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# Habitual foot strike pattern does not affect simulated Triceps Surae muscle metabolic energy consumption during running

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Wannes Swinnen<sup>1</sup>, Wouter Hoogkamer<sup>2</sup>, Friedl De Groote<sup>1</sup>, Benedicte Vanwanseele<sup>1</sup>

- <sup>1</sup>Human Movement Biomechanics Research Group, Department of Movement Sciences, KU
   Leuven, Leuven, Belgium
  - <sup>2</sup>Department of Kinesiology, University of Massachusetts Amherst, Amherst, USA

## 7 Abstract

8 Foot strike pattern affects ankle joint work and Triceps Surae muscle-tendon dynamics during running. 9 Whether these changes in muscle-tendon dynamics also affect Triceps Surae muscle energy 10 consumption is still unknown. In addition, as the Triceps Surae muscle accounts for a substantial 11 amount of the whole body metabolic energy consumption, changes in Triceps Surae energy 12 consumption may affect whole body metabolic energy consumption. However, direct measurements 13 of muscle metabolic energy consumption during dynamic movements is hard. Model-based 14 approaches can be used to estimate individual muscle and whole body metabolic energy consumption 15 based on Hill type muscle models. In this study, we use an integrated experimental and dynamic 16 optimization approach to compute muscle states (muscle forces, lengths, velocities, excitations and 17 activations) of 10 habitual mid-/forefoot striking and 9 habitual rearfoot striking runners while running 18 at 10 and 14 km/h. The Achilles tendon stiffness of the musculoskeletal model was adapted to fit 19 experimental ultrasound data of the Gastrocnemius medialis muscle during ground contact. Next, we 20 calculated Triceps Surae muscle and whole body metabolic energy consumption using four different 21 metabolic energy models provided in literature. Neither Triceps Surae metabolic energy consumption 22 (p > 0.35), nor whole body metabolic energy consumption (p > 0.14) was different between foot strike 23 patterns, regardless of the energy model used or running speed tested. Our results provide new 24 evidence that mid-/forefoot and rearfoot strike pattern are metabolically equivalent.

#### 25 Introduction

26 The metabolic energy consumed during submaximal running, often referred to as running economy, is 27 an important factor determining endurance running performance (Jones and Carter, 2000). Reduced 28 energy consumption corresponds to improved running economy and hence superior endurance 29 performance (Hoogkamer et al., 2016; Kipp et al., 2019). As such, runners seek to adopt a running 30 pattern with minimal metabolic energy consumption. One aspect of people's running pattern is foot 31 strike pattern. Although foot strike pattern is a continuum, generally three different foot strike 32 patterns are considered: forefoot strike, midfoot strike and rearfoot strike (Cavanagh and Lafortune, 33 1980).

34 While rearfoot striking is the most common running pattern during shod running (Hasegawa et al., 35 2007; Kasmer et al., 2013; Larson et al., 2011), there seems to be a widespread popular believe that 36 forefoot striking would be more economical than rearfoot striking. Previous research has 37 demonstrated that there is a greater percentage mid-/forefoot strikers among the first finishers in long 38 distance races (de Almeida et al., 2015; Hasegawa et al., 2007), which suggests that forefoot striking 39 may be more economical. However, studies comparing metabolic energy consumption between 40 habitual forefoot and habitual rearfoot strikers found no difference in whole body metabolic energy 41 consumption (Gruber et al., 2013) or even lower energy consumption in rearfoot strikers compared to 42 their forefoot striking colleagues at 11 and 13 km/h but not at 15 km/h (Ogueta-Alday et al., 2014).

