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Can the Structure of Motor Variability Predict Learning Rate?

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Recent studies show that motor variability is actively regulated as an exploration tool to promote learning in reward-based tasks. However, its role in learning processes during error-based tasks, when a reduction of the motor variability is required to achieve good performance, is still unclear. In this study, we hypothesized that error-based learning not only depends on exploration but also on the individuals' ability to measure and predict the motor error. Previous studies identified a less auto-correlated motor variability as a higher ability to perform motion adjustments. Two experiments investigated the relationship between motor learning and variability, analyzing the long-range autocorrelation of the center of pressure fluctuations through the α score of a *Detrended Fluctuation Analysis* in balance tasks. In Experiment 1, we assessed the relationship between variability and learning rate using a standing balance task. Based on the results of this experiment, and to maximize learning, we performed a second experiment with a more difficult sitting balance task and increased practice. The learning rate of the 2 groups with similar balance performances but different α scores was compared. Individuals with a lower α score showed a higher learning rate. Because the α scores reveal how the motor output changes over time, instead of the magnitude of those changes, the higher learning rate is mainly linked to the higher error sensitivity rather than the exploration strategies. The results of this study highlight the relevance of the structure of output motor variability as a predictor of learning rate in error-based tasks.

Public Significance Statement

Motor variability during a baseline period is interpreted as exploration strategies for promoting reward-based learning. However, in error-based learning, the initial variability is linked to performance and, thus, an individual's room for improvement, biasing the interpretation of the functional role of variability. This study highlights that error-based learning depends on an individual's ability to measure and predict their motor error rather than exploration strategies. The structure of motor variability measured through a *Detrended Fluctuation Analysis* reveals the system's capacity to perform motion adjustments to reduce the outcome error and predicts learning rate. This is the first study to relate the structure of motor variability to the error-based learning rate, avoiding the bias due to individuals' initial performance level differences.

Keywords: balance, learning rate, variability

Motor variability is described as the "noise" caused by stochastic neuromuscular function that must be minimized to increase task performance (Churchland, Afshar, & Shenoy, 2006; Harris & Wolpert, 1998; Osborne, Lisberger, & Bialek, 2005; Schmidt, Zelaznik, Hawkins, Frank, & Quinn, 1979; Shmuelof, Krakauer, & Mazzoni, 2012). While learning any motor skill, the magnitude of motor variability progressively decreases as movement execution improves (Caballero, Barbado, & Moreno, 2014; Stein, Gossen, & Jones, 2005). However, other approaches indicate that variability plays a functional role, allowing individuals to generate more adaptive responses to stressors (Goldberger, 1996; Goldberger, Peng, & Lipsitz, 2002). Motor variability reflects the motor system's ability to explore different motor configurations, looking for an optimal solution facilitating adaptive (Barbado, Sabido, Vera-García, Gusi, & Moreno, 2012; Manor et al., 2010; Zhou et al., 2013) and/or learning processes (Tumer & Brainard, 2007; Wu, Miyamoto, Gonzalez Castro, Olveczky, & Smith, 2014). However, although some studies have found that high motor variability predicts faster reward-based learning of different reaching tasks (Pekny, Izawa, & Shadmehr, 2015; Wu et al., 2014), there is limited evidence as to whether motor variability plays a similar role during error-based learning (Wu et al., 2014).

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Functional perspectives of motor variability are not in opposition to the traditional view. Variability seems to be a multidimensional feature of the motor system (Stergiou & Decker, 2011). Previous findings indicated the need for high-variability when exploration is required to learn a novel task, but low-variability improves accuracy, exploiting a viable solution (Woolley & Doupe, 2008; Wu et al., 2014). Nevertheless, when motor variability during a novel task is analyzed, it is difficult to estimate the extent to which motor variability is a consequence of stochastic neuromuscular noise, which must be reduced to improve motor performance, or whether it is being actively regulated to promote learning. Novices usually show higher motor variability but exhibit a higher learning-rate than experts. Therefore, how can we measure motor variability to reveal the system's functional properties during learning when a low magnitude of variability is required to perform the task properly?

Some mathematical tools allow for the discrimination between both concepts of variability. Scattering variables have been used to describe the magnitude of the variability (Stergiou & Decker, 2011), suggesting that the mean is the ultimate performance goal and diversion from the mean is the error. Nonlinear mathematical tools have been used to analyze the temporal organization of variability. For example, for a given time series, Detrended Fluctuation Analysis (DFA) analyzes long-range auto-correlation (Amoud et al., 2007; Peng, Havlin, Stanley, & Goldberger, 1995), whereas entropy tools measure regularity (Barbado et al., 2012; Rhea et al., 2011); both assess the extent to which further motor behavior is dependent on previous fluctuations. Less dependence on previous behavior (lower long-range auto-correlation or regularity) was interpreted as higher flexibility to perform motion adjustments (Amoud et al., 2007; Wang & Yang, 2012). Studies on balance tasks in older (Manor et al., 2010; Zhou et al., 2013) and young individuals (Barbado et al., 2012) revealed that individuals who showed lower long-range auto-correlation and less regularity of center of pressure (COP) fluctuations while standing on a stable surface demonstrated better performance with more difficult balance tasks. Therefore, an important question is how the structure of motor variability, demonstrated during the early stages, relates to learning rate during an error-based task and what it means.

To answer these questions, two experimental set-ups were carried out to analyze the relationship between motor variability and learning rate in balance tasks where the performance criterion was the reduction in the amount of variability. In Experiment 1, the learning rate in a standing balance task was assessed within-session. Based on the results of Experiment 1 and its limitations, a second experiment was performed using a less common and more difficult sitting balance task with longer trial times and an increased practice period. In both experiments, the learning rate was compared between the two groups and showed similar balance performance (magnitude of variability) but a different long-range auto-correlation of the postural sway fluctuations (structure of variability).

Experiment 1: Standing Protocol

Method

Participants. Thirty volunteers took part in Experiment 1 (mean age: 24.2 ± 4.6 years; mean height: 1.72 ± 0.09 m; mean mass: 69.0 ± 10.7 kg), 11 women (mean age: 23.4 ± 3.4 years; mean height: 1.64 ± 0.06 m; mean mass: 59.5 ± 5.0 kg) and 19 men (mean age: 24.6 ± 5.2 years; mean height: 1.77 ± 0.07 m; mean mass: 74.5 ± 9.2 kg).

All of the participants were healthy and without current knee or ankle injury or past pathology in these regions. All of the subjects reported having no neurological or musculoskeletal problems. No participant had previous experience in the balance task used in this study. Written informed consent was obtained from each participant prior to testing. The experimental procedures used in this study were in accordance with the Declaration of Helsinki and were approved by the Office for Research Ethics of Miguel Hernandez University (2013.83.OEP).

