Stride-to-stride variability is altered when running to isochronous visual cueing but remains unaltered with fractal cueing

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1   **Title**: Stride-to-stride variability is altered when running to isochronous cueing but remains

2   unaltered with a fractal one.

3 **Abstract**:

4 Running synchronized to external cueing is often implemented in both clinical and training

5 settings, and isochronous cueing has shown to improve running economy. However, such cueing

6 disregards the natural stride-to-stride fluctuations present in human locomotion reflecting higher

7 levels of adaptability. The present study aimed to investigate how alterations in the temporal

8 structure of cueing affects stride-to-stride variability during running. We hypothesized that running

9 using cueing with a fractal-like structure would preserve the natural stride-to-stride variability of

10 young adults, while isochronous and random cueing would b. Thirteen runners performed four 8-

11 min trials: one uncued (UNC) trial and three cued trials presenting an isochronous (ISO), a fractal

12 (FRC) and a random (RND) structure. Repeated measures ANOVAs were used to identify changes

13 in the dependent variables. We have found no effects on the cardiorespiratory parameters, whereas

14 a significant effect was observed in the temporal structure of stride-to-stride variability. During

15 FRC, the participants were able to retain the fractal patterns of their natural locomotor variability

16 observed during the UNC condition, while during the ISO and RND they exhibited more random

17 of fluctuations (i.e., lower values of fractal scaling). Our results demonstrate that cueing based on

18 the natural stride-to-stride fluctuations opens new avenues for training and rehabilitation.

19 **Key words**: running biomechanics, external pacing, metronome, gait complexity, detrended

20 fluctuation analysis

21

Introduction

22

23   External pacing strategies that target improvements in cadence, are implemented in both

24   clinical and training settings for runners. From a clinical standpoint, providing a faster cadence is

25   a relevant alternative as it reduces lower extremity joint loading and forces, as compared to a self-

26   selected cadence at equivalent running speed (Hafer et al., 2014; Heiderscheit et al., 2011; Hobara

27   et al., 2012; Lenhart et al., 2014; Lyght et al., 2016; Schubert et al., 2014). Thus, increasing

28   cadence is a viable strategy to reduce the risk of running-related injury and pain (Barton et al.,

29   2016; Hafer et al., 2014; Heiderscheit et al., 2011; Hobara et al., 2012; Lenhart et al., 2014; Lyght

30   et al., 2016; Schubert et al., 2014). For training, external pacing strategies are often implemented

31   to help beginners respond better to changes in pace during racing, and maintain cadence during

32   fatigue (Aranki et al., 2018; Fortmann et al., 2012). In both settings, isochronous auditory cueing

33   (i.e., equal time intervals between events) is often chosen as the external pacing strategy (Schubert

34   et al., 2014)

35   Isochronous cueing (i.e., metronome) has shown to improve running economy (Bood et

36   al., 2013). Yet, such isochronous cueing disregard the natural stride-to-stride fluctuations that are

37   present in human gait (Hausdorff et al., 1995, 1997; Jordan et al., 2006; Jordan & Newell, 2008),

38   because the cues present no temporal variability between events leading to a loss of stride-to-stride

39   variations. This was evidenced when individuals walked in synchrony to isochronous cueing (Hunt

40   et al., 2014; Marmelat et al., 2014; Vaz et al., 2019; Vaz, Rand, et al., 2020). Importantly, this

41   natural stride-to-stride variability in gait, presented as non-random but fractal fluctuations, is

42   considered a fundamental feature of health providing enhanced capabilities for adaptability and

43   stability (Almurad et al., 2018; Cavanaugh et al., 2017; Ezzina et al., 2021; Ravi et al., 2021;

44   Stergiou et al., 2006; Vaz, Knarr, et al., 2020). Fractals

45   Agresta et al. (2019) recently reported that enforced step rate using isochronous cueing did

46   not affect stride-to-stride variability of running. This contrasts with previously walking-related

47   studies showing walking to isochronous cueing negatively alters the temporal structure of stride-

