

## **Automated creation and tuning of personalised muscle paths for OpenSim musculoskeletal models of the knee joint**

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1 Automated creation and tuning of personalised muscle paths for OpenSim  
2 musculoskeletal models of the knee joint

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21 **Abstract**

22 Computational modelling is an invaluable tool for investigating features of human locomotion  
23 and motor control which cannot be measured except through invasive techniques. Recent  
24 research has focussed on creating personalised musculoskeletal models using population-based  
25 morphing or directly from medical imaging. Although progress has been made, robust  
26 definition of two critical model parameters remains challenging: (i) complete tibiofemoral (TF)  
27 and patellofemoral (PF) joint motions, and (ii) muscle tendon unit (MTU) pathways and  
28 kinematics (i.e., lengths and moment arms). The aim of this study was to develop an automated  
29 framework, using population-based morphing approaches to create personalised  
30 musculoskeletal models, consisting of personalised bone geometries, TF and PF joint  
31 mechanisms, and MTU pathways and kinematics. Informed from medical imaging,  
32 personalised rigid body TF and PF joint mechanisms were created. Using atlas- and  
33 optimisation-based methods, personalised MTU pathways and kinematics were created with  
34 the aim of preventing MTU penetration into bones and achieving smooth MTU kinematics that  
35 follow patterns from existing literature. This framework was integrated into the  
36 Musculoskeletal Atlas Project Client software package to create and optimise models for 6  
37 participants with incrementally increasing levels of personalisation with the aim of improving  
38 MTU kinematics and pathways. Three comparisons were made: (i) non-optimised (Model 1)  
39 and optimised models (Model 3) with generic joint mechanisms; (ii) non-optimised (Model 2)  
40 and optimised models (Model 4) with personalised joint mechanisms; and (iii) both optimised  
41 (Model 3 and 4) models. Following optimisation, improvements were consistently shown in  
42 pattern similarity to cadaveric data in comparison i and ii. For comparison iii, a number of  
43 comparisons showed no significant difference between the two compared models. Importantly,  
44 optimisation did not produce statistically significantly worse results in any case.

## 45 **Introduction**

46 Computational models of the human musculoskeletal system enable researchers to study  
47 internal biomechanics without invasive and expensive experiments. Rigid body  
48 musculoskeletal modelling tools, e.g., AnyBody Modeling Software AnyBody (AnyBody  
49 Technology, Aalborg, Denmark) and OpenSim (Delp et al. 2007; Seth et al. 2018) have been  
50 used to study a wide range of sport, health, and industrial questions, and used to estimate  
51 internal body mechanics such as muscle tendon unit (MTU) and joint contact forces during  
52 daily activities (Winby et al. 2009; Ackland et al. 2011; Cleather and Bull 2011; Guess et al.  
53 2014; Saxby et al. 2016; Konrath et al. 2017; Andersen 2018; Modenese et al. 2018). Typically,  
54 generic models of bone geometries and MTU pathways are used but are unlikely to reflect  
55 individual anatomy even when carefully scaled (Kainz et al. 2017; Davico et al. 2020a).  
56 Linearly scaled models may not well represent MTU moment arms, producing almost identical  
57 values across subjects despite measured differences in cadavers (Fick 1879; Draganich et al.  
58 1987; Visser et al. 1990; Spoor and van Leeuwen 1992; Buford et al. 1997; Pal et al. 2007;  
59 Wilson and Sheehan 2009; Arnold et al. 2010; Navacchia et al. 2017). Further, these generic  
60 models typically contain tibiofemoral (TFJ) and patellofemoral joints (PFJ) that do not permit  
61 6 degree of freedom (DOF) e.g., setting abduction/adduction and internal/external rotation to  
62 0. Consequently, these models may be inappropriate to accurately estimate common  
63 tibiofemoral variables from movement simulations (Gerus et al. 2013; Demers et al. 2014;  
64 Lerner et al. 2015). To overcome these limitations, personalised models can be used.  
65 Numerous features within musculoskeletal models can be personalised, including bone  
66 geometry, segment mass and inertia, joint anatomy and kinematics, and MTU internal  
67 parameters and pathways (Saxby et al. 2020). Previous research has shown the inclusion of  
68 personalised features has a significant effect on tibiofemoral variables from simulations (e.g.,  
69 joint moments (Reinbolt et al. 2007), and contact loading (Gerus et al. 2013; Lerner et al.  
70 2015)). Although several studies have presented methods to include personalised skeletal  
71 anatomy (Scheys et al. 2009; Wesseling et al. 2016; Valente et al. 2017; Modenese et al. 2018),  
72 and joint kinematic functions (Sancisi and Parenti-Castelli 2011a, b; Brito da Luz et al. 2017;  
73 Dzialo et al. 2018; Barzan et al. 2019; Smale et al. 2019), few studies have reported methods  
74 to define MTU pathways (Scheys et al. 2009; Nolte et al. 2016; Modenese et al. 2018;  
75 Modenese and Kohout 2020) in models with personalised bone geometry, joint anatomy, and  
76 joint kinematics. Many personalisation methods are reliant on human user input with few

77 comparisons made with, for example, cadaveric MTU kinematics, i.e., lengths and moment  
78 arms.