Procedure. The participants were asked to "stand as still as possible" (Cavanaugh, Mercer, & Stergiou, 2007; Duarte & Sternad, 2008) on a BOSU balance trainer (BOSU, Ashland, OH; diameter: 65 cm; height: 23 cm) with their feet placed 30 cm apart and their hands resting on their hips (see Figure 1). The BOSU pressure was constant between the participants (0.3 bar) and was checked before and after each participant's testing. To assess postural stability, this study used a force plate (Kistler, Switzerland, Mode 9287BA). The feet were positioned such that the line between their heels coincided with the medial-lateral axis of the platform. Trials were performed barefoot in front of a clear white wall with no visual reference. Although a safety rail was placed in front of the participant providing a secure bar to grasp if participants perceived they were unable to control their balance, all participants were able to maintain the standing posture, without grasping a support rail or stepping in any direction during the trials. Ground reaction forces were recorded at 1000 samples/s and were calibrated at the beginning of each participant's collection. Participants performed a 30-s pretest trial followed by 10 practice trials to analyze the effect of practice within the same day. Each practice trial lasted 15 s, with a 45-s rest between trials. A 30-s posttest was then performed under the same conditions as the pretest. Each data collection began when participants were relatively stable.

Data analysis and reduction. A custom software program in Labview, 2009 (National Instruments, Texas) was used for data analysis. There is little physiological significance to the COP signal frequencies above 10 Hz (Borg & Laxaback, 2010), and thus the COP time series were subsampled at 20 Hz. This also removed the artificial colinearities that could affect the variability analysis (Barahona & Poon, 1996; Rhea et al., 2011). The first 5 s of each trial were discarded to avoid nonstationarity related to the beginning of the trial (van Dieen, Koppes, & Twisk, 2010); thus, the length of the final time series was 500 data points for each participant. Finally, a low-pass filter (4th-order, zero-phase-lag, Butterworth, 5 Hz cut-off frequency) was performed, according to Lin, Seol, Nussbaum, and Madigan (2008).

Because the orientation of the participant was only approximately aligned with the axes of the force platform, the resultant distance (RD) was used as a global measure to quantify performance during the balance trials (Prieto, Myklebust, Hoffmann, Lovett, & Myklebust, 1996). RD was calculated as the average of the vector distance magnitude (mm) of the COP from the participant's own mean COP position. The absolute learning rate (ALR) and relative learning rate (RLR) were calculated as follows: the ALR was the RD differences between the pretest (RD_{PRE}) and posttest

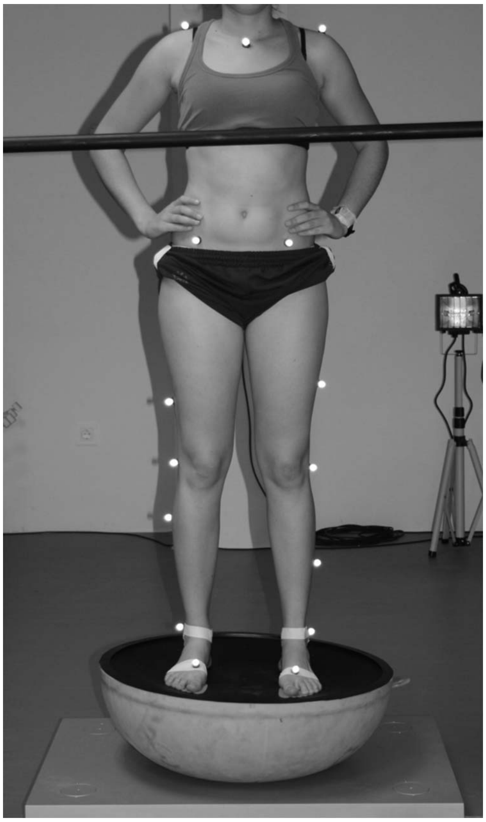

Figure 1. Participant performing a standing stability task on a BOSU surface.

(RD_{POST}), whereas the RLR was calculated relative to the initial performance of each individual [$100^*(RD_{PRE} - RD_{POST})/RD_{PRE}$].

To assess the structure of the variability, we used *Detrended Fluctuation Analysis* (DFA). DFA is a method based on the random walk theory, representing a modification of a classic root mean square analysis of the random walk, which evaluates the presence of long-term correlations within the time series by a parameter referred to as the scaling index α (Peng et al., 1994; Peng et al., 1995; M. Roerdink et al., 2006). Different values of α indicate the following: $\alpha > .5$ implies persistence (i.e., the trajectory tends to continue in its current direction); $\alpha < .5$ implies antipersistence (i.e., the trajectory tends to return to where it came from); and $\alpha = .5$ implies uncorrelated signal (M. Roerdink et al., 2006). Therefore, α identifies the extent to which further data are dependent on the previous (Jordan & Newell, 2008). Previous COP displacement in balance tasks have exhibited α-values ranging from 0.5 to 1.5 (Duarte & Sternad, 2008; Wang & Yang, 2012), and have been used to assess human adaptability to postural or motion adjustments (Amoud et al., 2007; Wang & Yang, 2012).

To maximize the long-range correlations and to reduce the estimation error of α, long-term correlation was characterized by the slope α obtained from the range of $4 \le n \le N/10$, where N is the data length (Chen, Ivanov, Hu, & Stanley, 2002). The participants were only approximately aligned with the axes of the force platform, and the α of each participant was calculated as the average α obtained from both axes.

Statistical analysis. Normality of the variables was evaluated through the Kolmogorov–Smirnov test with Lilliefors correction. First, Pearson's bivariate correlations were performed between RD_{PRE}, α_{PRE}, ALR and RLR to assess the initial performance and variability influence on learning rate. Second, to avoid the initial performance bias on learning rate, participants were grouped using a linear regression method. As demonstrated in Figure 2, participants were sorted according to their RD_{PRE} values. Three groups were then formed, consisting of the lowest, middle and highest RD_{PRE} scores, with 10 participants per group. Then, we performed a linear regression between RD_{PRE} and α_{PRE} in each performance group. Finally, participants were grouped according to their residual scores. The higher residual scores in each group were included in the "High auto-correlated variability" (HAV) group. The lower residual scores in each group were included in the "Low auto-correlated variability" (LAV) group. One-way ANOVA for independent measures was performed to assess the ALR and RLR differences between groups, with the initial structure of variability

