left and right posterior superior iliac spine, the right femur laterally and medially, the left and right fibula tip of the lateral malleolus, the left and right tibia tip of the medial malleolus, the left and right head of the first metatarsus, the left and right head of the fifth metatarsus, the tuberosity of the fifth metatarsus, the posterior surface of the calcaneus, the left and right acromion, the sternum jugular notch, the sternum xiphisternal joint, the seventh cervical vertebrae, and the midpoint between the inferior angles of most caudal points of the two scapulas. Two clusters of four markers were fixed to the lateral sides of the left and right thighs and the left and right shanks, respectively.

Data Processing

Physiological and Psychological Variables

Discrete HR values were recorded, blood lactate concentration samples were taken from the earlobe, and RPE values were

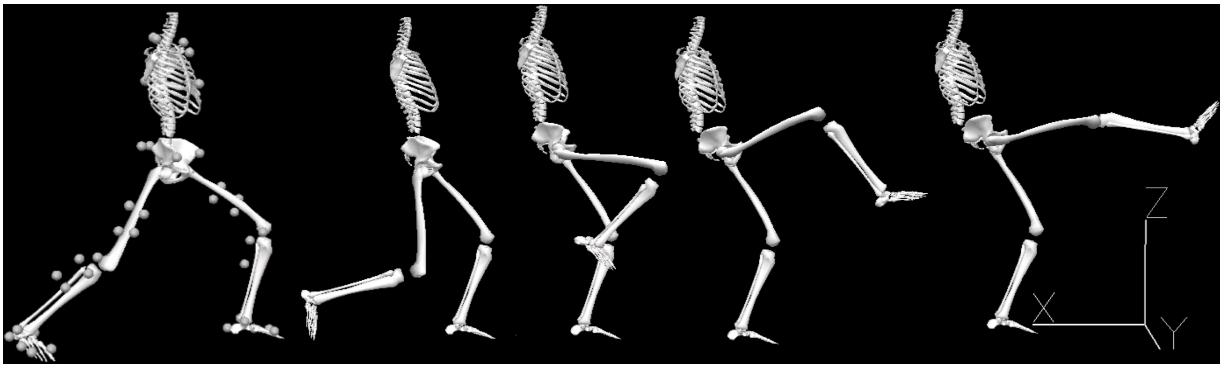

FIGURE 1 | Biomechanical model representing the *zenkutsu-dachi* starting stance (with 42 retroreflective markers fixed on anatomical landmarks) and the *mae-geri* kick sequence performed with the right leg. Adapted from Aragonés et al. (2018).

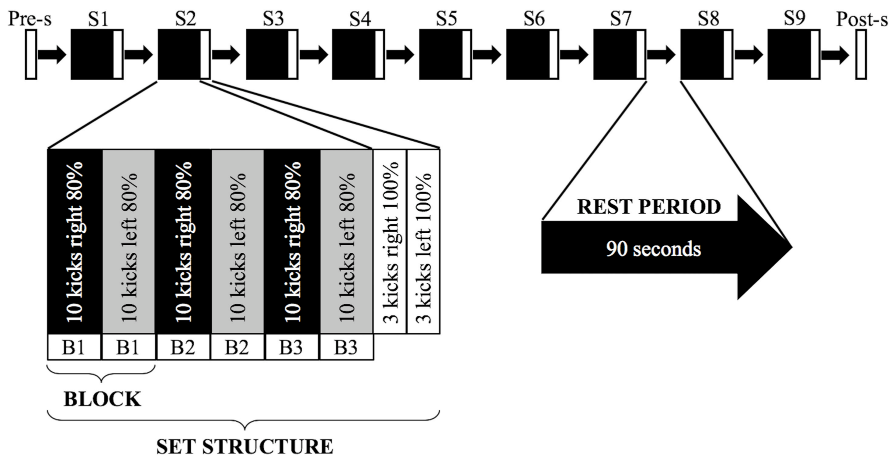

FIGURE 2 | Schematic of the test protocol. The experimental procedure consisted of one pre-set (Pre-s) followed by nine sets (S1–S9) with 90-s rest intervals in between and an additional post-set (Post-s) performed after a 10-min rest period. A deeper insight into the structure of the main elements is represented below. The pre-set and post-set consisted of six *mae-geri* kicks performed at maximal intensity (*K*-100). Adapted from Aragonés et al. (2018).

reported by the participants before the warm-up phase (i.e., baseline values), after the pre-set, after each of the nine sets during the rest period, and after the post-set, respectively. These variables were selected to monitor fatigue development.

Kinematic Variables

The kicks were analyzed from the moment the kicking foot moved forward on the x-axis to the maximum knee extension angle just before the leg returned (**Figure 1**). The marker trajectories were low-pass filtered with a sixth-order Butterworth zero-phase filter with a cut-off frequency of 15 Hz. A partial body model, based on the standard segments of the foot, shank, thigh, thorax, and the CODA pelvis segment (Charnwood Dynamics, Rothley, United Kingdom), was created for each participant in the standing position using Visual 3D Standard version 4.86.0 (C-Motion, Germantown, MD, United States). The joint angles were calculated with a Cardan sequence of rotation (Cole et al., 1993). The data were processed with Matlab version R2015b (The Mathworks, Natick, MA, United States). All variables were time-normalized to 101 data points, z-normalized, and scaled to the range $(-1, 1)$. The following nine joint angle waveforms were calculated in the x-, y-, and z-planes: the left and right ankle joint angle, the left and right knee joint angle, the left and right hip joint angle, the sternoclavicular joint angle, and the angles between the left and the right thighs to the thorax.

Data Analysis

Data Classification

The classification of karate patterns was based on 606 kicks [606 = 2 (left kicks + right kicks) $*$ 303 (270 K-80 + 33 K-100)] performed by each participant. For each kick, a concatenated vector of all 27 kinematic variables [2727 = 27 joint angle waveforms (9 joint and segment angles in the x-, y-, and z-planes) $*$ 101 data points] was built and used for classification purposes. The classification was based on a support vector machine, supervised machine-learning classifier (Boser et al., 1992; Cortes and Vapnik, 1995; Müller et al., 2001; Schölkopf and Smola, 2002) using a linear kernel and a grid search to determine the best cost parameter ($C = 2^{-5}, 2^{-4.75}, \ldots, 2^{15}$). The ability to distinguish karate patterns between participants (16-class classification) and within a participant between different combinations of blocks and sets (27-class classification), sets (nine-class classification), and blocks (three-class classification) was investigated in a multiclass classification setting. As presented in **Table 2**, due to the different classification tasks, the size of the matrices used for the classifications differed. Therefore, the prediction accuracies, F_1 scores, precision, and recall were calculated over a *k*-fold cross-validation depending on the minimal number of kicks included in a block in each classification task. Furthermore, for every classification task, the data were divided into training and test groups. The data in the test group were evenly distributed across all classes. This splitting of the data was stratified repeatedly depending on the number of sets [i.e., by participant (*K*-80 and *K*-100) and block-within-set classifications] and the minimal number of kicks in one block (i.e., block and set classifications) to obtain meaningful results. This procedure ensured that each kick was included in every classification task exactly once in the test set, thereby avoiding random imbalances in the prediction and making the results more reproducible. The classification was performed within Python version 3.6.3 (Python Software Foundation, Wilmington, DE, United States) using the scikit-learn toolbox (version 0.22.1) (Pedregosa et al., 2011).

Statistical Analysis of Movement Variance, Physiological, and Psychological Variables

To determine the variance of movement patterns over time, the coefficient of variation (CV) was calculated over the joint angle waveforms of each participant (Winter, 1984). The exact same data were used to calculate the CV as those used for the classification analysis described above. The CV was calculated according to each classification task. This means that, according to the inter-individual classification, the CV was calculated over the waveforms of all participants; in other words, according to intra-individual classification tasks in the block and set classifications over one block or one set of a participant as well as in the block-within-set classification over all three blocks within the sets.

The CV according to each classification problem, the HR, the lactate blood concentration, and the RPE were tested for normal distribution using the Shapiro–Wilk test. For data that did not deviate significantly from the normal distribution, descriptive statistics are presented in means and standard deviations (SDs). Statistical analysis was performed using repeated-measures analysis of variance (RM-ANOVA) with *post hoc* paired *t*-tests with Holm–Bonferroni correction. Data that deviated significantly from the normal distribution were statistically tested with Friedman ANOVA; *post hoc* analysis was performed with the Wilcoxon paired-rank test with Holm–Bonferroni correction. The results were considered significant at $p < 0.05$. Effect size was tested with η^2 eta-squared for the RM-ANOVA, Cohen's *d* for the *t*-test, and r-effect size for the Wilcoxon test, respectively. The analyses were performed using the Statistical Package for the Social Sciences version 23 software program (IBM Corporation, Armonk, NY, United States).

RESULTS

Inter-Individual Classification

As presented in **Table 3**, the classification of movement patterns between the participants achieved 100% accuracy at both the

TABLE 2 | Description of the input data and validation procedure depending on the different classification tasks.

Classification task and intensity	Size of matrix	Description of *x*-vector length	Training and test groups	Cross-validation * stratified splitting	Number of classes
Participant *K*-80	4320 × 2727	4320 = 16 participants * 270 kicks	Training: 16 participants * 30 kicks * 8 sets (= 3840 kicks) Test: 16 participants * 30 kicks * 1 set (= 480 kicks)	9-fold * 9	16
Participant *K*-100	528 × 2727	528 = 16 participants * 33 kicks	Training: 16 participants * 3 kicks * 10 sets (= 480 kicks) Test: 16 participants * 3 kicks * 1 set (= 48 kicks)	3-fold * 11	16
Block *K*-80	270 × 2727	270 = 27 combinations of sets and blocks (9 sets * 3 blocks) * 10 kicks	Training: 9 kicks * 27 blocks (= 243 kicks) Test: 1 kick * 27 blocks (= 27 kicks)	9-fold * 9	27
Set *K*-80	270 × 2727	270 = 9 sets * 30 kicks	Training: 27 kicks (9 per block) * 9 sets (= 243 kicks) Test: 3 kicks (1 per block) * 9 sets (27 kicks)	9-fold * 9	9
Block-within-set *K*-80	270 × 2727	270 = 3 Blocks * 9 sets * 10 kicks	Training: 10 kicks * 3 blocks * 8 sets (= 270 kicks) Test: 10 kicks * 3 blocks * 1 set	9-fold * 9	3

Kicks for classification are based on the left- or the right-footed kicks; 2727 = 1 leg ∗ 27 joint angle waveforms (x-, y-, and z-plane ∗ 9 joint angles) ∗ 101 data points.

TABLE 3 | Mean percentage values of accuracies, F_1 scores, precision scores, and recall scores of the different classification tasks and corresponding CVs.

Classification task and kick intensity	Leg	Accuracy (%)		F_1 Score (%)		Precision (%)		Recall (%)		Number of classes	Random baseline accuracy (%)	CV (%)	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*			*M*	*SD*
Participant *K*-80	Left	100.0	0.1	100.0	0.1	100.0	0.1	100.0	0.1	16	6.3	31.6	
	Right	100.0	0.1	100.0	0.1	100.0	0.1	100.0	0.1	16	6.3	32.2	
Participant *K*-100	Left	100.0	0.0	100.0	0.0	100.0	0.0	100.0	0.0	16	6.3	32.1	
	Right	100.0	0.0	100.0	0.0	100.0	0.0	100.0	0.0	16	6.3	33.3	
Block *K*-80	Left	42.9	2.3	52.3	2.4	48.1	2.5	62.0	2.5	27	3.7	16.3	2.4
	Right	42.9	1.8	52.2	1.9	47.7	1.6	62.5	2.7	27	3.7	16.6	2.2
Set *K*-80	Left	66.2	2.7	66.0	2.9	69.2	3.5	67.4	2.6	9	11.1	16.7	2.2
	Right	65.1	2.6	64.7	2.8	68.7	3.1	66.2	2.7	9	11.1	17.2	1.9
Block-within-set *K*-80	Left	55.6	3.6	54.5	4.0	57.3	3.9	56.3	3.0	3	33.3	17.9	1.9
	Right	66.0	1.3	64.9	1.8	68.1	1.1	66.3	1.4	3	33.3	18.3	1.7

*Mean (M) and standard deviation (SD) values of the classification rates calculated over the different training–test splits (**Table 2**). M and SD values of the CV over the waveforms for each classification task; for block, set, and block-within-set classification, M and SD values for all participants and classes are presented.*

maximal (*K*-100) and submaximal (*K*-80) intensities during the karate training process. The movement patterns of the participants can, therefore, be clearly distinguished. Only one left kick (1/4,320) and one right kick (1/4,320) at submaximal intensity were not correctly classified.

Intra-Individual Classification

As shown in **Table 3**, the classification of movement patterns over the 27 blocks in all sets (27 classes) resulted in a prediction accuracy of 42.9% ± 2.3% for the left kicks and 42.9% ± 1.8% for the right kicks; the classification of the movement patterns of the nine sets (nine classes) resulted in a prediction accuracy of 66.2% ± 2.7% for the left kicks and 65.1% ± 2.6 for the right kicks, and the classification of the movement patterns of the three blocks within the sets (three classes) resulted in a prediction accuracy of 55.6% ± 3.6% for the left kicks and 66.0% ± 1.3% for the right kicks. **Figure 3** shows the confusion matrices of the right and left kicks for all intra-individual classifications. It is noticeable that the true class has always been predicted more often and that the misclassifications are mainly distributed among the classes nearby.

This is also displayed in **Figure 4**, where the mean prediction accuracy is shown as a function of the distance to the true class. For both the left and right kicks, the true class was the most probable class, and the probability of prediction tends to decrease with increasing distance from the class. It is noticeable, however, that groups with a distance of three and multiples of three blocks again exhibit a higher probability than that of the class closer to them. A distance of three classes means that the class corresponds to the same block in the nearby set. Six classes correspond accordingly to the same block only with the distance of two sets between them. However, the set classification clearly shows that the probability of a misclassification decreases significantly with increasing distance of a class from the true class.

Inter- and Intra-Individual CV

As presented in **Table 3**, the inter-individual CVs of the waveforms of kicks with 80% intensity were 31.6% for the left kicks and 32.2% for the right kicks. The CVs of the waveforms of the kicks performed with maximal intensity using the left leg (32.1%) and the right leg (33.3%) are slightly higher. The mean CVs of the waveforms of the intra-individual comparisons, therefore, are lower, with values between 16.3 and 18.3%. What is noticeable here is that the CV of the waveforms of the right kicks is always slightly higher than that of the left kicks. **Figure 5** shows the CVs of waveforms dependent on blocks, sets, or blocks within sets. It was noticeable that the CV values of waveforms did not increase in any case during the fatigue-accumulating process. As shown in **Table 4**, the statistical comparisons of the CVs within the blocks and within the sets reveal a significant difference for the waveforms of the right kicks, while the CVs of the waveforms of the left kicks do not differ significantly. In paired *post hoc* comparisons only between sets 4 and 5, there was a statistically significant difference noted among the right kicks. Based on the descriptive CV values for the waveforms of the blocks and sets, it may be stated that the values for the first block and set do not increase.

Changes in Physical and Psychological Variables Between Sets

The baseline values [median (interquartile range)] for HR, lactate blood concentration and RPE were 67 (61.75–71.25) beats $*$ min^{-1}, 1.30 (1.20–1.53) mmol $*$ l^{-1}, and 6 (6–6). Both HR [$\chi^2(11) = 133.520$; $p < 0.001$], lactate blood concentration [$\chi^2(11) = 77.768$; $p < 0.001$], and RPE [$\chi^2(11) = 161.988$; $p < 0.001$] showed statistically significant differences over the course of the experiment with fatigue accumulation from baseline through the time points immediately following each set (**Figure 6**). All results of Friedman ANOVAs and Wilcoxon signed-rank *post hoc* tests are presented in **Supplementary**

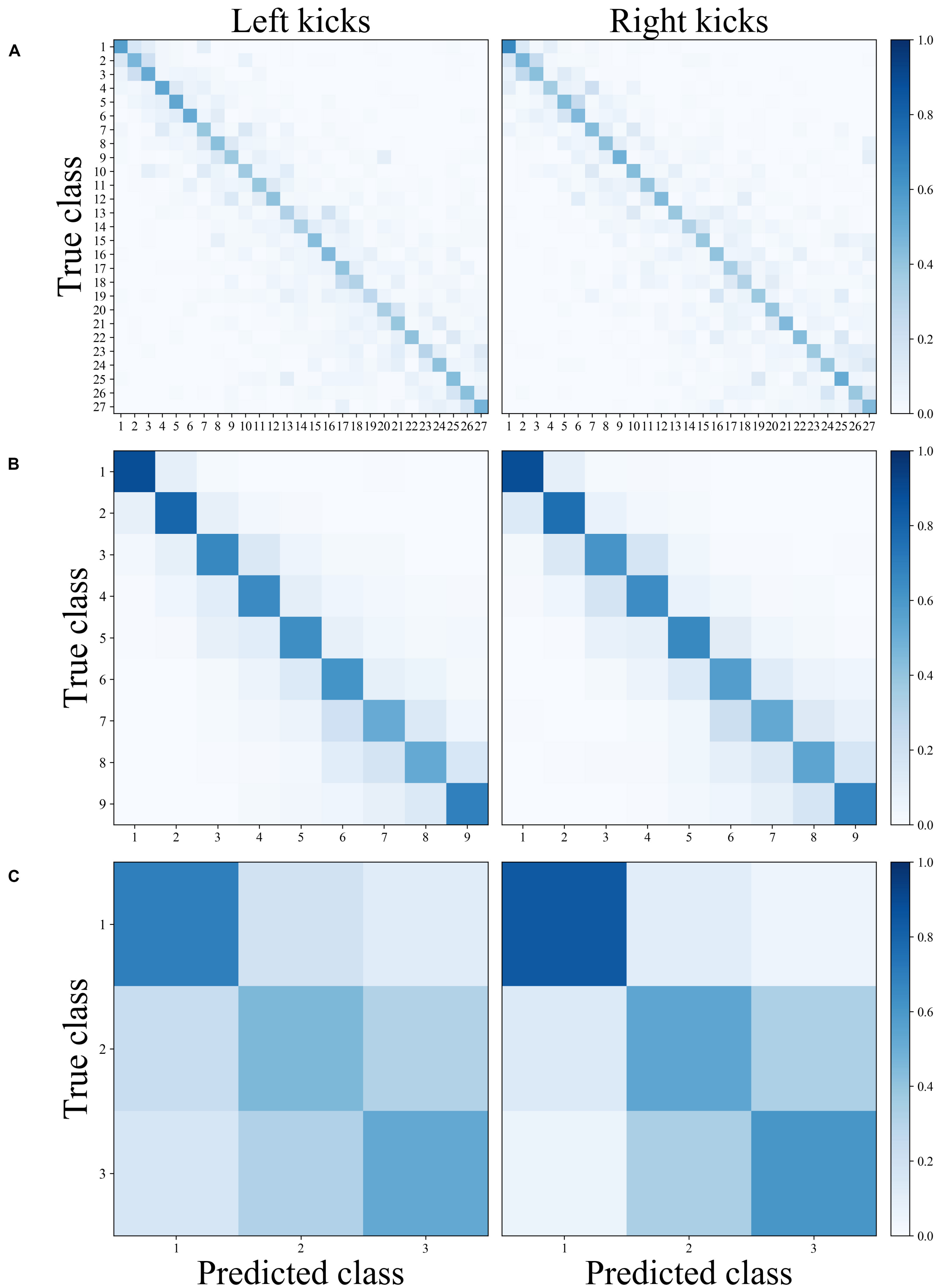

FIGURE 3 | Normalized confusion matrices of the classification's movement patterns of the left and right kicks depending on the different classification tasks. **(A)** Block classification, **(B)** set classification, and **(C)** block-within-set classification.

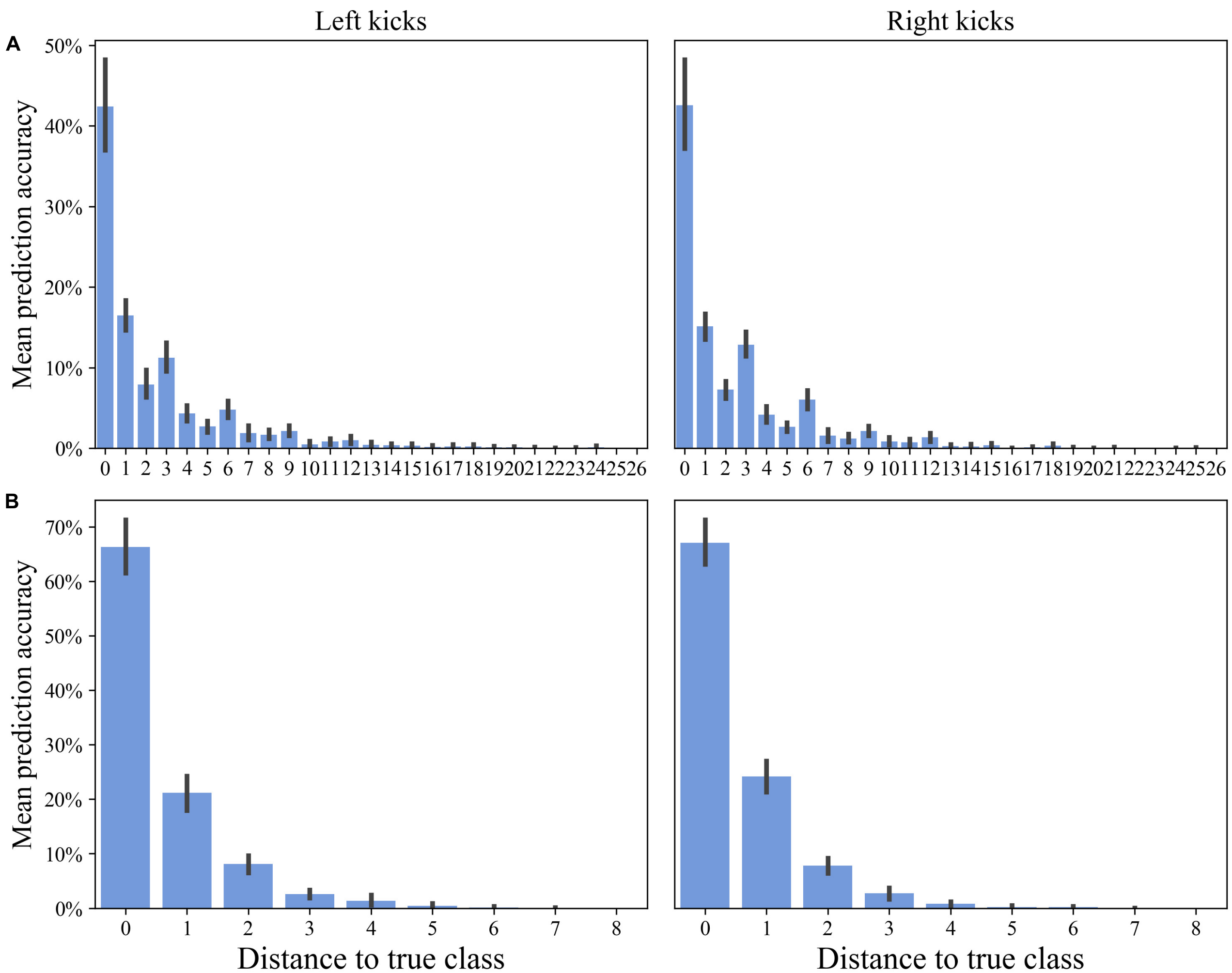

FIGURE 4 | Distances to true classes of the classification of the movement patterns of the left and right kicks depending on the classification task. Presented here are the means and SDs for each distance. A distance of zero to the true class refers to the prediction accuracy of the true class (e.g., a distance of two means that the predicted class is two classes next to the true class). **(A)** Block classification. Consider that distances of 14 and higher will not occur in all cases (e.g., block 14 has only 13 blocks before and 13 after). **(B)** Set classification. Consider that distances of five and higher will not occur in all cases.

Table S1. It was noticeable that the HR increased steadily over the course of a set and decreased by about 30–40 beats $* \min^{-1}$ in the 90-s set pauses. The maximum HR reached a median of 169 (150.25–175.50) beats $* \min^{-1}$ after the ninth set. A statistical comparison of the times directly after the completion of each set and the baseline measurement showed a significant increase until after the third set. There were no statistical differences between the third and ninth set, with the median HR over the course of the test increasing from 165 to 169 beats $* \min^{-1}$. The analysis of the blood lactate concentration showed only statistical differences between pairs of baseline measurements and all further sets. No statistical differences were found between the individual sets. However, up to the end of set 8, a trend can be observed that the mean lactate value increased continuously and reached a maximum of 4.95 (3.83–5.20) mmol $* \, l^{-1}$. In pairwise comparisons of the RPE, a steady increase was observed until the end of the ninth set. It is shown that the RPE increases significantly at the next, the next but one, or at the latest the third following set and reaches a maximum of 16 (14.75–17.25).

