

1 **Title** - Walking with increased step length variability increases the metabolic cost of walking

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3 **Running Title** - Metabolic Cost of Step Length Variability

4

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9

10 **Key Words:** Energetics, Step frequency, Gait variability, Locomotion, Visually guided stepping

11

12 **Summary Statement** - For every 1% increase in step length variability, there is an 0.7%
13 increase in the metabolic cost of walking.

14

15 **Abstract** - Older adults and neurological populations tend to walk with slower speeds, more gait
16 variability, and a higher metabolic cost. This higher metabolic cost could be related to their
17 increased gait variability, but this relationship is still unclear. The purpose of this study was to
18 determine how increased step length variability affects the metabolic cost of walking. Eighteen
19 healthy young adults completed a set of 5-minute trials of treadmill walking at 1.20 m/s while we
20 manipulated their step length variability. Illuminated rectangles were projected onto the surface
21 of a treadmill to cue step length variabilities of 0, 5 and 10% (coefficient of variation). Actual
22 step lengths and their variability were tracked with reflective markers on the feet, while
23 metabolic cost was measured using indirect calorimetry. Changes in metabolic cost across
24 habitual walking (no projections) and the three variability conditions were analyzed using a
25 linear mixed effects model. Metabolic power was largest in the 10% condition (4.30 ± 0.23
26 W/kg) compared to 0% (4.16 ± 0.18 W/kg) and habitual (3.98 ± 0.25 W/kg). The participant's
27 actual step length variability did not match projected conditions for 0% (3.10%) and 10%
28 (7.03%). For every 1% increase in step length variability, there is an 0.7% increase in metabolic
29 cost. Our results demonstrate an association between the metabolic cost of walking and gait step
30 length variability. This suggests that increased gait variability contributes to a portion of the
31 increased cost of walking seen in older adults and neurological populations.

32 INTRODUCTION:

33 With age and increased neurological impairment, people walk slower (Bohannon, 1997;
34 Steffen et al., 2002), with shorter steps (Osoba et al., 2019), greater gait variability (Owings &
35 Grabiner, 2004) and increased metabolic energy demands (Christiansen et al., 2009; Martin et
36 al., 1992; Zamparo et al., 1995). Increased metabolic cost of walking has been mentioned as a
37 potential risk factor for reduced gait speed and mobility in older individuals (Schrack et al.,
38 2012). Reduced gait speed is associated with mortality (Newman et al., 2006; Studenski et al.,
39 2011), cardiovascular disease, and other adverse effects (Abellan van Kan et al., 2009; Szanton
40 et al., 2021). As outlined by Boyer et al., (2023) "... the significant societal, economic, and
41 personal burdens associated with mobility limitations highlight the importance of understanding
42 the mechanisms for increased metabolic cost of walking...". While the association between
43 reduced gait speed and increased metabolic cost is well studied (but not yet fully understood;
44 Boyer et al., 2023), less is known about the potential association between other gait changes,
45 such as increased gait variability, and the metabolic cost of walking.

46 Increasing stride frequency from habitual (+15 strides / minute) increases metabolic cost
47 by approximately 19% during walking (Holt et al., 1991). As step frequency increases, there is a
48 greater cost of moving the legs (Doke et al., 2005). Decreasing stride frequency from habitual (-
49 15 strides / minute) increases metabolic cost by almost 30% (Holt et al., 1991). This is likely due
50 to the increased metabolic cost of redirecting the center of mass between steps (Donelan et al.,
51 2002). Indeed, people habitually self-select a step frequency which minimizes metabolic cost
52 (Holt et al., 1995).

53 However, people do not walk with consistent step lengths in daily life because walking
54 often occurs in short bouts (Seethapathi & Srinivasan, 2015), at variable speeds, and not on level
55 ground (Kowalsky et al., 2021; Voloshina et al., 2013). Varying step length can also be helpful
56 when encountering obstacles (Patla et al., 1991) or maintaining stability (Young & Dingwell,
57 2012). Even for a long walking bout, at a constant speed, on level ground, with one's optimal
58 average step length, there will be small variabilities in step length around this average - a mix of
59 steps that are both shorter and longer than optimal (Owings & Grabiner, 2004), due to intrinsic
60 sensory and neuromotor noise (Dean et al., 2007; Dingwell et al., 2017). Added variability can
61 be expected to be more metabolically costly (O'Connor et al., 2012), as each step deviates from
62 optimal step parameters (Holt et al., 1995).

