

Inclusion of image-based in vivo experimental data into the Hill-type muscle model affects the estimation of individual force-sharing strategies during walking.

Raphaël Hamard, François Hug, Nicole Kelp, Romain Feigean, Jeroen Aeles,

Taylor Dick

► To cite this version:

Raphaël Hamard, François Hug, Nicole Kelp, Romain Feigean, Jeroen Aeles, et al.. Inclusion of image-based in vivo experimental data into the Hill-type muscle model affects the estimation of individual force-sharing strategies during walking.. Journal of Biomechanics, 2022, 135, pp.111033. 10.1016/j.jbiomech.2022.111033 . hal-03618632

HAL Id: hal-03618632 https://hal.science/hal-03618632v1

Submitted on 22 Jul 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

Version of Record: https://www.sciencedirect.com/science/article/pii/S0021929022000896 Manuscript_be6b91cceb2fad227cbae50c9808ed3f

1Inclusion of image-based *in-vivo* experimental data into the Hill-type muscle model2affects the estimation of individual force-sharing strategies during walking

Raphaël Hamard¹, François Hug*^{1,2,3,4}, Nicole Y. Kelp², Romain Feigean⁵,
 Jeroen Aeles¹, Taylor J. M. Dick²

- ¹ Nantes Université, Movement Interactions Performance, MIP, UR 4334, F-44000 Nantes,
 France
- 7 ² The University of Queensland, School of Biomedical Sciences, Brisbane, Queensland,
- 8 Australia
- 9 ³ Institut Universitaire de France (IUF), Paris, France
- 10 ⁴ Université Côte d'Azur, LAMHESS, Nice, France
- ⁵ Laboratoire de Physiologie et Évaluation Neuromusculaire, Institut de Myologie, Paris,
- 12 France
- Keywords: B-mode ultrasound, Electromyography, Gastrocnemius, MRI, Muscle
 coordination
- 15 **Word count:** 3494
- 16 ***Corresponding author:**
- 17 Prof. François Hug
- 18 Université Côte d'Azur, LAMHESS
- 19 Campus STAPS
- 20 261 boulevard du Mercantour
- 21 06200 Nice (France)
- 22 E-mail address: francois.hug@univ-cotedazur.fr
- 23 ORCID: 0000-0002-6432-558X

24 ABSTRACT

The study of muscle coordination requires knowledge of the force produced by individual 25 26 muscles, which can be estimated using Hill-type models. Predicted forces from Hill-type 27 models are sensitive to the muscle's maximal force-generating capacity (F_{max}) , however, to 28 our knowledge, no study has investigated the effect of different F_{max} personalization methods 29 on predicted muscle forces. The aim of this study was to determine the influence of two 30 personalization methods on predicted force-sharing strategies between the human 31 gastrocnemii during walking. Twelve participants performed a walking protocol where we 32 estimated muscle activation using surface electromyography and fascicle length, velocity, and pennation angle using B-mode ultrasound to inform the Hill-type model. F_{max} was determined 33 using either a scaling method or experimental method. The scaling method used 34 35 anthropometric scaling to determine both muscle volume and fiber length, which were used to 36 estimate the F_{max} of the gastrocnemius medialis and lateralis. The experimental method used 37 muscle volume and fascicle length obtained from magnetic resonance imaging and diffusion 38 tensor imaging, respectively. We found that the scaling and the experimental method 39 predicted similar gastrocnemii force-sharing strategies at the group level (mean over the 40 participants). However, substantial differences between methods in predicted force-sharing strategies was apparent for some participants revealing the limited ability of the scaling 41 42 method to predict force-sharing strategies at the level of individual participants. Further personalization of muscle models using *in vivo* experimental data from imaging techniques is 43 44 therefore likely important when using force predictions to inform the diagnosis and 45 management of neurological and orthopedic conditions.

46 1. INTRODUCTION

Knowledge of the forces that individual muscles produce provides important insights into muscle coordination, and this information can be used to improve the diagnosis and management of many neurological and orthopedic conditions (Hug and Tucker, 2017). However, directly measuring human muscle force requires highly invasive techniques (Finni et al., 1998; Gregor et al., 1987; Komi, 1990), which are not feasible in clinical environments and remain limited in most research settings. To overcome this limitation, muscle models for predicting muscle forces have been developed.

54 The Hill-type model is the most ubiquitous muscle model in biomechanics (Eq. 1; Zajac, 1989). It takes into account most of the known determinants of muscle force, i.e. the 55 56 activation, the instantaneous length and velocity of the contracting muscle fibers, and the 57 maximal force-generating capacity (F_{max}). The Hill-type model can be personalized with 58 subject-specific data, such as time-varying muscle activation assessed using surface 59 electromyography (EMG) (Perreault et al., 2003) or time-varying fascicle length, fascicle 60 velocity, and pennation angle recorded using ultrasound imaging (Dick et al., 2017). An 61 important determinant of muscle force is F_{max} (Bujalski et al., 2018; Scovil and Ronsky, 62 2006), for which the vast majority of studies rely on scaled data using different methods. For 63 example, muscle volume, a determinant of F_{max}, has been personalized through values scaled 64 to the participant's body mass (Dick et al., 2017). Furthermore, optimal muscle fiber length, which is another determinant of F_{max}, is often scaled from generic musculoskeletal models 65 (Millard et al., 2013). An important limitation of these approaches is that they use the same 66 67 underlying equations to scale all individuals. This conceals the well-described inter-individual 68 variability in the distribution of F_{max} across muscles (Crouzier et al., 2018; Hug et al., 2015).