43 Available analyses of the kinetic and kinematic differences between foot strike patterns do not clearly 44 provide evidence for either differences in or unchanged energy consumption with foot strike patterns. 45 The shorter ground contact times (Di Michele and Merni, 2014; Mercer and Horsch, 2015), associated 46 with forefoot striking, may increase metabolic energy consumption according to Kram and Taylor's 47 cost of generating force hypothesis (Kram and Taylor, 1990). They established that the metabolic 48 energy consumption is inversely proportional to ground contact time, which implies that forefoot 49 strikers may consume more metabolic energy. In addition, forefoot strikers demonstrate greater 50 negative ankle work compared to rearfoot strikers (Stearne et al., 2014). This ankle work is 51 predominantly absorbed by the muscle-tendon unit (MTU) spanning the ankle joint, i.e., Triceps Surae 52 muscle and the in series connected tendinous tissue (SEE, series elastic element). Hence, differences 53 in ankle work may affect the MTU and subsequently the energy consumption of this Triceps Surae 54 muscle. We recently demonstrated that in habitual mid-/forefoot strikers the Gastrocnemius medialis 55 (GM) produces greater muscle force but at lower contraction velocities during early stance compared 56 to habitual rearfoot strikers (Swinnen et al., 2019). Higher muscle force production suggests more 57 muscle activation and thus higher metabolic energy consumption, whereas lower contraction 58 velocities are more force efficient and would therefore reduce muscle activation and thus metabolic 59 energy consumption. Hence, we hypothesized that the differences in metabolic energy consumption 60 would counteract each other and no difference in GM metabolic energy consumption would exist 61 (Swinnen et al., 2019). Yet, as Fletcher and MacIntosh (2017) estimated that 25 to 40% of the total 62 whole body metabolic energy is consumed by the Triceps Surae muscle, we would expect different 63 whole body metabolic energy consumption if Triceps Surae metabolic energy consumption would be 64 different between foot strike patterns.

Model-based approaches have been used to estimate individual muscle and whole body metabolic
energy consumption based on Hill type muscle models (Bhargava et al., 2004; Miller, 2014; Uchida et
al., 2016; Umberger, 2010; Umberger et al., 2003). However, to obtain reliable simulation results, a

68 close match between simulated and experimental data is essential. Here, we used experimental 69 dynamics ultrasound data from the Gastrocnemius medialis (GM) to improve our dynamic 70 optimization and as such, ensure more reliable estimations of muscle metabolic energy consumption. 71 We used four different metabolic energy models (Bhargava et al., 2004; Uchida et al., 2016; Umberger, 72 2010; Umberger et al., 2003) to calculate Triceps Surae muscle and whole body metabolic energy 73 consumption of habitual mid-/forefoot and rearfoot strikers running at 10 and 14 km/h. We 74 hypothesized that neither Triceps Surae nor whole body metabolic energy consumption would be 75 different between foot strike patterns.

#### 76 Methods

Participants. Ten habitual mid-/forefoot strikers (6 males, 4 females; body mass: 65.2 ± 7.7 kg;
body height: 1.78 ± 0.07 m) and 9 habitual rearfoot strikers (6 males, 3 females; body mass: 72.7 ± 12.5
kg; body height: 1.81 ± 0.08 m) participated in this study. All participants were regular runners who
ran at least 30 km/week, did not have any Achilles tendon or calf injury in the last six months and had
no prior Achilles tendon surgery. Written informed consent, approved by the local ethical committee
(Medical Ethical Committee of UZ Leuven), was obtained at the start of the experiment.

Experimental procedure. The experimental procedures have been described in detail in our earlier publication on gastrocnemius medialis muscle-tendon interaction and muscle force production in this group of runners (Swinnen et al., 2019). Briefly, after a 10 minutes warm-up, participants ran 5 minutes on a force measuring treadmill (Motekforce Link, Amsterdam, The Netherlands): 2.5 minutes at 10 and at 14 km/h, in randomized order. We collected kinetic, kinematic, muscle activation and ultrasound data of at least four strides during the last minute of each running speed. All measurements were synchronized through a trigger pulse signal sent from the ultrasound device.