DISCUSSION

In this study, the biomechanical movement patterns of experts in karate were investigated by executing the front kick, constituting a movement performed with a high level of expertise, multiple times, and through a fatigue-accumulating process in a training session. In relation to the first hypothesis, the results show that an individual's movement patterns can be clearly identified independently of fatigue-accumulating training. Regarding the second hypothesis, it was found that changes in the intra-individual movement patterns, which are not attributable to changes in variance, can be clearly identified within a training session. In detail, these changes in movement patterns appear to be dependent on different timescales. Whether these timescales

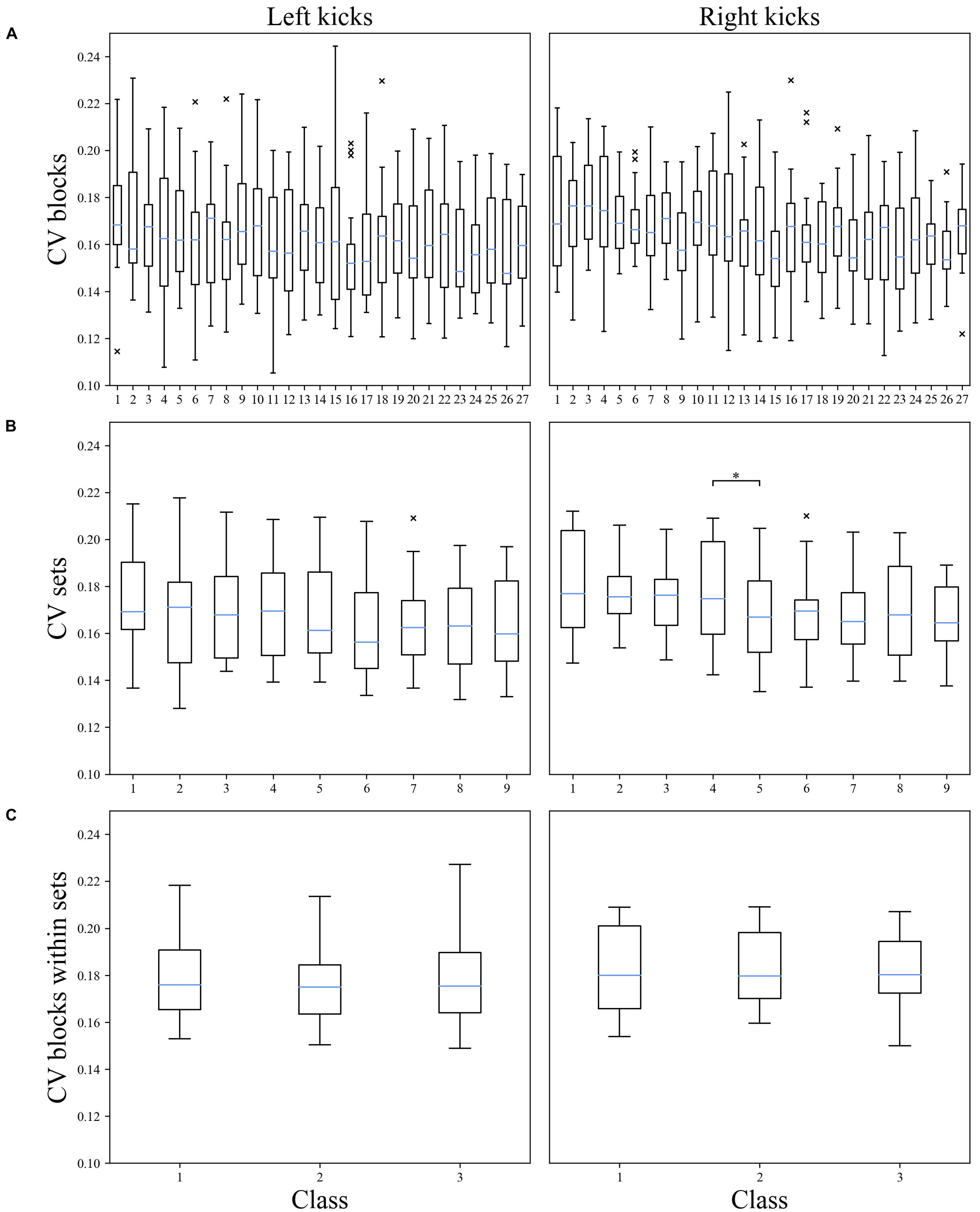

FIGURE 5 | Coefficient of variations of the joint angle waveform of the left and right kicks depending on each block and set. Presented here are the box plots for all participants; the *x*-axis shows the classes, and the *y*-axis shows the CV. Values are considered as outliers if they are outside the interval [Q_1 – 1.5 * (Q_3 – Q_1), Q_3 + 1.5 * (Q_3 – Q_1)]. × = Outlier (each × stands for one outlier); *Statistically significant difference in pairwise *post hoc* test. **(A)** CV of the waveforms of the blocks of each participant. There was a statistically significant result for right kicks. **(B)** CV of the waveforms of the sets of each participant. There was a statistically significant result for right kicks. **(C)** CV of the waveforms of the blocks within sets for all participants.

TABLE 4 | Statistical analysis of the intra-personal CV of the joint angle waveforms of the *K*-80 kicks.

Classification task	Leg	RM-ANOVA or Friedman ANOVA	*Post hoc* analysis
Block	Left	$\chi^2(26) = 37.881$, $p = 0.062$	
	Right	$\chi^2(26) = 54.696$, $p = 0.001^a$	
Set	Left	$F(3.933,59) = 2.212$, $p = 0.080$, $\eta^2 = 0.129$	Sets 4–5 [$p(15) = 0.0003^b$, $d = 0.499$]
	Right	$F(8,120) = 4.462$, $p < 0.001^a$, $\eta^2 = 0.229$	
Block-within-set	Left	$F(2,30) = 0.607$, $p = 0.552$, $\eta^2 = 0.039$	
	Right	$F(2,30) = 0.119$, $p = 0.888$, $\eta^2 = 0.008$	

Presented here are the results of the RM-ANOVA or the Friedman ANOVA to determine differences among all classes. Only the significant post hoc paired-samples t-test or Wilcoxon signed-rank test results are shown. [a]Significance level: $\alpha = 0.05$. [b]Holm–Bonferroni-corrected significance level: $\alpha_0 = 0.0016$.

are independent of each other, contain self-similar features, or correspond to timescales related to adaptation, warming up, and learning (Newell et al., 2001) will challenge future research.

Individuality of Movement Patterns

The results of the classification analysis showed that the movement patterns of all 16 participants could be clearly distinguished from each other, although all tried to imitate the same profile of the frontal foot kick (*mae-geri*). Unique movement patterns could be distinguished for each participant for both kicks performed at both maximal (*K*-100) and submaximal (*K*-80) intensities as well as with regard to the respective leg performing the kick. Interestingly, the unique characteristics of the individual movement patterns could be identified throughout the entire training session, despite breaks and the accumulation of fatigue. The results support the idea that detailed adaptations of movement patterns to new situations should only be sought on an individual level and not on the basis of a collective, person-independent profiles (Schöllhorn, 1993; Schöllhorn and Bauer, 1998; Janssen et al., 2011; Eekhoff et al., 2016; Horst et al., 2017b; Glazier and Mehdizadeh, 2019a,b). Despite all the fluctuations apparent in the kinematic variable waveforms, which were superimposed in this context by exercise-related fatigue accumulation during the 606 kicks performed by each person, individual foot-kicking patterns at the maximal and submaximal intensities could be clearly distinguished. Although all participants applied training approaches that were oriented on a collective (person-independent) profile, all ended up adopting their own individual kicking patterns that appeared to be fairly resistant against perturbations like fatigue-related changes. This indicates that, in the sense of the theory of system dynamics (Schöner and Kelso, 1988), each individual participant developed individual kicking patterns via a rather less–self-organized process. Individual movement patterns could be reproduced with a certain degree of fluctuations in different situations and influences. However, because the movement patterns were described by means of kinematic variables, no information about the kinetic changes was available. Further insight into whether the movement pattern adaptations become more or less effective by taking more or less advantage of gravitational and inertial forces is required.

Fatigue-Related Changes in Individual Movement Patterns Across Different Timescales

Within the range of individual movement patterns, fatigue-related changes in terms of disjunct changes could be distinguished using classification analysis. Despite a large inter-individual variance in physiological and psychological variables, all participants showed significant increases in these variables over the period under study. Recurrent HR values were above 90% of the theoretical HR maximum, blood lactate concentrations were at a maximum of almost 5 mmol $* \, l^{-1}$ and the RPE fell between "hard" and "very hard." These results confirm that the participants were highly motivated and that fatigue accumulated during the exploration. The classification of the 27 blocks (three blocks within each of the nine sets), which represent the entire fatigue-accumulating process continuously, showed a prediction accuracy of 42.9% each for the kicks with the left and the right legs. The prediction accuracies reached well above the random baseline accuracy of 3.7% and thereby suggested that the movement patterns of the respective 27 blocks could be distinguished from each other. When comparing the predicted and true blocks, shown in **Figure 3A**, it is noticeable that, for most misclassifications, a directly adjacent block was predicted. The increased misclassification of movement patterns of adjacent blocks of the true block further indicates that the movement patterns of kicks of adjacent blocks exhibit more similar patterns than those of kicks of more distant blocks. This observation is illustrated in **Figure 4A**, where the quantification of misclassifications is represented by the distance to the true class. Here, a distance of one means that, for example, the movement patterns of a kick within the sixth block was predicted to also be found in the fifth or seventh block, while, if the distance is three, the third or ninth block was similar accordingly. The misclassifications of the movement patterns of the kicks of a block decrease the further away the block is from the true block. Surprisingly, however, this general trend is interrupted by a brief increase in misclassifications for those blocks that are three or multiples of three blocks away from the true block. Interestingly, a distance of three blocks corresponds to the same block only in the adjacent set (e.g., the first block in set 3 to the first block in set 2 and the first block in set 4) and a distance of six accordingly corresponds to the same block in the sets after next (e.g., the first block in set 3 to the first block in set 1 and the first block in set 5).

The results of the classification, therefore, suggest that the movement patterns of the blocks contain common patterns within the sets, although the movement patterns seem to evolve over the entire course of the sets. Nevertheless, differentiating the movement patterns of the blocks was possible, despite that the time interval between two blocks was very short (**Figure 2**). However, it remains unclear how the movement patterns, which occur on timescales of a few tens of seconds, originate. An

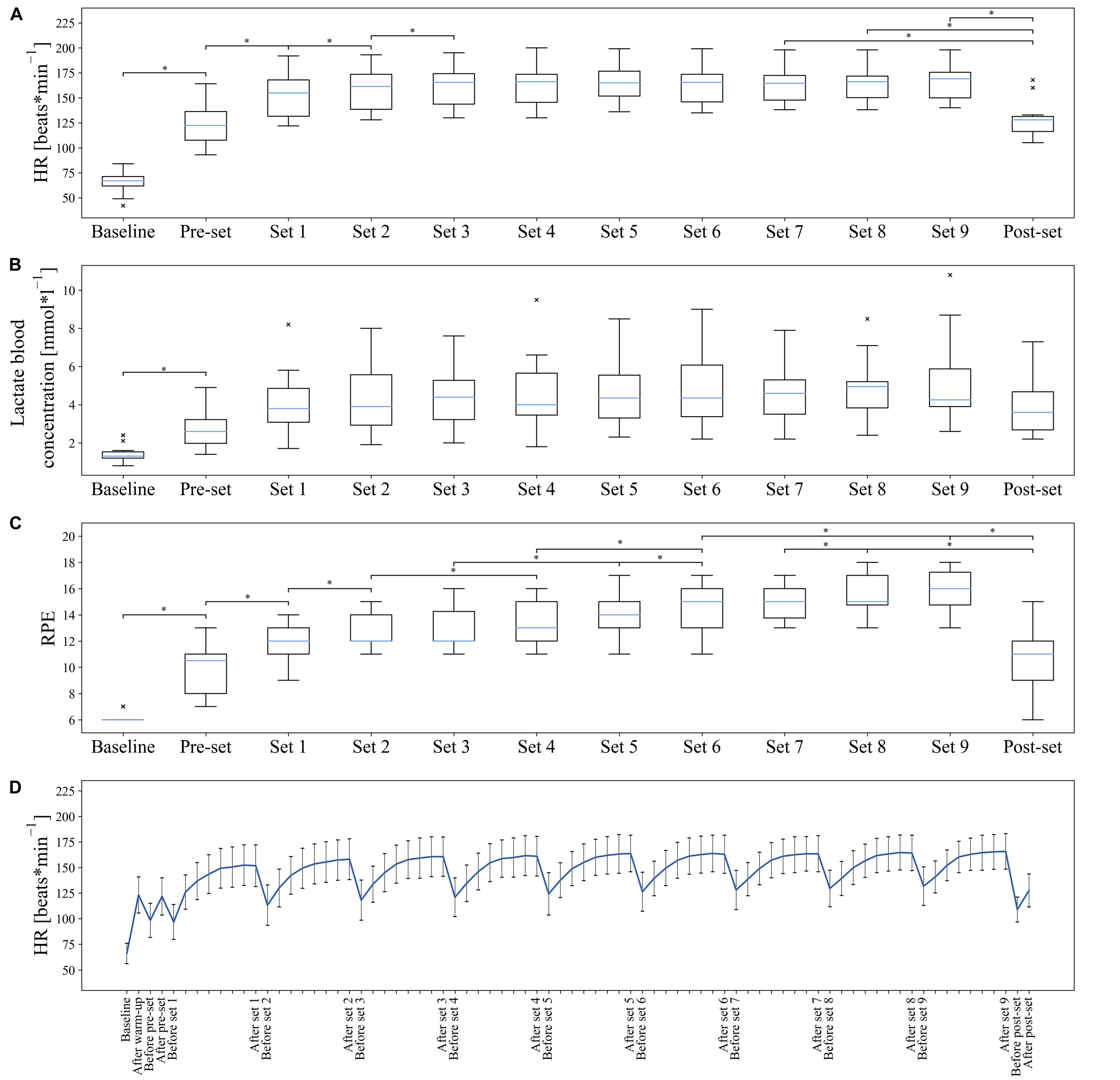

FIGURE 6 | Development of HR, lactate blood concentration, and RPE over the duration of the examination. Values are considered as outliers if they are outside the interval [Q_1 − 1.5 * (Q_3 − Q_1), Q_3 + 1.5 * (Q_3 − Q_1)]. × = outlier (each × stands for one outlier); *Statistically significant difference in pairwise *post hoc* test. **(A–C)** Shown are the box plots of HR, lactate blood concentration, and RPE from baseline measurement and according to the respective sets. HR, lactate blood concentration, and RPE showed significant results. For reasons of clarity, only significant adjacent pairs of *post hoc* comparisons are shown. If the difference to the nearest neighbor was not significant, the difference to the next but one neighbor was shown. If this difference was not significant either, the next neighbor was shown. An overview of all *post hoc* comparisons is presented in **Supplementary Table S1**. **(D)** The mean values and SDs of the continuous HR curve are shown.

explanation of the recovery of the movement system seems highly unlikely since the 90-s break provides some recovery but was not sufficient for a full recovery. An explanation of the rhythm of movement would be more likely. These breaks within the rhythm could be caused by executing the kicks with maximal intensity at the end of each set, which could cause a kind of "reset" of the submaximal kicks. It is also possible, however, that the 90-s break alone would be enough to achieve a similar effect. A short break in rhythm could allow the subsystems of the body responsible for changing the movement patterns on timescales of tens of seconds to recover or rebuild (MacPherson et al., 2009). In this context, the influence of interruptions in the rhythmic structure on the adaptations of movement patterns, as well as their effects on training processes and outcomes, requires further research.

The trend on a timescale of tens of minutes is confirmed by the results of the classification of the movement patterns of the nine sets. The prediction accuracy values of 66.2% for left kicks and 65.1% for right kicks indicate that the movement patterns within a person can be fairly distinguished between sets (random baseline accuracy: 11.1%). Furthermore, the classifications in relation to the distance to the true set (**Figure 4B**) show that the misclassifications clearly decrease with the increasing distance of the set from the true set. With an error tolerance of one set, the prediction rates would already be around 90%. The similarities on a timescale of several tens of seconds, that is, the similarity of movement patterns of the blocks within different sets, are also confirmed by the classification of the three blocks within all sets. Prediction accuracy values of 55.6% for the left kicks and 66.0% for the right kicks also point to a common pattern inherent in movement patterns, although the significantly higher random baseline accuracy (33.3%) should be taken into account here.

The results of the classification analysis suggest that, during a single training session, the execution of movements seems to adapt immediately to changing psycho-physiological conditions (increasing fatigue-related changes). More specifically, even with experts, it seems that repeated executions of a ballistic sports movement (associated with exercise-related fatigue accumulation) lead to disjunct changes within individual movement patterns on different timescales (Newell et al., 2006; Schöllhorn et al., 2009; Horst et al., 2017a). The disjunct changes of individual movement patterns during exercise-related fatigue accumulation in a training session indicate continuous dynamic adaptation processes of the movement system (Schöner and Kelso, 1988). In consequence, a continuous change of the intrinsic dynamics can be assumed in parallel. While prior studies have shown emotion-specific (Janssen et al., 2008) or time-specific (Horst et al., 2016, 2017a) movement patterns, these results indicate that the movement patterns of individuals are highly dependent on the situation. Due to the situative adaptation of the movement patterns of a single individual, the findings support the perspective that it is difficult—if even possible at all—to determine a single (time-independent) person-specific optimal movement pattern (Hatze, 1986; Glazier and Mehdizadeh, 2019a,b).

Fatigue-Related Changes in Movement Patterns, Not Variance

The present results showed that individual participants, despite practicing at an expert level of performance, were unable to repeat the kinematics of a karate front kick movement identically. As shown in **Figure 5**, there were slight changes in the time course of the CVs of the joint angle waveforms of the blocks and sets, although no specific trend could be identified. The variance in the movement kinematics of individuals, therefore, constantly fluctuates within a certain range. A statistically significant difference was noticed only in a period of tens of minutes (sets), between sets 4 and 5, where a decrease in the variance could be observed. However, due to the individual variance in movements across the sets, it is difficult to speak of a global trend but rather of local fluctuation. An increase in the short-term movement variance due to fatigue accumulation could not be shown within the sets. Together with the results of the classification, this leads to the conclusion that fatigue accumulation does not change the short-term movement-patterns variance but, more importantly, does change the overall kinematic movement patterns of a participant. This finding contradicts the results of previous studies (Côté, 2014; Mudie et al., 2017).

With additional evidence sourced from other research about the individuality of gait (Horst et al., 2017b, 2019), the optimal term should be considered to be individual. However, the results do show clear intra-individual shifts in movement patterns during training, which also calls into question the existence of a person-specific optimal movement pattern (Glazier and Mehdizadeh, 2019a,b). The results confirm the findings of the study by Aragonés et al. (2018), which already indicated altered movement patterns exist within individual kinematic variables. The results also are aligned with Quinzi et al. (2016) finding that there are movement pattern variations that occur even during the first 20 executions. Our results support the idea that, in this type of sportive action, the kinematic changes that occur with the accumulation of fatigue are temporary changes that span different timescales (Aragonés et al., 2013; Balagué et al., 2014). Aligned with changes at the task level, products of an evolving set of dynamic subsystems occur at multiple levels of analysis, each of which has its own timescale (Newell et al., 2009). Furthermore, the results of this study support the many findings of previous assessments of the stability and adaptability of movement concerning biomechanical forces (Newell et al., 1989; Schneider et al., 1989; Van Emmerik and Van Wegen, 2000; Bartlett, 2007). That is, the kinematic movement patterns of expert athletes are characterized by their ability to constantly adapt to new situations or intrinsic and extrinsic influences. Moreover, despite the situatedness, the movement patterns of an athlete are so individual that they clearly differ from those of other athletes.

Practical Implications

The findings of this study support far-reaching practical implications for sports science and training. The results delivered a fairly good separation of the movement patterns of blocks, which became even clearer with increasing time. This can be associated with different fluctuations at two different timescales. One timescale is related to the duration of blocks, while the other is linked to the duration of the whole series. An additional timescale has been associated with shifts of individual movement patterns at the timescale of years (Bauer and Schöllhorn, 1997; Horst et al., 2017b) and further timescales up to ontogenetic maturation and aging can be assumed. Looking at the timescales as outcome of naturally occurring fluctuations of different amplitudes and structure resulting from repeated executions of the same movement task, it can be derived as a practical consequence that repetitive (Gaulhofer and Streicher, 1924; Anochin, 1935; Miller et al., 1960; Gentile, 1972) and variable (Schmidt, 1975; Shea and Morgan, 1979; Newell, 1986; Davids et al., 2008) sports training approaches, which are understood in terms of person and time-independent fluctuations, need to be reconsidered carefully. This reconsideration concerns the definition of target profiles as orientation for movement learning and sports training, the diagnoses of the athlete's momentary performance, and their approximation to each other during the training process.

While the search for optimal movement solutions as target profiles in majority has been associated with a static, albeit individual, optimum movement pattern that seems to be impossible to define and to achieve (Hatze, 1986; Loeb, 2012; Glazier and Mehdizadeh, 2019a,b), one could imagine a dynamic optimum that has to be adjusted at every moment by measuring all available variables again and again. The idea of a dynamic optimum, however, also leads to the difficulty that even if the initial conditions are "completely" identified, the subsequent movement will modify the individual's variables due to the biological memory (Walker, 1972) of the movement system and, consequently, the outcome can no more be validated due to the irreversibility of biological systems. Moreover, a dynamic, time-dependent optimum would raise ample difficulties related to the target profile and the training athlete. In the first case, the difficulty is to decide which of the fluctuating patterns should serve as an orientation for training, and in the second case, the low probability of coherent fluctuations between the dynamic target profile and the athlete's fluctuating movement patterns will hardly allow to find a reliable intervention strategy. With regard to these issues, approaches that foster self-organized learning such as, for example, the differential learning approach (Schöllhorn, 2000), which take into account person-specific and timescale-dependent fluctuations and introduce variations without direct or indirect target profiles seem advantageous. The differential learning approach suggests increasing fluctuations in order to destabilize the movement system, thereby enabling self-organizing optimization processes (that do not require information about target profiles) (Schöllhorn et al., 2001). In this context, Schöllhorn et al. (2001) were able to find first indications of a greater extent of individualization in a group of juvenile sprinters after 6 months of training with increased fluctuations [according to the differential learning approach (Schöllhorn, 2000)] and without information about the ideal execution of movements, compared to a control group that trained according to a collective profile with error correction [according to the repetitive training approach (Jonath et al., 1995)].

The identified timescales also provide evidence of a continuously changing movement system that can be associated with the arrow of time. Apparently, athletes not only become accustomed to certain movements and, therefore, experience incremental learning over time, but also they can acclimate to a certain amount of fluctuations that blunt the sensitivity to the applied movement learning and training approach. In sports practice, it is speculated that, after a certain time of variable training, a period of repetitive training makes the movement system more sensitive to variable training again. In this context, special attention should be paid to the difference between finding an adequate description variable and assessing its impact on the training process by means of versatile types of interventions.

The amount of naturally occurring fluctuations during repetitive movements have already been considered for predicting the success of learning progress (Wu et al., 2014; Dhawale et al., 2017, 2019; Pacheco et al., 2020). Those fluctuations, however, are associated with a kind of passive dependence on the fluctuations momentarily produced by the athlete. Alternatively, the active application of subthreshold fluctuations at the foot soles led to improved posture performance (Collins et al., 1995; Priplata et al., 2002). Another type of active intervention that is based on the amplification of observed fluctuations according to the dynamic principles of systems provides promising results useful toward attaining a shortened training process (Schöllhorn, 1999) and boosting the potential for good sustainability after the intervention (Frank et al., 2008; Schöllhorn et al., 2009). How to take advantage of the passively occurring fluctuations to optimize the active fluctuations in the form of interventions demands more investigation.

In addition, the observed fluctuations in different timescales should lead us to reconsider the often-interpreted disadvantage of fatigue for movement learning. For example, the movement fluctuations that occur during the fatigue process in training could be used beneficially for movement learning. From a system dynamics view, fatigue could be considered as a type of fluctuation occurring across different timescales. With a growing focus on the individuality of movements and the sensitivity of training approaches, the situation of athletes engaged in profile-oriented sports training particularly is repeatedly disregarded and should experience an increased focus (Schöllhorn and Horst, 2019). Thereby, the detrimental effect of endurance-like training on the biomechanics of fast-contracting muscles may not be forgotten (Wilson et al., 2012).

Concerning the latent assumptions of acquisition of movement patterns, the individual, as well as the constantly fluctuating and shifting movement patterns, strongly tests the validity of the philosophy underlying repetitive sports training that is guided by collective profiles (Gaulhofer and Streicher, 1924; Anochin, 1935; Miller et al., 1960; Gentile, 1972). Theoretically, the orientation on target profiles *per se* could be detrimental for learning, regardless of whether the profiles are individual or collective. More differentiated intervention studies are required to decide whether the underlying training philosophy of collective (person-independent) profiles is deficient or whether the mostly accompanied repetitive learning approach is questionable. In the same context, whether training targeted toward an individually optimized profile will lead to individual movement patterns or at least will achieve those with less effort deserves attention. Having profiles in mind supports the disposition for comparison, which drags mental resources and increases the probability of frustration (Fillauer et al., 2020). As a consequence, this could suggest the need to move toward an alternative approach that is not oriented on set targets as in the closed-loop approach to learning (Adams, 1987) but instead fosters constant changes that support approaches originating from Far Eastern philosophy (Purser et al., 2016; Gallicchio and Ring, 2019) and which help one to be in the moment in order to achieve a brain state that is optimal for performing and learning (Henz and Schöllhorn, 2018). Being in the moment can be associated with the term situatedness as it is understood in pragmatism under contextuality (Dewey et al., 1982) or in phenomenology under situativity (Heidegger, 1927; Merleau-Ponty, 1945).

It can be expected that, with increasing the precision of measurement, tools for analysis of the unknown complexity (from a physics point of view) will be continuously decomposed and deployed in other regions or levels of interest. In combination with the knowledge about the sensitive dependence of a complex system's (from a physics point of view) development on its initial boundary conditions, we should be careful not to reawaken the Laplace demon and accumulate endless constraints. Considering the vast amount of possible variables of influence, reaching from historical and sociocultural up to physiological and genetic conditions as well as considering their interactions according to gravitational forces and epigenetics only provides a coarse impression in the undertaking to find key variables or key exercises that are independent of individuals and timescales as held out the prospect by movement learning approaches such as the constraints-led approach (Handford et al., 1997; Davids et al., 2004, 2008; Renshaw et al., 2019).

In consequence, on a rather biological level, the goal of training practices is to focus more on adaptation processes and consider the stabilization of movement patterns rather as a byproduct. Instead of discussing stability and flexibility colloquially as complementary opposites that the athlete and coach must balance (Hamill et al., 1999; Schöllhorn, 2000; Van Emmerik and Van Wegen, 2000; Schmidt and Lee, 2005; Bartlett et al., 2007; Glazier and Davids, 2009; Schöllhorn et al., 2009; Preatoni et al., 2013), a differentiated focus related to the description of a multitude of adaptation processes dependent on different timescales (Kelso et al., 1987; Newell et al., 2001) seems more adequate to the applied problems. An increased emphasis on timescale-dependent adaptation processes in training could also have a positive effect on competition practice. The assumption is likely that highly variable and varied training also improves adaptability in competition, whether it is quick adaptation to opponents, environmental conditions, or the compensation of fatigue through changes in movement patterns.