69 The aim of this study was to compare two different personalization methods of a Hill-type 70 model to predict human gastrocnemii forces during level and incline walking. The first 71 personalization method, herein referred to as the "scaling method", used anthropometric 72 scaling to determine both muscle volume and muscle fiber length to estimate F_{max} of the gastrocnemius medialis (GM) and lateralis (GL). The second method, named hereafter the 73 74 "experimental method", used muscle volume and fascicle length obtained from magnetic 75 resonance imaging (MRI) and diffusion tensor imaging (DTI), respectively. We specifically 76 investigated the force-sharing strategy between the two gastrocnemii muscles. Because the scaling method inevitably conceals interindividual variability in the distribution of F_{max} 77

- 78 between the GM and GL, we expected to observe substantial differences between methods
- 79 when comparing the gastrocnemii force-sharing strategy at the individual level. However, we
- 80 hypothesized that the two methods would predict similar force-sharing strategies at the group
- 81 level.

82 2. MATERIALS AND METHODS

83 2.1. Participants

Twelve adults with no recent (< 6 months) lower limb pain or injury gave informed written consent to participate in the study (5 females, 7 males, age: 25 ± 3.5 years, body mass: $75.4 \pm$ 16.4 kg, height: 1.71 ± 0.10 m; mean \pm standard deviation). This study was approved by the institutional ethics review committee at The University of Queensland (#2013001448).

88 2.2. Experimental data acquisition

By Data were collected over two experimental sessions. The first session consisted of two consecutive scanning sequences of the participant's dominant leg: a T1-weighted MRI scan to determine muscle volume, and a DTI scan to determine muscle fascicle lengths.

92 For the second session, participants walked on a treadmill (Nautilus Trimline T345, TX, USA) at their preferred walking speed $(1.1 \pm 0.1 \text{ m.s}^{-1})$, which was determined at the 93 94 beginning of the protocol (Dal et al., 2010). During walking, we recorded surface EMG and 95 B-mode ultrasound of the GM and GL of the dominant leg to measure muscle activation and 96 fascicle behavior, respectively. Foot position was measured using motion capture to identify 97 phases of the gait cycle. Participants walked under two conditions presented in a randomized 98 order: (i) 0% treadmill grade (level walking) and (ii) 10% treadmill grade (incline walking). 99 They performed two trials at each walking condition and repeated each condition a second 100 time, first to record EMG and second to measure fascicle behavior. The EMG and the 101 ultrasound recordings were conducted in separate trials to ensure that the measures were taken 102 on the same mid-region of the muscle belly. Participants also performed three isometric 103 plantar flexion maximal voluntary contractions (MVCs), with 120 s rest between contractions, 104 to determine maximal GM and GL EMG amplitude for EMG normalization. The EMG and 105 ultrasound data have been published elsewhere (Hamard et al., 2021).

106 **2.2.1.** MRI

Participants were placed in a 3T MRI scanner (Magnetom Prisma, Siemens, Germany) in a supine position. The dominant foot was secured into a custom-built MRI-compatible foot plate with the hip extended and the ankle positioned in a 90° angle. The dominant knee was positioned in slight flexion ($< 5^\circ$) by using a foam wedge under the knee. Details on the MRI parameters have been described elsewhere (Pinel et al., 2021). The T1-weighted MRI images were analyzed using a combination of semi-automated (Sashimi V1.1; Bolsterlee, 2020) and

manual segmentation software (ITK-SNAP v3.8.0, NIH, USA). We calculated total muscle
volume for the GM and GL as the sum of the volume of all voxels in each muscle (ITKSNAP v3.8.0, NIH, USA). These muscle volumes were included in the Hill-type model (see

116 2.3) for the experimental method.

117 **2.2.2. DTI**

DTI scans were performed with the same scanner as for the MRI. Detailed information on the DTI parameters, processing and data analyses has been described elsewhere (Aeles et al., 2021). Briefly, the muscle was divided into smaller muscle regions in the local muscle frontal plane. Then, fascicles were assigned to the muscle region that contained the fascicle midpoint and the median muscle fascicle length was calculated for each region. Finally, the mean of all muscle regions was calculated and used as an input for optimal fiber length.

124 **2.2.3.** 3D motion capture

125 3D motion capture (Flex 13, OptiTrack, Corvallis, OR, USA) was used to record a static 126 calibration trial with 8 marker clusters and 16 individual markers placed bilaterally on the 127 lower limbs and pelvis to scale a musculoskeletal model (Rajagopal et al., 2016) for each 128 participant (OpenSim v3.3). Then, during the walking protocol, we used the markers attached 129 bilaterally to the calcaneus and the fifth metatarsophalangeal joint to determine the timing of 130 the heel-strike and toe-off events using custom-written scripts based on foot vertical velocity 131 (O'Connor et al., 2007). Motion capture data were collected at 120 Hz (Motive, OptiTrack, 132 Corvallis, OR, USA) and raw marker positions were filtered using a second-order low-pass 133 Butterworth filter with a cut-off frequency of 10 Hz.

134 **2.2.4.** Electromyography

135 We shaved, abraded and cleaned the participant's skin with alcohol to reduce the skin-136 electrode impedance. We placed surface electrodes (Trigno Delsys Inc., Natick, USA; 10 mm 137 inter-electrode distance) over the GM and GL muscle bellies, aligned along the direction of 138 the muscle fascicles, determined using B-mode ultrasound. The EMG signals were amplified, digitized at 2048 Hz, band-pass filtered (20-500 Hz), and recorded in Spike2 (V7, CED Ltd, 139 140 Cambridge, UK). During post-processing, the MVC and walking EMG signals were band-141 pass filtered using a second-order Butterworth filter (20-500 Hz), rectified, and low-pass 142 filtered at 12 Hz. The maximal value of the EMG signal measured during the MVC trials was 143 considered as the maximal EMG amplitude (EMG_{max}). Then, the EMG signals from 15 gait 144 cycles were normalized to EMG_{max} . Finally, we interpolated the data from each gait cycle to 145 100 data points. We averaged all the cycles within a trial and then we averaged the resulting 146 two mean cycles from each trial to finally obtain a single mean cycle for each condition and 147 participant.