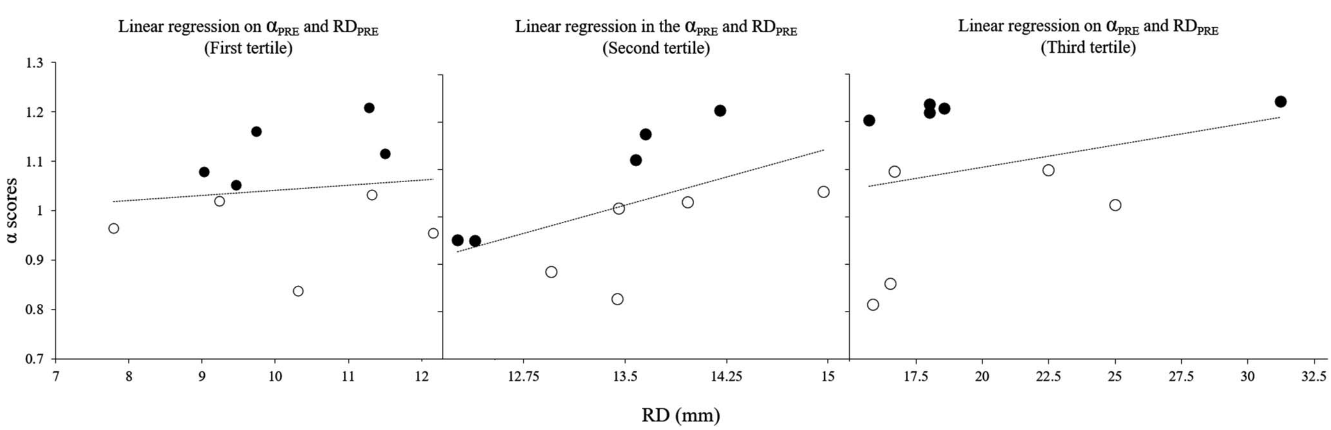

Figure 2. Linear regression of the initial structure of the variability (α_{PRE}) and the initial performance (RD_{PRE}) during a standing balance protocol in the three performance groups. Black dots represent the participants included in the "high auto-correlated variability" group (HAV), and white dots represent the participants included in the "low auto-correlated variability" group (LAV).

as an intersubject factor (HAV and LAV groups). A mixed-way ANOVA was performed with RD as a within-subject factor (PRE and POST) and with the initial structure of variability as an intersubject factor (HAV and LAV groups). The partial eta squared (η_p^2) was calculated as a measure of effect size. The values of an effect size $\geq$0.64 were considered strong, between 0.64 and 0.25 were considered moderate, and $\leq$0.25 were considered small (Ferguson, 2009).

Finally, to check the results obtained with the linear regression method, we performed a Principal Component Analysis (PCA) on the initial structure of the variability (α_{PRE}), the initial performance (RD_{PRE}), and the relative learning rate (RLR). This method reduces the dimensionality of interrelated measures (Jolliffe, 2002) and facilitates the interpretation of the results as it extracts features that are directly related to the original data set (Rocchi, Chiari, & Cappello, 2004). All statistical analyses were performed using IBM SPSS software 18.0, with significance level set at $p < .05$.

Results

Participants improved their performance, reducing their RD significantly after practice trials ($RD_{PRE} = 14.5 \pm 5.0$ mm; $RD_{POS} = 12.6 \pm 3.1$ mm; $F_{1,28} = 4.571$; $p = .041$; $\eta_p^2 = 0.136$). As shown in Table 1, the learning rate significantly correlated with the initial performance, while no significant correlations were found between the learning rate and the initial structure of variability. These results indicate that the learning rate is highly determined by the initial performance, while the initial structure of variability does not seem to influence it. That is, less skillful individuals have a higher room for improvement than more skillful ones. However, although no significant relationship was found between RD_{PRE} and α_{PRE}, it was close to being significant ($r = .319$; $p = .086$), suggesting that initial performance could bias the relationship between the variability and learning rate. That is, less skillful individuals who tend to show higher α_{PRE} values could show higher learning rates.

To assess the relationship between the initial structure of the variability (α_{PRE}) and the learning rate (ALR, RLR), avoiding the bias of the initial performance (RD_{PRE}), participants were grouped using a linear regression method (see Figure 2). The higher residual scores (black dots in Figure 2) in each performance level were included in the HAV group, whereas the lower residual scores (white dots) were included in the LAV group.

Table 2 shows the values of the two groups after the distribution of the participants. The groups were quite similar in the initial performance (RD_{PRE}: $F_{1,28} = 0.006$; $p = .938$: $\eta_p^2 = 0.001$) but different in the structure of the variability (α_{PRE}: $F_{1,28} = 24.614$; $p < .001$; $\eta_p^2 = 0.468$). After analyzing the effects of practice on the performance variables, no significant differences were found between groups in the learning rate, but the LAV group showed a trend for higher RLR values compared with the HAV group (RLR: $F_{1,28} = 3.735$; $p = .063$; $\eta_p^2 = 0.118$).

Nevertheless, as pairwise comparisons show (see Figure 3), whereas the LAV group reduced the RD significantly between pretest and posttest measures ($p = .015$), the HAV group did not show significant changes in RD ($p = .620$). Thus, only the LAV group showed an improved performance (see Figure 3).

Based on these results, we performed a PCA to examine the underlying relationships between the initial performance, the initial structure of the variability and the learning rate. The first principal component factor (PC_1) accounted for 55.14% of the total variance and showed that a higher RLR was mainly related to a higher RD_{PRE} (worse performance) and to a lesser extent to a higher α_{PRE}, supporting the notion that the learning rate is highly determined by the initial performance (see Table 3). In addition, less skillful individuals showed a high auto-correlated COP variability. PC_2, accounting for 34.94% of the total variance, showed that a higher RLR was related to a low α_{PRE} and was unrelated to RD_{PRE} (see Table 3). Figure 4 shows the relationship between these variables, indicating that individuals with low PC_2 values showed a higher learning rate ($R^2 = 0.229$; $p = .007$), lower auto-correlated COP variability ($R^2 = 0.817$; $p < .001$), and equivalent initial performances ($R^2 = 0.002$; $p = .793$) compared with individuals with high PC_2 values.

Table 1
Pearson's Bivariate Correlations Among Individuals' Initial Balance Performance (RD_{PRE}), Initial Structure of Variability (α_{PRE}), and Learning Rate in Absolute (ARL) and Relative (RLR) Values

Variable	α_{PRE}	ALR	RLR
RD_{PRE}	.319 (.086)	.799 (<.001)	.596 (<.001)
α_{PRE}		.053 (.782)	−.058 (.760)

Note. Pearson correlation coefficient (level of significance). α_{PRE} = long-range autocorrelation index shown in the pretest; RD_{PRE}= resultant distance shown in the pretest.

Discussion

Previous studies found a relationship between an individual's motor variability during a baseline period and learning rate in reward-based tasks, but limited evidence is available for error-based learning (Wu et al., 2014).

In this study, we found little evidence that motor variability predicted the rate of learning. However, our results suggest that an individual's initial performance level could bias the relationship between motor variability and learning rate. Specifically, based on PC_1 results (Tables 1 and 3), individuals with higher auto-correlated COP variability, which has been interpreted as an index of lower number of postural adjustments (Amoud et al., 2007; Wang & Yang, 2012; Zhou et al., 2013), tended to show poorer performance (high magnitude of variability) but learned to a higher extent. As previously described in balance learning (Ko, Challis, & Newell, 2003), individuals in the early stages of learning display an exploratory search behavior, characterized by large variability, for a more stable and efficient postural coordination mode compared with other motor solutions. It is reasonable to assume that participants in an earlier stage of learning would have greater room for improvement. On the other hand, individuals who showed lower auto-correlated motor fluctuations, this is, larger number of changes in COP excursion and consequently more postural adjustments, displayed better balance performance but lower learning rate. These results are in coherence with those found in a later stage of learning, whereby exploitation rather than exploration behavior is utilized (Herzfeld & Shadmehr, 2014; Wu et al., 2014).

