

1 **Gait variability predicts post-fatigue obstacle course performance among military cadets: an**  
2 **exploratory study**

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14 **Financial Disclosure Statement:** The first author was supported by a pre-doctoral training program grant  
15 (T03 OH008613) from the U.S. Centers for Disease Control and Prevention. The contents of this work are  
16 solely the responsibility of the authors and do not necessarily represent the official views of the Centers for  
17 Disease Control and Prevention or the Department of Health and Human Services.

18 **Conflict of Interest Statement:** The authors have no conflicts of interest to disclose.

19

20 **Abstract**

21 We explored the extent to which pre-fatigue gait variability during load carriage is associated with  
22 the ability of an individual to perform an obstacle course post-fatigue. Twenty-four military cadets  
23 were monitored during treadmill gait and completed an obstacle course before and after a full-  
24 body fatigue protocol. Gait variability measures were determined from spatiotemporal stride  
25 characteristics, joint angle trajectories, and inter-joint coordination. These measures were then  
26 used in multiple linear regression models to predict three measures of post-fatigue performance  
27 (i.e., hurdle completion time, maximum jump height, and maximum jump distance). Measures of  
28 joint kinematic variability predicted 73-89% of the variance in post-fatigue performance.  
29 Specifically, the significant predictors were sagittal plane variability of 1) hip angle and hip-knee  
30 coordination during swing phase; and 2) knee-ankle coordination during both stance and swing  
31 phase. Measures of joint kinematic variability obtained from gait thus appear relevant for  
32 predicting individual differences in adapting to fatigue, and such measures could aid in predicting  
33 post-fatigue performance in diverse dynamic tasks.

34 **Keywords:** Motor variability, Inter-joint coordination, Adaptability

35

36 **Glossary:**  
37 APFT: Army Physical Fitness Test  
38 CAV: coupling angle variability  
39 DFA: detrended fluctuation analysis  
40 GV: gait variability  
41 HCT: hurdle completion time  
42 **HR: heart rate**  
43 JAV: joint angle variability  
44 MJD: maximum jump distance  
45 MJH: maximum jump height  
46 PWS: preferred walking speed  
47 ROTC: Reserve Officers' Training Corps  
48 RPE: rating of perceived exertion  
49 SD: standard deviation

50

## 51 **1. Introduction**

52 Fatigue is of particular interest in military environments, given that soldiers are expected  
53 to perform consistently at a high level. Existing evidence has highlighted the adverse influence  
54 fatigue can have on motor control and balance (Johnston III et al., 1998; Lin et al., 2009; Nardone  
55 et al., 1997; Penedo et al., 2021) and how fatigue may alter natural kinematics and muscle activity  
56 patterns during gait, marching, and walking in challenging conditions, such as walking up and  
57 down inclines or stairs (Bloch et al., 2024; Chardon et al., 2022; Halder et al., 2023; Halder et al.,  
58 2021; Kao et al., 2023; Parijat and Lockhart, 2008; Pinniger et al., 2000; Qu and Yeo, 2011; Vieira  
59 et al., 2016). Furthermore, investigations in highly active populations, such as athletes, have  
60 indicated that fatigue may lead to increased injury risk and diminished performance (Augustsson  
61 et al., 2006; Dambroz et al., 2022; Johnston 3rd et al., 1998; Lisman et al., 2013; Pinniger et al.,

62 2000; Rodacki et al., 2002; Verschueren et al., 2020). While substantial inter-individual  
63 differences in fatigability and fatigue-related changes in task performance have been reported  
64 (Apte et al., 2021; Halder et al., 2023; Halder et al., 2021; Santos et al., 2019), relatively few  
65 reports have addressed whether fatigued performance of a dynamic task can be predicted by pre-  
66 fatigue measures.

67 Changes in performance following fatigue have been investigated previously in the sports  
68 domain, specifically related to cycling and jumping performance. Diverse measures – including  
69 ratings of perceived exertion (RPEs), peak power output during a maximal aerobic power test, and  
70 heart rate (HR) recovery – appear able to predict fatigue-related changes in cycling performance,  
71 accounting for variation in exercise duration (Crewe et al., 2008) and mean power (Balmer et al.,  
72 2000; Lamberts et al., 2010). However, these measures were often collected continuously or  
73 intermittently throughout the fatiguing task, and in some cases acquiring the measures impeded  
74 task performance. Alternatively, a largely unexamined issue is whether individual measures in an  
75 unfatigued state can explain performance while fatigued. If certain baseline characteristics are  
76 found to be predictive of an individual's response and adaptability to fatigue, this relationship may  
77 prove critical for performance evaluations and for developing performance-prediction tools,  
78 especially in a sport or military context.

79 Among candidate kinematic measures that might be useful for predicting performance,  
80 recent evidence involving high-performance situations (such as sports) has demonstrated that  
81 flexible movement patterns facilitate the maintenance of consistently high-levels of performance  
82 across diverse environmental conditions (Bartlett et al., 2007; Bradshaw et al., 2007; Cowin et al.,  
83 2022; Horst et al., 2020). The extent to which individuals exhibit such flexibility is captured by  
84 the construct of *motor variability*. Flexible movement strategies, as reflected in higher variability,

85 may allow an individual to maintain consistent high levels of performance and adapt to novel  
86 circumstances; specifically, by allowing for increased capacity to explore alternative motor  
87 solutions and to compensate for changes or perturbations (Bartlett et al., 2007; Falla and Farina,  
88 2007; van Dieën et al., 1993). In addition, our previous work has shown that certain measures of  
89 gait variability (GV) can predict short-term inter-individual differences in motor learning ability  
90 (Ulman et al., 2019). However, it remains unknown whether monitoring individual differences in  
91 motor variability – specifically in a highly trained and rather homogeneous population such as  
92 soldiers – has any functional relevance for predicting an individual’s ability to adapt to fatigue.