148 **2.2.5.** *B*-mode ultrasound

149 To image the GM and GL during walking, we placed two linear ultrasound probes (5-8 MHz, 150 60 mm field-of-view, LV8-5L60N-2, ArtUS, Telemed, Vilnius, Lithuania) on the same 151 location as used for the EMG electrodes. The probe orientation was optimized to be aligned in 152 the fascicle plane and secured with elastic bandages. Ultrasound data were recorded at 120 Hz 153 for 15 s of walking. Post data collection, we analyzed five gait cycles of ultrasound data per 154 trial using a validated (Cronin et al., 2011; Gillett et al., 2013) semi-automated tracking algorithm (UltraTrack; Farris and Lichtwark, 2016), combined with manual corrections (for 155 156 details, see Hamard et al., 2021). Ultrasound data were low-pass filtered at 12 Hz and fascicle 157 velocity was calculated as the first time derivative of fascicle length. We normalized fascicle 158 length to the mean fascicle length at heel-strike during level walking (L_{HS}; average group 159 value: 56.6 ± 8.0 mm and 65.4 ± 10.1 mm for the GM and GL, respectively). Similarly, 160 fascicle velocity was expressed as the normalized fascicle length per second. Ultrasound data 161 from each gait cycle were interpolated to 100 data points and we averaged the cycles within a 162 trial and then between both trials to create a mean cycle for each condition and participant.

163 2.3. Estimation of time-varying muscle force during walking

We estimated the time-varying forces produced by the GM and GL muscles during walkingusing a Hill-type model (Zajac, 1989):

166
$$F_{\rm m} = F_{\rm max} [\hat{a}(t)\hat{F}_{\rm a}(\hat{l}_{\rm f})\hat{F}_{\rm a}(\hat{v}) + \hat{F}_{\rm p}(\hat{l}_{\rm f})]\cos\beta. \tag{1}$$

167 The muscle force $F_{\rm m}$ (N) was calculated from the maximal force-generating capacity $F_{\rm max}$, 168 expressed in N, the time-varying normalized activation $\hat{a}(t)$, the normalized active $(\hat{F}_{\rm a}(\hat{l}_{\rm f}))$ 169 and passive $(\hat{F}_{\rm p}(\hat{l}_{\rm f}))$ forces as determined from the force-length relationship, the normalized 170 force $\hat{F}_{\rm a}(\hat{v})$ as determined from the force-velocity relationship and the cosine of the time-171 varying pennation angle β (°).

172 The normalized active force-length curve (Otten, 1987), was modelled as:

173
$$\hat{F}_{a}(\hat{l}_{f}) = e^{-\left(\frac{\hat{l}_{f}^{0.6} - 1}{0.3}\right)^{2.3}}.$$
 (2)

174 The normalized passive force-length curve (Otten, 1987) was modelled as:

175
$$\hat{F}_{\rm p} = 2.64 \hat{l}_{\rm f}^2 - 5.30 \hat{l}_{\rm f} + 2.66$$
 for $\hat{l}_{\rm f} > 1$, (3)

176
$$\hat{F}_{\mathrm{P}}(\hat{l}_{\mathrm{f}}) = 0 \quad \text{for} \quad \hat{l}_{\mathrm{f}} \le 1, \tag{4}$$

177 Where \hat{l}_{f} is the time-varying normalized fascicle length measured during walking.

178 The normalized force-velocity curve was modelled as:

179
$$\hat{F}_{a}(\hat{v}) = \frac{1 + \left(\frac{\hat{v}}{\hat{v}_{0}}\right)}{1 - \left(\frac{\hat{v}}{v_{0}\alpha}\right)} \quad \text{for} \quad \hat{v} \le 0, \tag{5}$$

180
$$\hat{F}_{a}(\hat{v}) = 1.5 - 0.5 \frac{1 - \left(\frac{\hat{v}}{\hat{v}_{0}}\right)}{1 + \left(\frac{7.56\hat{v}}{v_{0}\alpha}\right)}$$
 for $\hat{v} > 0$, (6)

181 Where \hat{v} is the time-varying normalized fascicle velocity recorded during walking. α 182 describes the curvature of the force velocity relationship and v_0 is the maximum unloaded 183 shortening velocity. We used intermediate values accounting for slow and fast muscle fibers 184 from numerous terrestrial species of 0.235 and -7.5 s⁻¹ for α and \hat{v}_0 , respectively (Wakeling 185 et al., 2012).

Finally, F_{max} is a function of the muscle's volume *Vol*, the optimal fiber length $l_{\text{f,opt}}$ and the maximum isometric stress of a muscle fiber σ_0 .

188
$$F_{\max} = \left(\frac{Vol}{l_{f,\text{opt}}}\right)\sigma_0. \tag{7}$$

189 σ_0 was estimated from the literature (22.5 N.cm⁻², Powell et al., 1984; Roy et al., 1982; 190 Spector et al., 1980). For the scaling method, $l_{f,opt}$ was estimated from a subject-specific 191 musculoskeletal model (Delp et al., 2007; Rajagopal et al., 2016). This 37 degrees of freedom 192 model with 97 muscle-tendon complex actuators was scaled to the individual anthropometry 193 of the participants based on the mass of the participant and markers positions recorded during 194 the static trial. For the scaling method, muscle volume was calculated using the regression 195 equations from Handsfield et al. (2014):

$$Vol = b1 \times BM + b2 \tag{8}$$

197 Where *Vol* (cm³) is a function of body mass, *BM* (kg) and two coefficients *b*1 and *b*2. 198 Coefficient *b*1 is 3.41 and 2.19 for the GM and GL, respectively, and *b*2 is 12.60 and -7.59 199 for GM and GL, respectively (Handsfield et al., 2014). Concerning the experimental method, 200 we used, as a substitute for the $l_{f,opt}$, the mean muscle fascicle length estimated from DTI and 201 we used the muscle volume measured from MRI for the GM and GL.