48   to-stride variability deteriorating its fractal patterns (Hunt et al., 2014; Kaipust et al., 2013;

49   Marmelat et al., 2014; Vaz et al., 2019; Vaz, Knarr, et al., 2020; Vaz, Rand, et al., 2020). These

50   studies further found that when cueing is presented with a fractal-like pattern, there are no

51   differences with uncued walking in healthy young adults. Importantly, Agresta et al.'s (Agresta et

52   al., 2019) quantified stride-to-stride variability in ~3-minute cued running trials, likely resulting in

53   reduced number of strides (i.e., < 300 data points), a critical aspect to obtain reliable measures of

54   stride-to-stride variability (Damouras et al., 2010). Regardless, the influence of cueing on stride-

55   to-stride variability during running remains poorly understood. However, such understanding is

56   important from both training and clinical perspectives as abovementioned.

57   Therefore, the purpose of this study was to determine how alterations in the temporal

58   structure of external cueing affects stride-to-stride variability during running. Assuming the

59   abovementioned limitation (Agresta et al., 2019) and considering the recent walking-related

60   research (Hunt et al., 2014; Kaipust et al., 2013; Marmelat et al., 2014; Rhea, Kiefer, D'Andrea,

61   et al., 2014; Rhea, Kiefer, Wittstein, et al., 2014; Vaz et al., 2019; Vaz, Knarr, et al., 2020; Vaz,

62   Rand, et al., 2020), we hypothesized that running using cueing with a fractal-like temporal

63   structure would preserve the natural stride-to-stride variability of healthy young adults, while

64   isochronous and random cueing would breakdown these fluctuations towards randomness.

65   Additionally, we sought to understand if running to different temporally structured cueing could

66   also change cardiorespiratory parameters. We hypothesized that cardiorespiratory response would

67   not be affected since speed was controlled in our experiment.

68

Materials and methods

70   Participants

71   *A priori* sample size calculation was determined based on the primary hypothesis. Fourteen

72 participants were recruited to this study providing an 80% power to detect an effect size of 0.92

73 (Vaz et al., 2019) at a significance level of 0.05. Participants were non-smokers and had no medical

74 history of cardiovascular or metabolic disease/disorders, nor of musculoskeletal disorders in the

75 past 6 months. Participants were instructed to avoid caffeine, alcoholic beverages, and strenuous

76 activity 24-hours prior to testing. Testing took place between 8am-10am to minimize potential

77 circadian effects. Participants signed an informed consent that the Institutional Review Board

78 previously approved.

79

80   Experimental Design

81   The participants visited the laboratory on three different days. They completed a baseline

82 and two experimental sessions. In the baseline session, participants completed an incremental test

83 to exhaustion to determine peak oxygen uptake ($\dot{V}O_{2peak}$), and the first ventilatory threshold (VT1).

84 Peak $\dot{V}O_2$ was recorded as the highest 30-second time average. VT1 corresponded to the $\dot{V}O_2$

85 when $\dot{V}E/\dot{V}O_2$ ($\dot{V}E$ – ventilation) and the final pressure of O_2 ($PETO_2$) began to increase without

86 a simultaneous increase in $\dot{V}E/\dot{V}CO_2$ and final CO_2 pressure ($PETCO_2$) (Wasserman et al., 1973).

87 These values were used to determine running intensity for the two experimental sessions.

88 Participants ran in the heavy intensity domain ($20\%\Delta = \left(VT1 + 0.20 \times \left[VO_{2peak} - VT1\right]\right)$)

89 during the experimental sessions. Breath-by-breath (Metamax 3Br2, Cortex, Leipzig, Germany)

90 exchange was collected to determine oxygen uptake ($\dot{V}O_2$) and ventilation ($\dot{V}E$). Heart rate (HR)

91 was collected during all sessions (Plux, Lisbon, Portugal). The first experimental session began

92 with a self-paced uncued (UNC) running condition. The stride time from UNC condition was used

93 to design individualized visual stimuli for 3 randomized cueing conditions: isochronous (ISO),

94 random (RND), and fractal (FRC). The first condition was completed 1-hour after the UNC

95 condition. Participants completed the remaining two randomized conditions, separated by 1-hour

96 of rest, in the second experimental session. The experimental running trials lasted for

97 approximately 8 minutes. A triaxial miniaturized accelerometer collecting at 1000Hz (Plux,

98 Lisbon, Portugal), placed at the lateral malleoli, was used to determine heel strike events.

99 The visual stimulus for the cueing conditions was provided via a moving horizontal bar

100 projected on a screen in front of the participant (Vaz et al., 2019; Vaz, Knarr, et al., 2020).