93         Therefore, the goal of this exploratory study was to quantify the extent to which GV is  
94 associated with the ability of an individual to perform when fatigued, specifically when completing  
95 a task requiring substantial whole-body strength and coordination – here, an obstacle course. We  
96 hypothesized that higher GV would be associated with an increased ability to perform when  
97 fatigued. Evidence of such a relationship would imply that quantifying GV could aid in the  
98 prediction of an individual’s response to diverse levels of fatigue and task difficulty.

99

## 100 **2. Methods**

101         A repeated-measures design was used in which participants completed obstacle course  
102 trials both before and after a fatigue protocol, and gait kinematics were captured during the first  
103 two minutes of loaded treadmill walking. The obstacle course was designed such that each obstacle  
104 reflected a typical athletic task performed in Reserve Officers’ Training Corps (ROTC) physical  
105 training (Harman et al., 2008). Further, the fatigue protocol was designed to resemble a more

106 intense version of a load carriage exercise regularly performed by ROTC cadets and to have clear  
107 measures of performance (see below).

## 108 ***2.1 Participants***

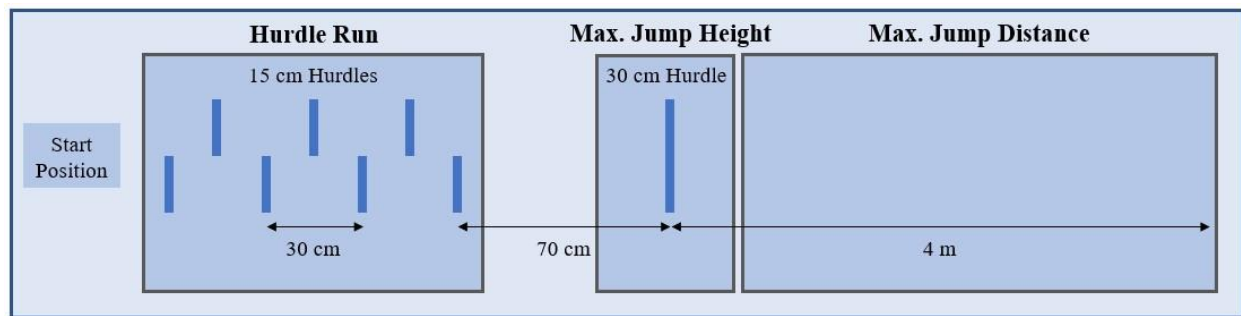
109 A sample of 25 senior ROTC cadets (20 male) completed this study, following written  
110 informed consent and procedures approved by the Virginia Tech Institutional Review Board. All  
111 participants reported having no recent history of musculoskeletal disorders or injuries. Their mean  
112 (SD) age, stature, and body mass were 21.9 (0.8) years, 1.8 (0.1) m, and 82.4 (12.7) kg,  
113 respectively. Fitness level was determined using Army Physical Fitness Test (APFT) scores  
114 (Knapik, 1989). This test records how many push-ups and curl-ups (or sit-ups) can be completed  
115 in a two-minute period, along with the completion time of a two-mile run; scores can range from  
116 180-300. All cadets reported their score from their most recent APFT, which for this sample was  
117 273.5 (24.3).

## 118 ***2.2 Procedures***

119 Initially, basic anthropometric and demographic measures were obtained. Then, passive  
120 reflective surface markers were placed bilaterally over anatomical landmarks on the lower limbs,  
121 including the anterior superior iliac spine, greater trochanter, lateral femoral epicondyle, and lateral  
122 malleolus, and on the most anterior (toe) and posterior (heel) points on the participants' personal  
123 shoes. These markers were used to track segmental kinematics (at 120 Hz) during obstacle course  
124 trials and to measure gait kinematics during the fatigue protocol, in both cases using a 13-camera  
125 motion capture system (Oqus 500 cameras, Qualisys, INC, Gothenburg, Sweden).

126 A three-task obstacle course was used (Figure 1), which consisted of seven 15 cm hurdles  
127 positioned ~30 cm apart in a staggered pattern, and one 30 cm hurdle placed ~0.7 m after the

128 shorter hurdles in the center of the course. Shorter hurdles were placed in a staggered orientation,  
129 so that each leg was required to independently step over a hurdle. This orientation simulated a “tire  
130 run”, which is a common obstacle in physical training courses. To complete the course, participants  
131 were required to step over each 15 cm hurdle as fast as possible, jump for maximum height over  
132 the 30 cm hurdle, and then, immediately after landing, jump forward for maximum distance.



133

134 **Figure 1.** Schematic diagram of the obstacle course (not to scale).

135 Participants were familiarized with the obstacle course, including being provided with a clear  
136 explanation of the tasks and a single walk-through. Participants were instructed to complete each  
137 task to the best of their ability, without resting between tasks, and to take off and land with both  
138 feet together. Participants then completed the obstacle course five times at maximal effort, with 10  
139 seconds of rest between each trial. These rest periods occurred as participants walked at a  
140 comfortable pace back to the beginning of the course. Five trials were collected both pre- and post-  
141 fatigue to account for potential learning effects. After completing the pre-fatigue obstacle course  
142 trials, participants were given five minutes of rest before starting the fatigue protocol.