202 2.4. <u>Statistics</u>

We conducted the statistical analyses in Statistica v8.0 (Statsoft, Tulsa, OK, USA). All data 203 204 passed the Kolmogorov-Smirnov test for normality. First, we compared the muscle volume, 205 fascicle length and F_{max} between the two methods and the two muscles using 2-way repeated-206 measures ANOVAs (factor: method [scaling, experimental], muscle [GM, GL]). Additionally, 207 the GM/(GM+GL) ratios of muscle volume, fascicle length and F_{max} were calculated and we 208 used paired t-tests to determine whether these ratios differed between the two methods. We also assessed the relationship between the two estimation methods for muscle volume, 209 210 fascicle length and F_{max} using Pearson's correlation coefficient. Finally, we used the root 211 mean square error (RMSE) to determine the discrepancy between methods for muscle volume, 212 fascicle length and F_{max}.

213 From the predicted force output, we extracted the peak force, corresponding to the maximal 214 force value during the gait cycle and the force integral, corresponding to the integral of the 215 time-varying force. To test our first hypothesis, we used 3-way repeated-measures ANOVAs 216 (factor: method [scaling, experimental], muscle [GM, GL] and condition [level, incline]) to 217 determine whether the peak force or the force integral systematically differed between 218 methods, muscles or conditions. Then, the GM/(GM+GL) ratios for peak force and force 219 integral were calculated to estimate the force-sharing strategy between the gastrocnemii. We 220 performed 2-way repeated-measures ANOVAs (factor: method [scaling, experimental] and 221 condition [level, incline]) on these ratios to assess whether they systematically differed 222 between methods and between conditions. Finally, we compared the peak force and force 223 integral between the two methods using the RMSE. For all tests, the level of significance was 224 set at *P*<0.05.

225 **3. RESULTS**

226 **3.1.** Maximal force-generating capacity

227 Fig. 1 depicts the results for volume, fascicle length and F_{max}. This paragraph, however, 228 presents only the results for F_{max} as they are more closely related to our aim. There was a 229 main effect of muscle (P < 0.001) on F_{max}, with no main effect of method (P = 0.744), nor a 230 muscle × method interaction (P=0.265). Specifically, the GM had a larger F_{max} (1072 ± 240) 231 N) than the GL (587 \pm 166 N) regardless of the method. Moreover, the correlation between 232 F_{max} estimated from the scaling method and F_{max} estimated from experimental data was strong 233 for both the GM (R=0.871; P<0.001) and the GL (R=0.739; P=0.006). Even though there was no statistical difference in the GM/(GM+GL) ratio of F_{max} between the methods (66.5 ± 0.5%) 234 235 for the scaling method and $63.0 \pm 5.6\%$ for the experimental method; *P*=0.056), inspection of 236 individual data indicated large differences between methods for some participants, with the 237 difference being up to 12.5% (Fig. 1). We found high RMSE values between methods for the 238 F_{max}, i.e. 186 N for the GM and 160 N for the GL corresponding to 18.1% and 26.3% of the 239 average F_{max}, respectively. Moreover, a discrepancy between calculation methods for F_{max} 240 was also observed for the GM/(GM+GL) ratios as indicated by a RMSE of 6.5%.

241 **3.2.** Force output

242 When considering the peak force, which occurred during the stance phase (Fig. 2), there was a 243 main effect of muscle (P < 0.001) and condition (P = 0.001), with no main effect of method 244 (P=0.513), nor any interaction (all $P \ge 0.303$) (Table 1). Similarly, when considering the force 245 integral calculated over the whole gait cycle, we observed a main effect of muscle (P < 0.001) 246 and condition (P=0.003), with no main effect of method (P=0.557), nor any interaction (all 247 $P \ge 0.333$). Overall, the GM produced more force compared to the GL during walking (+170 ± 248 96% and +159 \pm 100% for peak force and force integral, respectively), regardless of the 249 method. In addition, higher peak force $(+34 \pm 18\%)$ and force integral $(+27 \pm 14\%)$ were 250 predicted during incline walking compared to level walking, regardless of the muscle and 251 method.

When considering the peak force ratio (i.e. the force-sharing strategy between muscles), there was a main effect of condition (P=0.046), with no main effect of method (P=0.163) or a method × condition interaction (P=0.984). Specifically, the ratio of peak force was lower (closer to 50%) during incline walking compared to level walking (Table 2). When considering the ratio of the force integral, there was no main effect of method (P=0.137), nor an effect of condition (P=0.071) or a method × condition interaction (P=0.971).

258 Even though the group data did not exhibit significant differences between methods, 259 inspection of Fig. 2 and 3 revealed noteworthy differences between methods for some participants. The difference in model-predicted forces between the methods was greater than 260 261 30% for four participants for GM and for three participants for GL during level walking. 262 When considering the ratios (i.e. the force-sharing strategy between muscles), similar 263 observations were made, i.e. despite the between-methods difference being lower than 1% in 264 four participants for both peak force and force integral, the between-methods difference was 265 substantial (greater than 6%) for four participants. These individual differences led to 266 relatively high RMSE group values. When considering the peak force during level walking, 267 the RMSE between the two methods was 66 N for the GM and 28 N for the GL 268 corresponding to 19.0% and 22.1% of the group-averaged peak force, respectively. We also 269 found high RMSE values for the force integral, i.e. 20 N.s for the GM and 12 N.s for the GL 270 corresponding to 18.0% and 25.9% of the average force integral, respectively. Moreover, 271 discrepancy between methods was also observed for the GM/(GM+GL) ratios of peak force 272 and force integral. The RMSE between methods was 5.4% for peak force and 5.7% for the 273 force integral in level walking.