63 Few studies have tried to quantify the impact of step length variability on metabolic cost
64 (O'Connor et al., 2012; Rock et al., 2018). O'Connor et al. (2012) used virtual visual flow field
65 perturbations to increase gait variability and evaluate metabolic cost. At a constant speed of 1.25
66 m/s, high frequency medio-lateral rotations of the virtual visual flow field induced the largest
67 increase in metabolic cost (5.9%). Participants walked with increased step length variability in
68 this condition, but the metabolic increase was most strongly coupled with increased step width
69 variability. More recently, Rock et al. (2018) evaluated metabolic cost of transport and step
70 length variability across a range of walking speeds. Although speed had the greatest impact on
71 metabolic cost, at a constant speed of 1.25 m/s, each 1% increase in step length variability was
72 also associated with a 5.9% increase in metabolic cost. In these studies, the observed increases in
73 metabolic cost with increased step length variability could not be separated from changes in step
74 width variability or walking speed, respectively, so the isolated effects of increased step length
75 variability on the metabolic cost of walking are still unknown.

76 Therefore, we set out to quantify the isolated effects of increased step length variability
77 on the metabolic cost of walking. We used visual cues to increase step length variability by
78 projecting illuminated rectangles (stepping stones) on a treadmill progressing at the speed of the
79 belt (Hollands et al., 1995; Hoogkamer et al., 2015; Roerdink et al., 2009; Van Ooijen et al.,
80 2015). The stepping stones were spaced to the participant's habitual step length, with increasing
81 levels of step length variability per condition. By directly targeting step length variability, using
82 projected stepping stones, we were able to evaluate the metabolic cost of walking with increased
83 step length variability independent from other gait changes that may arise when using
84 perturbations that indirectly affect step length variability. We hypothesized that increases in step
85 length variability would increase the metabolic cost of walking.

86

87 **MATERIALS AND METHODS:**

88 **Participants:**

89 Eighteen healthy young adults (7F; 24.4 ± 3.7 years; 171.2 ± 17.2 cm; 70.5 ± 13.3 kg)
90 completed this study. Eligible participants were between the ages of 18 and 45 years old, had not
91 experienced lower extremity injuries or surgery within the past six months, and were free of any
92 existing orthopedic, cardiovascular or neuromuscular conditions. Written informed consent was

93 obtained from each participant prior to the study. All procedures were approved by the
94 Institutional Review Board at the University of Massachusetts Amherst (#3002).

95 **Procedures:**

96 We provided each participant with a pair of standardized shoes in their size (Speed
97 Sutamina, PUMA SE, Herzogenaurach, Germany). We placed retroreflective markers on each
98 foot at the fifth metatarsal head and calcaneus, and a four-marker cluster on the sacrum.

99 Participants first walked at a speed of 1.20 m/s (Das Gupta et al., 2019) for five minutes
100 to familiarize themselves with the dual-belt treadmill (Bertec, Columbus, OH, USA) and the
101 indirect calorimetry mouthpiece. Next, they walked for three minutes at 1.20 m/s for which we
102 evaluated habitual step length during the final 30 seconds. An eight-camera Miquis system
103 (Qualisys, Gothenburg, Sweden) recorded kinematic data at 100 Hz. We used kinematic data
104 from the left and right calcaneus to determine habitual step length using a custom Matlab script
105 (The MathWorks, Natick, MA, USA). Step length for each leg was calculated as the distance
106 between the anterior and posterior positions of the ipsilateral and contralateral calcaneus
107 markers, respectively, during the maximum anterior position of the calcaneus marker for each
108 step (Desailly et al., 2009). Mean step length and standard deviation were used to determine the
109 coefficient of variation, i.e., the mean step length divided by the standard deviation for each foot,
110 before averaging across feet.

111 Experimental conditions were: no projections (NP), 0%, 5% and 10% variability.
112 Throughout we consider step length variability in terms of the coefficient of variation of the step
113 length during a trial. At 0% variability, we projected stones with no variability in step lengths,
114 whereas for the 10% condition we projected stones with 10% variability in step lengths across
115 the entire trial. In a block randomized order, participants completed all four experimental
116 conditions, before completing them again in reverse, for a total of eight trials (e.g., NP, 10%, 0%,
117 5%, 5%, 0%, 10%, NP).