143 The fatigue protocol required participants to perform load carriage with a 16 kg load  
144 (rucksack) on a level treadmill (T101, Horizon Fitness, Inc., Cottage Grove, WI), at three speeds,  
145 for a total of 30 minutes. All cadets were required by their ROTC training to complete multiple

146 weekly marches with a standard load of 16 kg, and thus were familiar with the fatigue protocol.  
147 To further ensure familiarity, participants brought their personal rucksack issued by the ROTC  
148 program for testing. The specific speeds for the fatigue protocol were determined based on each  
149 participant's preferred walking speed (PWS), which was determined following an earlier report  
150 (Jordan et al., 2007). Participants began the fatigue protocol walking at their PWS. After five  
151 minutes, the speed was increased to 110% PWS, and it was subsequently increased to 120% PWS  
152 after another 5 minutes, the latter simulating a fast walking speed. Participants maintained the  
153 120% PWS speed for the next 20 minutes, or until they reached a rating of perceived exertion  
154 (RPE) of 18 or higher on the Borg 20-point RPE scale (Borg, 1998), whichever occurred earlier.  
155 Throughout the fatigue protocol, HR and RPEs were recorded every minute as indicators of  
156 fatigue. HR was recorded using a Polar monitor attached to a chest strap (Model H7, Polar Electro,  
157 Kempele, Finland). Upon completing the protocol, participants quickly doffed their rucksack,  
158 returned to the beginning of the obstacle course (requiring <20 seconds), then completed five post-  
159 fatigue obstacle course trials.

### 160 ***2.3 Data Processing and Analysis***

161 Marker data were low-pass filtered (5 Hz cutoff) using a recursive, 4<sup>th</sup>-order, Butterworth  
162 filter (Liddy et al., 2019; Terrier and Dériaz, 2011). Obstacle course performance measures were  
163 then derived from the filtered marker data over the toe, greater trochanter, and heel. Three  
164 performance outcome measures were derived: 1) hurdle completion time (HCT: time to complete  
165 the initial hurdle run); 2) maximum jump height (MJH); and 3) maximum jump distance (MJD).  
166 HCT was calculated as the duration from take-off immediately before the first hurdle to the time  
167 of foot contact (i.e., when either the heel or toe touched the ground) after the last hurdle. MJH was  
168 computed by subtracting the vertical location of the greater trochanter marker obtained from the

169 static standing trial from the maximum vertical location of this marker during the obstacle course  
170 trials. MJD was determined as the change in the anterior-posterior location of the left heel marker  
171 from take-off to landing during the final jump.

172 Participants completed five pre-fatigue trials to familiarize themselves with the obstacle  
173 course tasks, and pre-fatigue performance measures were determined as the best performance  
174 across the five trials for each obstacle (i.e., the shortest HCT, highest MJH, and longest MJD). Our  
175 selection process prioritized these performance metrics since they directly reflected the  
176 participants' abilities in the respective tasks. Preliminary analyses indicated that all participants  
177 had their best pre-fatigue performance within the first two trials, and thus, potential learning effects  
178 across repetitions were minimal. Post-fatigue performance measures were computed from a single  
179 trial collected immediately after the fatigue protocol.

180 Measures of GV were determined from gait kinematics during the first two minutes of  
181 loaded walking at PWS during the fatigue protocol. Two minutes of treadmill walking was  
182 determined to provide sufficient strides for all participants; a mean of 111 (SD 10) strides from  
183 each limb were extracted for each participant. It was also brief enough to minimize fatigue effects;  
184 RPE at two minutes was 8 (SD 2). From these walking trials, a coordinate-based algorithm was  
185 used to determine gait events (Zeni Jr et al., 2008). Heel strike was defined when the maximum  
186 distance occurred between the heel and the greater trochanter marker locations in the anterior-  
187 posterior direction, and toe-off was defined as the time of minimum distance between the toe and  
188 the greater trochanter marker location. Spatiotemporal stride characteristics and joint angle  
189 kinematics were derived for further analysis. Sagittal plane hip, knee, and ankle joint angles were  
190 calculated as Cardan angles between adjacent local segments, using a rotation order of flexion-  
191 extension, abduction-adduction, and internal-external rotation (Butler et al., 2013; Chao, 1980;

192 Grood and Suntay, 1983; Yu et al., 2006). No significant differences were found in GV measures  
193 between the two limbs (from paired  $t$  tests,  $p \geq 0.065$ ), and hence the left side was chosen arbitrarily  
194 for further analysis. Gait data from one male participant were discarded due to poor quality (i.e.,  
195 all subsequent analyses were based on a sample of 24 participants).

196 Mean and stride-to-stride standard deviations were calculated for all stride characteristics,  
197 which included duration measures (i.e., stance and swing times) and distance measures (i.e., stride  
198 length and step width). For joint angle time series, standard deviations were calculated across all  
199 strides by time-normalizing each gait cycle (100 points). Then, the overall standard deviation of  
200 each joint angle trajectory, or joint angle variability (JAV), was calculated from the root-mean-  
201 square of these standard deviations across time. Inter-joint coordination was quantified using a  
202 modified vector coding technique (Heiderscheit et al., 2002; Sparrow et al., 1987; Ulman et al.,  
203 2019), which was used to assess hip-knee and knee-ankle joint coupling angles in the sagittal plane.  
204 Briefly, coupling angles were calculated using the orientation of the resultant vector of each angle-  
205 angle plot relative to the right horizontal, between every two successive data points of each stride.  
206 Coupling angle variability (CAV), the standard deviation across all strides, was then calculated for  
207 each time point using circular statistics, and then pooled across the gait cycle by computing the  
208 overall root mean square across all time points. CAV was used as a measure of variability in  
209 stride-to-stride coordination. Lastly, detrended fluctuation analysis (DFA) was used to quantify  
210 serial correlations across consecutive strides for all spatiotemporal measures (Bohnsack-McLagan  
211 et al., 2016; Hausdorff, 2007).