Table 2
Mean ± SD Differences of the Initial Structure of Variability (α_{PRE}), the Initial Performance (RD_{PRE}), and the Absolute and Relative Learning Rate (ALR and RLR) Between Individuals With High or Low Initial Long-Range Auto-Correlation Grouped According to the Residuals of the Linear Regression Grouping Method

Variable	LAV group (n = 15)	HAV group (n = 15)	$F_{1,28}$	p	η_p^2
α_{PRE}	.96 ± .09	1.14 ± .09	24.614	<.001	.468
RD_{PRE}(mm)	14.41 ± 4.60	14.57 ± 5.55	.006	.938	.001
ALR (mm)	3.19 ± 4.29	.61 ± 5.30	2.183	.151	.072
RLR (%)	17.26 ± 26.57	−3.01 ± 30.72	3.735	.063	.118

Note. One-way ANOVA for independent measures. α_{PRE} = long-range autocorrelation index shown in the pretest; RD_{PRE}= resultant distance shown in the pretest; LAV group = Low auto-correlated variability group; HAV group = High auto-correlated variability group.

However, it may be reasonable to assume that individuals who display a higher ability to perform postural adjustments would also show a greater learning rate. When participants were grouped using the linear regression method and the initial performance bias was avoided, those individuals with low long-range auto-correlated COP variability (low α_{PRE}) tended to display greater performance improvement than those with high long-range auto-correlation. PC_2 confirmed these findings, supporting the hypothesis that individuals with a higher ability to perform postural adjustment have greater improvement potential.

In terms of limitations, it could be argued that the between-groups differences in the learning rate, based on the initial structure of variability, showed a small size-effect and were only significant when the learning rate was assessed in a relative sense. These results were influenced by the small learning rate observed after practice. Even so, some individuals showed a poorer performance after practice (see Figure 3), suggesting that the task was too easy or that the practice was not extensive enough to promote learning. If this were the case, there would have been no need for the motor exploration, thus decreasing the importance of the motor variability as a functional feature of learning (Woolley & Doupe, 2008; Wu et al., 2014). Another limitation could be related to the low reliability that scattering variables such as RD exhibit during the data series involving short easy tasks (Lee & Granata, 2008; van Dieen et al., 2010). If a balance task is too easy, participants might attempt to maintain balance with their center of mass at different locations relative to their support surface (Caballero, Barbado, & Moreno, 2015). In such cases, it is difficult to achieve stationarity of the time series, decreasing the reliability of the scattering variables such as RD (Caballero et al., 2015; Lee & Granata, 2008) and DFA (Caballero et al., 2015).

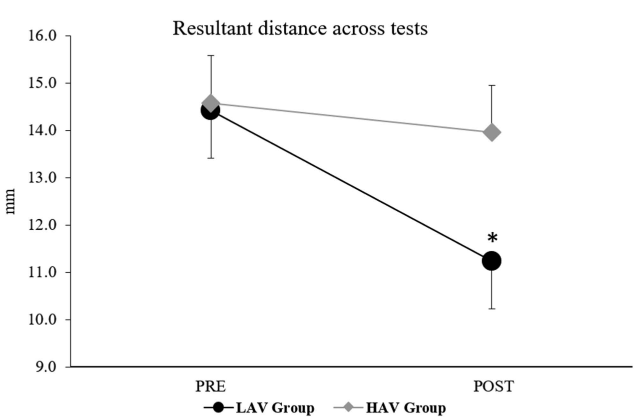

Figure 3. Pre- and posttest differences in the resultant distance (RD) between the “high auto-correlated variability” (HAV) and the “low auto-correlated variability” (LAV) groups. Participants were grouped in the HAV or LAV groups according to the residual scores of the linear regression method between the initial performance (RD_{PRE}) and initial structure of variability (α_{PRE}). *Significant pre- and posttest differences of the LAV group.

Taking the results and the aforementioned concerns into account, we tested the hypothesis in a second experiment using a less common and more difficult balance task with longer trial times and with an increased practice period.

Experiment 2: Sitting Protocol

Method

Participants. Twenty-two male volunteers took part in Experiment 2 (mean age: 24.6 ± 4.6 years; mean mass: 73.6 ± 7.5 kg, mean height: 1.74 ± 0.07 m; mean trunk moment of inertia: 5.22 ± 0.76 kg*m^2). The inclusion criteria were the same as the previous experiment. All subjects were healthy, without current pain in the hip or back or past pathology in these regions. All of the subjects reported having no neurological or musculoskeletal problems. No participant had previous experience in the balance task used in this study. Written informed consent was obtained from each participant prior to testing. The experimental procedures were in accor-

Table 3
Principal Component Factors (PC) Obtained From the Principal Component Analysis During the Standing Protocol

Components	PC_1	PC_2	PC_3
RD_{PRE}	.924	.049	−.378
RLR	.810	−.479	.338
α_{PRE}	.379	.904	.200

Note. α_{PRE} = long-range autocorrelation index shown in the pretest; RD_{PRE}= resultant distance shown in the pretest; LAV group = Low auto-correlated variability group; HAV group = High auto-correlated variability group.