Limitations and Future Work

This study examined changes in the kinematic movement patterns of expert athletes who performed the karate front kick multiple times during a single training session under an accumulation of fatigue. Whether these results can be transferred to other whole-body movements requires further research. Due to the biomechanical basis of this study, the multiple underlying physiological or psychological fatigue processes can only be speculated about (Pyne and Martin, 2011; Halson, 2014). Whether the identified changes provoked by the accumulated fatigue are caused by muscular, neuronal, metabolism, or psychological mechanisms or—most probably—a mixture of everything on different timescales demands further research. However, alterations in metabolic parameters like the increased lactate and HR levels by the end of the training session indicate at least fatiguing processes occurred in all athletes. Even if the lactate values of a maximum median of almost 5 mmol $* \, l^{-1}$ are not excessively high, the HR and the RPE clearly showed that the training was carried out at a high level of intensity and that fatigue accumulated over time. An interesting problem to pursue thereby would be the possibility of an assignment or decomposition of the situative fluctuations of the movement patterns to different timescales to specific fatigue mechanisms.

An additional limitation is related to the kicks having been performed in the air. In training and competitive karate, two major forms are executed. One is the fight against a virtual opponent, called kata, and mainly consists of a series of prescribed defense and offense movements, whereas, in the second form, called kumite, a fight against a real opponent where selected hits are scored is performed. Because of the original intention to ensure high external validity with the kata form, no transfer to kicks toward an object that would be related to *kumite* could be made. Consistent with the research by Błaszczyszyn et al. (2019), it can be speculated that kicking against resistance has a considerable effect on muscle contractions, especially by the end of the movement. Further research is necessary to discern whether this also influences inter- and intra-personal differences in the fatigue-related temporal change of the karate front kick.

The present study also examined the joint angle waveforms, mainly of the lower extremities. Additional attention should be paid to discern to what extent the upper extremities also have an effect on the movement pattern recognition by experts and thus possibly improve the intra-individual recognition. However, based on the selected variables from lower extremities, similar to in gait studies (Schöllhorn et al., 2002; Janssen et al., 2008; Horst et al., 2016), clear individual movement patterns already could be found. Furthermore, it was also determined that these individual patterns change from tiring out during training. To what extent these individual movement patterns change over longer periods of tiring out during training, and the nature of possible drifts outside the individual solution spaces requires further research.

CONCLUSION

Based on the classification of kinematic joint angle waveforms of karate front kicks during a training session (accompanied by increased fatiguing), unique movement patterns can be identified for individual athletes. In this research, unique movement patterns of the study individuals could be identified persistently at different execution intensities (maximal and submaximal) and with increasing fatigue. Fatigue-induced changes in individual movement patterns of the athletes could be observed in the sense of disjunctive adjustments in kinematic patterns rather than an increase in variance. These fatigue-related changes occur on different timescales (i.e., blocks in tens of seconds vs. sets in tens of minutes). The findings raise the question of to what extent the targeting of sports training on profiles, no matter whether these are derived collectively or individually, is rather a theoretical consideration (search) than a practically achievable solution. The orientation of sports training toward adaptation processes and variable situations instead of achieving and automating profiles could be a promising alternative in this context.

DATA AVAILABILITY STATEMENT

The data supporting the conclusions of this article will be made available by the authors, without undue reservation, to any qualified researcher.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Ethics Committee of the Medical Association of Rhineland-Pfalz (Ethik-Kommission bei EK LÄK RLP) Deutschhausplatz 3 D-55116 Mainz Rheinland-Pfalz Germany. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

DA and WS designed the experiments. AE and DA recorded and preprocessed the data. JB, FH, and WS conceived the presented idea. JB and FH performed the data analysis and designed the figures. JB, FH, and WS wrote the manuscript. JB, FH, DA, AE, and WS reviewed and approved the final manuscript. All authors contributed to the article and approved the submitted version.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2020.551548/full#supplementary-material

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Adaptability in Swimming Pattern: How Propulsive Action Is Modified as a Function of Speed and Skill

Christophe Schnitzler[1]*, *Ludovic Seifert*[2] and *Chris Button*[3]

[1] Laboratory Equipe d'accueil en Sciences Sociales (E3S, UR1342), Faculté des Sciences du Sport, Université de Strasbourg, Strasbourg, France, [2] Cetaps EA3832, Faculty of Sport Sciences, University of Rouen, Normandie, France, [3] School of Physical Education, University of Otago, Dunedin, New Zealand

The objectives of this study were to identify how spatiotemporal, kinetic, and kinematic parameters could (i) characterize swimmers' adaptability to different swimming speeds and (ii) discriminate expertise level among swimmers. Twenty male participants, grouped into (a) low-, (b) medium-, and (c) high-expertise levels, swam at four different swim paces of 70, 80, 90% (for 20 s), and 100% (for 10 s) of their maximal speed in a swimming flume. We hypothesized that (i) to swim faster, swimmers increase both propulsion time and the overall force impulse during a swimming cycle; (ii) in the frequency domain, expert swimmers are able to maintain the relative contribution of the main harmonics to the overall force spectrum. We used three underwater video cameras to derive stroking parameters [stroke rate (SR), stroke length (SL), stroke index (SI)]. Force sensors placed on the hands were used to compute kinetic parameters, in conjunction with video data. Parametric statistics examined speed and expertise effects. Results showed that swimmers shared similarities across expertise levels to increase swim speed: SR, the percentage of time devoted to propulsion within a cycle, and the index of coordination (IdC) increased significantly. In contrast, the force impulse (I^+) generated by the hand during propulsion remained constant. Only the high-expertise group showed modification in the spectral content of its force distribution at high SR. Examination of stroking parameters showed that only high-expertise swimmers exhibited higher values of both SL and SI and that the low- and high-expertise groups exhibited similar IdC and even higher magnitude in I^+. In conclusion, all swimmers exhibit adaptable behavior to change swim pace when required. However, high-skilled swimming is characterized by broader functional adaptation in force parameters.

Keywords: motor control, expertise, force, coordination, spectral analysis, constraint-led approach

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Giuseppe Vannozzi,
Foro Italico University of Rome, Italy

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Matteo Cortesi,
University of Bologna, Italy
Andrew B. Slifkin,
Cleveland State University,
United States

***Correspondence:**
Christophe Schnitzler
cschnitzler@unistra.fr
orcid.org/0000-0002-3801-8789

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INTRODUCTION

Three main categories of constraints shape human movement behavior, namely, the task (which refers to the task goal), environmental (physical variables in which the behavior takes place), and organismic constraints (which refers to the person's characteristics) (Newell, 1986). When constraints change, behavior changes accordingly. This study seeks to identify how stroking and kinetic parameters could characterize swimmers' adaptability to four different swimming speeds but also discriminate swimming expertise. As stated by Newton's second law, for a body with a constant mass, the acceleration undergone by this body is proportional to the resultant of the forces and inversely proportional to its mass. In swimming, moving forward requires the generation of propulsive forces (F_{prop}). However, water is a dense material (800 times more than air), and moving an object in water generates in return a drag force (F_{drag}) proportional to its speed. In the case of human bodies, the relationship between F_{drag} and swim speed can be approximated according to Equation (1) (Toussaint and Truijens, 2005).

$$F_{drag} \sim \mathrm{k{\cdot}S{\cdot}V}^{1.8-2.2} \tag{1}$$

where k is coefficient related to body shape; S, surface presented toward direction of travel in m²; V, speed in m s^{-1}.

When swimming at a constant speed, Equation 2 applies, according to Newton first law:

$$F_{prop} = F_{drag} \tag{2}$$

The implication is that when swimming fast, F_{drag} is high, and F_{prop} has to be scaled up accordingly.

Within the swim cycle, speed fluctuations occur (Schnitzler et al., 2010, 2011b; Barbosa et al., 2013), as F_{prop} is generated by arms and legs, which act at different moments within the swim cycle. In front crawl, the total propulsive time during one complete cycle is composed of two propulsive phases performed by the arms (one per arm, subdivided into pull-and-push phase), with time gap, continuity or superposition between those propulsive actions, and multiple leg beat kicks (typically two to six) (Chollet et al., 2000). Each of these propellers generates force over a short duration within the cycle, called propulsive impulses. Mathematically, an impulse represents the time integral of the resultant force acting on a body (Robertson et al., 2014). According to Alberty et al. (2009) over a swim cycle, the force impulse, I^{+} (N · s), is the integral over time of the total force production (Equation 3).

$$I^{+} = \int_{t2}^{t1} F\left(t\right) dt \tag{3}$$

with dt corresponding to the propulsive time duration.

Considering propulsive impulse only, Equation 4 applies

$$I^{+} = n{\times}(I^{+/}{}_{\mathrm{rightarm}} + I^{+/}{}_{\mathrm{leftarm}} + I^{+/}{}_{\mathrm{rightleg}} + I^{+/}{}_{\mathrm{leftleg}}) \tag{4}$$

n: number of cycles during the period considered

$I^{+/}_{\mathrm{rightarm}} + I^{+/}_{\mathrm{leftarm}} + I^{+/}_{\mathrm{rightleg}} + I^{+/}_{\mathrm{leftleg}}$: discrete impulses from arms (right and left) and legs (right and left) during a swim cycle.

Over this period of n cycles of period T, Equation 5 defines average force

$$F_{av} = \sum\nolimits_{i=1}^{n} I(i)\ + /\mathrm{T} \tag{5}$$

where F_{av} is average force; $I(i)+$ is force impulse over the ith swim cycle; T is duration of a swim cycle.

But only part of the force in Equation 5 generates propulsion. Studies analyzing fluid dynamics showed that part of this force provides kinetic energy to the water (Kudo et al., 2013). Hence, Toussaint et al. (1990) proposed to separate the total power output P_{tot} into two components: the power to overcome drag (P_d), and the power wasted in giving a kinetic energy change to the water (P_k), according to Equation (6).

$$\mathrm{P_{tot}} = P_d + P_k \tag{6}$$

As power is a linear combination of force and speed, Equation 7 also applies:

$$F_{av} = F_d + F_k \tag{7}$$

where F_{av} is the average force exerted by the swimmer, F_d is force to overcome drag, and F_k is force wasted in translating kinetic energy to move the water.

Should a swimmer need to increase his/her pace, this will impact upon the required force production as mechanical power output increases with pace (Toussaint and Truijens, 2005; Seifert et al., 2011). In that, when swimming at a faster pace, F_d and F_{av} have to be scaled accordingly. According to Robertson et al. (2014), there are four ways of making such adaptations: (a) by increasing the amplitude of the individual force impulses, (b) by increasing the duration of individual force impulses, (c) by increasing both amplitude and duration, and (d) by increasing the frequency of the individual impulses.

Both task (i.e., to swim as fast as possible over a fixed distance) and environmental constraints (i.e., the drag directly linked to the associated swim speed) influence swim adaptation. However, task and environmental constraints are only part of the explanation when studying swimmers' behavior, as different levels of adaptability can be observed. Adaptability relates to a subtle blend between stability (i.e., persistent behavior) and flexibility (i.e., variable behavior) (Seifert et al., 2014). Adaptability is a key feature of dexterity (Bernstein, 1996), which can be defined as the expertise to reach the goal of a task correctly, quickly, rationally, efficiently, and with resourcefulness. In competitive swimming, adaptability refers to the ability to modify the coordination to swim efficiently at different paces (Simbaña-Escobar et al., 2018). Highly skilled swimmers exhibit high stroke length (SL) and stroke index (SI), with both parameters linked to swimming efficiency (Costill et al., 1985; Toussaint and Truijens, 2005). To examine swimmers' adaptability, scanning tasks in which swim speed is incremented are often proposed (for example: Schnitzler et al., 2010, 2011a; Seifert et al., 2011; de Jesus et al., 2016). The literature reveals that this adaptability may occur at different levels, as both intralimb and interlimb coordinations are affected (Guignard et al., 2020). Intralimb coordination also varies as a function of swim condition, which in return affects temporal parameters of the stroke (Aujouannet et al., 2006). When swim pace increases, the relative time (in percentage) devoted to propulsion (PrP%) typically follows the same trend in proportion to the total duration of the cycle (Chollet et al., 2000; Seifert et al., 2004; Schnitzler et al., 2011a). The trajectory of the hand is also impacted, as lateral–medial trajectory of the hand seems to lose amplitude with speed (de Jesus et al., 2016), the acceleration pattern is modified (Samson et al., 2015b), and the time lag between two propulsive times from the arms [measured with the index of coordination (IdC); Chollet et al., 2000] diminishes significantly. In expert swimmers, these adaptations are employed to maintain swim efficiency constant across swim speed repertoire (Schnitzler et al., 2010; Seifert et al., 2011, 2013; de Jesus et al., 2016). Therefore, it appears that understanding and analyzing expertise in swimming require the comprehension of factors related to propulsive force generation and drag force minimization. In that regard, coordination and propulsion parameters are of particular interest (Costill, 1992).

The rapid development of theoretical research and swim technology (sensors and other portable devices) in recent years helped to get a more in-depth comprehension of swimmers' behavior, as it might potentially capture more data than what is usually done by motion capture systems. Stroking parameters were first examined (Craig et al., 1979, 1985), in parallel with propulsive kinetic parameters (Goldfuss and Arnold, 1971; Yeater et al., 1981). A method to calculate hand force produced in the water using force sensors was validated by Takagi and Wilson (1999) and subsequently improved (Kudo et al., 2013). The advantage of such empirical data over a model-based photometric method is the capacity to directly measure the complex unsteady fluid phenomena occurring during sculling without reconstruction from a putative model (Kudo et al., 2013; Takagi et al., 2014). However, testing took place on an artificial hand, and not in an ecological context (van Houwelingen et al., 2017). Last, all studies analyzing kinetic parameters (e.g., Schleihauf et al., 1983; Takagi and Wilson, 1999; Kudo et al., 2008; Schnitzler et al., 2011a; Seifert et al., 2011; Barbosa et al., 2013; Gourgoulis et al., 2015) focused on the analysis of the time domain (e.g., mean force, peak forces, standard deviation). In contrast, some experimental studies showed that the analysis of force in the frequency domain holds value in explaining the underlying motor control (Slifkin and Newell, 1998, 1999, 2000). Evidence suggests that systems that display more complexity are usually more adaptive to perturbations. This complexity can be assessed through different means; however, measurement of time–series structures of force signal has been widely used (Slifkin and Newell, 1998, 2000; Slifkin et al., 2000; Vaillancourt et al., 2001; Lipsitz, 2002). These authors showed that when these time–series structure changes from periodic/regular to more complex/random, there are related improvements in the quality of system performance. This was evidenced both in a case of a laboratory task (Slifkin and Newell, 1998, 2000; Slifkin et al., 2000) and in the context of system health (e.g., Vaillancourt et al., 2001; Lipsitz, 2002). The increases in time–series complexity are thought to reflect increased system degrees of freedom that allow for greater flexibility in adaptation to system perturbations or to task constraints. One way of assessing time–series complexity is through spectral analysis. A flatter and broader power spectrum (tending toward white noise) reflects increased time–series complexity. In that, examining the breadth of the force spectrum and its evolution at different paces might help to determine whether expert swimmers display more functional adaptability than less capable swimmers.

However, the impact of swim pace and expertise on force development in the frequency domain remains uninvestigated.

To summarize, when modifying swimming pace, adaptations of stroking and kinetic parameters are expected. This can be achieved by increasing stroke rate (SR) and/or SL, or any combination of these parameters (Craig and Pendergast, 1979; Seifert et al., 2004; Huot-Marchand et al., 2005; Potdevin et al., 2006). Finer motor adaptation may also occur, through coordination changes and/or changes in force production, adaptations that may vary according to the level of expertise. We aim to examine swimmer's adaptation to four different swim paces by simultaneously analyzing, stroking, coordination, and kinetic parameters in ecological conditions as a function of three expertise levels. We hypothesized that (i) to swim faster, front crawl swimmers increase both propulsion time and the overall force impulse during a swimming cycle; and (ii) in the frequency domain, expert swimmers are able to maintain the relative contribution of the main harmonics to the overall force spectrum.

MATERIALS AND METHODS

Participants

A convenience sample of 20 male swimmers participated in the present study. We subdivided this group into three distinct categories: low, medium, and high level of expertise, as a function of the percentage of world record in 100 m, they individually reached maximal speed during the test (**Table 1**). Before the experiment, a brief interview with each swimmer verified the absence of injuries and diseases. We also checked if they were able to swim front crawl. We obtained written informed consent from participants and (where necessary) their parents before testing began. We informed participants of all risks, sources of discomfort, and benefits involved in the study. Procedures were in accordance with the Helsinki Declaration of 1975, and the study was approved in advance by the participating institution's Human Ethics Committee (reference no. 06/190).

Data Collection

Calculation of v_{max} and Subvelocities

The swim trials took place in a motorized aquatic flume in a temperature- and humidity-controlled laboratory environment. All testing was conducted between 8 and 11 A.M. on weekdays, and participants were instructed to rest the day before and not to change their dietary, hydration, or sleep habits prior to the experiment. All participants were informed they had to complete the trial in front crawl. They performed a standardized 20-min warm-up provided by a coach in the flume before the experiment, which also served as a familiarization period. Prior to the experiment, their maximal swim speed (v_{max}) in the flume was determined. The water flow was set at a velocity between 0.5, 1.0, and 1.2 m s^{-1} (for low, medium, and high skill level, respectively), and participants were asked to swim as fast as possible over a distance of 5 m. Subsequent swim speed $v5$ was calculated according to Equation (9).

$$v5 = 5/t \tag{8}$$

where $v5$ is the velocity over 5 m relative to the mark on the floor, and t is the time to complete 5 m in the flume. To calculate

TABLE 1 | Main characteristics of the participants.

Expertise level	Training/wk (h)	Age (y)	Weight (kg)	Height (cm)	BMI (kg/m^2)	Hand surface area (cm^2)	Maximal speed (m · s^{-1})	% of world record speed (100 m)
Low ($n = 6$)	0.5	32.5 ± 4.0	72.5 ± 13.6	174.2 ± 7.0	23.8 ± 3.3	165 ± 25	1.24 ± 0.05	45.4 ± 3.7
Medium ($n = 6$)	4	27.0 ± 7.5	71.5 ± 9.2	178.2 ± 8.4	22.4 ± 1.4	172 ± 16	1.54 ± 0.1	69.3 ± 4.9
High ($n = 8$)	14	18.7 ± 2.9	71.0 ± 4.0	177.6 ± 6.1	22.5 ± 1.8	159 ± 14	1.82 ± 0.05	82.5 ± 2.6

TABLE 2 | Individual values for maximum swim velocities.

Subject n°	Expertise	V_{flow}	T_{5m}	V_{max}
1	High	1.2	7.1	1.90
2	High	1.2	8.2	1.81
3	High	1.2	8.2	1.81
4	High	1.2	8.2	1.81
5	High	1.2	8.3	1.80
6	High	1.2	8.3	1.80
7	High	1.2	8.3	1.80
8	High	1.2	10	1.70
9	Medium	1	8.2	1.61
10	Medium	1	8.2	1.61
11	Medium	1	8.3	1.60
12	Medium	1	10	1.50
13	Medium	1	10.4	1.48
14	Medium	1	11.6	1.43
15	Low	0.5	6.4	1.28
16	Low	0.5	6.4	1.28
17	Low	0.5	7.1	1.20
18	Low	0.5	7.1	1.20
19	Low	0.5	7.7	1.15
20	Low	0.5	7.7	1.15

individual maximal swim speed, $v5$ was added to flume's water speed flow according to Equation (8):

$$v_{max} = v_{flow} + v5 \tag{9}$$

where $v_{\max}$ is the maximal swim speed, v_{flow} is the water flow speed, and $v5$ is the speed over 5 m relative to the floor. Last, after 20-m rest, the flume was set at the calculated speed, and the participants were instructed to stay above a mark at the bottom of the flume as long as possible. The speed was considered maximal if participant could maintain their position between 10 and 15 s with the head above the mark at the bottom of the flume. The individual results are displayed in **Table 2**.

Four individual-specific speeds relative to $v_{\max}$ (or paces) were determined: pace 1 (70%), pace 2 (80%), pace 3 (90%), and pace 4 (100% of $v_{\max}$). For paces 1–3, we instructed the swimmers to stay within a delimited zone of 3 m at least 20 s to ensure that they kept following the pace. This duration was reduced to 10 s for pace 4 due to fatigue. To minimize fatigue effects, participants had at least 20-min rest between the determination of $v_{\max}$ and second part of testing. During this second part, a minimum of 4 min of rest was imposed between paces.

Before each swim bout, the water flow was set at the required speed. The swimmer was then instructed to hold onto a support rope in a streamline position at the center of the flume. The start position was standardized when the swimmer's head was aligned above a mark at the bottom of the flume. The swimmer was considered unable to follow the pace once his head passed a second mark placed 1.5 m behind the first mark. Once the data were collected, the swimmer could then either hold to a rope or go to the side to catch a rail. If any sign of weakness was observed (i.e., difficulty to maintain the pace, swimmer passing the second mark), the experimenter immediately stopped the flume. For security purposes, safety nets were placed 3 m behind the swimmers' feet, which would prevent a collision with the flume vanes behind the swimmer. However, this problem did not occur during our experimentation.

Three underwater 50-Hz digital video cameras were positioned around the flume from two front angles (45° left and right of the swimmer) and a right profile view. The videos and the force signal were synchronized at 50 Hz with the force signal using a digital control unit. More precisely, just before data collection, we pressed a button within the digital control unit that set a trigger that was visible in both signals (i.e., a spike in the force signal, a mark on all videos). Using this signal, we synchronized force and video signal at 50 Hz using Simi© motion reality system (Unterschleissheim, Germany) software. From the video, it was therefore easy to distinguish, within the force signal, the portion corresponding to the recovery phase and the portion corresponding to entry, catch, pull, and push phases with an accuracy of 0.02 s.

We used these synchronized videos to quantify SR and SL. We calculated each variable based on three complete representative swim strokes. The SL (in m · cycle^{-1}) and SI [(m² · (s · cycle)$^{-1}$] were derived from the mean speed (v, in m s^{-1}) and the movement frequency value (SR, expressed in Hz). We used Equations 11 and 12 to calculate SL and SI:

$$\text{SL} = v \times \text{SR}^{-1} \tag{11}$$

$$\text{SI} = \text{SL} \times v \tag{12}$$

Coordination Parameters

The mean duration of a complete stroke was the sum of the propulsive and non-propulsive phases. We derived the IdC as the time gap between the propulsion of the two arms as a percentage of the duration of the complete arm stroke cycle.

We divided arm stroke into four distinct phases:

Phase A: Entry and catch of the hand in the water, which corresponds to the time between the entry of the hand into the water and the beginning of its backward movement and by a sudden increase in the force developed within the water.

Phase B: Pull phase, which corresponds to the time between the end of phase A and its entry into the plane vertical to the shoulder.

Phase C: Push phase, which corresponds to the time between the end of phase B and the exit of the hand from the water or a null value obtained on the force graph.

Phase D: Recovery phase, which corresponds to the end of phase C and the entry of the hand into the water.

The total duration of these stroke phases was measured by two independent operators with a blind technique for each arm over three complete stroke cycles per pace with a precision of 0.02 s and expressed as a percentage of the duration of a complete arm stroke.

IdC was the mean of IdC_{left} and IdC_{right} (Equations 13 and 14):

$$IdC_{left} = \left[(Time_{\text{end of phase C for left}-\text{arm}} - Time_{\text{beginning of phase B for right}-\text{arm}}) \times 100\right] / duration_{\text{complete cycle}} \quad (13)$$

$$IdC_{right} = \left[(Time_{\text{end of phase c right}-\text{arm}}\ Time_{\text{beginning of phase b for left}-\text{arm}}) \times 100\right] / Duration_{\text{complete cycle}} \quad (14)$$

The total propulsive phase duration was calculated as the addition of pull-and-push phase duration (in seconds) and also expressed in relative (PrP%) duration, as a percentage of the cycle's time. For each pace, three cycles were analyzed per swim trial, which corresponded with the cycles taken to determine stroke (SR, SL) and coordination (IdC, propulsive phase) parameters.

Kinetic Parameters

The methodology used to determine kinetic parameters follows the methods from Takagi and Wilson (1999). On the swimmers' preferential hand, we glued four pairs of monoaxial pressure sensors (Kyowa, Tokyo, Japan, see **Figure 1**) to the surface of a glove on both the palmer and dorsal sides of metacarpophalangeal II, III, IV, and V. The load cell can transduce oscillations of frequencies over a range from 0 to 1,000 Hz. Force applied to the load cell resulted in changes in the electrical resistance of strain gauges housed in the load cell. The sensors were connected via a series of wires to a 12-entry amplifier, connected itself to a computer to record the force data, and calibrated in the water. We measured forces in units of 0.001 N (0.1 g). The sensors were paired by metacarpus; for example, the sensor of the palmer side of metacarpus II (PMII) was paired with metacarpus II of the dorsal side (DMII), as shown in **Figure 1**.

The hand plane area was measured. Each swimmer had their palmar face of the hand scanned, thumb adducted, and fingers fully extended and packed together. Then, we computed this area using Mesurim 3.3 software.

We measured pressure differential (P_A) so that in the absence of movement: P_A = PMII – DMII = 0. We calculated this difference in pressure for metacarpus III (P_B), metacarpus IV (P_C), and metacarpus V (P_D). After this first calibration of the sensor pairs in water, we were able to obtain the mean moving pressure using the Equation 15 (Takagi and Wilson, 1999).

$$P_{mean} = 0.045P_A + 0.186\,P_B + 0.554\,P_C + 0.013\,P_D + 7.558 \quad (15)$$

The obtained value was then multiplied by the hand plane area previously determined (m^2) to calculate the resultant propulsive peak-medium force.