118 The projected stepping stones were generated using a custom Matlab script. A vector of
119 step lengths for the entire trial was created based on the participant's habitual step length,
120 treadmill speed (1.20 m/s), and trial duration (5 minutes). A vector of corresponding step length
121 perturbations was created using the *randn* function in Matlab, which generates a list of normally
122 distributed random numbers with a mean of 0 and variance of 1. This step length perturbation
123 vector was scaled by the desired step length variability (0, 5 or 10% coefficient of variation) and

124 the habitual step length. A larger coefficient of variation increases the frequency of perturbed
125 steps relative to unperturbed, and of larger perturbations relative to smaller. To ensure that
126 differences in step length were perceivable by the participants, we discretized the perturbations
127 into bins that were 5% multiples of the participant's habitual step length. We limited
128 perturbations to a maximum of 15% in either direction, to prevent the possibility of unrealistic
129 perturbations at the tails of the normal distribution. Perturbations that fell within half of the
130 discretization interval above or below a perturbation target were reassigned to the target value
131 and applied. Thus, participants encountered distances that matched the habitual step length most
132 of the time, with less frequent longer and shorter perturbed steps (Fig. 1A).

133 We used an expired-gas analysis system (True One 2400, Parvo Medics, Salt Lake City,
134 UT, USA) to measure metabolic cost across the four experimental walking conditions. We added
135 a 3D printed extension to the three-way valve mouthpiece (Hans Rudolf Mouthpiece, Shawnee,
136 KS, USA) that pitched forward (5 cm) and up (5 cm) at a 45-degree angle (Fig. 1B). The
137 participants were then able to see the approaching stepping stones. Each trial was five minutes
138 long and data across the last two minutes of each trial was used to evaluate metabolic power. We
139 calculated metabolic power (W/kg) using oxygen uptake, carbon-dioxide production, and the
140 Péronnet and Massicotte equation (Kipp et al., 2018; Péronnet & Massicotte, 1991). Metabolic
141 power was averaged across the two trials for each condition (Barrons et al., 2024).

142 **Statistical Analysis:**

143 We used linear mixed effects models to evaluate changes in metabolic cost with
144 increasing step length variability. We used the actual step length variability that participants
145 walked with for each condition, rather than the projected step length variability for that
146 condition. All statistical analysis was performed in R studio (4.2.2) with a linear mixed effects
147 regression (Wilkinson et al., 2023) using lme4 (1.1 - 32) and sjstats (0.18.2) packages. A paired
148 t-test was used to compare metabolic power and step length variabilities between NP and 0%
149 conditions. A linear model was used to investigate the impact of step length variability on
150 metabolic power during walking. Random intercepts were adjusted for each participant using
151 equation 1 where COV is the coefficient of variation of the step lengths during a trial.

152

153 Eqn 1: Metabolic Power ~ COV + (1 | Participant)

154

155 Metabolic power was then evaluated using the mixed effect model with a random
156 intercept for each participant and an independent slope corresponding to the participant specific
157 metabolic power response using equation 2.

158

159 Eqn 2: Metabolic Power \sim COV + (COV | Participant)

160

161 We used a likelihood ratio to test for significance between a model excluding step length
162 variability and an alternative model that did not. Chi-squared (χ^2) and significance values are
163 reported. For all statistical tests, significance was set at an alpha level of 0.05.

164

165 **RESULTS:**

166 Metabolic power and step length variability were different between NP and 0%
167 conditions (3.98 ± 0.25 vs. 4.16 ± 0.18 W/kg; $p = 0.0002$ and $2.42 \pm 0.55\%$ vs. $3.10 \pm 0.58\%$; $p =$
168 0.001 , respectively; Figure 2). Thus, when pooling the true step length variability across
169 conditions, we excluded the NP condition (i.e., we included only data from the 0%, 5% and 10%
170 step length variability trials in our model). Overall, metabolic power increased with increasing
171 step length variability ($\chi^2 = 9.41$; $p = 0.002$; Fig. 3). For every 1% unit increase in step length
172 variability, there was an increase in metabolic power of 0.03 ± 0.01 W/kg, or 0.7%.

173

174 **DISCUSSION:**

175 In this study, we quantified the isolated effects of increased step length variability on the
176 metabolic cost of walking. In line with our hypothesis, increases in step length variability
177 resulted in increases in metabolic cost. Additionally, we observed a difference in metabolic cost
178 between walking without projections and with projections with no variability. Our results are
179 similar, but of smaller magnitude than observations from studies that indirectly increased step
180 length variability (O'Connor et al., 2012; Rock et al., 2018).