101 Participants were instructed to synchronize their right heel strike to the top of the moving bar's

102 path. The moving indicator turned red when reaching the top of the display. A visual apparatus,

103 instead of an auditory, was used given the natural dependence of gait on visual information during

104 locomotor tasks (Chien et al., 2015). It also enhances walking performance due to the attention

105 allocation to task-relevant information (Peper et al., 2012). Additionally, we have showed a visual

106 cueing paradigm is likely to improve synchronization (Vaz, Rand, et al., 2020).

107 The RND stimulus was generated using a normal distribution of random numbers. The

108 FRC stimulus was generated using an approximation of a -10 dB/decade filter with a weighted

109 sum of first order filters. The two stimuli were validated using Detrended Fluctuations Analysis

110 (DFA) – (RND: $\alpha = 0.5$; FRC: $\alpha = 1$). Both stimuli were scaled using the mean and standard

111 deviation of each participant's self-paced UNC stride-time. This scaling generated a set of subject-

112 specific stimuli and maintained the consistency of the stimulus patterns across subjects. The ISO

113 stimulus was generated using each participant's mean self-paced UNC stride-time and a standard

114 deviation of zero.

115

116 Data Analysis

117   Data from one participant was discarded due to technical issues. The first 15-seconds of

118 each trial were discarded prior to analysis to avoid transient effects of familiarization. A 4th order,

119 zero lag low-pass Butterworth filter with a cutoff frequency of 20Hz was applied to the

120 accelerometer signal. A custom MATLAB code was used to determine inter-stride intervals (ISI),

121 which were defined as the time difference between two consecutive heel strikes of the same foot.

122 The mean and standard deviation were calculated for each ISI time series. Outliers that fell outside

123 ± 2.5 standard deviations from the mean were removed from the time series. After outliers were

124 removed, coefficient of variation (CV), and long-range correlations were calculated for each ISI

125 time series. Asynchronies (ASYNC) were calculated as the time difference between the heel strike

126 and the metronome event. A negative value indicates that the heel strike occurred before the

127 stimulus. The mean ASYNC was calculated as a global indicator of synchronization performance.

128   DFA was used to determine the fractal-scaling exponent (α) for ISI time series. DFAα

129 quantifies the presence of the long-range correlations found in a physiological time series. DFA

130 integrates a time series, divided into window sizes of length n. In each window, a least squares line

131 of best fit is calculated. The data is then detrended by subtracting the integrated time series from

132 the least squares line. The root mean square is calculated for each window to determine the

133 magnitude of fluctuation, and is summed for the entire time series, F(n). This process is repeated

134 for a range of window sizes to determine the associated magnitudes of fluctuation for each window

135 size. Next, the log F(n) is plotted against log n (the root mean square is plotted against the window

136 sizes), and the slope of this line is the α-scaling exponent. When the α values are greater than 0.5,

137 they indicate a positively persistent long-range correlation. This means that increases tend to be

138 followed by increases and decreases tend to be followed by decreases. When the α values are less

139 than 0.5, they indicate anti-persistent correlations. This means that increases in the timeseries tend

140 to be followed by decreases, and vice versa. Window sizes of 16 to N/9 were used in the ISI

141 analysis, where N is the length of the data.