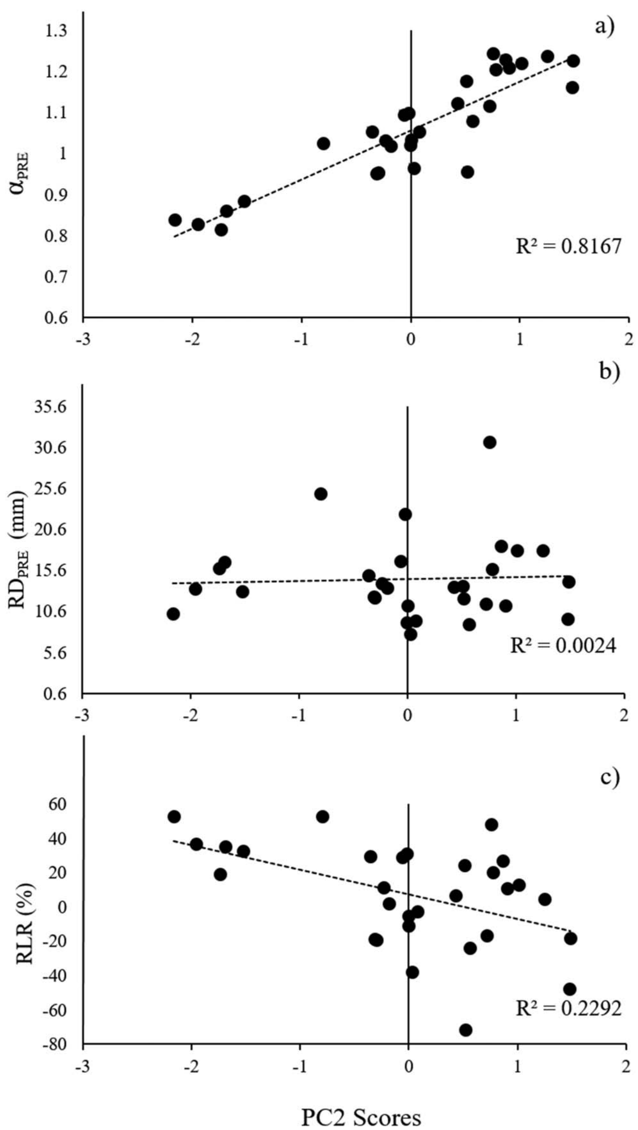

Figure 4. Relationship between PC2 scores and a) the initial performance (RD_{PRE}); b) the initial long-range autocorrelation of the COP variability (α_{PRE}) and c) the relative learning rate (RLR) during the protocol of Experiment 1.

dance with the Declaration of Helsinki and were approved by the University Office for Research Ethics.

Procedure. Participants sat upon a seat assembly consisting of a wooden platform (50 cm × 50 cm) affixed to the flat surface of a polyester resin hemisphere (diameter of hemisphere: 35 cm; height of the seat relative to the bottom of the hemisphere: 12 cm) (see Figure 5). The seat was equipped with wooden leg and foot supports to prevent lower body movement relative to the platform. Foot support height was individually adjusted to create a 90° knee angle and light plantar foot support, while elastic straps secured each participant's lower leg to the leg support. A safety rail was placed in front of the participant, thus providing a secure bar to grasp if participants perceived they were unable to control their balance, and to hold onto during rest periods (see Figure 6). In addition, a wooden stabilizing device was inserted under the seat platform during the rest periods, thus stabilizing the platform from any rocking motion. In this way, fatigue was avoided and participants were unable to gain further balance practice during the rest periods.

To analyze the effect of practice, participants attended 3 testing sessions spaced 1 week apart. Five 70-s trials were collected per session (15 trials in total) with 2 min of rest between trials. The 70-s of data collection began when they were relatively stable with their hands on their lateral chest at rib level. They were instructed to maintain their balance, keeping the unstable platform "as still as possible" (Cavanaugh, Mercer, & Stergiou, 2007; see Figure 5).

The seat assembly was placed atop a force plate (Kistler, Switzerland, Model 9286AA), which was sampled at 1000 Hz and calibrated prior to each test. The COP data were subsampled at 20 Hz following the same principle explained in Experiment 1.

Data analysis and reduction. Although the data analysis closely followed the procedure used in the previous experiment, there were a few differences. To avoid nonstationarity related to the beginning of the trial, the first 10 s of each trial were discarded (van Dieen et al., 2010). The length of the time series analyzed was 1200 data points.

Similar to the first experiment, because the orientation of the participant was only approximately aligned with the axes of the force platform, the resultant distance (RD) was used as a global

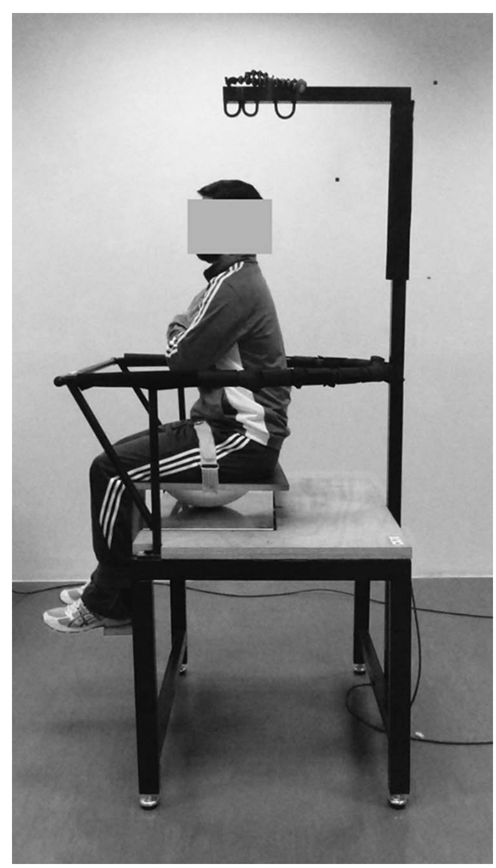

Figure 5. Participant performing the sitting stability task on the unstable seat.

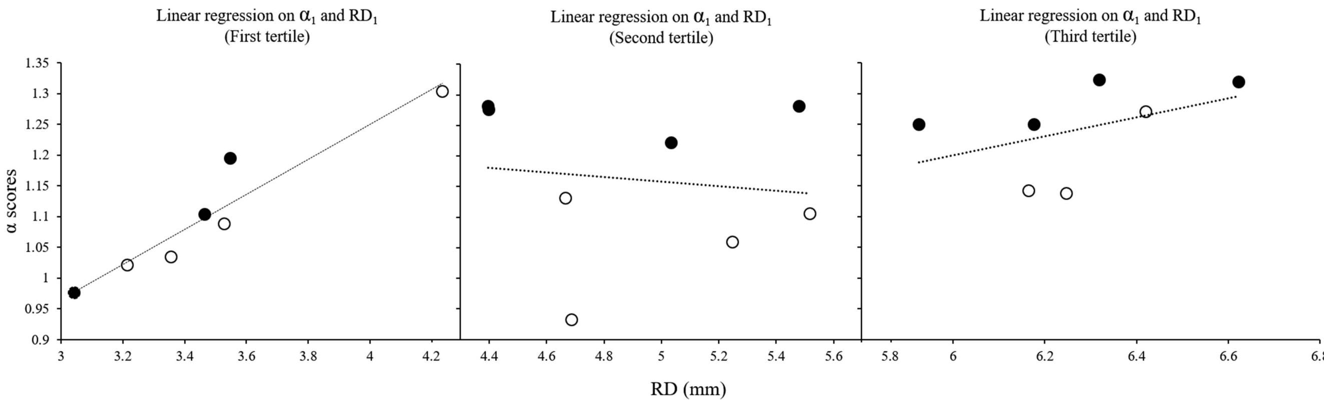

Figure 6. Linear regression of the initial structure of the variability (α_1) and the initial performance (RD_1) during the sitting balance protocol in the three performance groups. Black dots represent the participants included in the "high auto-correlated variability" group (HAV), and white dots represent the participants included in the "low auto-correlated variability" group (LAV).

measure to quantify the performance during the balance trials (Prieto et al., 1996), and the α scores of each participant were calculated as the average α obtained from both axes.