Because of technical limitations, we could only measure the force developed by one hand using Equation 15. In order to standardize conditions, the dominant hand of each subject was chosen for the collection of kinetic data. We analyzed force output over six consecutive swim cycles in both time and frequency domains, which are two complementary methods to examine kinetic parameters (Prandoni and Vetterli, 2008). In the

FIGURE 1 | Locations of the force sensors over the hand.

time domain, and with the help of the swim phases determined with the video analysis, we computed the force impulse during propulsive phases per cycle, which captures the magnitude of the fluctuations. In the frequency domain, we made a spectral analysis using fast Fourier transforms (FFTs), which measure the structure of the variability (Slifkin and Newell, 1999).

We superimposed both force and video signals on a single graphical user interface to calculate force impulse, at the frequency of 50 Hz. We reconstructed the force signal to only take into consideration the force developed during propulsive time (pull-and-push phases) to calculate the propulsive impulse (I^+). We used the force graph to measure peak pull and peak push force. **Figure 2** shows an example of two force curves and the correspondence with the swim phases (determined by video, not shown in this figure for the sake of clarity).

To minimize the error in calculating kinetic parameters, we examined a period of 6 cycles as a whole (Payton and Bartlett, 1995). We used a MATLAB signal processing toolbox (MATLAB 16, MathWorks, Natick, MA) routine to perform an FFT. The power spectrum of each trial was divided into 50 equal bins, ranging from 0 to 10 Hz. On all curves, we manually identified three main peaks. Each of them represents a specific source of variation within the force signal. The power in each of these three specific frequencies bin (Y1, Y2, and Y3) represented the portion of total power in the overall amplitude of force output oscillation that could be attributed to the frequency specified by each bin. Y1 was the fundamental frequency and typically occurred in a 0–3.33-Hz range. Y2 was the second in magnitude and occurred in 3.34–6.66-Hz range. Y3 was the smallest in magnitude and occurred in the 6.67–10-Hz range. To provide a measure of the spread of power in the power spectrum, we divided the peak power by the total power in the power spectrum. Therefore, we calculated the ratio between each specific frequency and the total power (obtained by numerical integration of the power spectrum curve) to examine the modification of force output according to pace [see Slifkin and Newell (1999)].

We used means and standard deviations to summarize the dependent variables as a function of expertise level. The assumed Gaussian distribution of the data was verified by the Shapiro-Wilk test and the homogeneity of variance using Bartlett test. Mixed-design analysis of variance (ANOVA) subject [repeated measure] × 4 pace levels [70, 80, 90, and 100% of $v_{\max}$] × 3 expertise levels [low, medium, high] compared the mean values for each variable. Tukey *post-hoc* tests were run to detect significant differences between pairs of condition means. Partial η^2 and its 95% confidence interval were used to estimate effect sizes. We set the threshold for significance at the 0.05 level of confidence. We used R software (R core team, 2017) for the statistical analysis.

RESULTS

The results of the three-way ANOVAs for different variables are arranged in **Table 3** (stroking parameters), **Table 4** (coordination parameters), and **Table 5** (kinetic parameters). To swim faster, all participants increased the SR and the SI (**Table 3**). At pace 2 (e.g., 80% of v_{max}), only high-level swimmers were able to increase SR and SL simultaneously. High-level swimmers were able to maintain both high SR and SL, whereas a medium-level swimmer had a higher SL.

When increasing swim pace, participants decreased the catch phase and increased pull phase duration, which increases propulsive phase duration in percentage and, subsequently, the IdC. Low-level swimmers had significantly longer propulsive phase duration (both in absolute and relative duration) and higher IdC, as compared to high- and medium-level swimmers. Across paces, catch phase (A) decreased significantly, whereas pull phase (B) increased significantly. Medium-level swimmers displayed significantly higher values for catch phase (A) and lower values for pull phase (B) as compared to both high and low levels. Finally, high-level swimmers presented significantly

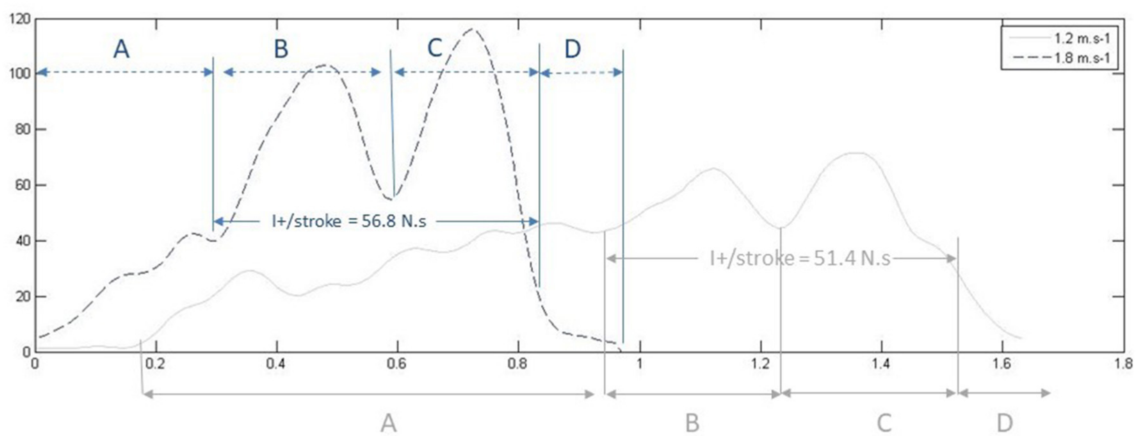

FIGURE 2 | Example force time series from a national level swimmer at two different paces (V1 = 1.2 m.s^{-1}, 70% vs. V4 = 1.8 m.s^{-1}, 100%), and the corresponding duration of the swim phases for each pace. The graph illustrates how two cycles can have comparable overall impulses (I^+/stroke) whereas Fpull and Fpush are of higher magnitude at V4 compared to V1.

TABLE 3 | Stroking parameters according to pace and expertise level.

Level	Pace	Speed (m · s^{-1})	Stroke index [m^2 · (s · cycle)$^{-1}$]	Stroke rate (cycle · min^{-1})	Stroke length (m · cycle^{-1})
High	1	$1.29 \pm 0.01^{b,c,d}$	2.81 ± 0.16^{d}	$35.75 \pm 2.24^{c,d}$	2.18 ± 0.13
High	2	$1.42 \pm 0.04^{a,c,d}$	3.14 ± 0.10	$38.30 \pm 2.91^{c,d}$	2.22 ± 0.11
High	3	$1.59 \pm 0.09^{a,b,d}$	3.40 ± 0.45	$44.70 \pm 2.35^{a,b}$	2.14 ± 0.18
High	4	$1.80 \pm 0.05^{a,b,c}$	3.60 ± 0.26^{a}	$54.09 \pm 3.99^{a,b}$	2.00 ± 0.13
Medium	1	$1.02 \pm 0.18^{b,c,d}$	2.16 ± 0.47^{d}	29.93 ± 7.62^{d}	2.11 ± 0.34
Medium	2	$1.2 \pm 0.11^{a,c,d}$	2.60 ± 0.48	34.15 ± 7.30	2.17 ± 0.37
Medium	3	$1.33 \pm 0.07^{a,b,d}$	2.86 ± 0.54	38.55 ± 8.46	2.15 ± 0.43
Medium	4	$1.53 \pm 0.07^{b,c,d}$	3.11 ± 0.47^{a}	46.05 ± 6.16^{a}	2.03 ± 0.28
Low	1	$0.75 \pm 0.08^{b,c,d}$	1.13 ± 0.29^{d}	30.63 ± 3.58^{d}	1.49 ± 0.26
Low	2	$0.91 \pm 0.08^{a,c,d}$	1.41 ± 0.31	36.23 ± 5.44^{d}	1.54 ± 0.27
Low	3	$1.01 \pm 0.07^{a,b,d}$	1.62 ± 0.32	38.64 ± 4.74	1.59 ± 0.24
Low	4	$1.21 \pm 0.06^{b,c,d}$	1.94 ± 0.29^{a}	$45.90 \pm 6.05^{a,b}$	1.61 ± 0.22
Pace effect		* $F_{(3, 68)} = 27.39$ $p < 0.001$, $\eta p^2 = 0.52$ CI [0.36–0.60]	* $F_{(3, 68)} = 7.09$ $p < 0.01$, $\eta p^2 = 0.20$ CI [0.07–0.32]	* $F_{(3, 68)} = 34.36$ $p < 0.001$, $\eta p^2 = 0.06$ CI [0.43–0.65]	NS $F_{(3, 68)} = 0.64$ $p = 0.6$, $\eta p^2 = 0.01$ CI [0.00–0.07]
Expertise effect		⊙ 1, 2, 3 $F_{(2, 68)} = 37.04$ $p < 0.001$, $\eta p^2 = 0.50$ CI [0.34–0.58]	⊙ 1, 2, 3 $F_{(2, 68)} = 33.98$ $p < 0.001$, $\eta p^2 = 0.48$ CI [0.31–0.56]	⊙ 1, 2 $F_{(2, 68)} = 7.3$ $p < 0.001$, $\eta p^2 = 0.15$ CI [0.04–0.26]	⊙ 2, 3 $F_{(2, 68)} = 19.94$ $p < 0.001$, $\eta p^2 = 0.34$ CI [0.18–0.45]
Pace × expertise		NS $F_{(6, 68)} = 0.09$ $p = 0.99$, $\eta p^2 = 0.00$ CI [0.00–0.09]	NS $F_{(6, 68)} = 0.12$ $p = 0.99$, $\eta p^2 = 0.07$ CI [0.00–0.001]	NS $F_{(6, 68)} = 0.35$ $p = 0.90$, $\eta p^2 = 0.05$ CI [0.00–0.04]	NS $F_{(6, 68)} = 0.36$ $p = 0.90$, $\eta p^2 = 0.05$ CI [0.00–0.04]

⊙significant difference between 1 (high and medium), 2 (high and low), and 3 (medium and low).
**significant difference among paces.*
Within expertise level, significant difference with a: pace 1, b: pace 2, c: pace 3, d: pace 4.
NS, non-significant difference.

higher values for pull phase (C) as compared to both medium and low levels.

To swim at faster speeds, participants tend to increase pull and push peak force, whereas the second harmonic of the force signal decreases significantly. High- and medium-level swimmers both exhibit higher values in these second (Y2) and third (Y3) harmonics, and also lower force impulse throughout the trial as compared to low level of swimmers.

DISCUSSION

Based on Newell (1986) constraint-led approach, the objective of this study was to provide a systemic view of how swimmers adapt to water flow (environmental constraints) in front crawl (task constraint) as a function of expertise (an organismic constraint). The results show that to swim faster, participants increase SR, IdC, propulsive phase duration, and force peak and modify the second harmonic of the force signal in the power spectrum. Higher SI and SL characterize high-level swimmers, whereas high-frequency contributions of the force signal were not shown by the low-level swimmers.

To swim at different swim paces, swimmers modify stroking parameters. The SI, in particular, increases significantly in all expertise levels across pace. As swim speed is the product of SR and SL, this modification is mainly explained by an increase in SR, whereas SL does not change significantly. Hence, swim speed is mainly controlled by modifying the SR, in accordance with past studies (Craig and Pendergast, 1979; de Jesus et al., 2016). However, coordination parameters show other adjustments occur as pace increases, as IdC and PrP% significantly increase over pace. These results are consistent with the current literature dealing with stroking and coordination parameters: when swim pace goes from low to high speed, there is a significant increase in PrP% and IdC toward a "superposition" mode, as catch phase (A) decreases, while pull phase (B) increases (Chollet et al., 2000; Seifert et al., 2004, 2011; Schnitzler et al., 2011a). According to Samson et al. (2015b), this modification in catch phase relative duration is bound to ensure the optimal horizontal balance of the body: at a low swimming speed, the hand stretches horizontally, and the resulting streamlining not only produces minimum energy expenditure and drag, but also optimizes the propulsive action of the opposite arm, whereas at high speed, the drag force generated during catch phase is higher but shorter, allowing high propulsive forces to be developed during the subsequent phases. In line with previous findings (Chollet et al., 2000; Seifert et al., 2004, 2011; Schnitzler et al., 2011a), these results show that swimmers of all levels were mostly flexible as they increased their IdC to increase their speed. Seifert et al. (2011) demonstrated that

TABLE 4 | Coordination parameters according to pace and expertise level.

Expertise level	Pace	Propulsive phase duration (s)	IdC (%)	Propulsive phase duration (%)	A (%)	B (%)	C (%)	D (%)
High	1	0.83 ± 0.11	−3.4 ± 3.2[d]	48.7 ± 5.0[d]	29.1 ± 6.8[d]	25.3 ± 3.3[d]	23.4 ± 5.0	22.2 ± 2.3
High	2	0.76 ± 0.07	−2.3 ± 4.1	47.6 ± 3.6	27.8 ± 7.0	24.9 ± 3.0	22.7 ± ± 3.9	24.6 ± 4.2
High	3	0.63 ± 0.05[a]	−1.6 ± 3.2	47.3 ± 2.3	28.6 ± 3.6	25.9 ± 1.9	21.8 ± 1.6	23.7 ± 2.6
High	4	0.61 ± 0.12[a]	6.4 ± 5.6[a]	56.7 ± 6.9[a]	21.1 ± 7.1[a]	30.3 ± 5.5[a]	26.4 ± 3.8	22.2 ± 3.1
Medium	1	0.87 ± 0.19	−8.1 ± 3.8[d]	41.8 ± ± 3.5[d]	38.8 ± 4.1[d]	18.5 ± 3.8[d]	22.3 ± 3.8	20.4 ± 3.1
Medium	2	0.77 ± 0.12	−6.9 ± 5.4	42.8 ± 3.8	36.4 ± 4.8	20.4 ± 4.1	22.3 ± 2.4	20.8 ± 2.2
Medium	3	0.70 ± 0.12[a]	−5.2 ± 3.5	44.3 ± 3.8	33.9 ± 6.0	21.6 ± 2.9	22.6 ± 2.6	21.8 ± 2.9
Medium	4	0.60 ± 0.06[a]	−2.5 ± 4.5[a]	48.4 ± 6.5[a]	28.3 ± 9.6[a]	24.4 ± 4.9[a]	24.0 ± 2.6	23.3 ± 3.8
Low	1	0.98 ± 0.17	1.2 ± 6.4[d]	49.9 ± 6.4[d]	27.3 ± 8.5[d]	23.4 ± 2.8[d]	26.4 ± 4.3	22.8 ± 3.9
Low	2	0.88 ± 0.17	3.2 ± 7.5	51.6 ± 6.8	25.3 ± 8.7	25.1 ± 4.3	26.5 ± 3.6	23.1 ± 3.1
Low	3	0.80 ± 0.13	4.2 ± 9.2	52.8 ± 10.0	22.9 ± 10.7	26.6 ± 4.9	26.2 ± 6.1	24.3 ± 2.1
Low	4	0.76 ± 0.13	7.5 ± 7.0[a]	57.3 ± 7.6[a]	18.8 ± 6.2[a]	30.0 ± 5.0[a]	27.4 ± 3.5	23.8 ± 2.6
Pace effect		* $F_{(3, 68)} = 6.95$ $p < 0.001$, $\eta p^2 = 0.23$ CI [0.07–0.31]	* $F_{(3, 68)} = 6.60$ $p < 0.001$, $\eta p^2 = 0.22$ CI [0.06–0.31]	* $F_{(3, 68)} = 6.95$ $p < 0.001$, $\eta p^2 = 0.23$ CI [0.7–0.31]	* $F_{(3, 68)} = 5.69$ $p < 0.001$, $\eta p^2 = 0.20$ CI [0.04–0.28]	* $F_{(3, 68)} = 7.75$ $p < 0.001$, $\eta p^2 = 0.25$ CI [0.08–0.33]	NS $F_{(3, 68)} = 1.53$ $p > 0.2$, $\eta p^2 = 0.06$ CI [0.0–0.12]	NS $F_{(3, 68)} = 0.79$ $p > 0.5$ $\eta p^2 = 0.03$ CI [0.0–0.09]
Expertise effect		⊙ 2, 3 $F_{(2, 68)} = 37.04$ $p < 0.001$, $\eta p^2 = 0.52$ CI [0.34 0.58]	⊙ 1, 2, 3 $F_{(2, 68)} = 19.03$ $p < 0.001$, $\eta p^2 = 0.35$ CI [0.18–0.44]	⊙ 1, 3 $F_{(2, 68)} = 37.04$ $p < 0.001$, $\eta p^2 = 0.52$ CI [0.34–0.58]	⊙ 1, 3 $F_{(2, 68)} = 13.88$ $p < 0.001$, $\eta p^2 = 0.28$ CI [0.12–0.37]	⊙ 1, 3 $F_{(2, 68)} = 13.49$ $p < 0.001$, $\eta p^2 = 0.28$ CI [0.11–0.37]	⊙ 2, 3 $F_{(2, 68)} = 6.63$ $p < 0.01$, $\eta p^2 = 0.16$ CI [0.03–0.25]	NS $F_{(2, 68)} = 2.5$ $p < 0.09$, $\eta p^2 = 0.06$ CI [0.0–0.14]
Pace × Expertise		NS $F_{(6, 68)} = 0.37$ $p = 0.99$, $\eta p^2 = 0.03$ CI [0.00 0.04]	NS $F_{(6, 68)} = 0.42$ $p = 0.86$, $\eta p^2 = 0.03$ CI [0.00–0.04]	NS $F_{(6, 68)} = 0.37$ $p = 0.99$, $\eta p^2 = 0.03$ CI [0.00–0.04]	NS $F_{(6, 68)} = 0.15$ $p = 0.98$, $\eta p^2 = 0.01$ CI [0.00–0.01]	NS $F_{(6, 68)} = 0.20$ $p = 0.98$, $\eta p^2 = 0.01$ CI [0.00–0.01]	NS $F_{(6, 68)} = 0.34$ $p < 0.91$ $\eta p^2 = 0.02$ CI [0.00–0.04]	NS $F_{(6, 68)} = 0.78$ $p < 0.59$, $\eta p^2 = 0.00$ CI [0.00–0.09]

**Significant difference among paces.*
⊙Significant difference between 1 (high and medium level), 2 (high and low level), and 3 (medium and low level).
Within expertise level, significant difference with a: pace 1, b: pace 2, c: pace 3, d: pace 4.

stroke cycle changes in arm coordination are linked to variations in aquatic resistance, as more overlapping of the two propulsion phases enables the swimmer to achieve higher swimming speeds.

Interestingly, this study also shows how these speed adaptations differ among expertise levels. In what concerns stroking parameters, SL and SI magnitudes are closely associated with expertise level, revealing underlying differences in swim efficiency (Costill et al., 1985; Craig et al., 1985; Toussaint, 1990; Seifert et al., 2011). These differences across expertise levels were mainly due to longer A and shorter B phase relative duration in medium-level swimmers. Consequently, the IdC values had a U-shaped relationship, with low- and high-level swimmers displaying higher values than average. Indeed, Dadashi et al. (2016) showed that IdC magnitude only predicts swimming performance in homogeneous expertise groups. The present data show that low-level swimmers start their propulsion early by shortening the catch phase, which might result in a less efficient positioning of the hand during the propulsive phase. As shown by Koga et al. (2020), inefficient propulsion is associated with a low angle of attack at the end of the catch phase. This is confirmed by the fact that at low speeds, the impulse force is higher, and the pull-and-push forces are similar to those of medium- and high-level swimmers. According to this reasoning, medium-expertise-level swimmers take more time than low-expertise-level swimmers to position their hand to improve the efficiency of the propulsion phase, whereas high-expertise-level swimmers seem to be able to combine a short catch phase duration with high propulsion phase efficiency. However, these proposals have yet to be confirmed experimentally, as the present study did not measure the efficiency of the propulsion phase. In line with previous findings (Schnitzler et al., 2010), low-level swimmers in our study exhibit higher IdCs. Seifert et al. (2014) suggested that low-expertise swimmers used an inefficient superposition mode, as they "slip" through the water, that is, producing insufficient force while increasing swim frequency. It appears that low-level swimmers "waste" much of their force production imparting kinetic energy of surrounding water, with force impulses significantly higher than high- and medium-expertise groups. Ultimately, these findings support Seifert et al.'s (2011) assertion that "a relative lack of skill and technique could lead to lower efficiency of propulsion generation."

TABLE 5 | Kinetic parameters according to pace and expertise level.

Level	Pace	Force impulse/cycle (N · s)	Pull Force (N)	Push force (N)	Y1/tot power	Y2/tot power	Y3/tot power
High	1	63.4 ± 14.4	58.8 ± 12.1	73.7 ± 17.8	0.28 ± 0.11	0.11 ± 0.05[d]	0.016 ± 0.007
High	2	68.3 ± 20.2	59.0 ± 12.1	77.6 ± 16.0	0.30 ± 0.15	0.07 ± 0.04	0.013 ± 0.004
High	3	65.1 ± 21.2	66.5 ± 13.2	80.1 ± 13.2	0.32 ± 0.12	0.06 ± 0.04	0.013 ± 0.005
High	4	75.4 ± 22.9	74.5 ± 18.4	84.9 ± 22.9	0.25 ± 0.09	0.03 ± 0.02[a]	0.013 ± 0.005
Medium	1	63.2 ± 23.3	55.9 ± 26.5	65.9 ± 26.5	0.19 ± 0.10	0.09 ± 0.05	0.022 ± 0.016
Medium	2	70.1 ± 17.6	68.8 ± 27.2	79.0 ± 23.1	0.25 ± 0.13	0.11 ± 0.05	0.018 ± 0.012
Medium	3	80.6 ± 20.2	73.424.8	90.8 ± 15.5	0.28 ± 0.14	0.07 ± 0.03	0.018 ± 0.008
Medium	4	82.6 ± 15.1	82.2 ± 30.1	97.9 ± 17.3	0.36 ± 0.25	0.08 ± 0.06	0.018 ± 0.013
Low	1	78.2 ± 6.8	51.6 ± 16.5	69.6 ± 20.3	0.24 ± 0.13	0.04 ± 0.05	0.005 ± 0.005
Low	2	87.9 ± 5.4	57.4 ± 14.0	80.2 ± 23.1	0.28 ± 0.11	0.04 ± 0.03	0.002 ± 0.015
Low	3	86.1 ± 10.5	60.1 ± 9.4	85.0 ± 23.4	0.26 ± 0.32	0.02 ± 0.01	0.006 ± 0.005
Low	4	83.7 ± 20.9	63.4 ± 17.1	82.6 ± 27.3	0.27 ± 0.27	0.02 ± 0.01	0.007 ± 0.008
Pace effect		NS $F_{(3, 68)} = 1.64$ $p < 0.18$, $\eta p^2 = 0.06$ CI [0.0–0.31]	* $F_{(3, 68)} = 3.06$ $p < 0.03$, $\eta p^2 = 0.11$ CI [0.07–0.31]	* $F_{(3, 68)} = 3.09$ $p < 0.03$, $\eta p^2 = 0.11$ CI [0.07–0.31]	NS $F_{(3, 68)} = 0.49$ $p < 0.61$, $\eta p^2 = 0.02$ CI [0.0–0.02]	* $F_{(3, 68)} = 3.45$ $p < 0.02$, $\eta p^2 = 0.13$ CI [0.01–0.21]	NS $F_{(3, 68)} = 1.04$ $p < 0.37$, $\eta p^2 = 0.04$ CI [0.0–0.09]
Expertise effect		⊙ 2, 3 $F_{(2, 68)} = 5.23$ $p < 0.008$, $\eta p^2 = 0.13$ CI [0.02–0.22]	NS $F_{(2, 68)} = 2.25$ $p < 0.11$, $\eta p^2 = 0.06$ CI [0–0.13]	NS $F_{(2, 68)} = 0.34$ $p < 0.7$ $\eta p^2 = 0.01$ CI [0.0–0.04]	NS $F_{(2, 68)} = 0.2$ $p < 0.80$, $\eta p^2 = 0.005$ CI [0.34–0.58]	⊙ 2, 3 $F_{(2, 68)} = 8.43$ $p < 0.001$, $\eta p^2 = 0.20$ CI [0.34–0.58]	⊙ 2, 3 $F_{(2, 68)} = 5.09$ $p < 0.009$, $\eta p^2 = 0.13$ CI [0.34–0.58]
Pace × expertise		NS $F_{(6, 68)} = 0.47$ $p < 0.99, \eta p^2 = 0.03$ CI [0.00–0.04]	NS $F_{(6, 68)} = 0.24$ $p < 0.96$, $\eta p^2 = 0.02$ CI [0.00–0.01]	NS $F_{(6, 68)} = 0.45$ $p < 0.84$, $\eta p^2 = 0.03$ CI [0.00–0.04]	NS $F_{(6, 68)} = 0.52$ $p < 0.79$, $\eta p^2 = 0.03$ CI [0.00–0.04]	NS $F_{(6, 68)} = 0.55$ $p < 0.7$, $\eta p^2 = 0.03$ CI [0.00–0.05]	NS $F_{(6, 68)} = 0.63$ $p < 0.7$, $\eta p^2 = 0.05$ CI [0.00–0.06]

**Significant difference with a: pace 1, b: pace 2, c: pace 3, d: pace 4.*
⊙Significant difference between 1 (high and medium), 2 (high and low), and 3 (medium and low).