4. DISCUSSION

We determined the influence of two different personalization methods on a Hill-type model's predicted force-sharing strategy between the gastrocnemii during walking. We found substantial differences between the scaling method and the experimental method in the predicted force-sharing strategies at the individual level. Therefore, generic scaling methods may be unable to estimate the force-sharing strategy at the level of individual participants.

280 Our main results indicate substantial differences between methods for some participants. This 281 is consistent with previous studies, which highlight that inclusion of subject-specific 282 musculoskeletal geometry (Wesseling et al., 2016) or muscle-tendon origin and insertion 283 (Bosmans et al., 2015) affects a model's force estimation. Furthermore, our results are similar 284 to previous studies that report high inter-individual variability in the distribution of maximal 285 force-generating capacity between synergist muscles from either the triceps surae (Crouzier et 286 al., 2018) or the quadriceps (Hug et al., 2015). However, here we also highlight that the force-287 sharing strategy varies markedly between individuals during walking - a dynamic task 288 whereby forces are submaximal. Furthermore, during walking, a substantial difference 289 between the scaling method and the experimental method (> 6%) for GM/(GM+GL) ratio of 290 either peak force or the force integral was observed in one third of the participants. Similar 291 levels of differences in the GM/(GM+GL) ratio (+6-10%) were shown in patients with 292 Achilles tendinopathy compared to asymptomatic individuals during submaximal isometric 293 contractions (Crouzier et al., 2019). It is therefore possible that the use of generic scaling 294 methods may reduce the ability to detect pathological force-sharing strategies for individuals 295 who deviate from the generic maximal force-generating capacity distribution, which is often 296 the case in clinical populations (Barber et al., 2011).

297 We compared model-predicted forces when using two different methods to estimate a 298 muscle's maximal force-generating capacity. However, an inherent limitation of such an 299 approach is the inability to evaluate our model against direct measurements of in vivo force. 300 We compared our predicted forces with forces previously estimated or measured using 301 different approaches during similar walking conditions. For the GM, we found similar peak 302 force levels (346 N) to those estimated using inverse dynamics analysis combined with 303 moment arm and PCSA calculations (~305 N in Farris and Sawicki, 2012). In addition, our 304 predicted forces are in agreement with tendon forces directly measured in vivo. Finni et al. 305 (1998) reported a peak Achilles tendon force of 1320 N for the triceps surae during an 12

analogous walking speed (1.1 m.s⁻¹). Similar to previous methods (Dick et al., 2016), we combined this peak force with the relative PCSA of the gastrocnemii within the triceps surae (~26% for the GM and 12% for the GL; Ward et al., 2009) and accounted for the relative gastrocnemii activation levels during walking relative to the triceps surae (~40% MG, 20% LG; Crouzier et al., 2019) to calculate a peak force of 365 N for the GM and 84 N for the GL – which is consistent with our predicted forces (346 N for the GM and 128 N for the GL for the experimental method).

313 Although our results revealed no difference between methods at the group level, this result is 314 difficult to generalize to other groups such as clinical populations. Moreover, we found a 315 similar estimation of muscle volume for group averages when using a scaling method 316 (Handsfield et al., 2014) versus MRI-derived muscle volumes (Fig. 1A) but, on the other hand, 317 the estimation of fascicle length varied more between the scaling and DTI methods (Fig. 1B). 318 This is likely because the scaling method uses subject-specific musculoskeletal models that 319 provide the theoretical optimal fiber length based on a constant muscle-tendon geometry 320 across all participants, whereas the DTI method provides the resting fascicle length at 90° of 321 plantarflexion and $< 5^{\circ}$ of knee flexion, which accounts for individual differences in resting fascicle lengths. Despite personalizing the maximal force-generating capacity, activation, 322 323 fascicle length and velocity, and pennation angle, some model parameters remained generic. 324 For example, the shape of the force-length and force-velocity relationships were consistent 325 across models and individuals whereas the inter-individual variability in these relationships 326 has been suggested in human GM (Hager et al., 2020) and vastus lateralis muscles (Brennan 327 et al., 2018). However, the influence of these parameters on predicted forces is likely small 328 given the relatively low sensitivity of Hill-type models to, for example, the curvature of the 329 force-velocity relationship and the maximum unloaded shortening velocity (Dick et al., 2017). 330 On the other hand, previous studies have shown that the Hill-type model is also sensitive to 331 tendon slack length and optimal fiber length (Bujalski et al., 2018; Scovil & Ronsky, 2006). 332 Further work is needed to test the effect of personalising these parameters on muscle force 333 estimation, although directly measuring these parameters in humans in vivo is currently not 334 possible.

In conclusion, when predicting individual muscle force-sharing strategies, our resultshighlight the importance for Hill-type models to be personalized with *in vivo* imaging data.

337 Future research is necessary to determine the sensitivity of Hill-type models to additional 13

- 338 subject-specific inputs, for example by using elastography to estimate the fascicle slack length
- and the muscle's passive force-length properties (Hug et al., 2013) or by estimating subject-
- 340 specific force-length relationships (Maganaris, 2003).

341 Acknowledgements:

- We thank Aiman Al-Najjar, Nicole Atcheson, and Donald Maillet from the UQ Centre for Advanced Imaging (CAI) for their support and expertise in MR imaging. We further thank Bart Bolsterlee (NeuRA & University of New-South Wales) for assistance in MRI and DTI
- 345 processing.

Declaration of competing interest

347 The authors in this paper have no financial or other relationships that might lead to a conflict348 of interest.

349 Funding

350 This work was supported by a University of Queensland Early Career Research Grant to

351 Taylor JM Dick. François Hug is supported by a fellowship from the Institut Universitaire de

352 France (IUF) and a travel grant from the Société de Biomécanique. Support was received

353 from the French national research agency (ANR-19-CE17-002, COMMODE project; to FH).