Kinetics, kinematic and foot strike angle. Thirteen infrared cameras (Vicon, Oxford Metrics,
 UK) captured the motion of forty-seven reflective markers at a sampling frequency of 150 Hz. We used
 OpenSim 3.3 (OpenSim, Stanford, USA) to first scale a musculoskeletal model based on the subject's
 dimensions (Hamner et al., 2010) and to subsequently compute joint kinematics using a Kalman
 smoothing algorithm (De Groote et al., 2008). Muscle tendon unit lengths were calculated using
 OpenSim's Muscle Analysis Tool.

96 Ground reaction force data, sampled at 900 Hz, was first low pass filtered with a cut-off frequency of 97 20 Hz and used to determine ground contact phase adopting a 30 N threshold. We determined foot 98 strike angle using a marker based method (Altman and Davis, 2012). At initial ground contact, we drew 99 a line through the first metatarsal-phalangeal joint marker and heel marker of the left foot. The angle 100 between this line and the ground was calculated and considered as the foot strike angle. Following

Altman and Davis (2012) runners with a foot strike angle greater than 8° were considered rearfoot strikers, while runners with a foot strike angle under 8° were considered mid-/forefoot strikers. Foot strike angle was averaged over the strides used for ultrasound analysis. Foot strike type (rearfoot or mid-/forefoot) was consistent within subjects across running speeds.

105 We calculated joint torques using OpenSim's Inverse Dynamics Tool based on joint kinematics and 106 ground reaction forces. Joint torques were low pass filtered using a recursive fourth order Butterworth 107 filter with cut-off frequency of 20 Hz.

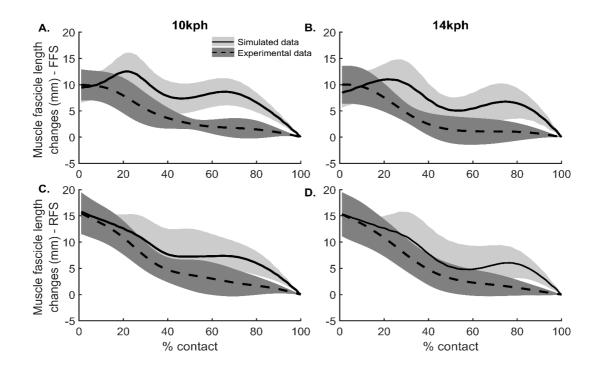
108 Dynamic ultrasound imaging. We collected dynamic ultrasound images of the GM muscle 109 fascicles of the left leg with a B-mode ultrasound system (Telemed Echoblaster 128 CEXT system) 110 sampling at 86 Hz. The linear transducer (UAB Telemed, Vilnius, Lithuania, LV 7.5/60/128Z-2) was 111 placed on the mid-belly of the muscle, aligned with the muscle fascicles and attached to the calf with 112 tape and bandages. To analyze the GM muscle fascicle lengths and pennation angles we used a semi-113 automatic tracking algorithm (Farris and Lichtwark, 2016). We analyzed at least four strides and 114 calculated fascicle length changes relative to fascicle length at toe-off. All data were splined to 100 115 data points per ground contact, starting at initial contact.

116Muscle activity. We used surface electromyography (EMG) to determine GM and Soleus (SOL)117muscle activity of the right leg through a wireless EMG acquisition system (ZeroWire EMG Aurion,118Milano, Italy) measuring at 900 Hz. EMG signals were first band-pass filtered (20-400 Hz), rectified and119low-pass filtered (20 Hz). For each subject and muscle, EMG waveforms were normalized to maximal120activation, determined as the maximal activation of each muscle using a moving average over 10 data121points. Due to technical issues, the EMG data of the GM of one participant (mid-/forefoot striker) and122SOL of three participants (2 mid-/forefoot strikers and 1 rearfoot striker) could not be used.

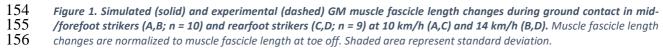
Comparison between experimental EMG and simulated activation of the GM and SOL demonstrated
 similar trends, yet due to our optimization criteria (minimization of muscle activation squared) pre activation is not predicted (Fig. S1).