79 Creating personalised high-fidelity musculoskeletal models entails collecting extensive sets of  
80 medical imaging. Statistical shape modelling permit population-based morphing from motion  
81 capture (MOCAP) data, or combined with minimal medical images (Zhang et al. 2014, 2016;  
82 Nolte et al. 2016, 2020; Bahl et al. 2019; Suwarganda et al. 2019; Bakke and Besier 2020;  
83 Davico et al. 2020a). These approaches have been implemented in the Musculoskeletal Atlas  
84 Project (MAP) Client (Zhang et al. 2014) that, compared to linear scaling are able to morph  
85 and create OpenSim models that accurately produce anatomical reconstruction (Zhang et al.  
86 2016; Bahl et al. 2019; Suwarganda et al. 2019; Davico et al. 2020a), which in turn produce  
87 improved simulation repeatability (Bakke and Besier 2020). However, automatic generation of  
88 MTU pathways from morphed data i.e., without the need for explicit muscle imaging, is  
89 undefined.

90 Hence, this paper presents a framework built atop the MAP-Client (Zhang et al. 2014) that  
91 automates the creation and tuning of personalised OpenSim musculoskeletal models with  
92 particular focus on the TFJ. Steps used to create these models are designed to automatically  
93 perform tasks typically performed manually, constrained by algorithms to mimic manual  
94 checks. These manual checks include ensuring MTU do not penetrate bone surfaces and MTU  
95 kinematics follow available data, i.e., measured lengths and moment arms. They also include  
96 checks that MTU perform the correct action i.e., extensor muscles produce an extension  
97 moment, which we refer to as MTU polarity. Personalised features include bone geometries,  
98 joint axes definitions, TFJ and PFJ kinematic mechanisms, MTU origins and insertions points,  
99 and intermediate pathways of selected TFJ spanning MTUs. The MAP- Client, along with the  
100 developed open-source software, was used to generate four OpenSim models with different  
101 levels of personalisation, which were then implemented and tested with the following three  
102 hypotheses. First ( $H_1$ ) optimisation of MTU wrapping surfaces would improve similarity of  
103 MTU kinematics with those reported in literature. Second ( $H_2$ ), wrapping surface optimisation  
104 would prevent MTU penetrating bones and MTU polarity errors. Third ( $H_3$ ), optimisation of  
105 MTU wrapping surfaces would improve MTU length and moment arm smoothness. Finally,  
106 ( $H_4$ ) models with optimised MTU wrapping surfaces and personalised TFJ and PFJ  
107 mechanisms would produce more physiological MTU kinematics (i.e., prevent MTU  
108 penetrating bones and MTU polarity error, and improve MTU length and moment arm  
109 smoothness) compared to models with optimised MTU wrapping surfaces but generic TFJ and  
110 PFJ mechanisms.

111 **Methods**

112 **Motion capture and magnetic resonance imaging**

113 Data were collected at Griffith University as part of an ongoing project (PES/36/10/HREC).  
114 Six participants were selected from a larger cohort to span the age, height, and mass range  
115 (Table 1). Participants had no history of musculoskeletal injury, trauma, or lower-limb  
116 surgeries. Each participant provided their written and informed consent prior to undergoing  
117 comprehensive MOCAP and medical imaging. Three-dimensional (3D) marker positions  
118 during a static calibration trial were converted from standard MOCAP (i.e., c3d) to OpenSim  
119 (trc) format using MOtoNMS (Mantoan et al. 2015) for use in the MAP-Client.

120

121 **[Table 1]**

122 Each participant underwent lower-limb magnetic resonance imaging (MRI) at a local radiology  
123 clinic (QScan Southport, QLD, Australia) performed on the same or preceding day as MOCAP.  
124 Axial T<sub>1</sub>-weighted 3D fast field echo sequences were acquired bilaterally from above the iliac  
125 crest to below the toes, while the participant lay supine in a 3 T MRI scanner (Philips Medical  
126 Systems, Netherlands). Images were acquired using a body coil in 5 stations, ~245 slices per  
127 station, 10 mm inter-station overlap throughout, 1 mm slice thickness, and 1 mm inter-slice  
128 gap with a voxel size of 0.79 mm<sup>3</sup> and field of view of 446 mm x 446 mm.