Data availability:

355 The predicted force data are available from figshare: 10.6084/m9.figshare.17099864

357 **REFERENCES**

- Aeles, J., Bolsterlee, B., Kelp, N. Y., Dick, T. J. M., & Hug, F. (2021). Regional variation in
 lateral and medial gastrocnemius muscle fibre lengths obtained from diffusion tensor *journal of Anatomy*. https://doi.org/10.1111/joa.13539
- Barber, L., Barrett, R., & Lichtwark, G. (2011). Passive muscle mechanical properties of the
 medial gastrocnemius in young adults with spastic cerebral palsy. *Journal of Biomechanics*, 44(13), 2496-2500. https://doi.org/10.1016/j.jbiomech.2011.06.008
- Bolsterlee. (2020). *GitHub—Bartbols/SASHIMI: SASHIMI segmentation is a Matlab App for semi-automatic interactive segmentation of multi-slice images.*https://github.com/bartbols/SASHIMI
- Bosmans, L., Valente, G., Wesseling, M., Van Campen, A., De Groote, F., De Schutter, J., &
 Jonkers, I. (2015). Sensitivity of predicted muscle forces during gait to anatomical
 variability in musculotendon geometry. *Journal of Biomechanics*, 48(10), 2116-2123.
 https://doi.org/10.1016/j.jbiomech.2015.02.052
- Brennan, S. F., Cresswell, A. G., Farris, D. J., & Lichtwark, G. A. (2018). The effect of
 muscle-tendon unit vs. Fascicle analyses on vastus lateralis force-generating capacity
 during constant power output cycling with variable cadence. *Journal of Applied Physiology*, *124*(4), 993-1002. https://doi.org/10.1152/japplphysiol.00356.2017
- Bujalski, P., Martins, J., & Stirling, L. (2018). A Monte Carlo analysis of muscle force
 estimation sensitivity to muscle-tendon properties using a Hill-based muscle model. *Journal of Biomechanics*, 79, 67-77. https://doi.org/10.1016/j.jbiomech.2018.07.045
- Cronin, N. J., Carty, C. P., Barrett, R. S., & Lichtwark, G. (2011). Automatic tracking of
 medial gastrocnemius fascicle length during human locomotion. *Journal of Applied Physiology (Bethesda, Md.: 1985), 111*(5), 1491-1496.
 https://doi.org/10.1152/japplphysiol.00530.2011
- Crouzier, M., Hug, F., Dorel, S., Deschamps, T., Tucker, K., & Lacourpaille, L. (2019). Do
 individual differences in the distribution of activation between synergist muscles
 reflect individual strategies? *Experimental Brain Research*, 237(3), 625-635.
 https://doi.org/10.1007/s00221-018-5445-6
- Crouzier, M., Lacourpaille, L., Nordez, A., Tucker, K., & Hug, F. (2018). Neuromechanical
 coupling within the human triceps surae and its consequence on individual forcesharing strategies. *The Journal of Experimental Biology*, 221(21), jeb187260.
 https://doi.org/10.1242/jeb.187260

- Crouzier, M., Tucker, K., Lacourpaille, L., Doguet, V., Fayet, G., Dauty, M., & Hug, F.
 (2019). Force-sharing within the Triceps Surae: An Achilles Heel in Achilles
 Tendinopathy. *Medicine & Science in Sports & Exercise, Publish Ahead of Print.*https://doi.org/10.1249/MSS.0000000002229
- 394 Dal, U., Erdogan, T., Resitoglu, B., & Beydagi, H. (2010). Determination of preferred
 395 walking speed on treadmill may lead to high oxygen cost on treadmill walking. *Gait & Posture*, *31*(3), 366-369. https://doi.org/10.1016/j.gaitpost.2010.01.006
- Delp, S. L., Anderson, F. C., Arnold, A. S., Loan, P., Habib, A., John, C. T., Guendelman, E.,
 & Thelen, D. G. (2007). OpenSim: Open-source software to create and analyze
 dynamic simulations of movement. *IEEE Transactions on Bio-Medical Engineering*,
 54(11), 1940-1950. https://doi.org/10.1109/TBME.2007.901024
- 401 Dick, T. J. M., Biewener, A. A., & Wakeling, J. M. (2017). Comparison of human
 402 gastrocnemius forces predicted by Hill-type muscle models and estimated from
 403 ultrasound images. *The Journal of Experimental Biology*, 220(9), 1643-1653.
 404 https://doi.org/10.1242/jeb.154807
- 405 Dick, T. JM., Arnold, A. S., & Wakeling, J. M. (2016). Quantifying Achilles Tendon Force In
 406 Vivo from Ultrasound Images. *Journal of biomechanics*, 49(14), 3200-3207.
 407 https://doi.org/10.1016/j.jbiomech.2016.07.036
- 408 Farris, D. J., & Lichtwark, G. A. (2016). UltraTrack : Software for semi-automated tracking
 409 of muscle fascicles in sequences of B-mode ultrasound images. *Computer Methods*410 *and Programs in Biomedicine*, *128*, 111-118.
 411 https://doi.org/10.1016/j.cmpb.2016.02.016
- 412 Farris, D. J., & Sawicki, G. S. (2012). Human medial gastrocnemius force-velocity behavior 413 shifts with locomotion speed and gait. Proceedings of the National Academy of 414 ofthe 109(3), 977-982. Sciences United States of America. 415 https://doi.org/10.1073/pnas.1107972109
- 416 Finni, T., Komi, P. V., & Lukkariniemi, J. (1998). Achilles tendon loading during walking:
 417 Application of a novel optic fiber technique. *European Journal of Applied Physiology*418 *and Occupational Physiology*, 77(3), 289-291. https://doi.org/10.1007/s004210050335
- Gillett, J. G., Barrett, R. S., & Lichtwark, G. A. (2013). Reliability and accuracy of an
 automated tracking algorithm to measure controlled passive and active muscle fascicle
 length changes from ultrasound. *Computer Methods in Biomechanics and Biomedical Engineering*, *16*(6), 678-687. https://doi.org/10.1080/10255842.2011.633516