142 Cardiorespiratory parameters (Oxygen uptake ($\dot{V}O_2$), ventilation ($\dot{V}E$), and heart rate

143 (HR)) were quantified to assess potential changes as a function of stride-to-stride variability. For

144 $\dot{V}O_2$ and VE data, readings from the last minute of each experimental trial were used to calculate

145 the mean and standard deviation for each experimental session. For HR, continuous data from each

146 condition was used for calculations. Inter-beat (RR) intervals were identified from the

147 electrocardiogram signal and converted to beats per minute (bpm). Mean and standard deviation

148 were calculated from bpm.

149

150 Statistical Analysis

151 Analyses were performed using R (R Core Team; Vienna, Austria) with the level of

152 significance set *a priori* to 0.05. Descriptive means, standard deviations, and confidence intervals

153 were calculated for all variables (ISI-α, ISI-CV, mean ASYNC, mean $\dot{V}O_2$, mean $\dot{V}E$, mean HR)

154 for each condition. To study concomitant changes between conditions, repeated measures analysis

155 of variance was used to determine if differences existed in participants' mean values across

156 conditions. The assumption of normality was tested using frequency histograms and q-q plots.

157   Based on visual inspection, data were normally distributed. Mauchly's Test of Sphericity was used

158   to test the assumption of equal variance of the difference between pairs of means. Greenhouse-

159   Geisser adjustment was used to assess within participant differences if sphericity was not met.

160   Bonferroni-adjusted pairwise comparisons were used to determine which condition produced

161   significantly different mean values from others. Effect sizes were calculated as partial eta squared.

162 **Results**

163   Thirteen participants were included for analyses (22.8±3.6yrs, 1.74±0.07m, 67.9±8.9kg).

164 Descriptive statistics for all the dependent variables are presented in Table 1. The average $\dot{V}O_2peak$

165 during the incremental test was 49.9±5.5 ml/kg/min. Participants performed the experimental trials

166 at the speed of 2.9 ± 0.2 m/s.

167   **[Insert Table 1]**

168   A significant main effect for condition was observed for ISIs-α ($F_{1.79, 21.52}$=17.35, p< 0.001,

169 η^2=.494). Pairwise comparisons showed that ISI-α was significantly higher in UNC (0.90±0.14)

170 and FRC (0.84±0.13) conditions than both RND (0.65±0.16) and ISO (0.54±0.18) (Figure 1). No

171 other significant differences were found (p>0.05). Further, a statistically significant difference was

172 attained for ISI-CV ($F_{1.86,22.29}$=5.05, p=0.017, η^2=.170). Pairwise comparisons showed ISI-CV was

173 significantly different between FRC (2.79±1.65) and UNC (1.52±0.43; t_{36}=3.77, p=0.004)

174 conditions. No other statistically significant differences were found (p>0.05).

175   No statistically significant main effect was observed for ASYNC, HR, $\dot{V}O_2$ nor $\dot{V}E$ (Table

176 1).

177   **[Insert Figure 1]**

178

179

Discussion and implications

180

181   The present study aimed to determine how changes in the temporal structure of external

182 cueing alters stride-to-stride variability of running. We hypothesized that running with a fractal-

183 like temporal structure cueing would preserve the natural stride-to-stride variability of healthy

184 young adults, while isochronous and random cueing would affect it. Additionally, to assess if

185 running to different temporally structured cueing would affect cardiorespiratory parameters. We

186 hypothesized that cardiorespiratory response would not be affected because speed was controlled

187 in our experimental design. The findings supported our hypotheses.

188   It has been reported that walking to an isochronous metronome results in reduced DFA α-

189 values and deterioration of the fractal patterns present in stride-stride variability as compared to

190 uncued (Hausdorff et al., 1996; Marmelat et al., 2014; Vaz et al., 2019) Additionally, recent studies

191 showed that using external cueing with a fractal-like structure, preserves the natural stride-to-stride

192 fluctuations present in uncued self-paced walking (Marmelat et al., 2014; Vaz et al., 2019) Our

193 results agree with these studies and expand their findings to another locomotor task, running.