129 The pelvis (excluding sacrum), femur, tibia-fibula, and patella were segmented using Mimics  
130 v19 (Materialise, Leuven, Belgium). Dedicated TFJ and PFJ scans were also acquired from a  
131 randomised limb (Table 1). Joint scans were comprised of 3D proton density 16 channel  
132 sequences acquired from mid-thigh to below the tibial tuberosity. Images were acquired in one  
133 station (~440 slices) with 0.6 mm slice thickness, and 0.3 mm inter-slice gap with a voxel size  
134 of 0.79 mm<sup>3</sup> and field of view of 446 mm x 446 mm. Images were used to segment the distal  
135 femur, proximal tibia, and patella bones as well as femoral, tibial, and patella cartilages, and  
136 anterior cruciate, posterior cruciate, and medial collateral ligament attachment regions.

137 **Creating personalised OpenSim models**

138 Four OpenSim models (Table 2) with incremental levels of personalisation were created.  
139 Models were compared based on their performance in producing MTU kinematics that were  
140 both physiologically and anatomically plausible (see below and Appendix 2). Briefly,  
141 physiologically plausible kinematics refer to kinematics that are smooth and follow the patterns  
142 of previously published measurements taken from cadavers (Fick 1879; Draganich et al. 1987;

143 Visser et al. 1990; Spoor and van Leeuwen 1992; Buford et al. 1997; Pal et al. 2007; Wilson  
144 and Sheehan 2009; Arnold et al. 2010; Navacchia et al. 2017). Anatomically plausible refers  
145 to MTU which do not penetrate bones or produce non-physical pathways (i.e., circumferential  
146 loop of wrapping surface).

### 147 **Personalised OpenSim model creation**

148 Models were created using the MAP-Client by combining MOCAP and MRI (Zhang et al.  
149 2016). The MAP-Client uses a graphical interface along with different geometry fitting  
150 methods to reconstruct (Bahl et al. 2019; Suwarganda et al. 2019; Davico et al. 2020a) certain  
151 bones of the lower-limb (i.e., pelvis, femur, tibia, fibula, and patella). Briefly, marker positions  
152 acquired in MOCAP were used to scale a model containing statistical shape models (SSM) of  
153 the pelvis, femur, tibia, fibula, and patella. Scaled SSM were then registered to MRI bone  
154 segmentation using an iterative closest point method. Registered SSM was then morphed using  
155 host-mesh fitting to closely match MRI segmentations. Finally, a point-to-point (i.e., local)  
156 morphing was used to refine the morphed SSM to match the MRI segmentation. This  
157 previously validated process (Suwarganda et al. 2019) was completed for each bone, these  
158 morphed bones were then used to create personalised OpenSim models.

159 Personalised OpenSim models are in fact generic OpenSim models (Delp et al. 2007) with  
160 personalised bone geometries, joint positions, body mass, and inertial properties (Zhang et al.  
161 2014, 2016). Only the pelvis, femur, tibia, fibula, and patella were personalised, while the  
162 ankle-foot was scaled isotopically as the MAP-Client is yet to support a statistical shape model  
163 of the foot-ankle complex.

### 164 **Defining the muscle-tendon unit pathway**

165 The MTU origin and insertion points were defined (Zhang et al. 2014, 2016) using a template  
166 based model, i.e., the SOMSO (Marcus Sommer SOMSO Modelle, Sonneberg, Germany). The  
167 SOMSO is a physical model used for anatomy education and contains a collection of lower-  
168 limb bones with their associated MTU attachment regions. On the SOMSO model several  
169 prominent bone sites and centroids of the MTU attachment regions were digitised. Using bone  
170 sites, MTU attachment centroids were projected to the closest node onto MAP-Client generated  
171 bones equivalent to the SOMSO bones. Subsequently, these centroids were used to define MTU  
172 origin and insertion points.

173 To generate MTU pathways, the MAP-Client used both fixed and conditional via points  
174 consistent with the generic model. However, via points often introduce discontinuities in MTU

175 kinematics (Garner and Pandy 2000; Hammer et al. 2019) and non-physiological muscle shapes  
176 (Appendix 1). To overcome these limitations and ensure consistency with recent OpenSim  
177 models (Arnold et al. 2010; Rajagopal et al. 2016; Catelli et al. 2019), wrapping surfaces were  
178 implemented.