With regard to kinetic data, prior research had identified different adaptive modes to changes in swimming speed. Using hand paddles, Gourgoulis et al. (2008) showed that increasing propelling surfaces resulted in a concomitant increase in both force and maximal speed. According to Tsunokawa et al. (2019), this was attributable to an increase on Froude efficiency when using paddles. However, Samson et al. (2015a) showed that propulsive hand forces did not vary significantly across swim paces. Furthermore, Koga et al. (2020) showed that the adoption of overmaximal SR did not help swimmers to reach higher swim speed, as this led to lower angles of attack, which induced lower hand propulsive force. Therefore, the increase in swimming pace is explained by the swimmer's capacity to maintain propulsive phases on higher stroke frequency rather than increasing force generation by orienting the hand in a favorable manner before the propulsive phases begin. Our results are in line with these studies, as force impulse during propulsive phases did not change significantly across paces, but low-expertise swimmer exhibited shorter catch phase as compared to medium-level swimmers. It is worth noting that pull and push peak forces increase, which indicates that adaptation nonetheless occurs at kinetic level. We analyzed force impulse as the numerical integration of the propulsive time duration of each cycle. As stroke frequency increases, the total duration of this time decreases, so without an adaptation, force impulse should follow the same trend. In line with Samson et al. (2015a), the fact that push, pull, and peak forces increase with speed suggests that to maintain these force impulses across different speeds, participants have to increase the absolute force they apply to water and reach this peak more quickly, thus delivering more power to the water during propulsive phases, which explains why the impulse per cycle did not decrease. This might explain why Morouço et al. (2018) found that intracyclic force variation increased with swim speed in tethered swimming conditions. Interestingly, low- and medium-level swimmers had similar SR. If the athletes who produce a greater speed should increase the absolute force they apply to water, the impulse of the medium-expertise level should be greater. This is not the case because the impulses of low-level swimmers are greater than those of medium- and high-level swimmers, suggesting that it is not generally increased force production but rather swimming efficiency that is the key to differentiating between levels of expertise.

We aimed to extend these kinetic analyses and examine measures of the structure of force variability through the analysis of the power spectrum of the force–time series. Spectral analysis decomposes a signal into its component frequencies so that the power assigned to each frequency in the spectral profile provides an index of the portion of total amplitude variability that can be attributed to each frequency. A modification in the profile spectrum provides insight about the frequency structure. Here, the power spectrum exhibited three clear peaks within the 0–12-Hz bandwidth. In each case, the first peak corresponded to the stroke frequency. What represents the second and third peak needs to be determined experimentally. Our results show that increasing swim pace modifies the relative duration of each of these phases. In the same vein, Samson et al. (2015a) outlined that the acceleration pattern of the hand changed with swim speed. Hence, the second peak could represent the modification of the propulsive vs. non-propulsive phase ratio. In what concerns the third peak, several authors pointed out that there was also a variation within the propulsive phase (Schleihauf et al., 1983; Monteil et al., 1994), which could be explained by the change in orientation between the pull and the push phase. This variation occurs at a higher frequency within the force signal, and its importance in explaining the overall signal could be represented by the third harmonic. Our data show that the power associated with the second harmonic decreases across pace in all expertise levels, which is consistent with the coordination data showing that propulsive phase represents ∼50% of the total at pace 1 to more than 67% at pace 4 in both high- and low-expertise levels. Our data show that the increase in average force is due to more frequent impulses, whereas coordination flexibility helps to maintain individual impulses constant, whatever the expertise level. It is interesting to note that in the Neptune and Herzog (2000) study, this flexibility occurs between muscles rather than within muscles, as these authors showed on a cycling task that pacing-related adaptations occurred through the magnitude of the electromyographic response rather than through a change in intramuscular coordination. These data were not available in the present study, but whether behavioral adaptability responses are specific to exercise mode is a worthy question for future research to address directly.

The examination of the kinetic frequency domain introduces new insight into swim expertise. According to our data, high- and medium-expertise swimmers exhibit higher second and third harmonic components, but only high-expertise swimmers are capable of modifying their second harmonic significantly with pace. This suggests a flatter and broader power spectrum as potential indicators of increased complexity within the force time–series signal. That might reflect the availability of more degrees of freedom in an expert system. Interestingly, it appears that this characteristic within the force spectrum, especially at high frequency, might be a relevant feature to characterize expertise.

Taken together, these novel results suggest that, independently of expertise, the modification of inter- and intra-arm coordination helps to maintain force impulses despite the shorter absolute duration of swim cycles. However, some limitations exist in this study. First, we only measured average force produced F_{av}, not propulsive force F_{d}, as the sensors were not oriented in space to detect the application of propulsive force. Second, we were not able to account for a complete description of the force development, as forces were measured at only one hand, whereas force generation patterns involves all the arms (Toussaint and Truijens, 2005). Third, active drag could not be measured, so whether the difference between skill levels was due to higher propulsive force, lower drag, or any combination of the two remains inconclusive. Fourth, a glove on only one hand could have an impact on performance. The glove could affect propulsion asymmetrically and affect coordination, as well as change the perception of water. However, we were still able to outline significant adaptations both at stroking and kinetic parameters, meaning they could be even larger in other settings. Fifth, because of technical limitations, only the force signal corresponding to one hand could be accurately measured, and we could not account for the role of the legs. This is problematic in a sense that asymmetries in arm force production are frequent, although better swimmers tend to be less asymmetric (Dos Santos et al., 2013). Sixth, the spectral analysis used in the current study differs from the usual analyses aimed at assessing time–series complexity. In the current study, three points were considered (Y1, Y2, and Y3). In contrast, in studies aimed at assessing time–series complexity, an assessment of the whole power spectrum is made. Last, these measurements took place in a flume, which modifies the kinematics of the stroke. As Guignard et al. (2019, 2020) recently pointed out, the action of the arms is impacted by the fluid flow in a flume, which constrains the action possibilities more than in a swimming pool. Future studies should provide means to estimate simultaneously the forces produced by both hands to provide a more accurate measurement of swim efficiency, as well as intralimb and interlimb coordination parameters. Additionally, it would be of interest to contrast whether behavioral adaptability to common features such as speed change is specific to exercise modes (such as swimming) or if they have general transferable properties as a function of the environment, whether it is terrestrial or aquatic.

Despite these limitations, this study was an important first step toward providing a simultaneous analysis of stroking, coordination, and kinetic parameters in an ecological context of swimming. It was also the first to examine force dynamics both in temporal and frequency domains. For the first time in front crawl swimming, we were able to examine the spectral content of the force development, which gives an insight into intrasegmental coordination, as outlined by Slifkin and Newell (1999). We identified three main frequencies in the spectrograms, in line with early studies about force development in front crawl (Yeater et al., 1981), but we showed that medium and high expertise levels exhibited a flatter and more broadband spectral content, but also that the adaptation across pace occurs only in high-expertise swimmers for the third harmonic.

CONCLUSION

This study proposed new insights into how swimmers of different skill levels adapt to front crawl swimming at different paces. There are implications in not only sports scientists, but also practitioners and coaches. The main results showed three different levels to take into consideration to perform such investigations: stroking, which expresses the result of the underlying motor control strategy used; coordination, which accounts for this motor control strategy; and kinetic levels, which shows how this motor control leads to force production. Continuing to explore the relationship between those three levels would be of interest in future work. Also, we surmised that these investigations should be carried out not only in the temporal but also in the frequency domain. Finally, to swim at different paces, participants across skill levels shared common characteristics: they all exhibited flexibility, notably in the stroking and the coordination levels. But only the more skilled swimmers were capable of finer intralimb coordination adjustments. In that, stroking, coordination, and kinetic parameters offer promising perspectives in characterizing not only expertise but also the evolution of motor adaptation at an individual level.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by otago university ethic committee reference number: 06/190. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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SYSTEMATIC REVIEW
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An Exploratory Meta-Analytic Review on the Empirical Evidence of Differential Learning as an Enhanced Motor Learning Method

Bruno Tassignon[1]*, *Jo Verschueren*[1], *Jean-Pierre Baeyens*[2,3,4], *Anne Benjaminse*[5,6], *Alli Gokeler*[7,8], *Ben Serrien*[2,9] and *Ron Clijsen*[2,3,10]

[1] Human Physiology and Sports Physiotherapy Research Group, Faculty of Physical Education and Physiotherapy, Vrije Universiteit Brussel, Brussels, Belgium, [2] Experimental Anatomy Research Group, Faculty of Physical Education and Physiotherapy, Vrije Universiteit Brussel, Brussels, Belgium, [3] Department of Physiotherapy, International University of Applied Sciences THIM, Landquart, Switzerland, [4] Faculty of Applied Engineering, Universiteit Antwerpen, Antwerp, Belgium, [5] Center for Human Movement Sciences, University Medical Center Groningen, University of Groningen, Groningen, Netherlands, [6] School of Sport Studies, Hanze University Groningen, Groningen, Netherlands, [7] Exercise Science and Neuroscience Unit, Department Exercise and Health, Faculty of Science, University of Paderborn, Paderborn, Germany, [8] Amsterdam Collaboration on Health and Safety in Sports, Amsterdam Universitair Medische Centra, Department of Public and Occupational Health, Amsterdam Movement Sciences, Vrije Universiteit Amsterdam, Amsterdam, Netherlands, [9] Epidemiology and Public Health, Sciensano, Brussels, Belgium, [10] Rehabilitation Research Laboratory 2rLab, Department of Business Economics, Health and Social Care, University of Applied Sciences and Arts of Southern Switzerland, Landquart/Manno, Switzerland

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San Francisco State University, United States

***Correspondence:**
Bruno Tassignon
bruno.tassignon@vub.be

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Background: Differential learning (DL) is a motor learning method characterized by high amounts of variability during practice and is claimed to provide the learner with a higher learning rate than other methods. However, some controversy surrounds DL theory, and to date, no overview exists that compares the effects of DL to other motor learning methods.

Objective: To evaluate the effectiveness of DL in comparison to other motor learning methods in the acquisition and retention phase.

Design: Systematic review and exploratory meta-analysis.

Methods: PubMed (MEDLINE), Web of Science, and Google Scholar were searched until February 3, 2020. To be included, (1) studies had to be experiments where the DL group was compared to a control group engaged in a different motor learning method (lack of practice was not eligible), (2) studies had to describe the effects on one or more measures of performance in a skill or movement task, and (3) the study report had to be published as a full paper in a journal or as a book chapter.

Results: Twenty-seven studies encompassing 31 experiments were included. Overall heterogeneity for the acquisition phase (post-pre; $I^2 = 77\%$) as well as for the retention phase (retention-pre; $I^2 = 79\%$) was large, and risk of bias was high. The meta-analysis showed an overall small effect size of 0.26 [0.10, 0.42] in the acquisition phase for participants in the DL group compared to other motor learning methods. In the retention phase, an overall medium effect size of 0.61 [0.30, 0.91] was observed for participants in the DL group compared to other motor learning methods.

Discussion/Conclusion: Given the large amount of heterogeneity, limited number of studies, low sample sizes, low statistical power, possible publication bias, and high risk of bias in general, inferences about the effectiveness of DL would be premature. Even though DL shows potential to result in greater average improvements between pre- and post/retention test compared to non-variability-based motor learning methods, more high-quality research is needed before issuing such a statement. For robust comparisons on the relative effectiveness of DL to different variability-based motor learning methods, scarce and inconclusive evidence was found.

Keywords: meta-analysis, contextual interference, sports, variability, motor learning, differential learning

INTRODUCTION

Motor learning is a set of processes associated with practice or experience leading to relatively permanent gains in the capability for skilled performance (Schmidt and Lee, 2013). From an applied point of view, the focus of motor learning is on how different practice variables impact performance to lead to relatively permanent changes in capability. Differential learning (DL) is a motor learning method that was proposed in 1999 (Schöllhorn, 1999) and considers learning of a movement or action as being dependent on the amount of noise (practice variability) that accompanies the acquisition process (etiology: *learning from differences*).

Traditional (= non-variability based) motor learning (TL) methods include, for instance, repetitive practice (REP) (Gentile, 1972) or methodological series of exercises (MSE) (Djatschkow, 1973) wherein practice variability is minimized to natural movement variability and a fixed progression of exercises. In contrast, methods such as variable practice (VP) (Schmidt, 1975), contextual interference (CtIt) (Shea and Morgan, 1979), DL (Schöllhorn et al., 2010a), structural learning (SL) (Braun et al., 2010; Hossner et al., 2016b), or the constraint-led approach (CLA) (Renshaw et al., 2010) utilize practice variability in an attempt to further enhance motor learning outcomes. Schöllhorn et al. (2009a) depicted these various motor learning methods in a continuum of increasing variability and noise, with optimal variability levels being dependent on subject and situational constraints (Schöllhorn and Horst, 2020). In practice, however, these different theoretical concepts are often merged when trainers or clinicians aim to improve the motor performance of athletes or patients.

DL distinguishes itself from the other methods in the sense that its rationale is based on the rebuttal of two implicit assumptions in other methods, namely, (1) the to-be-learned movement is considered independent of the individual and time, and (2) the movement performance can be improved by repetitions of (invariant parts of) the movement (Schöllhorn et al., 2010a). In brief, this implies that practicing a movement needs to be done in many varieties and thus no exact repetition, and without corrective feedback on the movement pattern (Hackfort et al., 2019). An example of Peter Valentiner utilizing the DL approach in shot put training can be found online[1] and implies that the athlete continuously varies the technique used in an attempt to explore movement patterns to discover what works best.

The inspiration for DL's crucial role of practice variability in learning comes from principles of self-organization and dynamical systems theory (Schöllhorn, 2000; Frank et al., 2008) and the concept of stochastic resonance. Although not a central component in the DL theory (Schöllhorn, 2016), the following explanations can be found on the concept of stochastic resonance: "*With an increasing number of offered exercises the probability increases of having one exercise for every group member where s/he will respond to in an adequate way*" (Schöllhorn, 2000). "*By confronting athletes with a high number of practice activities, the probability increases that any of the training exercises can get in resonance with the athlete's needs*" (Schöllhorn et al., 2006). Here, the rationale is for DL exercises to cover a maximal range (or plausible range) of motion patterns in order to maximize the chance that they get in resonance with the individual and time-dependent optimum. In other words, the learner discovers useful components during the exploration of various movement executions that are beneficial for the learner's specific constraints at that time point.

However, the theory and mechanism behind the DL method is not undebated (Schoner, 1995; Scholz and Schöner, 1999; Latash et al., 2007; Beek, 2011; Künzell and Hossner, 2012, 2013; Schmidt and Hennig, 2012; Willimczik, 2013; Schöllhorn et al., 2015; Hossner et al., 2016a; Schöllhorn, 2016). Experimental designs and theoretical rationales of DL have been put forward and discussed but require further examination (Schöllhorn et al., 2009a, 2010a; Schöllhorn and Horst, 2020). The most recent review (Schöllhorn and Horst, 2020) explains DL's enhanced learning rate by an overloading mechanism of the pre-frontal cortex with too many decisions regarding movement execution, which would subsequently enlarge the working memory of the motor control system. There is evidence based on EEG data that suggests DL to cause different brain processes immediately after a training session (Henz and Schöllhorn, 2016; Henz et al., 2018), but in isolation, these data cannot confirm the underlying neural mechanisms of DL and reveal the need for further research.

Regardless of the underlying neural mechanism at play, DL has been experimentally tested in various settings with a large range in the rates of success. The initial experiments were mainly oriented toward performance in a single movement in a sport

[1] https://www.youtube.com/watch?v=U2AMfyyUt5c.

context (Schöllhorn et al., 2004; Beckmann and Schöllhorn, 2006) or laboratory tasks (James, 2014; James and Conatser, 2014), but recently, it has been adopted within more complex tactical sport contexts (Mateus et al., 2015; Coutinho et al., 2018; Santos et al., 2018), clinical settings (Repšaite et al., 2015; Kurz et al., 2016; Benjaminse et al., 2017; Pabel et al., 2017, 2018; Gokeler et al., 2019), and industrial production processes (Weisner et al., 2019). Collectively, these findings hold valuable information which could support trainers in developing tailored athletic training programs and working toward maximal performance, and could aid clinicians working in injury prevention and rehabilitation.

Despite DL being proposed over 20 years ago, no comprehensive overview with additional analyses currently exists comparing the learning rate of DL with the learning rate of various other motor learning methods. Providing such an overview with analyses could help trainers and clinicians to make better-informed decisions concerning the choice of one or more particular motor learning method(s) in daily practice. However, to date, no systematic review and meta-analysis exists that examines the effectiveness of DL compared to traditional or other variability-based motor learning methods on the performance enhancement of skill (sport context: e.g., dribbling, shooting) or movement tasks (laboratory setting: e.g., unilateral arm rotations) in both the acquisition and retention phase. Therefore, the objective of this meta-analytical review is to examine the evidence from (cluster-)randomized experiments (S) that compared the learning rate of DL (I) to other motor learning methods (C: REP, MSE, VP, CtIt, CLA, and SL) in the performance of movement tasks or skills (O) in humans (P) (PICOS: Population, Intervention, Control, Outcome, Studies). Based on the dynamical systems model of DL by Frank et al. (2008) and the review of Lage et al. (2015), we hypothesized that the learning effectivity of DL would be larger in the retention phase than in the acquisition phase. Besides a systematic summary of the evidence, this meta-analytic review can also be used to explore whether the current empirical evidence supports the claim of DL being an enhanced learning method, to identify gaps in the current state of the art, and to stress various research methodological aspects that require improvement in future research.

METHODOLOGY

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement was followed for the development of the abovementioned research question and review protocol (Moher et al., 2015; Shamseer et al., 2015). The scope of the PICOS question was very broad and consequently stresses the fact that the meta-analysis is rather exploratory in nature. Patterns in the dispersion of results of different studies are as much of interest as the overall mean effects (Borenstein et al., 2009).

Information Sources

PubMed (MEDLINE), Web of Science, and Google Scholar were searched for relevant articles.

Eligibility Criteria

The a priori set inclusion criteria were as follows: (1) studies had to be (cluster-)randomized controlled experiments comparing DL to a different motor learning method; (2) the use of co-interventions (e.g., physical literacy and strength training) in both groups was allowed since they represent general practice in non-laboratory contexts and are in line with *representative learning design* directives to ensure functionality and action fidelity in training and learning environments (Pinder et al., 2011); (3) studies had to describe the effects on one or more measures of performance in a movement task; (4) the study report had to be published as a full paper in a journal or as a book chapter to be able to make a reliable risk-of-bias assessment. Exclusion criteria encompassed the following: (1) lack of practice for the control group; (2) the use of non-performance outcomes (e.g., movement patterns), as it is unclear what changes constitute improvement or deterioration, and would be in contradiction with the DL assumptions. In addition, no specific criteria were specified for the population. No restrictions were applied to language or year of publication. DL was defined according to the definition in the Dictionary of Sport Psychology (2019) (Hackfort et al., 2019).

Search Process

The search strategy was developed by two authors (BS and BT). The following search string was used in PubMed: *[((differential-learning) OR differential-training) OR differencial-learning] OR differencial-training[all]*. The last search was carried out on February 3, 2020. To ensure a sensitive search strategy, additional searches were done based on the reference lists of included articles and reviews, and on the ResearchGate profiles of authors of included articles.

Screening Procedure

All retrieved titles, abstracts, full texts, and citations were integrated in the Rayyan web application (https://rayyan.qcri.org) (Ouzzani et al., 2016). After removal of duplicates, titles and abstracts were screened, followed by an inspection of the full text. All full texts were independently screened by two authors (BS and BT). In case of disagreement on the eligibility of a study, a third researcher (JV) checked the variable in the original study and agreement was sought by consensus. The following information was extracted: first author, year of publication, study design, description of participants (number, age, gender, and other characteristics), description of the movement task and the performance variable, and description of the training intervention of the DL and other groups (context of the intervention, duration, frequency, number of exercises, number of repetitions, and description of the exercises).

Risk of Bias Assessment

The included studies were assessed using the Cochrane Risk of Bias Tool, analyzing eight sources of bias: selection, performance, detection, attrition, reporting, and other reasons of bias (Moher et al., 2010). This was done independently by two authors (BS and BT) and discrepancies were resolved through discussion. In case of disagreement, a third researcher (JV) was consulted and agreement was sought by consensus.

Calculation of Effect Sizes for Quantitative Synthesis

The effect size of choice was a standardized mean difference (Morris, 2008):

$d = \frac{c \times [(M_{post,DL} - M_{pre,DL}) - (M_{post,C} - M_{pre,C})]}{SD_{pre}}$, where c represents a correction factor for small sample sizes (close to 1 for large samples), M are means, SD_{pre} is the pooled standard deviation at the pre-test, and C is the control group (other motor learning method). This effect size represents a standardized difference in learning rate between the DL and control group. Learning rate was presented as the order parameter most relevant for DL (Frank et al., 2008). The same effect size was used for the retention test (retention – pre). When a study reported more than one retention test, the latest test was used in our analysis. Results on transfer tests to other than the target movement were not included because there were too few studies on transfer effects. In studies that provided no means and SEs or SDs, but the individual change scores (δ) were given, the effect size was calculated as $d = \frac{c \times (M_{\delta,DL} - M_{\delta,C})}{SD_{\delta,pooled}}$. To estimate the standard error of d, we needed the pre–post correlation, but this was not included in any report. For the primary analysis, we took $r = 0.50$ as a reasonable mean estimate. Sensitivity analyses were performed with $r = 0.15$ and 0.85 to examine the influence of this parameter on the overall results of the meta-analysis. In case of a discrete outcome measure (e.g., fail or pass on an exam), the log odds ratio was calculated for the data presented in this study and then converted to a standardized mean difference with the formulas presented in Borenstein et al. (2009) (chapters 5 and 7). Similar procedures were applied for studies reporting log odds ratios. For studies that reported multiple outcome variables, we calculated the weighted average effect size. When a study did not report all outcomes, authors were contacted by email. When authors did not respond, but the article contained figures with enough information to calculate the effect size, a software program (GetData-Graph-Digitizer.com) was used to extract the raw study data. However, when authors did not respond and data could not be extracted via other means, the article was excluded from the final quantitative analysis. The interpretation of the effect sizes was done in accordance with Cohen's (1988) guidelines: "negligible," $d < 0.2$; "small," $0.2 < d < 0.5$; "medium," $0.2 < d < 0.8$; "large," $d > 0.8$ (Cohen, 1988).

Meta-Analyses

Separate meta-analyses for the effects of acquisition (pre-test vs. post-test) and learning (pre-test vs. retention test) were carried out. Subgroup analyses were performed based on the type of task (e.g., sport performance, technical skill) and type of contrasted learning method (e.g., DL vs. TL and DL vs. CtIt). Subgroups based on the type of task were defined by the following separation criteria: (1) "sport performance" encompassed outcomes focusing on the speed or strength component of the skill performed by the participant. For example, how far a participant could throw, how fast a participant sprinted in a straight line or around the track, how high a participant jumped, how hard a participant could kick a ball, etc. (i.e., shot put, high jump, hurdle racing, ice skating race, and countermovement jump); (2) "sport technical skills" focused more on the precision aspect of skills (e.g., shooting/passing/kicking/serving accuracy as measured by the error with respect to a target, reception of a pass as measured by the distance from the reception point, completion of a technical/agility circuit against time); (3) "sport tactical behavior (skills)" included outcomes assessed during match play (e.g., triple threat position/give-and-go/explore 1-on-1 game/field goals characterized as whether the behavior was successful or not; these variables were then normalized); (4) "fine motor skills": healthy participants had to carry subtle or refined movement tasks or skills outside the sport context (i.e., toothbrushing, dental surgery, handle rotation, and standing as still as possible); (5) "rehabilitation": injured or post-operative participants (this category was left out of the meta-analysis, since the two studies could not be included in the quantitative analyses). All meta-analyses were carried out in Review Manager 5.3 (Cochrane Collaboration). Studies that used different subgroups (e.g., based on age) were entered separately in the meta-analysis. Random effects models were used throughout as between-study variation was expected based on the heterogeneity of movement tasks, subject characteristics, study designs, and performance variables (Borenstein et al., 2009). The inverse of the variance was used to weigh each study result on the overall mean and 95% CI. For the interpretation of heterogeneity, Higgins' I^2 values were calculated (Higgins et al., 2003). Publication bias was visually inspected with a funnel plot. Supplementary material may be found online at https://osf.io/m4sje/.

RESULTS

Qualitative Synthesis

The flowchart in **Figure 1** shows the results of the search and screening process, as well as the numbers of articles included. For the qualitative synthesis, there are 27 original studies included that contain 31 original experiments. For the quantitative synthesis (acquisition phase), there are 23 original studies included that contain 27 original experiments. For the quantitative synthesis (learning phase), there are 12 original studies included that contain 12 original experiments. The features of the included articles are described in **Table 1**.