## 212 ***2.4 Statistical Analysis***

213 To first confirm that fatigue was induced, paired sample  $t$ -tests were performed to compare  
214 pre- and post-fatigue results for HCT, MJH, and MJD. Subsequently, inspection of the post-fatigue

215 performance (outcome measures) and GV data (predictors) indicated that linear relationships were  
216 present between these two sets of data. Thus, we addressed the study aims using four separate sets  
217 of linear models with the following predictors:

- 218 • Model Set 1: Physical characteristics (age, body mass, stature, and APFT score)
- 219 • Model Set 2: Fatigue indicators (maximum RPE, maximum HR, change in HR, and PWS)
- 220 • Model Set 3: Spatiotemporal stride characteristics pre-fatigue (both mean and variability  
221 measures)
- 222 • Model Set 4: Joint angle kinematic variability pre-fatigue (JAV and CAV)

223 Given the number of independent variables included for model sets 3 and 4, Lasso regressions  
224 (Meier et al., 2008; Ranstam and Cook, 2018; Tibshirani, 1996) were used, if needed, to select  
225 four predictors for each model set and for each post-fatigue performance measure. For model sets  
226 3 and 4, corresponding pre-fatigue performance measures were included in each model as  
227 covariates. Sex was not included as a covariate given the very unbalanced distribution of the  
228 volunteers in our study. For each regression model, significant predictors and the proportion of  
229 variance explained ( $R^2$  and  $R_{adj}^2$ ) are reported. Residuals were examined to verify parametric model  
230 assumptions. For hypothesis testing, statistical significance was concluded when  $p < 0.05$ , and the  
231 Statistical Package for the Social Sciences (SPSS) Statistics for Windows (version 24.0, IBM,  
232 Armonk, NY, USA) was used for all statistical analyses.

### 233 3. Results

234 Participants completed the hurdle run pre-fatigue in 1.62 (SD 0.19) s, jumped 0.33 (SD  
235 0.10) m high, and jumped 2.19 (SD 0.32) m in length. At the start of the fatigue protocol, HR and  
236 RPE were 119.0 (SD 15.5) beats/min and 8.0 (SD 2.0), respectively, and PWS was 1.5 (SD 0.1)

237 m/s. No participant reported an RPE of  $\geq 18$  during the fatigue protocol, and hence all completed  
238 the full 30-minutes. At the end of the fatigue protocol, all participants were determined to be  
239 sufficiently fatigued as significant changes in HR and RPE were observed, with respective values  
240 of 162.0 (SD 12.5) beats/minute and 16.0 (SD 1.0), and with  $p < 0.001$  for both. Post-fatigue, HCT  
241 significantly increased (1.71 s, SD 0.21 s;  $p = 0.001$ ), whereas both MJH (0.28 m, SD 0.10 m) and  
242 MJD (2.06 m, SD 0.39 m) significantly decreased ( $p < 0.001$  for both).

243 As a first step in predicting post-fatigue performance, physical characteristics (i.e., age,  
244 stature, body mass, and APFT score) were used (Model Set 1). These models were not significant  
245 in predicting post-fatigue HCT or MJD (respective  $p$ -values = 0.703 and 0.137). However, post-  
246 fatigue MJH was significantly associated with stature ( $p = 0.021$ ), and the resulting model  
247 including all four predictors had  $R^2 = 0.41$ ,  $R_{adj}^2 = 0.29$ , and  $p = 0.031$ . Models including indicators  
248 of fatigue (Model Set 2 with max RPE, max HR, change in HR, and PWS as predictor variables)  
249 did not significantly predict post-fatigue HCT ( $p = 0.052$ ), but were successful in predicting post-  
250 fatigue MJD and MJH. Specifically, post-fatigue MJD was significantly associated with max HR  
251 ( $p = 0.032$ ) and change in HR ( $p = 0.011$ ), and resulted in a model with  $R^2 = 0.41$ ,  $R_{adj}^2 = 0.31$ , and  
252  $p = 0.011$ . Similarly, post-fatigue MJH was significantly associated with max HR ( $p = 0.036$ ) and  
253 PWS ( $p = 0.007$ ), and resulted in a model with  $R^2 = 0.40$ ,  $R_{adj}^2 = 0.30$ , and  $p = 0.012$ .

254 In Model Set 3, spatiotemporal gait measures (i.e., means, stride-to-stride SDs, and DFA  
255 exponents of stance time, swing time, stride length, and step width) were used to predict post-  
256 fatigue performance measures (results in Table 1). In addition to pre-fatigue performance, mean  
257 stance time, swing time, and stride length were selected in the Lasso procedure as predictors of  
258 post-fatigue HCT, with  $R^2 = 0.55$ ,  $R_{adj}^2 = 0.47$ , and  $p = 0.001$ . However, only pre-fatigue HCT was  
259 significantly associated. The resulting model for post-fatigue MJD included swing time SD, mean

260 step width and stance time, and pre-fatigue MJD, and had  $R^2 = 0.86$ ,  $R_{adj}^2 = 0.84$ , and  $p < 0.001$ .  
 261 Similarly, only pre-fatigue MJD was significantly associated with the post-fatigue MJD.  
 262 Alternatively, post-fatigue MJH was significantly associated with step width SD and pre-fatigue  
 263 MJH. Mean stride length and stance time were also selected as predictors, and the MJH model had  
 264  $R^2 = 0.83$ ,  $R_{adj}^2 = 0.80$ , and  $p < 0.001$ . Correlations between actual and predicted post-fatigue  
 265 performance for Model Set 3 are shown in Figure 2.