126 Estimating muscle and whole body metabolic energy consumption. Several models for 127 estimating muscle metabolic energy rate have been proposed and it is yet unclear which model yields 128 the most valid results. We, therefore, used multiple models primarily to assure that our results are 129 independent from the metabolic energy model used. Our goal was not to compare the different energy 130 models (for comparison between metabolic energy models see Miller 2014). All models required the 131 muscle states (i.e., muscle activations, excitations, lengths, velocities and forces) as inputs. To obtain 132 these muscle states we solved the muscle redundancy problem using a dynamic optimization 133 algorithm that takes into account muscle-tendon dynamics (i.e., muscle activation and contraction

134 dynamics) of the 43 lower limb muscles of the left leg in our model (De Groote et al., 2009; De Groote 135 et al., 2016). Individual muscle moment arms, muscle tendon unit lengths and muscle properties were 136 extracted from the scaled OpenSim model and were input to the muscle redundancy solver. We scaled 137 maximal isometric muscle force based on the subject's body mass and height (Handsfield et al., 2014). 138 To avoid maximal muscle activations and unrealistically high reserve actuator forces, muscle forces 139 were multiplied by 3 for all participants. The Triceps Surae muscles, containing the GM, Gastrocnemius 140 lateralis (GL) and SOL, were modeled as three separate muscle-tendon units, with the tendon 141 representing the Achilles tendon. To ensure a close match between experimental GM muscle fascicle 142 length changes and simulated GM muscle fascicle lengths, we adjusted the normalized tendon 143 stiffness, a scaling factor to calculate GM, GL, SOL tendon stiffness based on the ratio between maximal 144 isometric force and tendon slack length, to a value of 5 for all participants (Figure 1). Gerus et al. (2015) 145 previously stated that the Achilles tendon is more compliant than the generic tendon stiffness as 146 described by Zajac (1989). We tested multiple other values (ranging from 4 to 35) where 5 gave the 147 best match. The normalized stiffness for all other muscles was kept on the default value of 35. Joint 148 torques served as inputs to solve the muscle redundancy problem by minimizing the squared muscle 149 activation. We solved the dynamic optimization problem through direct collocation using GPOP-II 150 software (Patterson and Rao, 2014). Subsequently the resulting nonlinear equations was solved using 151 ipopt (Wächter and Biegler, 2006). In 9 out of the 154 ground contact analyzed the optimization 152 algorithm failed to find an optimal solution, these strides were excluded.



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Next, the simulated muscle states were used as input in four models to estimate muscle metabolic
energy rate *E* that are consistent with Hill based muscle dynamics: Umberger, Gerritsen and Martin
(2003) (U2003), Bhargava, Pandy and Anderson (2004) (B2004), Umberger (2010) (U2010) and Uchida *et al.* (2016) (U2016). All these models had the same general form to calculate energy expenditure:

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$$E = H_A + H_M + H_{SL} + cW$$

Where  $H_A$ ,  $H_M$  and  $H_{SL}$  are the heat production rates of the muscles for activation, maintenance and 162 163 shortening/lengthening respectively, W is the muscle mechanical work rate where concentric work is 164 defined positively and C is weighting factor depending on the type of work (concentric of eccentric). 165 Major differences between the models are how they treat eccentric muscle work and how they weight 166 muscle lengthening heat rate. While in U03 and U16 negative mechanical work (i.e., metabolic energy 167 generation) is incorporated, B04 and U10 are restricted to positive mechanical work only, negative 168 mechanical work is excluded and the lengthening heat rate coefficient is adapted. Apart from these 169 differences, the heat rate calculations have similar terms between the models, though the scaling 170 factors used are different. Activation and maintenance heat rates are generally defined by muscle 171 mass/force, length and fiber type composition while shortening/lengthening heat rate depend on 172 muscle contraction velocity. U03, U10 and U16 scale these heat rates by muscle activation whereas 173 B04 does not. We refer to the specific papers for more detailed information on the models.