Twenty-seven articles met the inclusion criteria, resulting in 31 experiments providing data on 897 participants (DL group: $n = 453$; control group: $n = 446$). DL has been used in a variety of contexts: (1) sport performance outcomes (i.e., shot put, high jump, hurdle racing, ice skating race, and countermovement jump); (2) technical skills in a single sports movement (i.e., service in volleyball/tennis; soccer: passing, shooting accuracy, and ball control; hockey: goal shooting precision); (3) tactical skills in a sport context (i.e., during match play in basketball or soccer); (4) fine motor skills (toothbrushing, dental surgery, handle rotation, and balance); and (5) rehabilitation (Repšaite et al., 2015; Kurz et al., 2016). Mateus et al. (2015), Santos et al. (2017), and Coutinho et al. (2018) assessed the effects

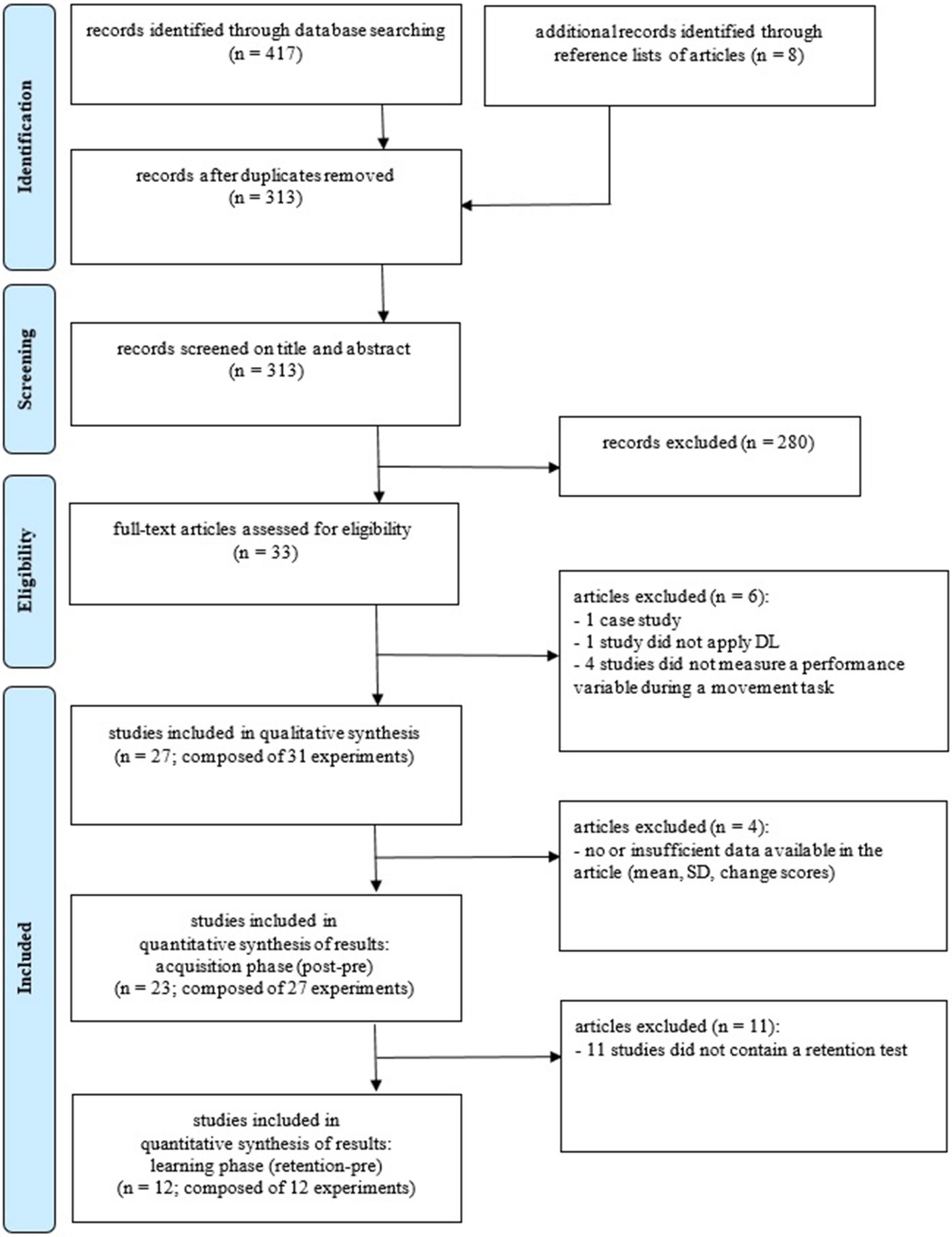

FIGURE 1 | Flowchart of the search and screening process (based on the PRISMA statement template). DL, differential learning; TL, traditional learning; CtIt, contextual interference; SL, structural learning (Moher et al., 2015).

TABLE 1 | Design, participants, movement tasks, performance variables, and training interventions of studies included in the qualitative synthesis.

First author, year, design	Participants	Context	Movement task	Performance variable	Duration, frequency	Differential learning	Other training
Schöllhorn et al. (2004) (exp. 1) PPC: DL vs. TL	Trained soccer players (M) in the German regional league (age 21.9 ± 3.7) DL: $n = 10$ TL: $n = 10$	Supplemental to normal club training	Soccer: goal shooting (sport technical skills)	Points scored over 35 trials divided over 4 initial ball locations (optimal target locations received more points)	6 weeks 2 sessions week^{-1} (25 min)	nr. of exercises: ? nr. of repetitions: 1 exercises described: no, only sources of variation feedback: no	TL: REP nr. of repetitions: ? reference of optimal motion: yes feedback: yes, corrective instructions
Schöllhorn et al. (2004) (exp. 2) PPC: DL vs. TL	Trained soccer players (M) from a senior (age 23.5 ± 3.8) and a junior (12.1 ± 1.7) soccer team. DL: $n = 8$ senior + 14 junior TL: $n = 8$ senior + 13 junior	Supplemental to normal club training	Soccer: dribbling and passing	Passing the ball toward a target at 20 m in front of the subjects. Straight pass 6 points, less points for deviations to the left and right. Task was performed 5 times.	4 weeks 3 sessions week^{-1} (20–40 min)	nr. of exercises: ? nr. of repetitions: 1 exercises described: no feedback: no	TL: REP nr. of repetitions: ? reference of optimal motion: yes feedback: yes, corrective instructions
Schöllhorn et al. (2004) (exp. 3) PPC: DL vs. TL	Soccer players from the German provincial and regional leagues. DL: $n = 12$ (mean age 23.8) TL: $n = 13$ (mean age 28.1)	Supplemental to normal club training	Soccer: ball reception test	Distance between initial ball contact and the position of the ball after control when receiving the ball.	4 weeks 7 sessions of 15–20 min	nr. of exercises: 18–24 per session nr. of repetitions: 1 exercises described: no feedback: ?	TL: REP nr. of repetitions: ? reference of optimal motion: yes feedback: yes, corrective instructions
Schöllhorn et al. (2006) (exp. 1) PPC: DL vs. TL	Senior soccer team 5th German division (M). Allocation based on pre-test scores. DL: $n = 8$ TL: $n = 8$	Supplemental to normal club training	Soccer: dribbling and passing	Passing the ball toward a target at 20 m in front of the subjects. Straight pass 6 points, less points for deviations to the left and right. Task was performed 5 times.	4 weeks 3 sessions week^{-1} (20–40 min)	nr. of exercises: ? nr. of repetitions: 1 exercises described: no feedback: no	TL: REP nr. of repetitions: ? reference of optimal motion: yes feedback: yes, subjects received a detailed description of ideal pattern and corrective instructions
Schöllhorn et al. (2006) (exp. 2) PPRC: DL vs. TL	Players from the 5th and 7th German national soccer division (M). Allocation based on pre-test scores. DL: $n = 9$ TL: $n = 9$	Supplemental to normal club training	Soccer: goal shooting	Points scored over 35 trials divided over 7 initial ball locations (optimal target locations received more points)	6 weeks 2 sessions week^{-1} (25 min, no goal shooting during regular training) retention test: 1 year after post-test	nr. of exercises: ? nr. of repetitions: 1 exercises described: no, only sources of variation feedback: ?	TL: MSE nr. of repetitions: 5–10 per exercise feedback after every shot: error descriptions, movement-oriented corrections, metaphoric instructions
Beckmann and Schöllhorn (2006) PPRC: DL vs. TL	Sports science students (12 M + 12 F, age 22.1 ± 3.8). No experience in shot put. Allocation to groups was based on pre-test scores. DL: $n = 12$ (6M + 6F) TL: $n = 12$ (6M + 6F)	University sports class	Shot put (mass of the shot: F = 3, 4 kg, M = 6.25 k)	The average shot distance of three trials. Sufficient recovery time between trials.	4 weeks 2 sessions week^{-1} (60 min) retention tests: 2 and 4 weeks after post-test	nr. of exercises: ± 30 per session nr. of repetitions: 1 exercises described: no, only sources of variation feedback: no	TL: MSE nr. of repetitions: 10–15 per exercise reference of optimal motion: yes feedback: yes, corrective instructions

(Continued)

TABLE 1 | Continued

First author, year, design	Participants	Context	Movement task	Performance variable	Duration, frequency	Differential learning	Other training
Torrents et al. (2007) Longitudinal follow-up:	Two female national standard aerobic gymnasts (age 20 and 21)	Integrated during regular training sessions	(1) One-armed push-ups: right (2) One-armed push-ups: left (3) Hinge push-ups (4) Leap jump (5) Straddle jump (6) Half turn straddle jump	Absolute time of execution to complete push-up as fast as possible within 4 s. Flight time of each jump. Each test was repeated 3 times and the best time was analyzed.	18 weeks 6 sessions week^{-1} (3 h): - 5 weeks TL - 8 weeks DL - 5 weeks TL Performance was evaluated weekly by means of 6 tests	nr. of exercises: ? nr. of repetitions: ? exercises described: ? feedback: ?	TL: MSE nr. of repetitions: ? reference of optimal motion: yes feedback: ?
Schöllhorn et al. (2008) PPRC: DL vs. TL	3 F + 9 M well-trained tennis players (tennis experience: between 17 and 34 years in regional tennis league). Allocation to groups was based on pre-test scores. DL: $n = 6$ TL: $n = 6$	Supplemental to normal club training	Tennis service	3 × 4 services from the left and right side toward different target zones. According to the tactical advantage of each zone, the service received 1/2/3/4 points. Sum of the points is the performance variable.	6 weeks 2 sessions week^{-1} retention test: 2 weeks after intervention	nr. of exercises: ± 90 services per session nr. of repetitions: ? exercises described: no, only sources of variation feedback: no	TL: MSE nr. of exercises: ± 90 services per session nr. of repetitions: ? reference of optimal motion: yes feedback: yes, corrective instructions
Schöllhorn et al. (2009a) PPRC: DL vs. TL	36 M, 21 F novice high jumpers, age 22.8 ± 2.2. Allocation was based on the results of the pre-test. DL: $n = 19$ TL: $n = 19$	?	Fosbury flop and jump and reach test.	Best performance of two trials (maximal height)	4 weeks 2 sessions week^{-1} retention: 10 days after post-test	nr. of exercises: ? nr. of repetitions: 1 exercises described: no, only sources of variation feedback: no	TL: MSE nr. of exercises: ? nr. of repetitions: ? reference of optimal motion: yes feedback: yes, corrective instructions
Schöllhorn et al. (2010b) PPC: DL vs. TL	Athletic club athletes, age 13.2 ± 1.7. DL: $n = 15$ TL: $n = 13$	Supplemental to normal club training	60 m hurdle race	Time to finish (measured with light barriers)	6 weeks 4 sessions week^{-1} (90 min of which 30 min for hurdle training)	nr. of exercises: ? nr. of repetitions: 1 exercises described: no, only sources of variation gradual DL: every exercise was combined with a new instruction that was related to the previous exercise, but with an additional task. feedback: no	TL: MSE nr. of exercises: ? nr. of repetitions: 3 per exercise reference of optimal motion: yes feedback: yes, corrective instructions and explanations about technique of world class athletes through video and photographs.

(Continued)

TABLE 1 | Continued

First author, year, design	Participants	Context	Movement task	Performance variable	Duration, frequency	Differential learning	Other training
Beckmann et al. (2010) PPRC: DL1 vs. DL2 vs. DL3 vs. CtIt	Experienced hockey players. DL1: $n = 9$ DL2: $n = 9$ DL3: $n = 9$ CtIt: $n = 9$	Supplemental to normal club training	Hockey: push and flick toward goal (targets bottom right and top left, respectively).	Target precision (measured with an optic measurement system)	6 weeks 2 sessions week^{-1} retention: 2 and 4 weeks after post-test	nr. of exercises: 20 for push and 20 for flick DL1: targets were varied in randomized order and no targets were aimed twice. DL2: no target variations, but movement variations DL3: combination of DL1 and DL2 nr. of repetitions: 1 exercises described: no feedback: no	CtIt (no variations, but subjects practiced the push and flick in randomized order) nr. of repetitions: 20 for push and 20 for flick reference of optimal motion: no
Savelsbergh et al. (2010) PPC: DL vs. TL	Adult recreational ice skaters (M), age 44.2 ± 9.8 with 100-m time > 13 s. Allocation to groups was based on pre-test scores. DL: $n = 9$ TL: $n = 9$	Supplemental to normal club training	Ice skating start in a straight line from a stand still position.	Split times were taken at 5, 10, 25, and 49 m. Five trials were performed in a 1-h period.	1 week 3 sessions of 60 min	nr. of exercises: 14 (different start positions) nr. of repetitions: 1 exercises described: yes feedback: no	TL: REP nr. of repetitions: 14 feedback: yes, corrective instructions on starting position reference of optimal motion: yes
Schöllhorn et al. (2012) PPRC: Dlr vs. Dlb vs. TL	8th division of German soccer league. DLr: $n = 4$ (age 24.5 ± 2.1, soccer experience 20.5 ± 1.0) DLb: $n = 4$ (age 24.5 ± 2.1, soccer experience 20.8 ± 3.4) TL : $n = 4$ (age 23.8 ± 3.9) soccer experience 18.5 ± 4.7)	Supplemental to normal club training	Soccer: ball control test and goal shooting test.	Distance between initial ball contact and the position of the ball after control when receiving the ball. Points scored over 35 trials divided over 7 initial locations (optimal targets received more points).	4 weeks 2 sessions week $^{-1}$	nr. of exercises: 20 exercises on ball control and 20 on goal shooting per session nr. of repetitions: 1 exercises described: yes feedback: no DLr: random changes between exercises for ball control and goal shooting DLb: blocked sequence of exercises for ball control and goal shooting	TL: REP nr. of repetitions: 20 repetitions of ball control and 20 of goal shooting per session reference of optimal motion: yes
Reynoso et al. (2013) PPRC: DL vs. TL	Students with no volleyball experience. 11 F, 21 M DL: $n = 10$ (age 21.0 ± 0.94) TL: $n = 11$ (age 22.0 ± 2.10) Before the pre-test, all subjects received an audio-visual introduction to the correct execution of the service (reference to guidelines provided).	?	Volleyball service test. 4 sets of 8 services to a specified target.	Speed and accuracy of the service (measured with radar gun and video camera).	3 weeks 11 sessions	nr. of exercises: 3 sets of 15 exercises per session nr. of repetitions: 1 exercises described: no feedback: in the first two sessions audio-visual information was supported with verbal info when the subjects requested it.	TL: REP nr. of repetitions: 3 sets of 15 repetitions per session feedback: no

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TABLE 1 | Continued

First author, year, design	Participants	Context	Movement task	Performance variable	Duration, frequency	Differential learning	Other training
James, 2014 PPC: DL vs. TL	14 M, 19 F (age 25.2 ± 4.2) DL: $n = 16$ REP: $n = 17$	Laboratory experiment	Standing as still as possible on one/two legs with eyes open, looking at a dot on the wall.	RMSJ of the head and CoM in AP and ML directions	1 session pre-test, training and post-test on 1 day (15 min seated rest between training and post-test).	nr. of exercises 15 postural training trials of 1 min duration with 30s rest between trials exercises described: yes	TL: REP nr. of repetitions: 15 postural training trials that repeated the 2-leg stance task.
James and Conatser, 2014 PPRC: DL vs. TL	12 M, 15 F (age 23.9 ± 3.8) DL: $n = 13$ REP: $n = 14$	Laboratory experiment	Rotations of a handle (180°) with extended elbows by radioulnar and shoulder in/external rotations. Goal was to make smooth movements to the beat of a metronome (1 and 2 Hz).	RMSJ of the hand during the movement	2 weeks 2 sessions week^{-1} post-test: 24h after last training, retention-test: 2 weeks after post-test 20 practice trials of 1 min per session (1 min rest between trials).	nr. of exercises: 20 per sessions (trials of 1 min, 1 min rest between, self-selected pace and range of motion) nr. of repetitions: 1 exercises described: yes feedback: no	TL: REP nr. of repetitions: 20 per sessions (trials of 1 min, 1 min rest between, self-selected pace and range of motion) feedback: no (but they received the smoothness instruction each session)
Repšaite et al. (2015) PPC: mixed DL-OT vs. OT	Patients that had suffered a cerebral infarction in the left hemisphere who followed occupational therapy courses. 9 M, 18 F (age 73.9 ± 7.7) mixed DL-OT: $n = 12$ OT: $n = 15$	Physical medicine and rehabilitation department (hospital), 10–14 days after stroke onset.	Wolf motor function test which includes 15 functional tasks that have to be completed within 120 s.	Time on each of the tests.	32 days 5 sessions week^{-1} (30 min). Both groups received the same co-interventions.	mixed DL-OT 3 sessions OT week^{-1} and 2 sessions DL week^{-1} modified tools of OT, no specific descriptions included of the variations	TL: OT, exercises and tools for strengthening upper limb muscles, range-of-motion, fine motor skills and coordination nr. of repetitions: ?
Mateus et al. (2015) PPC: DL vs. TL	Physical education students (age 20.4 ± 1.9). DL: $n = 38$ TL: $n = 38$	University sports class	Basketball: technical skills (agility test and taco bell challenge) and tactical skills (4v4 small sided game).	Technical skills: total time to conduct the tests. Tactical skills were assessed with a 4-a-side game (video recording): (un)successful attempts were counted for 4 actions (triple threat position, field goals, give-and-go, explore-1-on-1 game).	8 weeks 2 sessions week^{-1} (120 min) warm-up, small sided games and 5-a-side basketball games within each session was the same for both groups.	nr. of exercises: ? nr. of repetitions: ? exercises described: no feedback: ?	TL: REP nr. of repetitions: ? feedback: ? reference of optimal motion: no
Kurz et al. (2016) PPC: DL vs. TL	Patients after a knee ($n =$ 15) or hip ($n = 11$) replacement surgery (age 65.7 ± 9.9). All patients needed to be able to bear their full weight. DL: $n = 14$ TL: $n = 12$	Patients in a rehabilitation center for gait training.	(1) timed up-and-go test (2) 4- and 10-m run test (3) 6-min run test (4) one-leg standing test with eyes open/closed. The transfer test was a variation of (1)	(1) time to complete (2) time to complete (3) distance covered (4) time subject could stand on one leg	3 exercise sessions of 25 min between pre- and post-test	nr. of exercises: ? nr. of repetitions: 1 exercises described: few examples and sources of variation are given feedback: no	TL: REP nr. of repetitions: ? feedback: no reference of optimal motion: no, but demonstrations by physiotherapist were given

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TABLE 1 | Continued

First author, year, design	Participants	Context	Movement task	Performance variable	Duration, frequency	Differential learning	Other training
Hossner et al. (2016b) (exp. 1) PPC: DL vs. DL+FB vs. TL	Players (M) from a Swiss soccer club. Allocation based on pre-test scores, age and soccer experience. DL: $n = 10$ DL+FB: $n = 9$ TL : $n = 9$	Supplemental to normal club training.	Soccer: 16 goal shots (8 shots from a left and right position subdivided into 4 shots each to a target in the left and right corner of the goal (red disks, 0.2 m diameter).	Shots were filmed: average radial error to target center.	6 weeks 2 sessions week^{-1} (30 min) post-test: 1 week after last session absent sessions: 0.9 ± 1.1 (no difference across groups).	DL: nr. of exercises: 30–35 nr. of repetitions: ? exercises described: no, only sources of variation (initial only 1 source of variation, later combinations were used) feedback: no DL+FB: same as DL with individual feedback when non-optimal performance was noticed that could not be attributed to the current task variant. Augmented feedback was also given to the whole group.	TL: MSE 30–35 shots per session nr. of repetitions per exercise: ? feedback: yes reference of optimal motion: yes
Hossner et al. (2016b) (exp. 2) PPRC: DL vs. SL vs. TL	Sports science students (13 F, 23 M). Allocation based on pre-test score, age, height, sex, shot-put experience, motivation to take part in the study. DL: $n = 12$ TL: $n = 12$ SL: $n = 12$	University sports, students received credits.	Shot put (mass of the shot: F = 4 kg, M = 6.25 kg)	Average distance of 3 shots (sufficient recovery time between trials)	4 weeks 2 sessions week^{-1} (consecutive days) absent sessions: 0.7 ± 0.7 (no difference across groups). Post-test during last session, retention: 2 and 4 weeks after last session	nr. of exercises: 32 per session (last session: 20) exercises described: no, only sources of variation, 2 sources combined per practice trial (random order) Exercises were explained with illustrations nr. of repetitions: 1 feedback: no	TL: MSE nr. of exercises: ? nr. of repetitions: ? (32 trials in total, last session: 20) reference of optimal motion: yes feedback: yes SL: same practice variants as DL, only the order of the variants was different: the sequence of variants was determined in order to minimize the difference between subsequent variants.
Pabel et al. (2017) CRT-PO: DL vs. TL	Third-year students in a preclinical course in operative dentistry (Germany). Both groups had the same laboratory, but no clinical experience. DL: $n = 32$ TL: $n = 41$	University course on operative dentistry.	Preparation of a gold partial crown (dentistry) on training models of the upper and lower jaw fixed in phantom heads.	The exam consisted of preparing a gold crown on tooth 46 within 90 min. Four examiners evaluated the preparation anonymously and independent. Criteria for exam failure are indicated. Pass/fail was the performance variable.	4 days 4 hours training per day	All subjects viewed a video demo with verbal explanations before the training. nr. of exercises: 5 day^{-1} nr. of repetitions: 30 min per exercise exercises described: yes feedback: no	All subjects viewed a video demo with verbal explanations and received demonstration models of an "ideal" preparation and assessment criteria: the ideal dimensions and parameters. TL: MSE nr. of exercises: ? nr. of repetitions: ? feedback: yes (oral and written)

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TABLE 1 | Continued

First author, year, design	Participants	Context	Movement task	Performance variable	Duration, frequency	Differential learning	Other training
Santos et al. (2017) PPC DL vs. TL	Seventy-six college students in physical education (age = 20.4 ± 1.9 years): *Non-structured path* (*n* = 14) DL: *n* = 6 TL: *n* = 8 *Early specialization* (*n* = 34) DL: *n* = 19 TL: *n* = 15 *Late specialization* (*n* = 28) DL: *n* = 13 TL: *n* = 15	University sports class	Basketball: technical skills (agility test and taco bell challenge) and tactical skills (4v4 full-court basketball game).	Technical skills: total time to conduct the tests. Tactical skills were assessed with a 4-a-side game (video recording): (un)successful attempts were counted for 4 actions (triple threat position, field goals, pass-and-cut, explore-1-on-1 game).	8 weeks in total; 16 classes; two practical classes per week (120 min/class).	*TL group:* nr. of exercises: 7 session^{-1} nr. of repetitions: 45 min in total exercises described: yes feedback: ? *DL group:* nr. of exercises: 30 session^{-1} nr. of repetitions: 45 min in total exercises described: yes feedback: ? *Both groups (DL vs. TL):* Warm-up (10 min) Small-sided games (30 min) Basketball game (15 min)	TL: REP nr. of repetitions: ? feedback: ? reference of optimal motion: no
Pabel et al. (2018) PPRC: DL vs. TL	Children 6–9 years from 1 school (Germany). Allocation was stratified on first/second grade. DL: *n* = 18 TL: *n* = 18	School-based intervention: during lunch break at the school's washrooms.	Tooth brushing	Evaluated by a blinded examiner on two parameters: gingival inflammation (PBI) and plaque scores (T-QHI).	15 working days (3 intervals of 2 days each).	All children were given a toothbrush (changed every 21 days), no other oral hygiene products were allowed (brushing at home could not be controlled). Initial verbal instruction and demonstration on a model. nr. of exercises: 15 (1 per day) nr. of repetitions: 3 min exercises described: yes feedback: no	TL: REP All children were given a toothbrush (changed every 21 days), no other oral hygiene products were allowed (brushing at home could not be controlled). Initial verbal instruction and demonstration on a model. nr. of repetitions: 3 min reference to optimal motion: yes feedback: yes
Santos et al. (2018) PPC: DL vs. TL	Portuguese youth soccer players (two different U13 and U15 teams at regional level). DL-U13: *n* = 10 (age 11.1 ± 0.5, experience 4.4 ± 2.9) DL-U15: *n* = 10 (age 13.1 ± 0.3, experience 7.1 ± 1.5) TL-U13: *n* = 10 (age 11.4 ± 0.5, experience 5.3 ± 2.5) TL-U15: *n* = 10 (age 13.0 ± 0.8, experience 6.8 ± 1.6)	Supplemental to normal club training.	Soccer: 5 vs. 5 small sided game, 2 bouts of 6 min (3 min rest between)	Games were recorded and behavior was assessed with notational analysis. Fails, attempts, fluency, versatility and originality occurrences were recorded for passes, dribbles and shots.	5 months 3 sessions week^{-1} (30 min before the regular club training)	nr. of exercises: ? nr. of repetitions: ? exercises described: yes (sources of variation and many examples of each) feedback: no	TL: small-sided-games with fewer variations than DL nr. of repetitions: ? feedback: ?