In this experiment, the RD and α of each participant were averaged over the three last trials of each session. The ALR was now calculated as the RD differences between the third and second sessions relative to the first ($ALR_{1–2}$ and $ALR_{1–3}$). The RLR was similarly calculated relative to the initial performance of each individual ($RLR_{1–2}$ and $RLR_{1–3}$).

Statistical analysis. The statistical analysis performed in Experiment 2 was similar to Experiment 1. Normality was evaluated through the Kolmogorov–Smirnov test with Lilliefors correction. First, a Pearson's correlation was performed between the performance (RD_1) and long-range autocorrelation (α_1) in the first session, and the learning rate ($ALR_{1–2}$, $ALR_{1–3}$, $RLR_{1–2}$ and $RLR_{1–3}$) to assess the initial performance and variability influence on the learning rate. Second, to avoid the initial performance bias on the learning rate, participants were grouped using a linear regression method. Specifically, participants were classified into three groups according to their RD_1. A linear regression was then performed between RD_1 and α_1 in each performance group. Similar to the first experiment, participants were grouped according to their residual scores: higher residual scores made up the HAV group and the lower scores comprised the LAV group. One-way ANOVA for independent measures was performed to assess learning rate ($ALR_{1–2}$, $ALR_{1–3}$, $RLR_{1–2}$ and $RLR_{1–3}$) differences between the groups with the initial structure of the variability as an intersubject factor (HAV and LAV groups). A mixed-way ANOVA was performed with RD as a within-subject factor (Session 1, Session 2 and Session 3) and with the initial structure of the variability as an intersubject factor (HAV and LAV groups). Partial eta squared (η_p^2) was calculated to measure effect size. Effect size ≥0.64 were considered strong, between 0.64 and 0.25 moderate, and ≤0.25 were considered small (Ferguson, 2009).

Finally, PCA was performed (Table 6 and Figure 9) to check the results obtained with the linear regression method and to extract underlying relationships between the initial structure of the variability (α_1), initial performance (RD_1) and relative learning rate ($RLR_{1–3}$).

Statistical analyses were performed using IBM SPSS software 18.0, using a significance level of $p < .05$.

Results

All participants improved their performance and significantly reduced their RD between the 3 sessions ($RD_1 = 4.9 \pm 1.2$ mm; $RD_2 = 4.3 \pm 1.0$ mm; $RD_3 = 3.3 \pm 0.8$ mm; $F_{2,42} = 32.694$; $p < .001$; $\eta_p^2 = 0.598$). Nevertheless, the effect size indicated the learning rate in Experiment 2 was higher than that of in Experiment 1. As Table 4 shows, learning rate significantly correlated

Table 4
Pearson's Bivariate Correlations Between the Individual's Initial Balance Performance (RD_1), Initial Structure of the Variability (α_1), and Learning Rate in Absolute ($ALR_{1–2}$, $ALR_{1–3}$) and Relative ($RLR_{1–2}$, $RLR_{1–3}$) Values

Variable	α_1	$ALR_{1–2}$	$RLR_{1–2}$	$ALR_{1–3}$	$RLR_{1–3}$
RD_1	.537 (.010)	.536 (.010)	.407 (.060)	.723 (<.001)	.485 (.022)
α_1		.350 (.111)	.332 (.131)	.283 (.202)	.161 (.474)

Note. Pearson correlation coefficient (level of significance). α_1 = long-range autocorrelation index shown in the first session; RD_1 = Resultant distance shown in the first session; $ALR_{1–2}$ = absolute learning rate between sessions 1 and 2; $ALR_{1–3}$ = absolute learning rate between sessions 1 and 3; $RLR_{1–2}$ = relative learning rate between sessions 1 and 2; $RLR_{1–3}$ = relative learning rate between sessions 1 and 3.

with initial performance, while no significant correlations were found between learning rate and the initial structure of the variability. Again, these results indicate that the learning rate is highly determined by initial performance, whereas the initial structure of the variability does not seem to influence it. However, a significant relationship was found between RD_1 and α_1, supporting that initial performance biased the relationship between variability and the learning rate. That is, less skillful individuals who show higher α_1 values have a higher learning rate.

As in Experiment 1, to assess the relationship between the initial structure of variability (α_1) and learning rate ($ALR_{1–2}$, $ALR_{1–3}$, $RLR_{1–2}$, $RLR_{1–3}$) while avoiding the bias of the initial performance (RD_1), participants were grouped using a linear regression method (see Figure 6). Again, higher residual scores (black dots in Figure 6) in each performance level were included in the HAV group, whereas lower residual scores (white dots) were included in the LAV group.

Table 5 shows the group mean values after participants were divided in the HAV and LAV groups. Although groups were quite similar in initial performance (RD_1: $F_{1,20} = 0.038$; $p = .847$: $\eta^2_p = 0.002$) they differed in the structure of variability (α_1: $F_{1,20} = 24.614$; $p < .001$; $\eta^2_p = 0.468$). After analyzing the effects of practice on performance variables, significant between-groups differences were found in $ALR_{1–3}$ and $RLR_{1–3}$. The LAV group showed a higher learning rate than the HAV group.

The mixed measure ANOVA showed a performance improvement after practice in both groups ($F_{1,20} = 32.694$; $p < .001$; $\eta^2_p = 0.598$). However, the LAV group showed higher improvements between Sessions 3 and 1 than the HAV group (Interaction $F_{1,20} = 4.389$; $p = .049$; $\eta^2_p = 0.180$). Pairwise comparisons showed significant between-groups differences in RD in Session 3 ($p = .006$; see Figure 7).

Although the differences between participants with different α scores do not seem to be apparently different through visual inspection, Figure 8 shows the most representative examples about the differences in learning rate (%) two participants with different initial α scores but similar initial performance level (RD_{PRE}). This figure shows the pretest and posttest data series of two participants, where the α scores and relative learning rate (%) can be observed. Participant A showed lower long-range auto-correlation in the pretest and higher learning rate than Participant B.

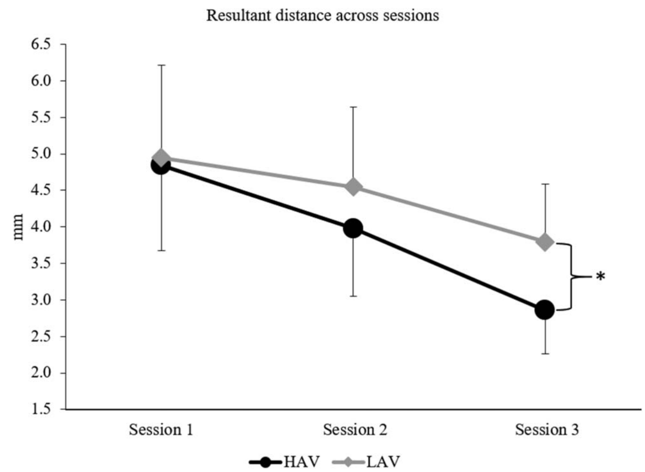

Figure 7. Resultant distance values (RD) from the "high auto-correlated variability" (HAV) and "low auto-correlated variability" (LAV) groups across sessions. *Significant differences between the groups in Session 3.