174 Muscle metabolic energy rate was integrated over time to obtain metabolic energy consumption 175 during one stance phase which was then multiplied by 2, to account for both legs, and multiplied by 176 the stride frequency to obtain metabolic energy rate in Watts. The metabolic energy consumed by the 177 Triceps Surae muscles was normalized to their respective muscle mass. We computed whole body 178 metabolic energy expenditure as the sum of metabolic energy consumed by all 43 muscles included in 179 the model and added a basal rate of 1.2 W/kg (Waters and Mulroy, 1999). Whole body metabolic 180 energy consumption was normalized to body mass.

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**Statistics.** All data are presented as mean ± standard deviation. We categorized our data in four groups: mid-/forefoot strike at 10 km/h (FF 10), mid-/forefoot strike at 14 km/h (FF 14), rearfoot strike at 10 km/h (RF 10) and rearfoot strike at 14 km/h (RF 14). First, normality was checked with the Shaprio-Wilk test. If data from all groups followed a normal distribution a mixed analysis of variance (ANOVA) was used to determine interaction and main effects (foot strike pattern and running speed) using SPSS v.24 (IBM SPSS, Armonk, New York, USA). Yet, if not all the data in the groups followed a

188 normal distribution, the non-parametric Mann-Whitney U test was performed to compare foot strike

189 pattern differences at 10 and 14 km/h separately. To determine the effect of running speed for these

190 datasets, the data was first grouped according to running speed and again checked upon normality. If

191 both datasets were then normally distributed, a paired t-test was performed, if not we performed a

- 192 Wilcoxon signed-rank test. Statistical significance was considered when p < 0.05.
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## 194 <u>Results</u>

195 Although mean foot strike angle was more than  $15^{\circ}$  different between both foot strike groups (p < 196 0.01; Table 1), Triceps Surae metabolic energy consumption was not different between foot strike 197 patterns, regardless of speed or metabolic energy model (p > 0.35; Figure 2). Moreover, metabolic 198 energy consumed by the individual Triceps Surae muscles, i.e. GM, GL and SOL, was not different 199 between foot strike patterns (p > 0.10) independent of the model used or running speed. Furthermore, 200 estimated whole body metabolic energy consumption was not different between foot strike patterns 201 regardless of model or running speed tested (p > 0.14; Figure 3). As one would expect, running faster 202 resulted in greater metabolic energy consumption in the Triceps Surae muscle group (p < 0.01) as well 203 as in all three Triceps Surae individually (p < 0.02). Also, whole body metabolic energy consumption 204 was greater when running at 14 km/h compared to 10 km/h (p < 0.01).

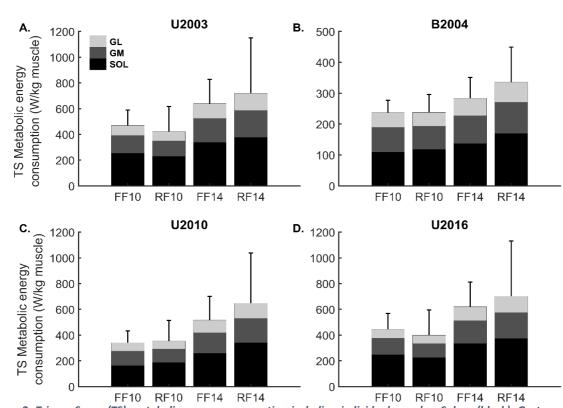
The ratio of metabolic energy consumed by the Triceps Surae relative to whole body metabolic energy consumption ranged between 22 and 32% across foot strike patterns and running speeds but was not different between foot strike patterns (p > 0.19). In contrast, the different models revealed inconsistent results when the effect of speed on this ratio was considered. While U03 and U16 did not show significant differences in this ratio between running speeds (p > 0.07), U10 showed a significant greater ratio at 14km/h compared to 10 km/h (p = 0.01), whereas B04 showed a significant smaller ratio at 14 km/h than at 10 km/h (p = 0.02).