181 Our findings suggest a modest contribution of step length variability to the metabolic cost
182 of walking (0.7% increase in metabolic power per 1% increase in step length variability; Fig. 3)
183 at a common walking speed of 1.20 m/s. At this speed, every percent change in step length
184 variability increases metabolic cost by 0.03 W/kg. This increase is almost five times smaller than
185 the 0.14 W/kg increase in metabolic cost, for every 1% increase in variability, modeled by Rock

186 et al (2018). This difference is likely related to our direct manipulation of step length variability
187 at a single, constant speed, eliminating the metabolic penalty of walking slower than preferred
188 (Ralston, 1958). Additionally, the work of O'Connor et al. (2012), reported greater step width
189 variability (+65%), mean step width (+19%) and an increased metabolic cost (5.9%) while
190 walking with virtual visual flow perturbations (high frequency medio-lateral rotations). This
191 suggests that step width variability has a larger effect on metabolic cost than step length
192 variability. Indeed, walking with increased step width comes at a metabolic cost (Donelan et al.,
193 2001).

194 Two mechanisms can be expected to play a role in elevating the metabolic cost of
195 walking with increased step length variability. First, adjusting to a closer stepping stone (i.e.,
196 reducing step length), increases the metabolic cost of moving limbs at a higher rate (Doke et al.,
197 2005). Second, an adjustment to a farther stepping stone (i.e., increasing step length) increases
198 the cost of lifting the center of mass over the point of collision (Donelan et al., 2001). An
199 additional possible mechanism, that relates to the need to step accurately on each stone, is an
200 increase in muscle co-contraction, commonly observed with increased accuracy demands
201 (Gribble et al., 2003). While some of the increased metabolic cost of walking could be attributed
202 to increased accuracy demands, an additional portion could be related to the cost of consistently
203 regulating steps across projected stones, degrading the contribution of passive dynamics to
204 walking (Wezenberg et al., 2011). These additional mechanisms could help explain the
205 differences in metabolic cost between walking with no projections (habitual) and with 0% step
206 length variability projections that closely matched habitual gait characteristics (Fig. 2).

207 Beyond slower gait with shorter steps and longer double support phases, older adults
208 have more gait variability and increased metabolic energy demands (Boyer et al., 2023; Schrack
209 et al., 2012). The larger gait variability in older adults and in those with neurological
210 impairments could contribute to their increased metabolic cost of walking as compared to young
211 (e.g., +8%; Martin et al., 1992) or neurologically healthy adults (+17-170%; Compagnat et al.,
212 2020; Jeng et al., 2020; Rooney et al., 2022). At matched speeds, older adults walk with higher
213 step length variability than younger adults (Almarwani et al., 2016; Kang & Dingwell, 2008),
214 more so if the older adult has mobility impairments, with a reported 2.7% increase in step length
215 variability (James et al., 2020). Our data suggest that a 2.7% increase in step length variability
216 would increase the metabolic cost of walking by 1.7%. At their preferred speeds, adults with

217 neurological impairments have been reported to walk with step length variabilities that are
218 approximately 2.5%, 3.0%, and 6.0% larger than neurologically healthy controls, for Parkinson's
219 disease, Multiple Sclerosis, and Cerebellar Ataxia, respectively (Buckley et al., 2018; Noh et al.,
220 2020; Roemmich et al., 2012; Socie et al., 2013). Our data suggests that these increases in step
221 length variability will increase the metabolic cost of walking by 1.8, 2.1 and 4.2%, respectively.
222 The metabolic cost of walking with increased step length variability only contributes a small part
223 to the total increased metabolic cost (17– 170%) of walking observed across these populations
224 (Compagnat et al., 2020; Jeng et al., 2020; Martin et al., 1992; Rooney et al., 2022).