Finally, the PCA performed among the initial performance (see Table 6), initial structure of variability, and learning rates between Sessions 1 and 3 supported the aforementioned results. PC_1 accounted for 60.28% of the total variance, showing that a higher $RLR_{1–3}$ was related to a higher RD_1 and α_1. Thus, less skillful individuals had greater room for improvement than more skillful ones but showed higher auto-correlation of COP variability. PC_2 accounted for 27.99% of the total variance and showed that a higher $RLR_{1–3}$ was related with low α_1, yet unrelated to RD_1. As shown in Figure 9, individuals with low PC_2 values demonstrated a higher learning rate ($R^2 = 0.446$; $p < .001$), lower auto-correlated COP variability ($R^2 = 0.373$; $p = .003$) and no difference in their initial performance ($R^2 = 0 .001$; $p = .920$) when compared with individuals with high PC_2 values.

Table 5
Mean ± SD Differences of the Initial Structure of the Variability (α_1), the Initial Performance (RD_1), and the Absolute and Relative Learning Rate ($ALR_{1–2}$, $ALR_{1–3}$, $RLR_{1–2}$, $RLR_{1–3}$) Between Individuals With High or Low Initial Long-Range Auto-Correlation Grouped According to the Residuals of the Linear Regression Grouping Method

Variable	LAV group ($n = 11$)	HAV group ($n = 11$)	$F_{1,20}$	p	η^2_p
α_1	1.11 ± .11	1.22 ± .11	6.437	.020	.243
RD_1	4.84 ± 1.18	4.95 ± 1.26	.038	.847	.002
$ALR_{1–2}$	.86 ± .73	.40 ± .88	1.834	.191	.084
$ALR_{1–3}$	1.98 ± .83	1.15 ± 1.02	4.389	.049	.180
$RLR_{1–2}$	16.85 ± 15.18	5.59 ± 19.54	2.277	.147	.102
$RLR_{1–3}$	39.69 ± 10.32	20.46 ± 17.81	9.599	.006	.324

Note. One-way ANOVA for independent measures. α_1 = long-range autocorrelation index shown in the first session; RD_1 = resultant distance shown in the first session; $ALR_{1–2}$ = absolute learning rate between sessions 1 and 2; $ALR_{1–3}$ = absolute learning rate between sessions 1 and 3; $RLR_{1–2}$ = relative learning rate between sessions 1 and 2; $RLR_{1–3}$ = relative learning rate between sessions 1 and 3; LAV group = Low auto-correlated variability group; HAV group = High auto-correlated variability group.

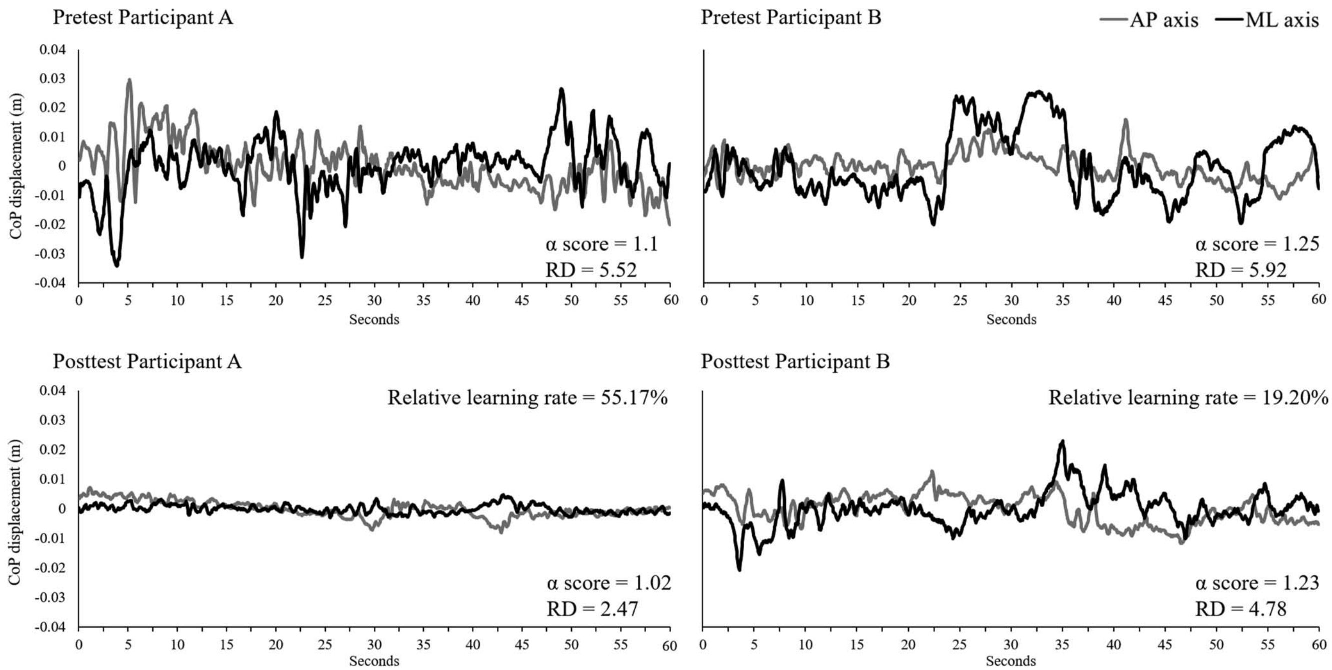

Figure 8. Representative example of two participants with similar pretest performance (RD: resultant distance) and different long-range auto-correlation (α score) of COP displacement

Discussion

Our second experiment, using a sitting balance task, confirmed the preliminary results found in Experiment 1. On the one hand, individuals with less auto-correlated COP variability showed a better performance but a lower learning rate. Conversely, when the bias caused by initial performance was controlled, individuals with less auto-correlated COP variability showed a higher learning rate in both the relative and absolute values. Despite the fact that the statistical procedures used in both experiments are correlational and they do not permit the establishment of causal links, a less auto-correlated COP variability during the balance tasks suggests a higher ability to perform postural adjustments. This allows individuals to achieve better performance and faster learning. The lower learning rate found in Experiment 1 compared with the results found in the second experiment could indicate that in a daily basic movement, such as standing still, exploitation strategies prevailed over exploration ones (Herzfeld & Shadmehr, 2014; Wu et al., 2014). Nevertheless, even in such easy and common tasks in which the exploitation of the current knowledge prevailed, individuals who showed higher motor exploration (lower α_1) also demonstrated a higher learning rate, suggesting that they are forgoing, in some way, their performance in view of an increased learning rate. A higher effect-size found in Experiment 2 indicates that during unusual and more difficult tasks, such as the sitting balance, exploration strategies prevail, increasing the functional role of the variability as a learning facilitator. Overall, these results agreed with previous findings on both reward-based and error-based pointing tasks (Wu et al., 2014). However, to the best of our knowledge, this is the first study to assess the relationship between the structure of motor variability and learning rate, while avoiding the influence of the initial performance level and using a task where performance criterion was the reduction in the amount of variability.