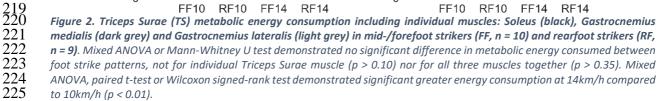
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216	Table 1 Comparison between mid-/forefoot and rearfoot strikers and between 10 and 14 km/h. All data are expressed as
217	mean $\pm$ SD. $^{a}$ significant main foot strike effect. $^{b}$ significant running speed effect. $^{c}$ significant interaction effect.

		speed	Forefoot strike	Rearfoot strike
Foot strike angle		10 km/h	-0.4 ± 4.4	14.8 ± 3.7
(°) <sup>a</sup>		14 km/h	0.3 ± 5.3	17.2 ± 5.4
	U03 <sup>c</sup>	10 km/h	26 ± 4	22 ± 8
		14 km/h	25 ± 3	25 ± 8
Ratio (%)	B04 <sup>b</sup>	10 km/h	26 ± 3	27 ± 6
$(E_{TS}/E_{WB})$		14 km/h	23 ± 4	26 ± 6
	U10 <sup>b</sup>	10 km/h	27 ± 4	28 ± 9
		14 km/h	28 ± 5	32 ± 10
	U16 <sup>c</sup>	10 km/h	27 ± 4	23 ± 8
		14 km/h	26 ± 3	26 ± 9







#### 227 Discussion

228 This study investigated the effect of habitual foot strike pattern on simulated Triceps Surae muscle and 229 whole body metabolic energy consumption. We used a dynamic optimization approach in which the 230 Achilles tendon stiffness of the musculoskeletal model was adapted to better match experimental GM 231 ultrasound data (Figure 1). Four different metabolic energy models were incorporated to ensure model 232 independency. In line with our hypothesis, none of the individual Triceps Surae muscles, nor whole 233 body metabolic energy consumption demonstrated significant differences between mid-/forefoot 234 strikers and rearfoot strikers (Figure 2 and Figure 3). Faster running increased both simulated Triceps 235 Surae muscle and whole body metabolic energy consumption.

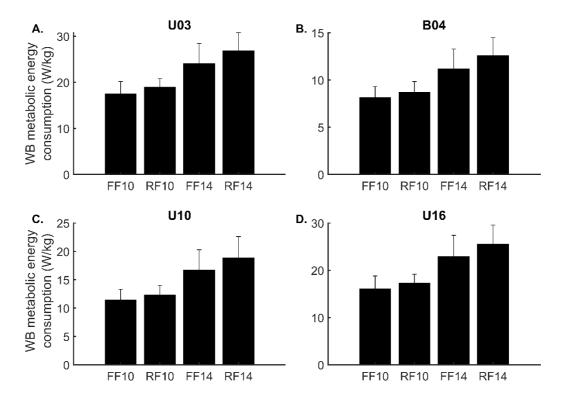


Figure 3. Estimated whole body (WB) metabolic energy consumption for all four metabolic energy models used for mid-/forefoot strikers at 10 km/h (FF10) and 14 km/h (FF14) and rearfoot strikers at 10 km/h (RF10) and 14 km/h (RF14). U03
Umberger, Gerritsen and Martin (2003), B04 = Bhargava, Pandy and Anderson (2004), U10= Umberger (2010) and U16 = Uchida et al. (2016). Mixed ANOVA or Mann-Whitney U test demonstrated no significant difference between foot strike patterns (p > 0.14). Mixed ANOVA, paired t-test or Wilcoxon signed-rank test demonstrated significant increase in energy consumption when running at 14 km/h compared to 10 km/h.