225 **Limitations and future directions:**

226 To ensure that the step length variations were perceivable to participants, we binned step
227 lengths into 5% multiples, not exceeding 15% of their habitual step length. Normal walking does
228 not contain such discretized step length variability. Although the perturbed conditions do not
229 perfectly reflect real-world gait variability, they provide an upper limit for the increases in
230 metabolic cost in young healthy individuals. Most participants were unable to exactly match the
231 discretized step length variabilities that were projected; while the use of 5% bins is different than
232 real-world gait variability, participants still had trouble maintaining accuracy across the stepping
233 stones without additional feedback. We were limited in identifying how participants altered their
234 step length. In future research it could be insightful to evaluate whether participants took larger
235 or shorter steps when aiming for the stone targets, as well as the frequency and magnitude of
236 their errors. This would not change the relationship between step length variability and metabolic
237 cost, but it could help in relating task performance to step length variability within a condition.
238 While few participants were able to walk with 5 and 10% step length variability, 0% step length
239 variability was unachievable – the lowest value for a single participant was 2%. This is in line
240 with observations that walking inherently contains some variability in step length (Collins &
241 Kuo, 2013) which might also be distinct between participants.

242 Participants did not receive feedback on how well they were performing during a trial.
243 Feedback could have improved task performance (Shull et al., 2014) to better align with our
244 variability conditions. To investigate whether co-contraction, to maintain accuracy (Gribble et
245 al., 2003), contributes to the increased metabolic cost of walking with variable step lengths,
246 future studies should quantify foot placement accuracy and muscle activity across similar virtual
247 projections. Finally, to clarify the relationship between variability and gait deficiencies for

248 populations already experiencing increased step length variability, further investigations should
249 be conducted with these populations specifically.

250

251 **Conclusion:**

252 Older adults and those with neurological conditions walk with greater step length
253 variability and increased metabolic cost. In a population of healthy young adults, we found that
254 metabolic cost increases by approximately 0.7% (0.03 W/kg) for every 1% increase in step
255 length variability. Although most of our participants were unable to exactly match the projected
256 conditions, our virtual visual perturbation successfully increased step length variability and
257 metabolic cost across step variability conditions. The metabolic cost per unit of variability was
258 smaller than reported in previous work, indicating that step length variability plays a modest,
259 albeit significant role in the metabolic cost of walking.

260

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263 piloting and data collection, the Kinesiology staff at the University of Massachusetts Amherst,
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265 tactfully compare humans walking over it.

266

267 **Competing interests**

268 The authors declare no competing or financial interests.

269

270 **Author contributions**

271 Conceptualization: M.E.W., W.H.; Methodology: A.B.G., M.E.W., W.H. Formal analysis:
272 A.B.G., M.E.W., W.H. Investigation: A.B.G., M.E.W.; Resources: A.B.G., W.H.; Data curation:
273 A.B.G., M.E.W., W.H; Writing - original draft: A.B.G., M.E.W., WH; Writing - review &
274 editing: A.B.G., D.N.M., W.H; Visualization: A.B.G; Supervision: D.N.M., W.H.; Project
275 administration: W.H.; Funding acquisition: D.N.M., W.H

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Figures:

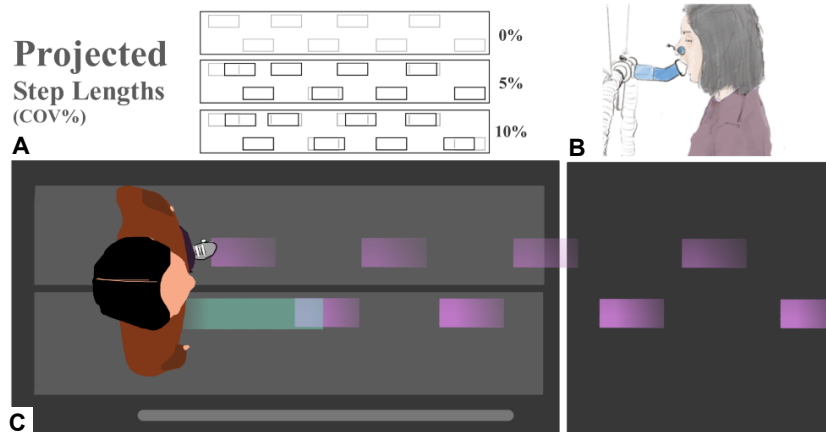


Figure 1. (A) Diagram of example step length conditions for 0, 5, and 10% variability. Grey rectangles are stepping stone targets projected at a participant's specific habitual step length. Black rectangles are the lengthwise deviations of perturbed stones generated randomly from discretized bins. (B) Illustration of indirect calorimetry including pitched 45-degree extension used to open participant field-of-view. (C) Top-down visual of a participant targeting projected stepping stones (purple; moving from right to the left) for 0% variability.