266 **Table 1.** Model Set 3: Results using Lasso regressions to generate models predicting post-fatigue  
 267 performance

	Estimate	Std. Error	<i>t</i> value	<i>p</i> value
<b>Post-Fatigue HCT (<math>R^2 = 0.55</math>, <math>R_{adj}^2 = 0.47</math>, RMSE = 0.14, <math>p = 0.001</math>)</b>				
Pre-Fatigue HCT	0.817	0.170	4.804	< <b>0.001</b>
Stance Time M	1.624	1.390	1.168	0.255
Swing Time M	-4.698	3.779	-1.243	0.226
Stride Length M	0.033	0.300	0.109	0.914
<b>Post-Fatigue MJH (<math>R^2 = 0.83</math>, <math>R_{adj}^2 = 0.80</math>, RMSE = 0.04, <math>p &lt; 0.001</math>)</b>				
Pre-Fatigue MJH	0.799	0.108	7.370	< <b>0.001</b>
Step Width SD	-6.159	2.448	-2.516	<b>0.019</b>
Stance Time M	-0.156	0.228	-0.684	0.501
Stride Length M	0.140	0.100	1.394	0.177
<b>Post-Fatigue MJD (<math>R^2 = 0.86</math>, <math>R_{adj}^2 = 0.84</math>, RMSE = 0.15, <math>p &lt; 0.001</math>)</b>				
Pre-Fatigue MJD	1.105	0.104	10.582	< <b>0.001</b>
Swing Time SD	25.287	21.284	1.188	0.247
Stance Time M	0.083	0.787	0.106	0.917
Step Width M	1.432	1.275	1.123	0.273

268 Note: Significant predictors noted with bold *p* values.

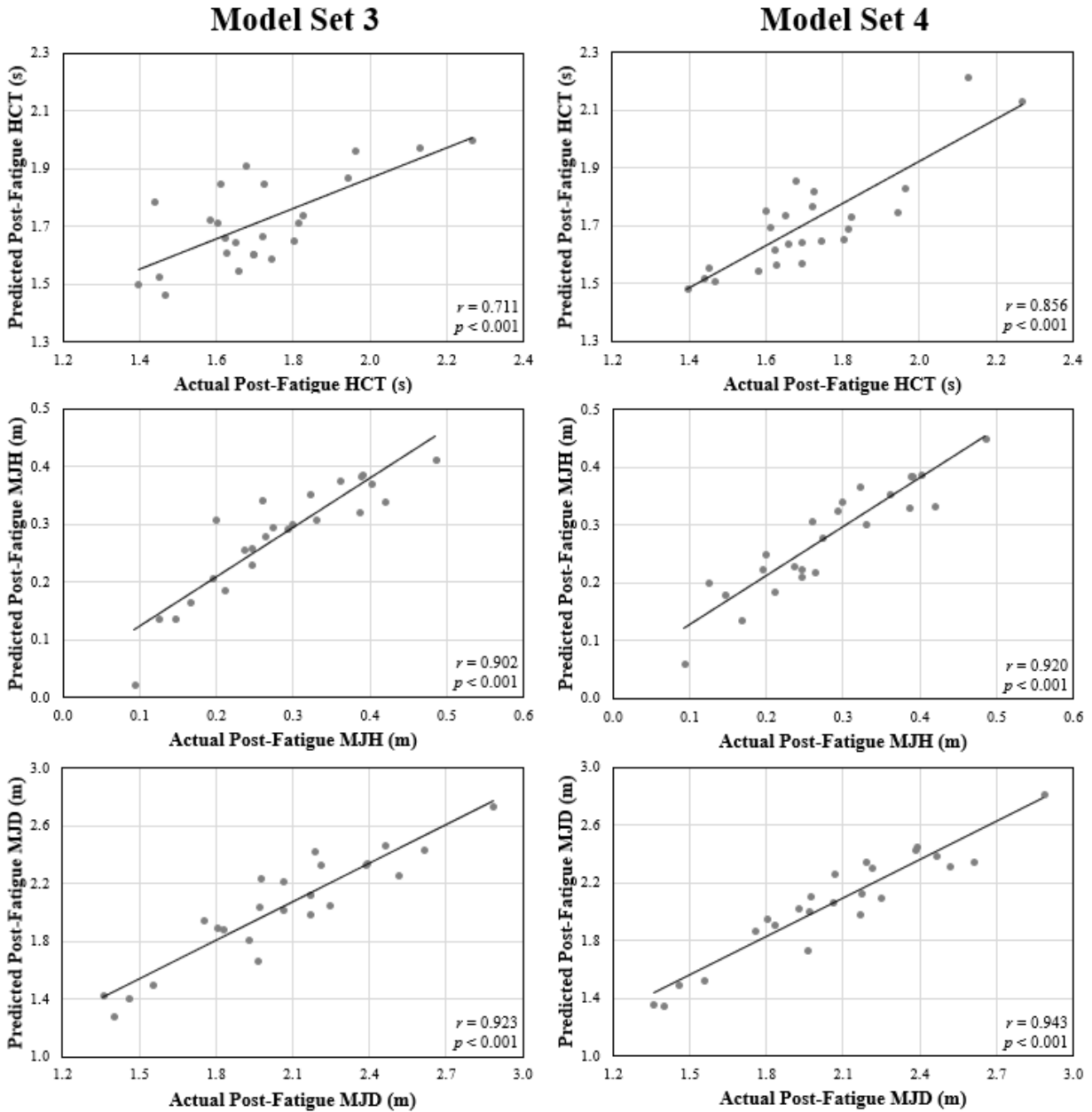
269 In Model Set 4, joint angle kinematic variability (i.e., JAV and CAV) was used to predict  
 270 post-fatigue performance measures (results in Table 2). For post-fatigue HCT, all selected  
 271 predictors were significantly associated, with  $R^2 = 0.73$ ,  $R_{adj}^2 = 0.68$ , and  $p < 0.001$ . In addition to  
 272 pre-fatigue HCT, hip JAV, hip-knee CAV, and knee-ankle CAV during swing phase were  
 273 significantly associated with post-fatigue HCT. The resulting model for post-fatigue MJH included  
 274 ankle JAV during both stance and swing phase, knee-ankle CAV during stance phase, and pre-

275 fatigue MJH, with  $R^2 = 0.85$ ,  $R_{adj}^2 = 0.81$ , and  $p < 0.001$ . However, beyond pre-fatigue MJH, only  
 276 knee-ankle CAV during stance phase was found to be significantly associated. Lastly, only pre-  
 277 fatigue MJD was significantly associated with post-fatigue MJD. Hip JAV and knee-ankle CAV  
 278 during swing phase and knee JAV during stance phase were also selected as predictors, and the  
 279 MJD model had  $R^2 = 0.89$ ,  $R_{adj}^2 = 0.87$ , and  $p < 0.001$ . Correlations between predicted and actual  
 280 post-fatigue performance for Model Set 4 are included in Figure 2.