194 Specifically, the isochronous (α = 0.54±0.18) and random (α = 0.65±0.16) cueing conditions

195 negatively altered the stride-to-stride variability patterns towards more random type of fluctuations

196 (i.e., α values closer to 0.5). Moreover, no difference between the fractal-like cueing and self-

197 paced uncued running was found. Altogether, these results indicate that fractal cueing preserves

198 the natural stride-to-stride fluctuations present in running; while external cueing with no, or

199 random variability affects these physiological healthy patterns. Furthermore, we found that the

200 magnitude or amount of variability, measured here as the coefficient of variation from inter-stride-

201 intervals, was globally unaltered between conditions. We did find a statistical difference between

202 the fractal and the uncued conditions. However, it does not appear to have a substantial

11

203 physiological consequence given the absolute difference between the two conditions (i.e., ~1%).

204 This indicates that the use of cues in running is unlikely to affect the magnitude of variability.

205 Increases in the magnitude of variability are likely to increases metabolic cost (O'Connor et al.,

206 2012) resulting in poorer performance. Thus, this latter finding supports and corroborates our

207 findings that no changes in the cardiorespiratory function would be observed. Specifically, our

208 experimental design took this into consideration by using the mean and standard deviations from

209 the uncued running condition to individualize the external cueing cadence. Consequently, the

210 findings observed in the cardiorespiratory parameters are not being affected by this particular but

211 highly relevant methodological aspect.

212   Our results support previous research (Jordan et al., 2006; Jordan & Newell, 2008) that

213 showed evidence of fractal patterns in human locomotion. Particularly, the uncued condition

214 revealed α-values as those typically found in young adults walking (~0.9). However, it is not clear

215 whether this type of patterns in stride-to-stride variations of running are associated to performance

216 or injury risk; currently, the literature is inconclusive. For example, it has been reported that there

217 is a breakdown (~0.85 to ~0.75) of these patterns toward randomness as speed increases (Mann et

218 al., 2015). Yet, others showed an inverted U-shape in which its minimum corresponded to the

219 preferred running speed (Jordan et al., 2007; Jordan & Newell, 2008); while others showed no

220 changes at all (Fuller et al., 2016; Nakayama et al., 2010), in both runners (~0.7) and non-runners

221 (~0.9) (Nakayama et al., 2010). In addition, experienced runners have lower fractal patterns in

222 their stride-to-stride variations (Agresta et al., 2019; Nakayama et al., 2010). However, in the

223 presence of fatigue they exhibit more fractal-like patterns than in inexperienced runners [~0.72 to

224 ~0.69 and ~0.74 to ~0.75, for inexperienced and experienced, respectively (Mo & Chow, 2018)].

225 Also, previous injury lead to lower fractal patterns (0.79) than controls (~0.96) (Meardon et al.,

226 2011), although one study reported no differences (~0.85) (Mann et al., 2015). A major limitation

227 of most of these studies is the use of self-preferred speed. Self-preferred speed is often under or

228 overestimated by non-runners compared to runners leading to misinterpretations. It is then crucial

229 to develop studies where the running speed is set based on its physiological capacity, as conducted

230 in this study. Furthermore, the short time series (ranged from 160 to 424) previously used (Agresta

231 et al., 2019; Fuller et al., 2016; Mann et al., 2015; Mo & Chow, 2018) can lead to imprecise α-

232 values, hardly comparable between studies. Additionally, the DFA box sizes is also variable

233 between studies, and underreported. Solid methodological research that accounts for both running

234 speed control and assure the requirements (e.g., number of data points) for appropriate calculation

235 of the relevant metrics is a crucial next step in this area of research. It will enable a better

236 understanding of the potential value of fractal properties in the temporal structure of stride-to-

237 stride variations to running performance. In the present study, we followed the recommendations

238 of ~600 data points and box sizes from 16 to N/9 (Damouras et al., 2010).