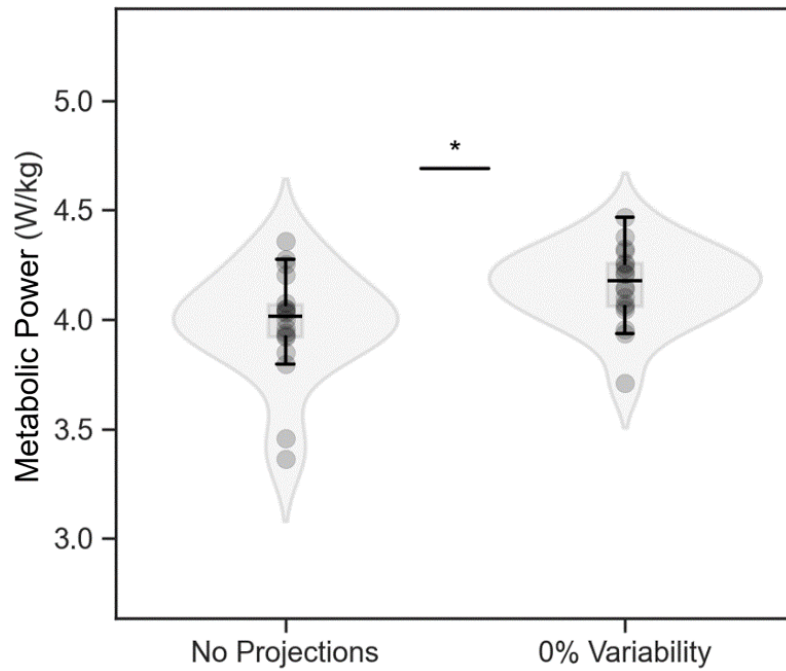


Figure 2. Metabolic power ($n = 18$) was lower for walking without any projected stepping stones than for walking over stepping stones projected without any step length variability. Values are mean \pm s.d., * $p < 0.05$

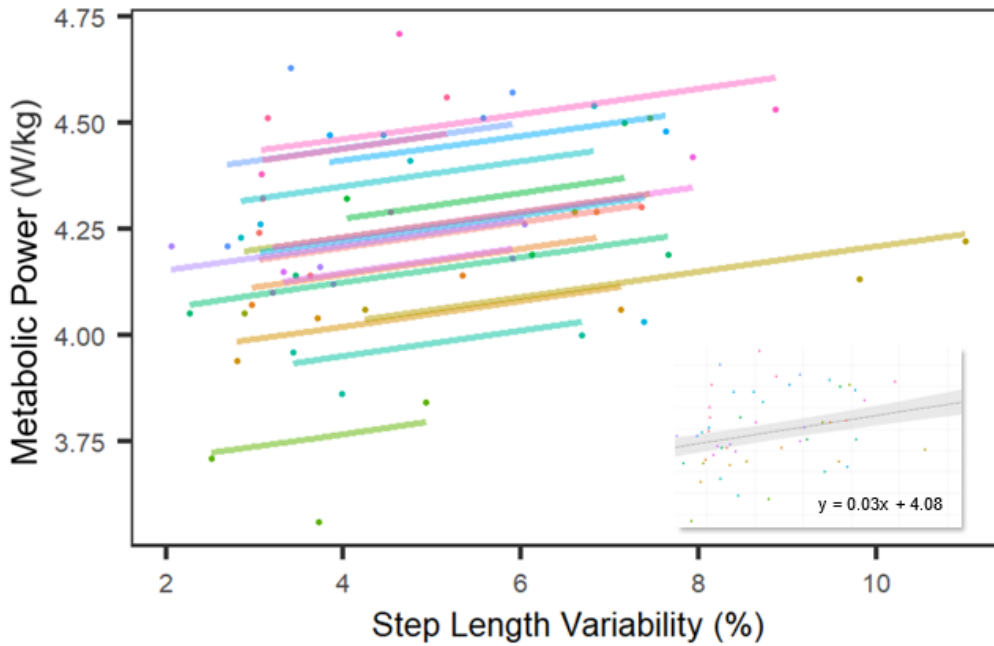


Figure 3: For every percentage increase in step length variability, there is a 0.03 W/kg (0.7%) increase in metabolic power, averaged between conditions and across participants (inset). Linear mixed effects models identified linear trends for each subject (n =18; colored lines) across conditions.