281 **Table 2.** Model Set 4: Results using Lasso regressions to generate models predicting post-fatigue  
 282 performance.

	Estimate	Std. Error	<i>t</i> value	<i>p</i> value
<b>Post-Fatigue HCT (<math>R^2 = 0.73</math>, <math>R_{adj}^2 = 0.68</math>, RMSE = 0.11, <math>p &lt; 0.001</math>)</b>				
Pre-Fatigue HCT	0.724	0.128	5.643	< <b>0.001</b>
Hip JAV Swing	-0.099	0.036	-2.793	<b>0.012</b>
Hip-Knee CAV Swing	0.011	0.004	3.103	<b>0.006</b>
Knee-Ankle CAV Swing	-0.012	0.005	-2.523	<b>0.021</b>
<b>Post-Fatigue MJH (<math>R^2 = 0.85</math>, <math>R_{adj}^2 = 0.81</math>, RMSE = 0.04, <math>p &lt; 0.001</math>)</b>				
Pre-Fatigue MJH	0.764	0.096	7.949	< <b>0.001</b>
Ankle JAV Stance	0.024	0.071	0.331	0.744
Ankle JAV Swing	-0.092	0.052	-1.762	0.094
Knee-Ankle CAV Stance	0.016	0.005	3.268	<b>0.004</b>
<b>Post-Fatigue MJD (<math>R^2 = 0.89</math>, <math>R_{adj}^2 = 0.87</math>, RMSE = 0.13, <math>p &lt; 0.001</math>)</b>				
Pre-Fatigue MJD	1.054	0.100	10.489	< <b>0.001</b>
Hip JAV Swing	0.025	0.053	0.468	0.645
Knee JAV Stance	0.132	0.108	1.220	0.237
Knee-Ankle CAV Swing	0.012	0.006	1.972	0.063

283 Note: Significant predictors noted with bold *p* values.



284

285 **Figure 2.** Correlations between actual and predicted post-fatigue performance from Model Sets 3  
 286 and 4.

287 **4. Discussion**

288 Our goal in this study was to explore the extent to which pre-fatigue measures of gait  
 289 variability (GV, obtained during treadmill walking) are associated with post-fatigue performance

290 when completing an obstacle course. Measures of joint kinematic variability were most successful  
291 in predicting post-fatigue performance, with variability in sagittal plane hip angle and hip-knee  
292 coordination during swing phase and knee-ankle coordination during both stance and swing phase  
293 found to be significant predictors.

294 Numerous reports have shown that physical characteristics and/or performance measures  
295 can be predictive of obstacle course performance (Bishop et al., 1999; Harman et al., 2008; Jette  
296 et al., 1990; Pandorf et al., 2002). Here, we first analyzed physical characteristics to determine  
297 whether more advanced measures were needed. As expected, post-fatigue HCT and MJD were not  
298 explained by age, stature, body mass, or APFT score. Stature, though, was a significant predictor  
299 in (Model Set 1) for post-fatigue MJH, explaining 41% of the variance. The latter suggests that  
300 more advanced measures, such as GV, may not be needed to predict changes in performance for  
301 tasks involving vertical jumping. However, additional measures could likely improve model  
302 predictability of post-fatigue performance.

303 Bishop et al. (1999) similarly used various anthropometric measures and results from  
304 numerous physical ability tests (i.e., skinfolds, aerobic and anaerobic power, muscular strength,  
305 and endurance) to predict obstacle course time. While several predictors were significantly  
306 correlated with performance, the best regression model only accounted for 35% of the variation in  
307 obstacle course completion time. Alternatively, Jette et al. (1990) conducted VO<sub>2</sub> max and strength  
308 tests in a laboratory setting, and were able to predict 81% of the variance in performance time on  
309 an extended obstacle course. Using more “field-expedient” measures – such as body mass,  
310 horizontal and vertical jump distances, a 3.2 km run, and the maximum number of sit-ups and  
311 push-ups performed in one attempt – Harman et al. (2008) developed a model that accounted for  
312 ~82% of the variation in completion time.

313 Furthermore, while earlier studies were successful in predicting obstacle course  
314 performance, primarily defined as total completion time, all predictor variables were either  
315 individual physical characteristics or measures specific to the obstacle course. These studies did  
316 not investigate whether an individual's baseline movement characteristics (e.g., gait variability)  
317 were associated with their performance in the obstacle course, or their ability to maintain  
318 performance while fatigued.