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Our results provide additional scientific evidence that mid-/forefoot and rearfoot strike patterns are energetically equivalent. We recently showed that GM muscle force production is greater while muscle contraction velocity is smaller in mid-/forefoot strikers compared to rearfoot strikers, especially during early ground contact (Swinnen et al., 2019). Here, we provide further evidence that the greater muscle forces in mid-/forefoot strikers are more economically produced due to the lower muscle contraction

249 velocities and hence no difference in GM, GL or SOL metabolic energy consumption between foot 250 strike patterns exist. Moreover, previous experimental research already demonstrated that 251 differences in whole body metabolic energy consumption between foot strike patterns are small 252 (Ogueta-Alday et al., 2014) or even non-existing (Cunningham et al., 2010; Gruber et al., 2013; Lussiana 253 et al., 2017; Perl et al., 2012). Studies investigating the effect of gait retraining from rearfoot to 254 forefoot strike running do not find an effect on the metabolic energy consumption during running 255 when enough training sessions (≥8) were offered (Ekizos et al., 2018; Roper et al., 2017). However, 256 when only two training sessions were provided an initial increase in metabolic cost is reported (Ekizos 257 et al., 2018), indicating the need for habituation. Hence, since habituation is necessary when switching 258 foot strike pattern and switching ultimately does not result in a reduced metabolic cost, switching foot 259 strike pattern seems to be ineffective from a performance point of view.

260 Next to estimated Triceps Surae muscle and whole body metabolic energy rate, the contribution of the 261 Triceps Surae to the whole body metabolic energy rate (i.e. ratio) was also not different between foot 262 strike patterns. However, the effect of running speed was less clear. Two models (U03 and U16) did 263 not find a speed effect, while U10 and B04 did find a speed effect, but in opposing directions. With 264 faster running the relative contribution of joint power/work during ground contact seems to gradually 265 shift more towards proximal joints (i.e. hip), especially at running speeds closer to sprinting (Schache 266 et al., 2015). Hence, if a shift in muscle metabolic energy consumption would occur, a shift in the same 267 direction as joint power would have been expected, implying a decreased relative contribution of the 268 Triceps Surae with increasing running speed. However, the difference in running speeds tested in this 269 study was small and our fastest speed did not approach sprinting. Therefore, to better understand the 270 effect of running speed on the distribution of muscle metabolic energy consumption across lower 271 extremity muscles a wider range of running speeds should be investigated.

272 Dynamic optimization allowed us to account for muscle-tendon interactions when estimating muscle 273 states. A good match between experimental and predicted muscle states is crucial for good 274 estimations of muscle metabolic energy. We found that it was important to adapt Achilles tendon 275 stiffness to obtain a close match between simulated and measured GM fiber lengths. Using a generic 276 normalized tendon stiffness value of 35 resulted in negligible length changes of the tendinous tissues 277 and as a consequence muscle fascicle length changes were no longer uncoupled from length changes 278 of the entire muscle tendon unit (Fig. S2). Nevertheless, there is ample experimental evidence that the 279 tendinous tissue interacts with the Triceps Surae muscles, uncoupling the muscle fascicle length 280 changes from the length changes of the entire MTU (Fukunaga et al., 2002; Lai et al., 2015; Lichtwark 281 and Wilson, 2008), allowing the muscle fascicles to contract at much slower - more force-efficient -282 velocities implying lower metabolic energy consumption (Hill, 1922; van der Zee, Lemaire and van

283 Soest, 2019). As a result, predicted Triceps Surae muscle metabolic energy consumption with the 284 generic stiff tendon was on average 80% higher compared to the adapted Achilles tendon stiffness 285 (Fig. S3). Also, estimated whole body metabolic energy consumption was on average 23% higher 286 compared to the adapted Achilles tendon stiffness (Fig. S4). The discrepancy between the results based 287 on the generic and adapted tendon stiffness values illustrates the importance of a good match 288 between computed and experimental muscle states to obtain reliable results of muscle metabolic 289 energy consumption. Moreover, the increased metabolic energy consumption associated with the stiff 290 tendon emphasizes the importance of the muscle-tendon unit interaction on the metabolic energy 291 consumption during running.