(Continued)

TABLE 1 | Continued

First author, year, design	Participants	Context	Movement task	Performance variable	Duration, frequency	Differential learning	Other training
Coutinho et al. (2018) CRPP: DL vs. TL	Portuguese youth soccer players (attackers only) from two teams. DL-U15: *n* = 9 (age 14.2 ± 0.8, experience 6.4 ± 3.2) DL-U17: *n* = 6 (age ?, experience 6.4 ± 3.2) TL-U15: *n* = 9 (age 13.9 ± 0.5, experience 6.1 ± 3.1) TL-U17: *n* = 6 (age 16.1 ± 0.7, experience 8.0 ± 2.1)	Supplemental to normal club training.	Soccer: technical skills (vertical jump, speed, agility), and tactical behavior [5 vs. 5 small sided game, 3 bouts of 6 min (3 min rest)]	Vertical jump: counter movement. Speed: 30-m sprint test. Agility: repeated change of direction task: 6 × 20 m sprints with 4 100° change of direction (optical timing system used for all tests). Games were recorded and assessed with notational analysis. Fails, attempts, fluency, versatility and originality occurrences for passes, dribbles, and shots.	10 weeks 2 sessions week^{-1} (25 min intervention + 65 min regular training) intervention: 10 min physical literacy + 15 min small-sided games	nr. of exercises: ? nr. of repetitions: ? exercises described: yes (sources of variation and many examples of each) feedback: no	TL: regular club training nr. of exercises: ? nr. of repetitions: ? feedback: ?
Bozkurt, 2018 PPC: DL vs. TL	Turkish soccer players (U15 team) DL: *n* = 6 TL: *n* = 6	Supplemental to normal club training.	Soccer: technical skills test battery	Passing: Mor-Christian soccer passing test, German Football Association agility and dribbling test, feet juggling test.	4 weeks 3 sessions week^{-1} 8/12 players attended the full program	nr. of exercises: 9 exercises for target-passing, 9 for dribbling and 9 for feet-juggling techniques (blocked order) nr. of repetitions: ? exercises described: no (only sources of variation) feedback: no	TL: MSE nr. of exercises: 9 exercises for target-passing, 9 for dribbling and 9 for feet-juggling techniques (blocked order) reference to optimal motions: no nr. of repetitions: ? feedback: yes
Weisner et al. (2019) PPRC: DL vs. TL	Assembly line workers. DL: *n* = 11 (4F, age 22–64, median experience 2) TL: *n* = 11 (4F, age 21–61, median experience 3)	Field study: industrial engineering training center (Institute of Production Systems, Dortmund)	Production of a 2-speed-gearbox in 6 assembly cycles.	Assembly cycle times and assembly errors (test duration *n* = 60 min).	3 weeks 5 sessions total (60 min session $^{-1}$)	nr. of products: 28 nr. of exercises: ? exercises described: no (only sources of variation) feedback: no	TL: REFA-Work instructions (based on optimal pattern) feedback: yes
Gaspar et al. (2019) PPC: DL vs. TL	Portuguese soccer players (U15) with at least 2 years of soccer-specific training experience DL: *n* = 20 TL: *n* = 20	Integrated during regular training sessions	Soccer kicking performance and countermovement jump	Kicking task: (1) Ball velocity (2) Ball speed (3) Accuracy Jump height	1 day 1 training session: 36 repetitions from the same 3 kicking locations with 18 different kicking variations. Each variation was completed from kicking a static ball and after a 5-m dribble	*DL* nr. of exercises: 18 nr. of repetitions: 2 exercises described: yes (sources of variation and many examples of each) feedback: no	TL: MSE nr. of exercises: 6 exercises for static ball kicking after 5-m run up, 6 exercises for ball kicking after a 5-m dribble. reference to optimal motions: yes nr. of repetitions: 6 feedback: yes

(Continued)

TABLE 1 | Continued

First author, year, design	Participants	Context	Movement task	Performance variable	Duration, frequency	Differential learning	Other training
Serrien et al. (2019) PPRC DL vs. CtIt	Students or teaching/research assistants in physical education, movement science, physiotherapy or manual therapy: DL: $n = 16$ (3F; age = 24 ± 2 years; exercise/week = 4 ± 1 h) CtIt $n = 16$ (4F; age = 23 ± 2 years; exercise/week = 4 ± 1 h)	Laboratory experiment	Goalkeeping mimicking task	Visuomotor reaction time: extinguish LED-lights placed on a wall as fast as possible.	1 day 1 training session: 180 stimuli for both DL and CtIt group (± 30 min) Post-test immediately after training session; Retention-test: same day, after 1 h of rest	*DL* nr. of exercises: 30 nr. of repetitions: 6 exercises described: yes feedback: mean response time and number of missed targets during warmup	CtIt: blocked reference of optimal motion: no nr. of exercises: 3 nr. of repetitions: 2 × 30 exercises described: yes feedback: mean response time and number of missed targets during warmup
Ozuak and Çaglayan (2019) PPC: DL vs. TL	Turkish soccer players (age 11–13) DL: $n = 26$ TL: $n = 26$	Supplemental to normal club training.	(1) Illinois Agility Test (2) Creative Speed Test (3) Ball Dribbling Test (4) Ball Juggling Test (5) Passing Test	(1) time to complete (2) time to complete (3) time to complete (4) nr. of times they keep the ball in the air while juggling (5) number of passes (out of 12) that reached the target	8 weeks, 3 sessions week^{-1}, (40–50 min session^{-1}), after which, the participants continued with soccer training	nr. of exercises: 14 nr. of repetitions: 1 exercises described: yes feedback: no	TL: regular club training nr. of exercises: ? nr. of repetitions: ? feedback: ?

exp, experiment; PPC, pre-test–post-test design with control group; PPRC, pre-test–post-test design with retention test and control group; CRT-PO, cluster-randomized trial post-test only; CRPP, cluster-randomized pre-test–post-test design; M, male; F, female; DL, differential learning; TL, traditional learning (REP and MSE); REP, repetitive practice; CtIt, contextual interference; SL, structural learning; RMSJ, root-mean-square-jerk; CoM, center-of-mass; AP, antero-posterior; ML, media-lateral; MSE, methodological series of exercises; OT, occupational therapy; ?, not described in the article/chapter or only generic statements regarding the content.

of DL on both technical and tactical skills. The majority of studies examined the effects of DL directly after the intervention (acquisition effect), while only 12/27 experiments included a retention test (learning effect). When available in the manuscript, **Table 1** summarizes the timing of post- and retention tests and delays between them. Most post-tests were organized on the same day or within 24 h of the last training session whereas some post-tests were organized a week after the last training session. The time between post-test and retention test varied between 1 h and 1 year (most studies between 1 and 2 weeks).

Risk of Bias Analysis

Table 2 gives an overview of the risk of bias of each study (experiment). Concerning randomization, 15/31 experiments had a low risk of bias and the other were unclear, whereas two studies used cluster randomization (high risk). Allocation concealment was unclear in all but four experiments with high risk of bias and two with low risk of bias. Given the nature of the experiments, blinding of participants and personnel was not possible. Outcome assessment was blinded in 7/31 experiments and unclear otherwise (blinded researcher or computerized registrations). Incomplete outcome data were high risk or unclear in 8/31 experiments, the rest had low risk. Selective outcome reporting was high risk of bias in 9/31 experiments (reported no means, standard deviations, and/or statistics and did not respond to emails for further inquiry). Other reasons of bias were an incomplete description of the training/control intervention and outcome variables that are susceptible to subjective interpretation. With exception for the studies from the groups of Savelsbergh, James, Hossner, Pabel, and Serrien, risk of bias was overall high for all studies (fewer than 4/7 items with low risk of bias).

Quantitative Synthesis of Results

To compare the effects of DL vs. other motor learning methods, effect sizes were extracted from the original research papers and grouped according to relevant context and outcomes. All data on individual effect sizes, 95% CI, overall estimated effect sizes, and heterogeneity are presented in **Figure 2** (acquisition phase) and **Figure 3** (learning phase). Given the relatively low number of experiments and heterogeneity between them, no further selection on quality was done and all experiments that provided data were used in the meta-analysis.

Acquisition Phase (Post – Pre, in Accordance With q30)

The forest plot of the acquisition phase can be found in **Figure 2**. Twenty-seven experiments reported the effects of DL in the acquisition phase compared to other motor learning methods (Schöllhorn et al., 2004, 2006, 2008, 2009b, 2010b; Beckmann and Schöllhorn, 2006; Beckmann et al., 2010; Savelsbergh et al., 2010; Reynoso et al., 2013; James, 2014; James and Conatser, 2014; Mateus et al., 2015; Hossner et al., 2016b; Pabel et al., 2017, 2018; Santos et al., 2017, 2018; Bozkurt, 2018; Coutinho et al., 2018; Gaspar et al., 2019; Ozuak and Çaglayan, 2019; Serrien et al., 2019). The overall effect was small and in favor of DL (d = 0.27, 95% CI = [0.12–0.42], p = 0.0006), and the test for overall subgroup differences was statistically significant (χ^2 = 15.7, p = 0.02, I^2 = 61.7%), indicating different effects of DL among the several subgroup analyses.

Performance Outcomes in Sport Contexts

Nine experiments were included in this subgroup analysis (Beckmann and Schöllhorn, 2006; Schöllhorn et al., 2009b, 2010b; Savelsbergh et al., 2010; Reynoso et al., 2013; Hossner et al., 2016b; Coutinho et al., 2018; Gaspar et al., 2019; Serrien et al., 2019). Participants in the DL group showed greater improvements from pre- to post-test than those in the TL group in seven of the eight experiments with a relatively small overall effect size (d = 0.37, 95% CI = [0.05–0.69], I^2 = 58%). The study of Beckmann and Schöllhorn (2006) was considered an outlier across the entire meta-analysis. Only one study compared performance outcomes after SL to DL, with participants in the DL group showing less improvement than participants in the SL group (d = −0.19, 95% CI = [−1.00, 0.62]) (Hossner et al., 2016b). Also, one single study compared performance outcomes after CtIt to DL, with participants exposed to DL showing greater improvement than the CtIt group (d = 0.98, 95% CI = [0.56–1.40]) (Serrien et al., 2019).

Technical Skills in Sport Contexts

Fourteen experiments documented the effects of DL compared to TL (Schöllhorn et al., 2004, 2006, 2008, 2012; Reynoso et al., 2013; Mateus et al., 2015; Hossner et al., 2016b; Santos et al., 2017; Bozkurt, 2018; Coutinho et al., 2018; Gaspar et al., 2019; Ozuak and Çaglayan, 2019). Participants in the DL group showed on average greater improvements from pre- to post-test than participants exposed to TL in 12 out of the 14 experiments. The overall effect size and 95% CI was positive but small (d = 0.34, 95% CI = [0.17–0.51], I^2 = 30%). Subgroup analysis on one study evaluating the effects of DL compared to CtIt revealed a negligible negative effect size (d = −0.04, 95% CI = [−0.48, 0.39]) (Beckmann et al., 2010).

Tactical Behavior in Sport Contexts

Four experiments were included in this subgroup analysis, showing a small positive overall effect size (d = 0.20, 95% CI = [−0.03, 0.44], I^2 = 77%) with the DL group showing on average greater improvements from pre- to post-test in two of the four experiments (Mateus et al., 2015; Santos et al., 2017, 2018; Coutinho et al., 2018).

Fine Motor Skills

This subgroup analysis encompassed four experiments evaluating the effects of DL compared to TL (James, 2014; James and Conatser, 2014; Pabel et al., 2017, 2018). On average, participants in the DL group showed greater improvements from pre- to post-test than those in the TL group in three of the four experiments, but the overall effect size was negative but negligible (d = −0.12, 95% CI = [−1.04, 0.79]; I^2 = 97%).

Learning Phase (Retention – Pre, in Accordance With q30)

The forest plot of the acquisition phase can be found in **Figure 3**. Twelve experiments reported the effects of DL in the retention

TABLE 2 | Risk of bias analysis.

References	A	B	C	D	E	F	G	
Schöllhorn et al. (2004) (exp. 1)	+	?	–	?	?	–	–	*
Schöllhorn et al. (2004) (exp. 2)	+	?	–	?	?	–	–	*
Schöllhorn et al. (2004) (exp. 3)	+	?	–	?	?	–	–	*
Schöllhorn et al. (2006) (exp. 1)	?	?	–	?	+	+	–	*
Schöllhorn et al. (2006) (exp. 2)	+	?	–	?	+	+	–	*
Beckmann and Schöllhorn (2006)	+	?	–	?	+	+	–	*
Torrents et al. (2007)	–	–	–	–	?	+	?	
Schöllhorn et al. (2008)	+	?	–	?	+	–	–	*
Schöllhorn et al. (2009b)	+	?	–	?	+	–	–	*
Schöllhorn et al. (2010b)	+	?	–	?	+	–	+	*
Beckmann et al. (2010)	+	?	–	+	+	–	–	*
Savelsbergh et al. (2010)	+	?	–	+	?	+	+	*
Schöllhorn et al. (2012)	?	?	–	?	–	+	+	*
Reynoso et al. (2013)	+	?	–	?	+	+	–	*
James (2014)	?	?	–	+	+	+	+	*
James and Conatser (2014)	?	?	–	+	+	+	+	*
Mateus et al. (2015)	?	?	–	?	+	+	–	*
Repšaite et al. (2015)	?	?	–	+	+	–	–	
Kurz et al. (2016)	?	?	–	–	–	+	–	
Hossner et al. (2016b) (exp. 1)	+	?	–	?	+	+	+	*
Hossner et al. (2016b) (exp. 2)	+	?	–	?	+	+	+	*
Pabel et al. (2017)	–	–	–	+	+	+	+	*
Santos et al. (2017)	?	+	?	?	+	+	–	*
Pabel et al. (2018)	+	?	–	+	+	+	+	*
Bozkurt (2018)	?	?	–	?	–	+	–	*
Santos et al. (2018)	?	?	–	?	+	+	–	*
Coutinho et al. (2018)	–	–	–	?	+	+	–	*
Weisner et al. (2019)	?	?	–	?	+	–	–	
Gaspar et al. (2019)	–	–	–	?	+	+	+	*
Serrien et al. (2019)	+	+	–	?	+	+	+	*
Ozuak and Çaglayan (2019)	?	?	–	?	+	+	–	*

*A, random sequence generation; B, allocation concealment; C, blinding of participants and personnel; D, blinding of outcome assessment; E, incomplete outcome data; F, selective reporting; G, other bias; *, study included in meta-analysis; +, low risk; ?, unclear risk; –, high risk.*

phase compared to other motor learning methods (Beckmann and Schöllhorn, 2006; Schöllhorn et al., 2006, 2008, 2009b, 2012; Beckmann et al., 2010; Reynoso et al., 2013; James and Conatser, 2014; Hossner et al., 2016b; Pabel et al., 2017, 2018; Serrien et al., 2019). Not one experiment or outcome encompassed tactical behavior. The overall effect size was moderate in strength and in favor of DL ($d = 0.61$, 95% CI = [0.30–0.91], $p < 0.0001$) and the test for overall subgroup differences was statistically significant at the 5% level ($\chi^2 = 20.29$, $p = 0.001$, $I^2 = 75\%$) indicating different effects of DL among the several subgroup analyses.

Performance Outcomes in Sport Contexts

Six experiments were included in total, with four of them looking into DL-TL comparisons, only one experiment examining DL-CtIt, and one other researching DL-SL (Beckmann and Schöllhorn, 2006; Schöllhorn et al., 2009b; Reynoso et al., 2013; Hossner et al., 2016b; Serrien et al., 2019). Participants in the DL group demonstrated on average greater improvements from pre- to retention test than participants in the TL group in three of the four experiments with an overall large positive effect size ($d = 1.00$, 95% CI = [−0.27, 2.28], $I^2 = 89\%$) (Beckmann and Schöllhorn, 2006; Schöllhorn et al., 2009b; Reynoso et al., 2013; Hossner et al., 2016b). Only one study compared performance outcomes of DL to SL, with participants in the DL group showing on average less improvement with a negligible negative effect size ($d = -0.18$, 95% CI = [−0.99, 0.63]) (Hossner et al., 2016b). Also, one study compared performance outcomes after CtIt to DL, with the DL group showing negligible more improvement from pre- to retention test compared to CtIt ($d = 0.13$, 95% CI = [−0.27, 0.54]) (Serrien et al., 2019).

Technical Skills in Sport Contexts

Subgroup analysis on four experiments evaluating the effects of DL compared to TL showed on average stronger improvements from pre- to retention tests for the DL group ($d = 0.63$, 95% CI = [0.34–0.91]) (Schöllhorn et al., 2006, 2008, 2012; Reynoso et al., 2013). When comparing DL to CtIt for technical skills, only one study could be included, and a negligible effect of DL compared to CtIt was observed ($d = 0.07$, 95% CI = [−0.37, 0.50], $I^2 = 0\%$) (Beckmann et al., 2010).

Fine Motor Skills

Three experiments were included in this subgroup analysis and all studies showed superior improvements from pre- to retention test for DL compared to TL with large effect sizes (overall effect: $d = 1.14$, 95% CI = [0.73–1.55]) (James and Conatser, 2014; Pabel et al., 2017, 2018).

Sensitivity Analyses

Table 3 presents the results of the sensitivity analyses on the calculation of the effect size variances, using various levels of the pre–post correlation. The results are fairly robust under a wide range of plausible correlation coefficients.

Publication Bias

Figure 4 presents the funnel plot of all included studies. Visually, a moderate asymmetry toward the right is present in both funnel plots, but this is primarily due to the presence of strong outliers in both directions (Beckmann and Schöllhorn, 2006; Schöllhorn et al., 2006; James and Conatser, 2014). However, not every study could be included in the meta-analysis, which biases the interpretation of the funnel plots. In addition, the presence of many unpublished abstracts (e.g., https://sport.uni-mainz.de/publikationsliste/) indicates that publication bias is present and affected the results of the meta-analysis.

DISCUSSION

The objective of this meta-analytical review was to examine the evidence of studies that compared the effectiveness of DL to other motor learning methods in the performance of skills and movement tasks. We included 27 articles reporting outcomes of

Study or Subgroup	Std. Mean Difference	SE	Weight	Std. Mean Difference IV, Random, 95% CI
3.3.1.1. Performance outcomes in sport contexts: DL vs TL				
Beckmann, 2006	2.52882	0.57761	1.2%	2.53 [1.40, 3.66]
Coutinho, 2018 (U15)	0.15256	0.2807	2.4%	0.15 [-0.40, 0.70]
Coutinho, 2018 (U17)	0.61833	0.36293	2.0%	0.62 [-0.09, 1.33]
Gaspar, 2019	0.27841431	0.16028748	3.0%	0.28 [-0.04, 0.59]
Hossner, 2016 (exp. 2)	0.24105	0.41519	1.8%	0.24 [-0.57, 1.05]
Reynoso, 2013	-0.18916301	0.44465175	1.6%	-0.19 [-1.06, 0.68]
Savelsbergh, 2010	0.11698	0.24027	2.6%	0.12 [-0.35, 0.59]
Schöllhorn, 2009	0.1299201	0.23165909	2.7%	0.13 [-0.32, 0.58]
Schöllhorn, 2010	0.79734828	0.5538011	1.3%	0.80 [-0.29, 1.88]
Subtotal (95% CI)			**18.6%**	**0.37 [0.05, 0.69]**
Heterogeneity: Tau² = 0.12; Chi² = 19.10, df = 8 (P = 0.01); I² = 58%				
Test for overall effect: Z = 2.29 (P = 0.02)				
3.3.1.1. Performance outcomes in sport contexts: DL vs CtIt				
Serrien, 2019	0.98263528	0.21462196	2.8%	0.98 [0.56, 1.40]
Subtotal (95% CI)			**2.8%**	**0.98 [0.56, 1.40]**
Heterogeneity: Not applicable				
Test for overall effect: Z = 4.58 (P < 0.00001)				
3.3.1.1. Performance outcomes in sport contexts: DL vs SL				
Hossner, 2016 (exp. 2)	-0.19038	0.41452	1.8%	-0.19 [-1.00, 0.62]
Subtotal (95% CI)			**1.8%**	**-0.19 [-1.00, 0.62]**
Heterogeneity: Not applicable				
Test for overall effect: Z = 0.46 (P = 0.65)				
3.3.1.2. Technical skills in sport contexts: DL vs TL				
Bozkurt, 2018	0.26808	0.30048	2.3%	0.27 [-0.32, 0.86]
Gaspar, 2019	-0.33685	0.32092818	2.2%	-0.34 [-0.97, 0.29]
Hossner, 2016 (exp. 1, DL)	0.25587	0.46962	1.5%	0.26 [-0.66, 1.18]
Hossner, 2016 (exp. 1, DL+FB)	0.35107	0.48463	1.5%	0.35 [-0.60, 1.30]
Mateus, 2015	-0.0581	0.16429	3.0%	-0.06 [-0.38, 0.26]
Ozuak, 2019	0.593984	0.128526	3.2%	0.59 [0.34, 0.85]
Reynoso, 2013	0.4726741	0.18586765	2.9%	0.47 [0.11, 0.84]
Santos, 2017 (early specialisation)	0.05142	0.24762	2.6%	0.05 [-0.43, 0.54]
Santos, 2017 (late specialisation)	0.32996	0.27309	2.4%	0.33 [-0.21, 0.87]
Santos, 2017 (non-struct path)	0.20275	0.39307	1.9%	0.20 [-0.57, 0.97]
Schöllhorn, 2004 (exp. 1)	0.65513	0.46914	1.5%	0.66 [-0.26, 1.57]
Schöllhorn, 2004 (exp. 2, junior)	0.84883	0.40931	1.8%	0.85 [0.05, 1.65]
Schöllhorn, 2004 (exp. 2, senior)	0.6181	0.5264	1.3%	0.62 [-0.41, 1.65]
Schöllhorn, 2004 (exp. 3)	0.2001	0.28782331	2.4%	0.20 [-0.36, 0.76]
Schöllhorn, 2006 (exp. 1)	1.91986	0.64708	1.0%	1.92 [0.65, 3.19]
Schöllhorn, 2006 (exp. 2)	0.86547	0.50772	1.4%	0.87 [-0.13, 1.86]
Schöllhorn, 2008	0.29728018	0.60065118	1.1%	0.30 [-0.88, 1.47]
Schöllhorn, 2012 (blocked)	0.41286	0.56835	1.2%	0.41 [-0.70, 1.53]
Schöllhorn, 2012 (random)	0.37562	0.58242	1.2%	0.38 [-0.77, 1.52]
Subtotal (95% CI)			**36.5%**	**0.34 [0.17, 0.51]**
Heterogeneity: Tau² = 0.04; Chi² = 25.87, df = 18 (P = 0.10); I² = 30%				
Test for overall effect: Z = 3.82 (P = 0.0001)				
3.3.1.2. Technical skills in sport contexts: DL vs CtIt				
Beckmann, 2010 (DL1)	-0.05682059	0.3879652	1.9%	-0.06 [-0.82, 0.70]
Beckmann, 2010 (DL2)	-0.12008602	0.36527202	2.0%	-0.12 [-0.84, 0.60]
Beckmann, 2010 (DL3)	0.0707072	0.40526253	1.8%	0.07 [-0.72, 0.87]
Subtotal (95% CI)			**5.6%**	**-0.04 [-0.48, 0.39]**
Heterogeneity: Tau² = 0.00; Chi² = 0.12, df = 2 (P = 0.94); I² = 0%				
Test for overall effect: Z = 0.19 (P = 0.85)				
3.3.1.3. Tactical behavior in sport contexts: DL vs TL				
Coutinho, 2018 (U15)	0.65987	0.20396	2.8%	0.66 [0.26, 1.06]
Coutinho, 2018 (U17)	0.35775	0.25069	2.6%	0.36 [-0.13, 0.85]
Mateus, 2015	-0.03925	0.0826	3.4%	-0.04 [-0.20, 0.12]
Santos, 2017 (early specialisation)	-0.11262	0.12485	3.2%	-0.11 [-0.36, 0.13]
Santos, 2017 (late specialisation)	-0.21554	0.14474	3.1%	-0.22 [-0.50, 0.07]
Santos, 2017 (non-struct path)	0.03234	0.19911	2.8%	0.03 [-0.36, 0.42]
Santos, 2018 (U13)	0.66131	0.23851	2.6%	0.66 [0.19, 1.13]
Santos, 2018 (U15)	0.65625	0.2344	2.7%	0.66 [0.20, 1.12]
Subtotal (95% CI)			**23.2%**	**0.20 [-0.03, 0.44]**
Heterogeneity: Tau² = 0.08; Chi² = 29.88, df = 7 (P < 0.0001); I² = 77%				
Test for overall effect: Z = 1.68 (P = 0.09)				
3.3.1.4. Fine motor skills: DL vs TL				
James, 2014a	0.59023	0.14917	3.1%	0.59 [0.30, 0.88]
James, 2014b	-1.77238	0.21413	2.8%	-1.77 [-2.19, -1.35]
Pabel, 2017	0.32051	0.27116	2.5%	0.32 [-0.21, 0.85]
Pabel, 2018	0.34049	0.10571	3.3%	0.34 [0.13, 0.55]
Subtotal (95% CI)			**11.6%**	**-0.12 [-1.04, 0.79]**
Heterogeneity: Tau² = 0.84; Chi² = 92.90, df = 3 (P < 0.00001); I² = 97%				
Test for overall effect: Z = 0.26 (P = 0.79)				
Total (95% CI)			**100.0%**	**0.27 [0.12, 0.42]**
Heterogeneity: Tau² = 0.18; Chi² = 196.40, df = 44 (P < 0.00001); I² = 78%				
Test for overall effect: Z = 3.45 (P = 0.0006)				
Test for subgroup differences: Chi² = 15.68, df = 6 (P = 0.02), I² = 61.7%				

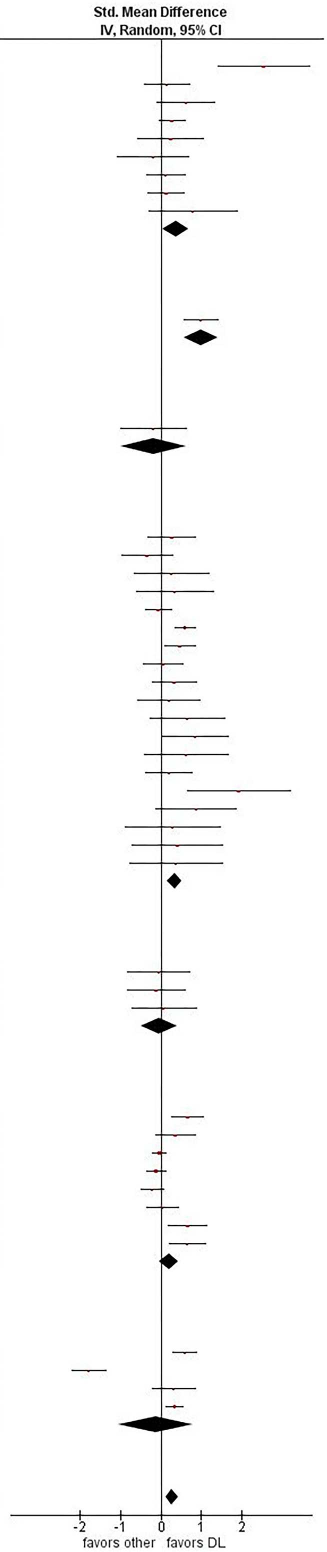

FIGURE 2 | Acquisition phase (post – pre). Forest plot for the effects of differential learning vs. other methods grouped by category of movement task. DL, differential learning; TL, traditional learning; CtIt, contextual interference; SL, structural learning.