239 For each condition, asynchronies were calculated to study the lag between the runner's foot

240 strike and sensory external cue. This was calculated to compare the runner's ability to match the

241 presented cue, which could affect the other parameters under investigation. Runners participating

242 in this experiment were able to match very well each temporal manipulation as suggested by no

243 differences in asynchronies. This is an important consideration for accurate data collection and

244 analysis verifying our novel experimental design. It ensures that the participants' foot strikes

245 followed the prescribed temporal patterns and corroborated that our findings are not affected by

246 different matching performances. Similar findings have previously been reported during walking

247 using a similar experimental protocol (Marmelat et al., 2014; Vaz et al., 2019). This supports that

248 our experiment was able to expand these findings to running.

249   Our findings agree with the optimal movement variability model (Stergiou et al., 2006) and

250   expand it to another locomotor task, running (Figure 1). We have shown that running in synchrony

251   to an isochronous cueing, with no variability between cues, takes the runner to a less adaptable

252   state (i.e., lower complexity). This is also the case with a random cueing modality (i.e., lower

253   complexity). Whereas the fractal cueing allows patterns like those that we have in self-paced

254   conditions (i.e., higher complexity). Importantly, higher physiological requirements of running can

255   be detrimental to performance; therefore, the impact of the temporal structure of external cueing

256   on cardiorespiratory parameters should be considered if this approach is to be used in a practical

257   setting. No differences were observed across conditions for the physiological parameters. This

258   suggests that differences in the temporal structure of the external cueing at a given running speed

259   do not alter cardiorespiratory demand. This is important for manipulation of running cadence in

260   experimental and clinical settings, so that adjustments to external cueing's structure do not

261   inadvertently alter the physiological intensity of the running task. In the presence of injury or

262   during rehab, the use of a fractal metronome may be beneficial to restore these complex patterns

263   (i.e., fractal). Although it lacks experimental testing, a runner with highly adaptable and complex

264   patterns would have more motor solutions while running. Future investigations should address

265   how fractal cueing impacts long-distance overground running performance. This is particularly

266   important given the fatigue accumulation during the late stages of the running trial. Theoretically,

267   if the runners have more motor solutions while running to a fractal metronome, it will work as an

268   advantage to deal with fatiguing states.

269

270

Conclusion

Our findings suggest that manipulating running cadence using a visual fractal external cueing preserves the gait patterns observed in self-selected running cadence without altering the cardiorespiratory responses. These findings build upon recent studies investigating walking gait and expand these findings of manipulating cadence structure with external pacing strategy during running. Practically, the use of a fractal-like metronome based on an individual's self-selected cadence may be more beneficial to training and rehabilitation than the traditional isochronous metronome. Finally, the preservation of the running stride-to-stride fluctuations with the fractal external cueing, like that of self-paced cadence, can prevent the fractal patterns breakdown that occurs while running to an isochronous metronome. It remains to be investigated, however, whether the maintenance or breakdown of these fractals are relevant for performance.