Table 6
Principal Component Factors (PC) Obtained From Principal Component Analysis During the Sitting Protocol

Components	PC_1	PC_2	PC_3
RD_1	.897	−.023	−.442
$RLR_{1–3}$	.732	−.611	.302
α_1	.684	.683	.255

Note. α_1 = long-range autocorrelation index shown in the first session. RD_1 = resultant distance shown in the first session; $RLR_{1–3}$ = relative learning rate between sessions 1 and 3.

One of the aims of this study was to test whether the analysis of the motor variability structure reveals motor system properties that promote learning when a low magnitude of the variability is required to have a good performance and what it does mean during an error-based task. During reward-based learning, motor variability magnitude is successfully interpreted as the exploration needed to find the most beneficial solutions, which will subsequently be exploited (Pekny et al., 2015; Wu et al., 2014). It has been observed that individuals increase their motor variability when they do not achieve success during an attempted motor task, which has been interpreted as a search for rewarding outcomes (Galea, Ruge, Buijink, Bestmann, & Rothwell, 2013; Pekny et al., 2015). However, during the learning process of an error-based task, thought to depend mainly on the cerebellum (Smith & Shadmehr, 2005), learning not only depends on the exploration capacity but also on the ability to measure and predict motor error. That is, the

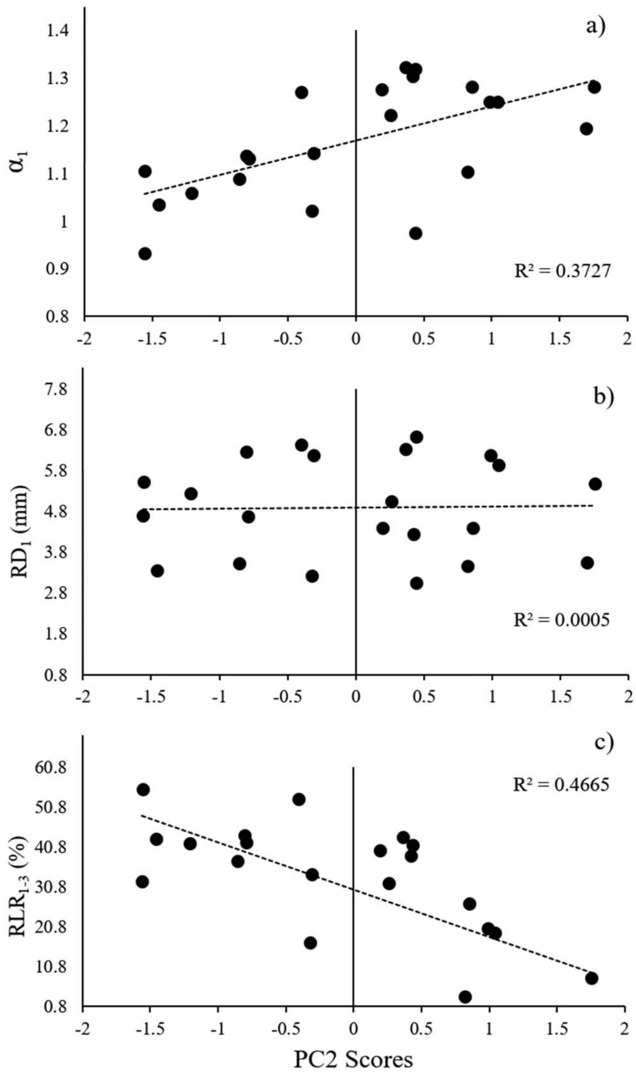

Figure 9. Relationship between PC_2 scores and the three variables analyzed: (a) the initial long-range autocorrelation of the COP variability (α_1), (b) the initial performance (RD_1), and (c) the relative learning rate (RLR_{1-3}) during the protocol of Experiment 2.

capacity to detect differences between the desired behavior and the actual motor outcome (Smith & Shadmehr, 2005). It would be expected that when individuals are more sensitive to their own motor error, increased motion adjustment is needed to reduce it. Previous literature suggests that motor variability during error-based learning helps determine differences between the desired motor behavior and the true motor output, facilitating motion adjustments to reduce motor error (Wu et al., 2014). However, there is still a lack of studies analyzing the ability to perform motion adjustments and how they relate to motor learning rate. The analysis of the structure of the variability through DFA reveals how the motor output changes over time instead of the magnitude of those changes. Therefore, the relationship between the α-scores and learning rate found in this current study would be more related to an individual's error sensitivity rather than exploration processes. Previous studies that assessed long-range auto-correlation of step-by-step variability during gait (Jordan, Challis, & Newell, 2007) or postural sway during balance tasks (Amoud et al., 2007; Wang & Yang, 2012) identified lower auto-correlated motor variability as an individual's greater ability to perform motion adjustments. In our experiments, individuals with lower auto-correlated COP variability showed generally better performance, indicating that the α-scores are an index related to skill level. That is, high skillful individuals are more sensitive to their own motion, allowing them to reduce the magnitude of their body fluctuation. Additionally, when compared with their counterparts who had similar performance but higher auto-correlated variability, they showed a higher learning rate. Therefore, the analysis of the structure of motor variability without the influence of performance level seems to reveal that the ability to perform motion adjustment is conditioned by the individual sensitivity to one's own motor errors (Herzfeld & Shadmehr, 2014; Smith & Shadmehr, 2005).

Finally, it should be noted that motor variability can be a motor system feature that is actively and centrally regulated to promote learning (Churchland et al., 2006; Mandelblat-Cerf, Paz, & Vaadia, 2009; Sober, Wohlgemuth, & Brainard, 2008). Previous studies have shown that motor variability depends largely on individual factors, such as effort, motivation or attention (Borg & Laxaback, 2010; Diniz et al., 2011; Roerdink, Hlavackova, & Vuillerme, 2011; Stins, Michielsen, Roerdink, & Beek, 2009; Van Orden, Holden, & Turvey, 2003). In this sense, Correll (2008) assessed the influence of the effort on the time-response latencies during a " decision-making shooting task" and found that higher effort was associated with a lower auto-correlated time response variability. Under this perspective, and taking into account the results of our study, low long-range autocorrelation values mean that the participants have a high implication to perform motion adjustment to reduce motor output error.

Despite these implications, our results point out that the analysis of the structure of variability can be useful in predicting individual learning rate, but the underlying processes that influence it are still uncertain. Future studies should address the extent to which individual constraints affect the structure of variability and whether it can be modulated during the practice period to promote faster learning.

In conclusion, our findings show that analysis of long-range autocorrelation reveals a relevant role for motor variability during motor error-based learning, even when a reduction of the magnitude of the output variability is required to achieve a good performance and individuals show a similar performance level.

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