- Gregor, R. J., Komi, P. V., & Järvinen, M. (1987). Achilles Tendon Forces During Cycling. *International Journal of Sports Medicine*, 08(S 1), S9-S14. https://doi.org/10.1055/s2008-1025698
- Hager, R., Poulard, T., Nordez, A., Dorel, S., & Guilhem, G. (2020). Influence of joint angle
 on muscle fascicle dynamics and rate of torque development during isometric
 explosive contractions. *Journal of Applied Physiology*, *129*(3), 569-579.
 https://doi.org/10.1152/japplphysiol.00143.2019
- Hamard, R., Aeles, J., Kelp, N. Y., Feigean, R., Hug, F., & Dick, T. J. M. (2021). Does
 different activation between the medial and the lateral gastrocnemius during walking
 translate into different fascicle behavior? *The Journal of Experimental Biology*,
 224(12), jeb242626. https://doi.org/10.1242/jeb.242626
- Handsfield, G. G., Meyer, C. H., Hart, J. M., Abel, M. F., & Blemker, S. S. (2014).
 Relationships of 35 lower limb muscles to height and body mass quantified using MRI. *Journal of Biomechanics*, 47(3), 631-638.
 https://doi.org/10.1016/j.jbiomech.2013.12.002
- Hug, F., Goupille, C., Baum, D., Raiteri, B. J., Hodges, P. W., & Tucker, K. (2015). Nature of
 the coupling between neural drive and force-generating capacity in the human
 quadriceps muscle. *Proceedings. Biological Sciences*, 282(1819).
 https://doi.org/10.1098/rspb.2015.1908
- Hug, F., Lacourpaille, L., Maïsetti, O., & Nordez, A. (2013). Slack length of gastrocnemius
 medialis and Achilles tendon occurs at different ankle angles. *Journal of Biomechanics*, 46(14), 2534-2538. https://doi.org/10.1016/j.jbiomech.2013.07.015
- Hug, F., & Tucker, K. (2017). Muscle Coordination and the Development of Musculoskeletal
 Disorders. *Exercise and Sport Sciences Reviews*, 45(4), 201-208.
 https://doi.org/10.1249/JES.00000000000122
- Komi, P. V. (1990). Relevance of in vivo force measurements to human biomechanics. *Journal of Biomechanics*, 23, 23-34. https://doi.org/10.1016/0021-9290(90)90038-5
- 450 Maganaris, C. N. (2003). Force-length characteristics of the in vivo human gastrocnemius
 451 muscle. *Clinical Anatomy*, *16*(3), 215-223. https://doi.org/10.1002/ca.10064
- Millard, M., Uchida, T., Seth, A., & Delp, S. L. (2013). Flexing Computational Muscle:
 Modeling and Simulation of Musculotendon Dynamics. *Journal of Biomechanical Engineering*, 135(2). https://doi.org/10.1115/1.4023390

- 455 O'Connor, C. M., Thorpe, S. K., O'Malley, M. J., & Vaughan, C. L. (2007). Automatic
 456 detection of gait events using kinematic data. *Gait & Posture*, 25(3), 469-474.
 457 https://doi.org/10.1016/j.gaitpost.2006.05.016
- 458 Otten, E. (1987). A myocybernetic model of the jaw system of the rat. *Journal of*459 *Neuroscience Methods*, 21(2), 287-302. https://doi.org/10.1016/0165-0270(87)90123460 3
- Perreault, E. J., Heckman, C. J., & Sandercock, T. G. (2003). Hill muscle model errors during
 movement are greatest within the physiologically relevant range of motor unit firing
 rates. *Journal of Biomechanics*, *36*(2), 211-218. https://doi.org/10.1016/s00219290(02)00332-9
- Pinel, S., Kelp, N. Y., Bugeja, J. M., Bolsterlee, B., Hug, F., & Dick, T. J. M. (2021).
 Quantity versus quality : Age-related differences in muscle volume, intramuscular fat,
 and mechanical properties in the triceps surae. *Experimental Gerontology*, *156*,
 111594. https://doi.org/10.1016/j.exger.2021.111594
- 469 Powell, P. L., Roy, R. R., Kanim, P., Bello, M. A., & Edgerton, V. R. (1984). Predictability of
 470 skeletal muscle tension from architectural determinations in guinea pig hindlimbs.
 471 *Journal of Applied Physiology*, 57(6), 1715-1721.
 472 https://doi.org/10.1152/jappl.1984.57.6.1715
- 473 Rajagopal, A., Dembia, C. L., DeMers, M. S., Delp, D. D., Hicks, J. L., & Delp, S. L. (2016).
 474 Full-Body Musculoskeletal Model for Muscle-Driven Simulation of Human Gait.
 475 *IEEE Transactions on Biomedical Engineering*, 63(10), 2068-2079.
 476 https://doi.org/10.1109/TBME.2016.2586891
- 477 Roy, R. R., Meadows, I. D., Baldwin, K. M., & Edgerton, V. R. (1982). Functional
 478 significance of compensatory overloaded rat fast muscle. *Journal of Applied*479 *Physiology*, 52(2), 473-478. https://doi.org/10.1152/jappl.1982.52.2.473
- 480 Scovil, C. Y., & Ronsky, J. L. (2006). Sensitivity of a Hill-based muscle model to
 481 perturbations in model parameters. *Journal of Biomechanics*, *39*(11), 2055-2063.
 482 https://doi.org/10.1016/j.jbiomech.2005.06.005
- Spector, S. A., Gardiner, P. F., Zernicke, R. F., Roy, R. R., & Edgerton, V. R. (1980). Muscle
 architecture and force-velocity characteristics of cat soleus and medial gastrocnemius :
 Implications for motor control. *Journal of Neurophysiology*, *44*(5), 951-960.
 https://doi.org/10.1152/jn.1980.44.5.951