292 Although our conclusions are independent of the metabolic energy model used, the wide variability in 293 absolute energy rates between the metabolic energy models are remarkable. While B04 and U10 294 predict experimental whole body metabolic energy consumption rather close to experimental data, 295 whole body metabolic energy consumption predicted by U03 and U16 are almost twice as high as 296 experimentally observed (Batliner et al., 2018; Kipp et al., 2018). The major difference is that U03/U16 297 neglect eccentric work whereas B04/U10 account for eccentric work. Instead of accounting for 298 negative work, U03/U16 reduce the lengthening heat rate coefficient. Our results (lower energy rates 299 with U03/U16) illustrate that the reduction of the lengthening heat rate more than offsets the 300 exclusion of eccentric muscle work. While we seem to have a good understanding of the energy cost 301 of isometric and concentric muscle contractions, the energy cost during eccentric or stretch-shortening 302 muscle contraction is more debatable. It is clear that eccentric muscle work is more efficiently 303 produced compared to concentric muscle work (Hill, 1960), and therefore it appears reasonable to 304 allow eccentric muscle work and muscle lengthening to reduce the metabolic energy consumption rate 305 of a muscle, however a clear consensus on how to treat eccentric work is still lacking. Also the energy 306 cost associated with the stretch-shortening of a muscle is still controversial (Holt et al., 2014; van der 307 Zee et al., 2019). Nevertheless, in contrast to the absolute differences, the relative increase in 308 metabolic energy consumption based on all muscle metabolic models when running faster 309 corresponds quite well with the experimental data. Experimental data indicates that increasing the 310 running speed from 10 km/h to 14 km/h would corresponds with an increase in whole body metabolic energy consumption of approximately 40 to 45% (Batliner et al., 2018; Kipp et al., 2018). The energy 311 312 models predict similar increases of 40% (U03), 41% (B04), 49% (U10) and 45% (U16). In summary, while 313 metabolic energy models do a good job for predicting relative changes, absolute values are not in 314 accordance with experimental data. Therefore, experimental muscle research on how to account for 315 the energy cost of eccentric and stretch-shortening muscle contractions is necessary before 316 recommendations on how to implement these contractions in metabolic energy models can be made.

317 Our study has some limitations. First, we did not measure Achilles tendon stiffness from our 318 participants and assumed equal normalized Achilles tendon stiffness for all subjects. Kubo et al. (2015) 319 found no difference in Achilles tendon stiffness between foot strike patterns and thus, on average, we 320 can assume equal normalized Achilles tendon stiffness. Mid-/forefoot strikers are reported to earlier 321 activate their Gastrocnemii muscles (Ahn et al., 2014; Swinnen et al., 2019). However due to our 322 optimization criteria (i.e. minimization of muscle activation squared) pre-activation of the Triceps 323 Surae muscles is not predicted. Still, our simulations demonstrate a slightly earlier Triceps Surae 324 muscle activation in mid-/forefoot strikers than rearfoot strikers (Fig. S1). Furthermore, our 325 musculoskeletal model has some limitations. For example, the musculoskeletal model lacks a midfoot 326 arch, which has been shown to store and release energy and subsequently reduce the metabolic rate 327 during running (Ker et al., 1987; Stearne et al., 2016). Moreover, we only took metabolic energy 328 expenditure during ground contact into account, according to Arellano and Kram (2014) only 329 considering ground contact would lead to an underestimation of 7% of the net metabolic energy 330 expenditure. We used ultrasound data to validate our simulations, a well-known limitation of 331 ultrasound data is that these 2D images represents a 3D muscle structure, possibly resulting in 332 underestimation of muscle fascicle length changes when there is out of plane muscle movement.

333 In conclusion, we demonstrated that - in contrast with the widespread belief in the running 334 community – none of the foot strike patterns induce a reduction in metabolic energy consumption of 335 the Triceps Surae muscle while running. In agreement with previous experimental research, simulated 336 whole body metabolic energy consumption was also similar between foot strike patterns. Hence, we 337 conclude that none of the foot strike patterns can be associated with a superior running energetics. 338 Yet, we looked into differences in metabolic rate during sub-maximal running, an important 339 performance parameter in distance running. It should be noted that for sprinting energy rate is not as 340 important due to the short distance/time.

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#### 343 Competing interests

344 No competing interests declared.

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