319 We found that measures of fatigue were not strong predictors of inter-individual variability  
320 in post-fatigue performance (Model Set 2). In general, better post-fatigue performance was  
321 associated with lower maximum HRs and smaller changes in HR throughout the fatigue protocol.  
322 The strongest predictor, specifically of higher post-fatigue MJH, was faster PWS. These  
323 associations lack novelty, though, as it may be assumed that lower maximum HRs and faster PWS  
324 naturally correlate with better aerobic fitness (de Araújo et al., 2017; Wu and Zhao, 2021), and  
325 thus better performance while fatigued. However, significant models only explained 40% and 41%  
326 of the variance in post-fatigue MJH and MJD performance, respectively. This moderate predictive  
327 ability may be the result of relatively small inter-individual variances in the fatigue measures (RPE  
328 SD: 1.0, HR SD: 12.5), or a consequence of the current study methodology. In previous work,  
329 elevated fatigue parameters were inversely associated with motor control and balance performance  
330 (Johnston III et al., 1998; Lin et al., 2009; Nardone et al., 1997), and induced fatigue caused altered  
331 gait mechanics (Parijat and Lockhart, 2008; Qu and Yeo, 2011; Vieira et al., 2016). Fatigue-  
332 induced decreases in performance have also been predicted successfully from perceived exertion  
333 and changes in HR during cycling and jumping tasks (Crewe et al., 2008; Lamberts et al., 2010).  
334 However, these predictors were measured during task performance. In contrast here, all fatigue  
335 indicators were collected during a fatiguing task separate from the performance task (obstacle

336 course). Our measures were, thus, perhaps less strongly related to task performance post-fatigue.  
337 These findings highlight that, if the primary goal is to predict adaptability to fatigue, future studies  
338 should consider separating the collection of fatigue indicators from task performance measures.

339 Models using spatiotemporal measures (both mean and variability) were partially  
340 successful in predicting post-fatigue performance (Model Set 3; Table 1), specifically for MJH.  
341 While 55% and 86% of inter-individual differences in post-fatigue HCT and MJD were explained,  
342 respectively, only pre-fatigue performance was found to be a significant predictor in each model.  
343 Alternatively, 83% of the variance in post-fatigue MJH was explained, and step width variability  
344 was a significant contributor. Specifically, higher post-fatigue MJH was predicated by reduced  
345 variability in step width. Increased variability in spatiotemporal stride characteristics, particularly  
346 step width, appears to be an indicator of unsteady gait (Heiderscheit, 2000), and a successful  
347 predictor of fall risk in elderly populations (Gabell and Nayak, 1984; Hausdorff et al., 1997; Maki,  
348 1997). Hence, an increase in these measures was expected to be indicative of an inability to adapt  
349 or compensate to intrinsic or extrinsic factors, such as fatigue or perturbations. However, the  
350 relationship between spatiotemporal variability and post-fatigue performance was inconsistent  
351 across tasks. This lack of association between spatiotemporal measures and both post-fatigue HCT  
352 and MJD could be due to the presence of a small range of variability in spatiotemporal measures  
353 across participants. While gait is a simple and familiar task, treadmill gait specifically considerably  
354 reduces spatiotemporal gait variability compared to over-ground gait (König et al., 2014; Paterson  
355 et al., 2009). As a result, a low level of between-subject variance in measures of spatiotemporal  
356 variability may have been present and insufficient for predicting post-fatigue performance from a  
357 more dynamic obstacle course task (e.g., the hurdle run or horizontal jump).

358           Regarding joint kinematic variability, **previous** studies have found relationships between  
359 adaptability and variability during challenging dynamic tasks (Bartlett et al., 2007; Cazzola et al.,  
360 2016; Wilson et al., 2008). Specifically, there is some evidence suggesting that increased  
361 variability is associated with increased adaptability, defined as the ability to maintain or improve  
362 performance (Falla and Farina, 2007; van Dieën et al., 1993). For example, increased joint angle  
363 variability during different striking actions used in combat sports was found to be associated with  
364 an individual's ability to maintain performance as the environment or task demands changed (Orth  
365 et al., 2018). Similarly, a lesser 10 m sprint time was associated with increased variability in ankle  
366 step velocity at the start of a sprint (Bradshaw et al., 2007). Authors of the latter study further  
367 claimed that this increase in motor variability allowed the sprinters to adapt their joint coordination  
368 patterns to suit the demands of the task. Variability in coordination patterns have also been  
369 proposed to enhance adaptability to external perturbations, such as uneven ground, by attenuating  
370 impact shocks (Hamill et al., 1999; Heiderscheit et al., 1999; Heiderscheit et al., 2002). While the  
371 relationship between adaptability and motor variability, especially in the sports domain, has been  
372 discussed extensively, earlier research did not focus on whether an individual's natural level of  
373 variability (e.g., gait variability) is associated with their ability to maintain performance in a  
374 separate task, or whether variability measures could be used to predict an individual's adaptability  
375 to fatigue.

376           Here, we **have** found that measures of joint kinematic variability obtained from a separate  
377 gait task predicted 73%, 85%, and 89% of the respective variance in post-fatigue obstacle course  
378 performance in HCT, MJH, and MJD (Model Set 4). While only pre-fatigue performance was a  
379 significant predictor of post-fatigue MJD, joint kinematic variability was found to be additional  
380 significant predictors of post-fatigue HCT and MJH (Table 2). However, not all significant

381 predictors exhibited the same directional relationship with increased performance. In some cases,  
382 larger GV corresponded to worse post-fatigue performance. In the hurdle completion task, for  
383 example, worse fatigued performance (longer HCT time) was associated with reduced variability  
384 in sagittal hip angle and knee-ankle coordination during the swing phase. Yet, worse performance  
385 was also associated with increased variability in hip-knee coordination during swing phase.  
386 Therefore, while our results imply that GV is associated with adaptability to fatigue, it also seems  
387 that there is not a consistent direction for this relationship across all GV measures.