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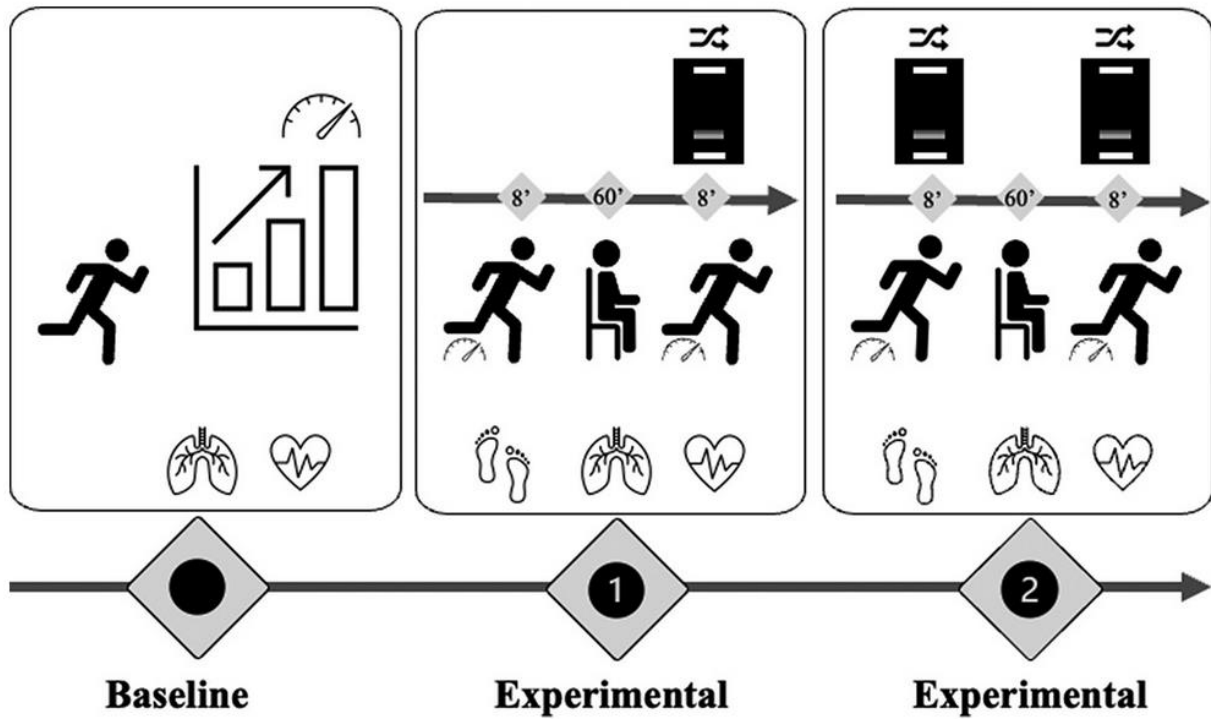414   https://doi.org/10.1152/jappl.1973.35.2.236

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417   **Table 1.** Descriptive statistics for each dependent variable in each running condition, listed as

418   mean ± standard deviation and 95% confidence intervals.

	Uncued		Isochronous		Random		Fractal		ANOVA	
	M±SD	95% CI	M±SD	95% CI	M±SD	95% CI	M±SD	95% CI	*p-value*	η^2
ISIs-α	0.91 ± 0.14	0.84, 0.95	0.54 ± 0.18	0.47, 0.66	0.66 ± 0.16	0.57, 0.63	0.85 ± 0.13	0.78, 0.91	<0.001	0.494
ISIs-CV (%)	1.52 ± 0.43	1.29, 1.76	1.96 ± 1.08	1.38, 2.55	1.89 ± 0.67	1.53, 2.26	2.79 ± 1.65	1.89, 3.69	0.017	0.170
ASYNC (ms)	–	–	−77.1 ± 79.8	−126.5, −27.6	49.6 ± 64.0	−84.4, −14.8	−39.7 ± 85.6	−86.2, 6.9	0.478	0.028
Heart Rate (bpm)	168.6 ± 10.4	162.9, 174.2	167.5 ± 11.7	161.1, 173.8	167.0 ± 9.6	161.8, 172.3	165.7 ± 11.2	159.6, 171.8	0.249	0.01
$\dot{V}O_2$ (mL/kg/min)	42.3 ± 2.5	40.9, 43.6	42.6 ± 2.4	41.3, 44.0	42.7 ± 3.0	41.1, 44.3	43.0 ± 3.2	41.3, 44.7	0.421	0.009
$\dot{V}E$ (L/min)	76.4 ± 12.2	69.8, 83.0	83.8 ± 16.7	74.4, 93.2	78.4 ± 15.1	70.2, 86.6	78.0 ± 14.1	70.4, 85.7	0.190	0.031

419   CI – Confidence Intervals; ISIs – Inter Stride Intervals; CV – Coefficient of Variation; ASYNC – Asynchronies; $\dot{V}O_2$ – Oxygen Uptake; $\dot{V}E$ – Ventilation per minute.

420 **Figure 1.** Violin plots of ISIs-α across all running conditions. Black bullets represent groups'

421 mean values and grey small bullets represent individual data points. Higher complexity is related

422 with larger values on the Y-axis, while lower complexity with lower. UNC – Uncued; ISO –

423 Isochronous; RND – Random; FRC – Fractal

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