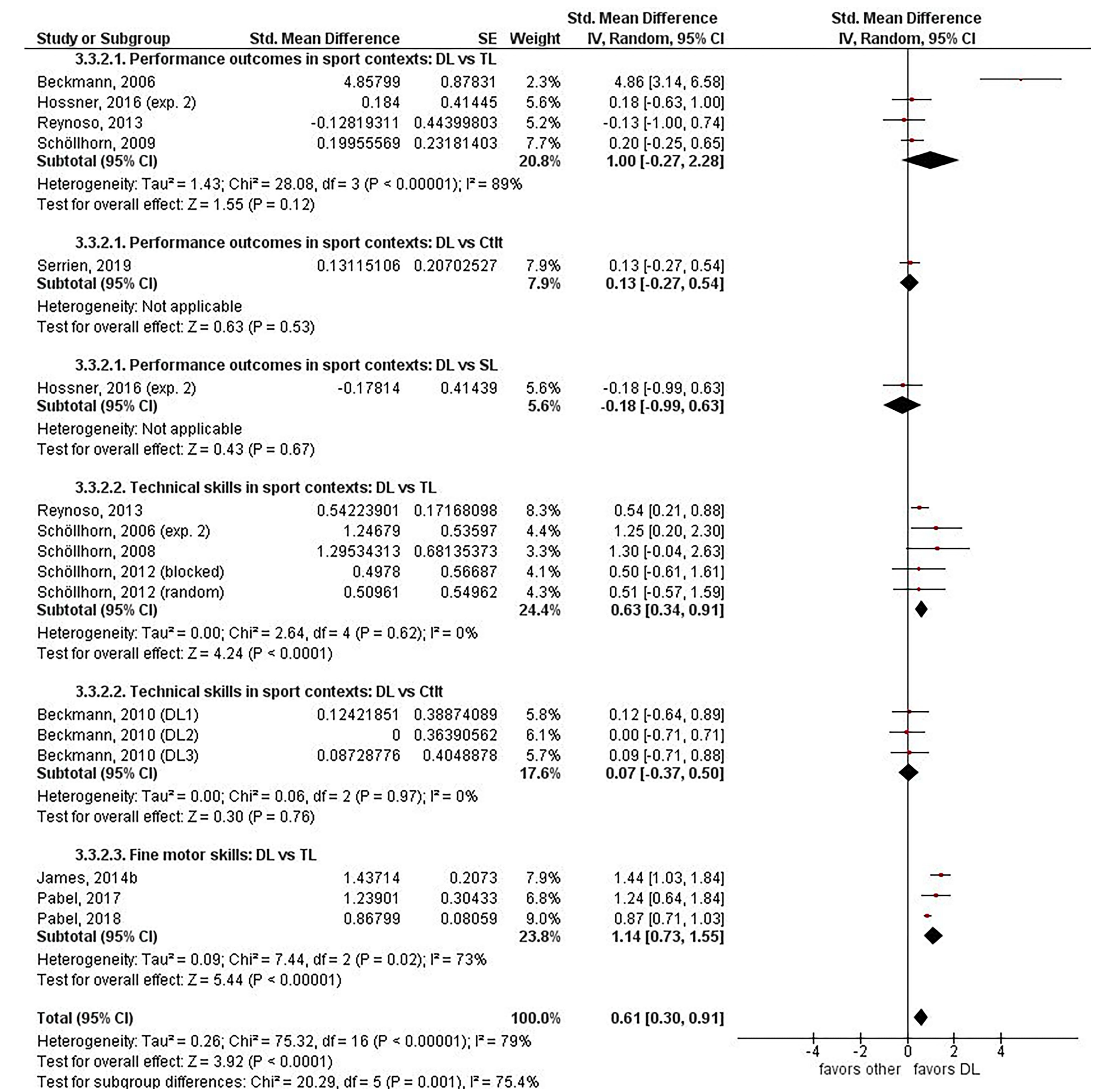

FIGURE 3 | Learning phase (retention – pre). Forest plot for the effects of differential learning vs. other methods grouped by category of movement task. DL, differential learning; TL, traditional learning; CtIt, contextual interference; SL, structural learning.

31 experiments, with only 12 experiments documenting outcome measures in the retention phase. In the acquisition phase, DL is more effective compared to other motor learning methods with an overall small effect size of 0.27 [0.12, 0.42]. In the retention phase, however, DL appears on average to be more effective than other motor learning methods with an overall effect size of 0.61 [0.30, 0.91]. At first sight, one might be tempted to conclude that variability-based motor learning, DL in this case, culminates in higher improvements following practice than other motor learning methods (Frank et al., 2008; Lage et al., 2015; Schöllhorn and Horst, 2020). Nevertheless, it is important to emphasize that overall heterogeneity for the acquisition phase as well as for the retention phase was large, $I^2 = 78\%$ and $I^2 = 79\%$, respectively. Also, the included papers in general had low sample sizes and showed high risk of bias and possible publication bias. The funnel plot (**Figure 4**) indicates that overall effect sizes should be carefully interpreted and warrants more high-quality research.

TABLE 3 | Sensitivity analysis of the effect sizes [95% CI] based on various levels of the pre–post correlation coefficient.

Acquisition phase	**Pre–post correlation**		
	***r* = 0.15**	***r* = 0.50**	***r* = 0.85**
Performance outcomes in sport contexts: DL vs. TL	0.37 [0.03, 0.72]	0.37 [0.05, 0.69]	0.33 [0.08, 0.57]
Performance outcomes in sport contexts: DL vs. CtIt	0.98 [0.56, 1.40]	0.98 [0.56, 1.40]	0.98 [0.56, 1.40]
Performance outcomes in sport contexts: DL vs. SL	−0.19 [−1.25, 0.87]	−0.19 [−1.00, 0.62]	−0.19 [−0.64, 0.26]
Technical skills in sport contexts: DL vs. TL	0.35 [0.19, 0.52]	0.34 [0.17, 0.51]	0.35 [0.19, 0.51]
Technical skills in sport contexts: DL vs. CtIt	−0.04 [−0.61, 0.53]	−0.04 [−0.48, 0.39]	−0.04 [−0.28, 0.20]
Tactical behavior in sport contexts: DL vs. TL	0.17 [−0.07, 0.42]	0.20 [−0.03, 0.44]	0.14 [−0.24, 0.52]
Fine motor skills: DL vs. TL	−0.11 [−0.97, 0.74]	−0.12 [−1.04, 0.79]	−0.13 [−1.17, 0.90]
Learning phase	**Pre-retention correlation**		
	***r* = 0.15**	***r* = 0.50**	***r* = 0.85**
Performance outcomes in sport contexts: DL vs. TL	1.06 [−0.42, 2.53]	1.00 [−0.27, 2.28]	0.78 [−0.05, 1.61]
Performance outcomes in sport contexts: DL vs. CtIt	0.13 [−0.27, 0.54]	0.13 [−0.27, 0.54]	0.13 [−0.27, 0.54]
Performance outcomes in sport contexts: DL vs. SL	−0.18 [−1.24, 0.88]	−0.18 [−0.99, 0.63]	−0.18 [−0.63, 0.27]
Technical skills in sport contexts: DL vs. TL	0.65 [0.25, 1.04]	0.63 [0.34, 0.91]	0.69 [0.38, 1.00]
Technical skills in sport contexts: DL vs. CtIt	0.07 [−0.50, 0.63]	0.07 [−0.37, 0.50]	0.07 [−0.17, 0.31]
Fine motor skills: DL vs. TL	1.13 [0.73, 1.54]	1.14 [0.73, 1.55]	1.16 [0.73, 1.60]

The default estimate of r = 0.50 is shown as reference (same as in forest plots and manuscript).
DL, differential learning; TL, traditional learning; CtIt, contextual interference; SL, structural learning.

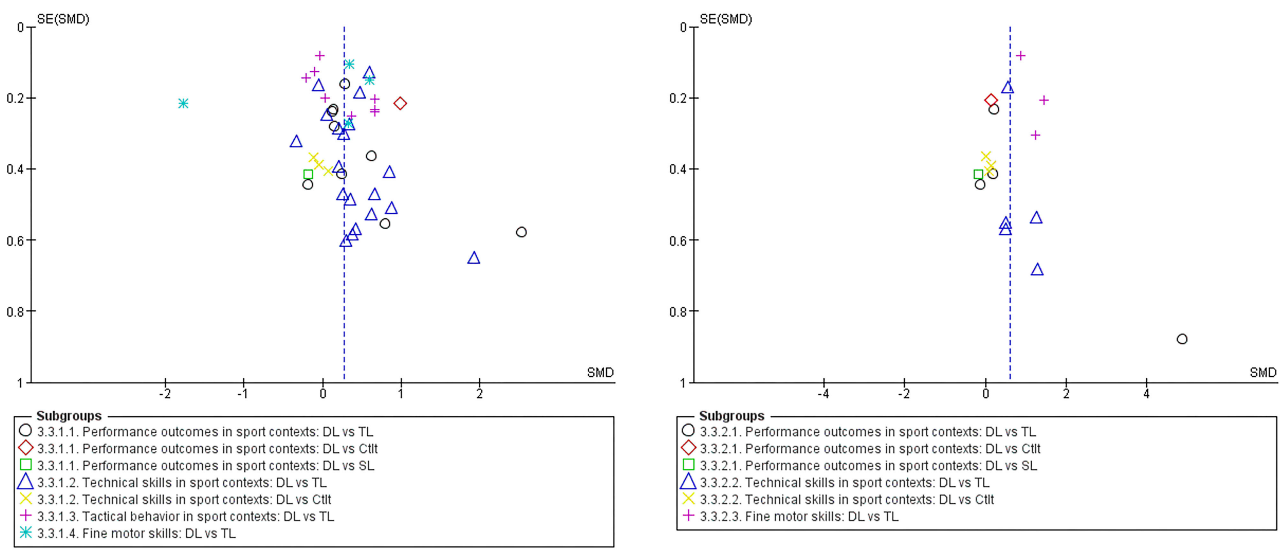

FIGURE 4 | Funnel plots of the effect sizes of the acquisition phase (left) and learning phase (right). Vertical dashed line shows the overall effect size. DL, differential learning; TL, traditional learning; CtIt, contextual interference; SL, structural learning.

Critical Interpretation on the Effects of DL in the Acquisition Phase

Bearing in mind that overall large heterogeneity ($p < 0.00001$, $I^2 = 78\%$) was found across the included studies, interpreting the results regarding improvements following practice of DL compared to other motor learning methods in the acquisition phase should be made with considerable care. At the subgroup level, concerning performance outcomes in sport contexts, DL showed higher improvements following practice than TL with a relatively small overall effect size. However, it is more than likely that the true effect size is lower, since the study of Beckmann and Schöllhorn (2006) had a strong influence on this subgroup's effect size. Heterogeneity between effects was large ($I^2 = 58\%$), indicating the presence of unexplained factors, such as the type of performance outcome (e.g., ice skating speed vs. throwing distance). Furthermore, the included studies did not show unanimous positive results, while the CIs for all studies, except the study of Beckmann and Schöllhorn (2006), crossed the line of null effect. Remarkably, the study of Hossner et al. (2016b, exp. 2) used a similar sample (size), similar context, duration, frequency, amount of exercises, and task as the study of Beckmann and Schöllhorn (2006) but the effect size was 10.5 times larger in the latter study than the former. Differences in the application of feedback and demonstrations probably contributed to these vastly different outcomes, although this alone might not sufficiently explain the big difference in effect sizes between these two studies. Moving on to another subgroup, DL might enable slightly higher improvements following practice in tactical behavior in sports. Nevertheless, also in this case large heterogeneity was present across the included experiments of this subgroup ($I^2 = 77\%$). This can be partially explained by differences in population (e.g., experience level, age) and used outcome measures (e.g., basketball vs. soccer). Another possible factor contributing to this high level of heterogeneity could have been the subjective nature and interpretation of some tactical variables (e.g., creative components). Although these studies were the first to research tactical outcome measures and play an important role in the development of motor learning research by providing insights in this previously unexplored area, more objective tactical outcome measures should be included in future research. Regarding fine motor skills, DL performed on average better than TL. Yet, the overall effect size was negative and the CI covered zero ($d = -0.12$, [−1.04, 0.79]) largely due to a strong negative outlier causing large heterogeneity ($I^2 = 97\%$). The "technical sport skills (DL vs. TL)" was the only subgroup with a relative low amount of heterogeneity ($I^2 = 30\%$). Here, a small positive effect was found for DL compared to TL. These results should nonetheless be interpreted with caution, as not all included studies demonstrated effects favoring the DL method; the CIs of the majority of studies crossed the line of null effect, and most of the experiments were carried out by the same research group. The results of three subgroups [DL vs. CtIt (sport performance outcomes), DL vs. CtIt (sport technical skill), and DL vs. SL (sport performance outcomes)] should not be interpreted separately, since an insufficient number of experiments (1) and participants were included in each subgroup.

In summary, the test for overall effect shows a statistically significant difference favoring DL over other motor learning methods in the acquisition phase ($p = 0.0006$). Nevertheless, as already stated above, to interpret this total summary, statistical results would be premature in light of the considerable amount of heterogeneity. Given that this information is less meaningful, it is recommended to devote more attention to the subgroup analyses. Three out of seven subgroups had very large variances due to low sample sizes, while three other subgroups only encompassed one study, which limits generalizability of the results. Therefore, the validity of the improvements following practice estimate for each subgroup is uncertain, as individual trial results are inconsistent. Despite the circumstantial and low-quality evidence, it seems that the acquisition could be slightly enhanced when applying DL in comparison to TL. When comparing DL to other variability-based motor learning methods (i.e., SL and CtIt), not one motor learning method currently appears to be superior for acquisition. Although it might be too early to assert these general statements, the discrepancy in results and the large heterogeneity proclaim the need for further high-quality research on this topic by independent research groups and clear demarcation of both the DL method and other motor learning methods.

Critical Interpretation on the Effects of DL in the Retention Phase

Given that the overall heterogeneity was large across the included studies in the retention phase ($p < 0.00001$, $I^2 = 79\%$) and the amount of included experiments was low ($n = 12$), interpreting the results regarding improvements following practice of DL compared to other motor learning methods in the retention phase should be made with great caution if they are to be made at all. Comparable to the acquisition phase, similar disconcerting patterns emerge regarding heterogeneity, low sample sizes, low power, etc. Even though fewer studies could be included during the retention phase, averaged across all subgroup comparisons, the effect of DL was two to three times larger in the retention phase ($d = 0.61$, [0.30, 0.91]) compared to the acquisition phase ($d = 0.26$ [0.10, 0.42]). Nevertheless, readers should critically interpret and reflect on these effect sizes. Similar to the acquisition effect for shot put training, both studies of Beckmann and Schöllhorn (2006) and Hossner et al. (2016b) found a better learning effect for DL compared to TL, but a very large discrepancy was observed for the effect sizes. Despite their similar designs, the study of Beckmann and Schöllhorn (2006) demonstrated a 27 times larger effect size than the study of Hossner et al. (2016b). Mainly fine motor skills and sports technical skills seem to be better retained after DL intervention in comparison to TL. Although sensible interpretations should be made on these two topics. The sport technical skills subgroup mainly encompassed studies from one research group with the CIs of some studies exceeding the line of null effect, while the fine motor skills subgroup encompassed a large amount of heterogeneity ($I^2 = 73\%$). Furthermore, three out of seven subgroups (all DL vs. other variability-based motor learning methods) could only include one study, which implicates very low generalizability and minimal attributable value to potential inferences based on these results. Nevertheless, the result of the overall effect shows a statistically significant difference favoring DL over other motor learning methods ($p < 0.0001$). However, general interpretations about the effectiveness of DL compared to other motor learning methods in the retention phase should be made with great caution. This is due to the large amount of heterogeneity, the limited number of studies, low sample sizes, and considerable risk of bias across all studies.

Does the Current Empirical Evidence on DL Support Its Theoretical Rationale and the Variability-Based Continuum?

The findings of the meta-analysis are partly in line with the theoretical rationale of DL that strives to achieve an individual optimal level of variability in practice, allowing the athlete to discover different aspects of his/her dynamic movement landscape and withhold the most efficient and effective movement solution as part of the motor learning process. Recently, the DL method received a high degree of attention in research and practice, partly due to its hypothesis of potentially being an enhanced motor learning method (= provides the learner with a higher learning rate than other methods), partly due to researchers' critical attitude toward the DL method (Pabel et al., 2017, 2018; Bozkurt, 2018; Coutinho et al., 2018; Santos et al., 2018; Gokeler et al., 2019; Serrien et al., 2019; Weisner et al., 2019).

The differences of DL with other methods that employ practice variability are the amount and/or structure of the exercise variations. Schöllhorn et al. (2009a) depicted various motor learning methods in a continuum of increasing variability and noise (REP, MSE, VP, CtIt, CLA, SL, and DL) with DL being hypothesized to exemplify the highest learning rates (Schöllhorn et al., 2009a; Schöllhorn and Horst, 2020). However, the results of the current meta-analysis question the validity of this continuum. For a robust comparison of DL to other motor learning methods inspired by variability (VP, CtIt, CLA, SL), scarce and inconclusive evidence exists to examine and infer whether DL is superior or inferior in terms of learning rate. Additionally, we want to draw attention to the difficulty in distinguishing between DL and SL (Hossner et al., 2016b; Schöllhorn, 2016). Both methods use a large overall practice variability, but SL tries to minimize trial-to-trial variability (subsequent exercises are different in only a small detail). This led to the terminology of "gradual DL" as synonym for SL and "chaotic DL" for the classical interpretation that uses random trial-to-trial variability (Henz et al., 2018; Schöllhorn and Horst, 2020).

Based on the meta-analyses and in light of the low methodological quality of the included studies, DL shows potential to be considered as an enhanced motor learning method in comparison to TL methods when aiming to improve motor learning during the acquisition and retention phase. For both the acquisition and retention effect, the study with the lowest risk of bias (Pabel et al., 2018) was in line with the subgroup and omnibus effect size estimate.

Furthermore, the theory and mechanism behind the DL method is not undebated (Schoner, 1995; Scholz and Schöner, 1999; Latash et al., 2007; Beek, 2011; Künzell and Hossner, 2012, 2013; Schmidt and Hennig, 2012; Willimczik, 2013; Schöllhorn et al., 2015; Hossner et al., 2016a; Schöllhorn, 2016). Nevertheless, a detailed discussion on the theoretical background, key features, underlying (supposed) mechanisms, predictions, and limitations of DL in comparison to other motor learning methods is beyond the exploratory and practical focus of this systematic review and meta-analysis. Readers should thus also be aware of the following key points when interpreting the results of this study: (1) some fundamental limitations exist with the theoretical framework of DL, (2) DL studies are mostly focused on learning effectiveness rather than learning rate and that the effectiveness is assessed imperfectly when a pre- to post-test design is used rather than a design that also includes a retention/transfer test, (3) there are alternative methods available that predict benefits of VP but for different reasons than DL (e.g., schema theory, uncontrolled manifold hypothesis), and (4) CtIt and SL can be used to schedule VP.

How Can These Results Impact Motor Learning in Sport or Rehabilitation Contexts?

Trainers and clinicians often merge different theoretical motor learning concepts with the aim to improve athletes' or patients' motor or movement skill performance. The results of this meta-analysis do not allow for strong recommendations in favor of a specific motor learning method toward trainers or clinicians. However, a well-considered use of (increasing) variability appears to be beneficial over more traditional or repetitive motor learning methods. Farrow and Robertson (2017) discuss the role of variability-based learning within a skill acquisition periodization framework. They stress the role of variability in countering tedium, but refrain from giving general guidelines on where in the periodization of micro-, meso-, and macrocycles this is most optimal as the literature is not able to substantiate evidence-based criteria. In line with the model of Schöllhorn and Horst (2020), Farrow and Robertson (2017) propose a practical continuum of variability that can be offered to athletes, trainers, clinicians, and researchers.

Important in real-world training situations, whether it be performance or clinically oriented, is to shift focus toward individuality and specificity. Other important variables such as instruction, feedback, focus of attention, motivation, etc should also be considered besides the amount and structure of provided variability since these variables have also been shown to play an important role in motor learning in sport and rehabilitation contexts (Wulf and Lewthwaite, 2016; Gokeler et al., 2019). In a sport context, the integration of variability in motor learning possibly promotes motivation by increasing the challenge of training (Guadagnoli and Lee, 2004) as well as promoting fun and enhanced expectancies during practice (Wulf and Lewthwaite, 2016). In a clinical context, focusing on the current capacity, the individual needs and goals of the patient are essential in order to select the most fitting motor learning method. Implementing insights from DL (together with other variability-based motor learning methods) and a well-considered use of variability can improve task performance on the short term allowing for enhanced motor learning during the acquisition phase, while fine motor skills likely benefit the most from the retention effect of DL (Pabel et al., 2017, 2018). Restoring gross and fine motor skills are an important aspect of neurological and musculoskeletal rehabilitation given the known persistence of sensorimotor impairments (Repšaite et al., 2015; Gokeler et al., 2019). Increasing variability in rehabilitation should always be performed in a safe context, allowing for successful but challenging exercises to allow the patient to explore efficient and effective movement strategies that transfer to real-world scenarios (Guadagnoli and Lee, 2004). Nevertheless, data on the application of DL during a rehabilitation process after injury or in a sport injury risk mitigation plan is scarce to non-existent.

In training/rehabilitation contexts, the learning of a single movement is rarely the goal. Regarding transfer effects, many experiments that were included assessed the effects of DL on more than one movement (Schöllhorn et al., 2012) or included several different outcome variables of the same movement (Reynoso et al., 2013) or outcome variables from different movements (Mateus et al., 2015; Santos et al., 2017, 2018). Studies that explicitly used a transfer test (e.g., Beckmann et al., 2010) were scarce and not included in any meta-analysis. DL uses variability with the aim to prepare subjects to be able to cope with a large range of unforeseen situations (Schöllhorn et al., 2010a); therefore, we recommend future studies to address transfer effects to unforeseen situations or to related movements.

Limitations

Publication bias and missing data for the meta-analysis may have influenced the results. The meta-analysis was based on a very heterogeneous sample of studies with widely varying populations, motor tasks, and control conditions. These high levels of heterogeneity stress the importance to interpret these results with caution and call for high-quality future research. For the acquisition phase, the subgroups based on type of task and type of control condition were a significant factor in explaining the heterogeneity. However, only one study compared DL to SL (Hossner et al., 2016b), while one study compared it to CtIt, and all others compared it to TL. Future analyses may consider further subgroups for REP and MSE comparisons. Regarding heterogeneity in sample characteristics, future analyses must consider additional subgroup analyses based on age and/or level of expertise as we grouped results from complete novices and experts in the same analysis. Also, dividing the meta-analysis into different subgroups based on the type of task (e.g., performance, technical skill) might not be ideal for a holistic interpretation on this topic, though an overall effect size was calculated for both the overall acquisition and retention phase. From a theoretical perspective, the most important covariate to be considered in future meta-analyses is likely the noise level of the training intervention. A difficulty here will be to find a proper common metric that quantifies this outcome.

Besides co-interventions representing general practice in non-laboratory contexts and being in line with representative learning design directives to ensure functionality and action fidelity in training and learning environments (Pinder et al., 2011), the inclusion of experiments with co-interventions (Mateus et al., 2015; Repšaite et al., 2015; Santos et al., 2017) might also be a potential confounder of the results. However, as noted earlier, in practical contexts, several methods are often combined, so these experiments can provide important information. Furthermore, studies without assessment of performance variables (Menayo et al., 2014; Henz and Schöllhorn, 2016; Henz et al., 2018) were not included in this meta-analysis although they provide valuable information on specific aspects of DL. These studies are especially important for inquiry about the individuality and situation specificity of the stochastic resonance.

A final limitation is the unknown pre–post and pre-retention correlations in the study reports. The sensitivity analysis showed that this parameter had only a small influence on the overall effect sizes and their 95% CI, but this assumed a fixed correlation coefficient across all studies and may potentially have a larger influence. The overview of effect sizes and their 95% CI may be used in the design of future interventions.

Implications for Future Research

In general, further high-quality research is necessary with low risk of bias RCTs and publications in peer-reviewed journals (Beek, 2011). Given the nature of motor learning experiments, it is challenging and, in many cases, impossible to blind participants, researchers, trainers, and therapists to which condition they are assigned to. Therefore, future studies should make a bigger effort in addressing the other risk of bias items in their study design and report them accordingly. Also a major recommendation for future research is to better define, design, and report the used control conditions in the study of DL. When motor learning refers to the study of cognitive, perceptual, motor, and physiological responses that explain motor skill acquisition, more attention should be devoted to the retention effects of motor learning interventions both in the short term and in the long term. Future research should also aim to encompass more robust designs, increase sample sizes, and clearly define the motor learning method that is experimentally tested as well as the motor learning method used to compare with, and to be published in international peer-reviewed journals. In particular, studies researching the differences between variability-based methods (DL, SL, CtIt, VP, and CLA) at the theoretical and the practical level are much needed. Potential interesting variables to address in future research could be the amount and structure of applied variability. Besides variability, other variables like instruction, feedback, focus of attention, motivation, level of expertise, etc should also be considered. Given the focus on individuality in DL, it will be important to study the relationships between dose (variability) and response (learning rate), and to identify factors that predict optimal amounts in specific populations and situations (Caballero et al., 2017). Also, the problem on the role of variability in motor learning periodization requires further investigations (Farrow and Robertson, 2017). Single-subject analyses may prove valuable for these fundamental questions.

CONCLUSION

Given the large amount of heterogeneity, low availability of studies, low sample sizes, and considerable risk of bias across all studies, inferences about the effectiveness of DL should be made with prudence. Considering these methodological flaws, DL shows potential to be considered as an enhanced motor learning method in comparison to TL methods when aiming to improve motor learning in the acquisition and retention phase. A robust comparison and conclusion on the relative effectiveness of DL to other motor learning methods inspired by variability (i.e., SL and CtIt) would be premature, since scarce and inconclusive evidence was found. Future research should aim to perform more high-quality research. Once more high-quality research becomes available, the results of this meta-analysis should be updated in combination with stricter inclusion criteria concerning study design, risk of bias, and publication policy.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://osf.io/m4sje/.

AUTHOR CONTRIBUTIONS

The conception and drafting of the work and the acquisition and the analysis of data were carried out by BT and BS. All authors made substantial contributions to the design of and interpretation of data for the work. All authors revised the manuscript critically for important intellectual content and provided approval for publication of the content. All authors agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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