388         Similar to the hurdle completion task, better post-fatigue performance in the vertical jump  
389 task (higher MJH) was significantly associated with greater variability in knee-ankle coordination  
390 during the stance phase. Thus, while the direction of the relationship between GV and adaptability  
391 to fatigue appears to be dependent on the specific GV measure, the directionality of this  
392 relationship may remain consistent across tasks. Although only approaching statistical  
393 significance, it is noteworthy that greater variability in both knee-ankle coordination ( $p = 0.063$ )  
394 and sagittal hip angle ( $p = 0.645$ ) during the swing phase also corresponded with better post-fatigue  
395 performance in the horizontal jump task (longer MJD). Therefore, it may be postulated that greater  
396 variability in sagittal hip angle and knee-ankle coordination during swing phase captured during  
397 unfatigued (baseline) gait is predictive of an individual's increased ability to adapt to fatigue across  
398 dynamic tasks. Alternatively, other GV measures, such as hip-knee coordination variability during  
399 swing phase, may be indicative of an individual's lack of ability to adapt to fatigue.

#### 400 ***4.1 Limitations***

401         There were potential limitations of the current study that should be emphasized. One  
402 limitation was that only two minutes of gait were captured to compute GV measures. Further,  
403 treadmill and over-ground gait differ in aspects of variability, and hence may have influenced our

404 results (König et al., 2014; Paterson et al., 2009). While **previous** work (Owings and Grabiner,  
405 2003) has suggested that up to 400 strides might be needed to reliably assess GV from treadmill  
406 gait, our pilot work showed that this procedure itself could induce fatigue among the participants.  
407 Hence, GV measures were computed on ~111 (SD 10) strides across participants. In future work,  
408 a similar analysis should be performed using over-ground gait kinematics, during which fewer  
409 strides are required to reliably estimate kinematic GV (König et al., 2014). Using over-ground gait  
410 might result in more significant spatiotemporal predictors, since treadmill gait reduces  
411 spatiotemporal GV compared to over-ground gait (König et al., 2014; Paterson et al., 2009). Given  
412 the exploratory nature of our study, future work is also necessary to assess the reliability of the  
413 identified predictors and to further validate our findings using multiple trials to ensure accuracy  
414 for practical application in real-life scenarios. **For example, RPE and HR were parameters used to**  
415 **determine fatigue, however both have specific strengths and limitations based on the context of**  
416 **data collection and interpretation. Future work should validate the findings of the current study**  
417 **and related studies using more robust measures of fatigue, such as electromyography (EMG) data**  
418 **or lactate measurements.**

419 **One additional limitation of our current study was the selection of the best performance**  
420 **trial pre-fatigue. This approach was deliberate, as it prioritized peak performance and allowed use**  
421 **to assess an individual's maximal capability for the given tasks. It also minimized the influence of**  
422 **errors or suboptimal trials that may have occurred due to external factors such as fatigue,**  
423 **distraction, or variability in execution. However, it is possible that the best performance trial was**  
424 **been influenced by chance, and thus computing a mean or median could have enhanced reliability.**  
425 **Given that our primary focus was to determine maximum capacity under pre-fatigue conditions,**  
426 **we consider the selection of the best performance trial to best represent a participant's true peak**

427 performance. We addressed potential concerns about unreliability by ensuring that only high-  
428 quality trials were included (e.g., excluding trials with errors such as hitting a hurdle or not  
429 completing the task correctly). Additionally, the consistency of best performances within the first  
430 two trials across participants further suggests that selecting the best trial likely captured maximum  
431 capacity without introducing significant bias.

432 It is also important to note that the generalizability of our findings to other populations or  
433 types of dynamics tasks is currently unknown, for two reasons. First, we tested a young, healthy,  
434 and relatively homogenous group of cadets that all experienced the same long-term training  
435 program. Since a focus of our study was to translate to a broader population of soldiers that are all  
436 required to continue similar training throughout their military careers, ROTC cadets were chosen  
437 for testing. However, our results may not be generalizable to a more diverse population, in terms  
438 of anthropometry, sex, activity level, or activity type (e.g., sports). Second, post-fatigue  
439 performance were best predicted by diverse GV measures. The variance in post-fatigue HCT and  
440 MJH was best explained using joint kinematic variability measures, while the variance in post-  
441 fatigue MJD was best explained using indicators of fatigue. Although this outcome stresses the  
442 importance of considering a variety of measures of GV when assessing adaptability to fatigue, it  
443 also suggests that our findings might not be generalizable to other dynamic tasks. These limitations  
444 should be addressed in future studies by testing a more diverse population and incorporating  
445 additional tasks and performance measures.

## 446 ***4.2 Conclusions***

447 These results indicate that measures of joint kinematic variability obtained from gait (pre-  
448 fatigue) can be used to predict individual differences in short-term function; in the current case,  
449 post-fatigue performance during a dynamic obstacle course task. Across various research domains,

450 motor variability has been shown to be an important aspect of movement for maintaining  
451 performance, such as in sport-related activities and for assessing injury risk in different clinical  
452 populations. The current results, however, also support the potential functional significance of GV  
453 for predicting a soldier's adaptability following fatigue. Specifically, variability in sagittal plane  
454 hip angle and hip-knee coordination during swing phase, and knee-ankle coordination during both  
455 stance and swing phase, were found to be significant predictors of post-fatigue performance. The  
456 performance prediction models developed here indicate that quantifying GV could aid in the  
457 prediction of a soldier's response to diverse levels of fatigue. Furthermore, GV measures could be  
458 useful targets during training protocols to enhance performance among soldiers, and others.

#### 459 **Acknowledgements**

460 The first author was supported by a pre-doctoral training program grant (T03 OH008613) from the  
461 U.S. Centers for Disease Control and Prevention. The contents of this work are solely the  
462 responsibility of the authors and do not necessarily represent the official views of the Centers for  
463 Disease Control and Prevention or the Department of Health and Human Services.

#### 464 **Conflict of Interest**

465 The authors have no conflicts of interest to disclose.

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