- Wakeling, J. M., Lee, S. S. M., Arnold, A. S., de Boef Miara, M., & Biewener, A. A. (2012).
 A Muscle's Force Depends on the Recruitment Patterns of Its Fibers. *Annals of Biomedical Engineering*, 40(8), 1708-1720. https://doi.org/10.1007/s10439-012-05316
- Ward, S. R., Eng, C. M., Smallwood, L. H., & Lieber, R. L. (2009). Are Current
 Measurements of Lower Extremity Muscle Architecture Accurate? *Clinical Orthopaedics and Related Research*, 467(4), 1074-1082.
 https://doi.org/10.1007/s11999-008-0594-8
- Wesseling, M., De Groote, F., Bosmans, L., Bartels, W., Meyer, C., Desloovere, K., &
 Jonkers, I. (2016). Subject-specific geometrical detail rather than cost function
 formulation affects hip loading calculation. *Computer Methods in Biomechanics and Biomedical Engineering*, *19*(14), 1475-1488.
 https://doi.org/10.1080/10255842.2016.1154547
- Zajac, F. E. (1989). Muscle and tendon: Properties, models, scaling, and application to
 biomechanics and motor control. *Critical Reviews in Biomedical Engineering*, 17(4),
 359-411.

504 TABLES AND FIGURES

	Level walking				Incline walking			
	GM		GL		GM		GL	
	Scaling	Experimental	Scaling	Experimental	Scaling	Experimental	Scaling	Experimental
Peak force (N)	378 ± 127	346 ± 137	$120 \pm 41*$	$128 \pm 55*$	467 ± 152†	423 ± 155†	186 ± 64*†	195 ± 74*†
Force integral (N.s)	123 ± 36	114 ± 43	43 ± 15*	45 ± 17*	149 ± 48†	136 ± 52†	61 ± 21*†	65 ± 26*†

505 Table 1: Force parameters estimated using the Hill-type model during level and incline walking.

Values are presented for the gastrocnemius medialis and lateralis during both level and incline walking. The maximal force-generating capacity was estimated using either the scaling or experimental method. GM, gastrocnemius medialis, GL, gastrocnemius lateralis. Values are reported as mean \pm standard deviation. *Indicates a significant difference with GM. †Indicates a significant difference with level walking. n = 12. No difference between methods was found for any muscle or condition.

511 Table 2: Gastrocnemius medialis to gastrocnemius lateralis [GM/(GM+GL)] force ratio 512 estimated using the Hill-type model during level and incline walking.

	Level	walking	Incline walking		
	Scaling method	Experimental method	Scaling method	Experimental method	
Peak force ratio (%)	75.4 ± 6.2	72.4 ± 7.3	71.1 ± 7.8†	$68.0 \pm 7.9 \dagger$	
Force integral ratio (%)	74.1 ± 6.2	71.2 ± 7.3	70.5 ± 7.0	67.4 ± 7.5	

513 Values are presented for both level and incline walking. The maximal force-generating capacity was estimated

514 using either a scaling or experimental method. Values are reported as mean ± standard deviation. †Indicates

515 significant difference with level walking. n = 12. No difference between methods was found for any muscle or 516 condition.

517 FIGURE LEGENDS

518

519 Fig. 1: Individual data for muscle volume (A), fascicle length (B) and maximal force-

520 generating capacity (F_{max} ; C) determined using the scaling and experimental methods.

521 Data are depicted for both the gastrocnemius medialis (GM) and gastrocnemius lateralis (GL).

522 The ratio between these muscles [GM/(GM+GL)] is also depicted for each variable. Each

523 graph depicts individual data obtained with the scaling method (top) and experimental method 524 (bottom). Each color represents an individual participant and the mean group value is

- (bottom). Each color represents an individual participant and the mean group value is
 presented as a black diamond. Because the scaling method uses the same underlying
- 526 equations to scale all individuals, we can observe that the inter-individual variability in ratios
- 527 between muscles is concealed.
- 528

529 Fig. 2: Individual time-varying forces estimated by the Hill-type model during level

530 walking for each participant (P). The GM (green) and GL (purple) forces are depicted by

531 solid lines (experimental method) and dashed lines (scaling method). Heel-strike occurred at

532 0% on the x-axis and the dashed vertical lines represent the timing of toe-off during the gait

- 533 cycle. Each plot represents an individual participant. Predicted forces for incline walking are
- 534 presented in Fig. S1.
- 535

536 Fig. 3: Individual data for peak force (A and B) and force integral (C and D) for level 537 walking (white area; A and C) and incline walking (grey area; B and D), determined using the scaling and experimental methods. Data are depicted for both the gastrocnemius 538 539 medialis (GM) and gastrocnemius lateralis (GL). The ratio [GM/(GM+GL)] is also depicted 540 for each variable. Each graph depicts individual data obtained with the scaling method and 541 experimental method. Each color represents an individual participant and the mean group 542 value is presented as a black diamond. The scaling method and the experimental method seem 543 to predict similar muscle force and force-sharing strategy during walking at the group level 544 but substantial differences between methods was apparent for some participants.

545 SUPPLEMENTARY FIGURE

- 546 Fig. S1: Individual time-varying forces estimated by the Hill-type model during incline
- 547 walking for each participant (P). The GM (green) and GL (purple) forces are depicted by
- 548 solid lines (experimental method) and dashed lines (scaling method). Heel-strike occurred at
- 549 0% on the x-axis and the dashed vertical lines represent the timing of toe-off during the gait
- 550 cycle. Each plot represents an individual participant.