179 Wrapping surface parameters, i.e., location, orientations, and dimensions, were based on  
180 analytical shapes fit to bone regions and the position of MTU path points. Wrapping surface  
181 parameters were automatically defined using the MAP-Client and compared with the Fullbody  
182 Model (Rajagopal et al. 2016). However, this approach does not guarantee MTU kinematics  
183 (i.e., lengths and moment arms) that were physiologically and anatomically plausible and  
184 required further optimisation.

185 Optimisation of the wrapping surfaces' geometric parameters was performed to produce  
186 physiologically plausible MTU kinematics and anatomically plausible MTU pathways. The  
187 optimisation used *pyswarm* (*A Python package for particle swarm optimization (PSO) with*  
188 *constraint support*, Abraham D. Lee, <https://pythonhosted.org/pyswarm/>) with two objective  
189 and three penalty custom functions (See Appendix 2 for detailed explanations). Previous  
190 studies have reported differences between cadaveric specimens in terms of the magnitude of  
191 MTU kinematics (Fick 1879; Draganich et al. 1987; Visser et al. 1990; Spoor and van Leeuwen  
192 1992; Buford et al. 1997; Pal et al. 2007; Wilson and Sheehan 2009; Arnold et al. 2010;  
193 Navacchia et al. 2017). Therefore, the first objective, termed normalised gradient error,  
194 encouraged tracking of the cadaveric literature based on MTU kinematic patterns, rather than  
195 absolute magnitudes, using normalised gradients. The latter was the change in magnitude of  
196 MTU length or moment arm with respect to the change in joint angle (i.e., gradient) divided by  
197 the target (i.e., cadaveric) data gradient. The second objective, termed smoothness, encouraged  
198 MTU kinematic patterns to be smooth. Penalty functions produced *anatomically plausible*  
199 MTU pathways. The first, reduced the possibility of modelled MTU pathways penetrating  
200 bones. Penetration was detected using a ray casting method. A ray is defined between each  
201 adjacent MTU path point. The bones which the MTU can penetrate (based on the joints it spans)  
202 are loaded and the distance from each point on the bone mesh to the ray is calculated. If this  
203 distance is below a specified value, it is deemed to penetrate the bone. The second, termed  
204 polarity error, prevented moment arms inappropriately changing their mechanical actions, e.g.,  
205 a flexor turning into an extensor and the third reduced the possibility of non-anatomical  
206 wrapping scenarios (Appendix 2). Once wrapping surface optimisation was completed for each



207 participant, the MAP-Client was used to generate personalised TFJ and PFJ kinematic  
208 mechanisms.

### 209 **Joint mechanism definitions**

210 Two different sets of TFJ and PFJ mechanisms were created: scaled generic (Models 1 and 3)  
211 and personalised (Models 2 and 4). The range of motion for the tibiofemoral joint was restricted  
212 from 0 (full extension) to -100 degrees (flexion), covering the range of motion during both  
213 walking and running (Novacheck 1998). Scaled generic TFJ mechanisms were three degree of  
214 freedom (DOF) joints with an independent flexion-extension DOF with two dependant  
215 translational DOFs (i.e., anterior/posterior and superior/inferior translations) defined as a  
216 function of TFJ flexion-extension. Translation functions were splines defined to maintain the  
217 distance between the medial and lateral femoral and tibial condyles throughout the range of  
218 motion using the neutral position as a reference (Zhang et al. 2016). Remaining DOFs (i.e.,  
219 medial/lateral translation, abduction/adduction rotation, and internal/external rotation) were  
220 locked to zero. Next, a patella and PFJ was added, with patella origin located consistent with a  
221 previous model (Arnold et al. 2010) and its position fixed with respect to the tibia.

222 Personalised TFJ and PFJ mechanisms were then created from MRI segmentations (Sancisi  
223 and Parenti-Castelli 2011a, b; Brito da Luz et al. 2017; Barzan et al. 2019). Segmented  
224 anatomical structures (i.e., bones, cartilages, and ligaments) were imported into 3-matic v10  
225 (Materialise, Leuven, Belgium), where surfaces and landmarks (e.g., ligament attachment  
226 regions) necessary to define joint mechanisms were identified. Multiple Objective Particle  
227 Swarm Optimisation (Multi-Objective Particle Swarm Optimization (MOPSO) by Yarpiz,  
228 2015) was then used to ensure physiological solutions, producing numerous candidate  
229 solutions, fit by a series of spline functions completely describing 6 DOF TFJ motions: 1  
230 independent DOF (i.e., flexion-extension), and 5 dependant DOF (i.e., secondary kinematics).  
231 Each TFJ solution was paired with a unique PFJ mechanism solution chosen based on  
232 correlation with cadaveric PFJ kinematics (Brito da Luz et al. 2017; Barzan et al. 2019).  
233 Candidate personalised TFJ-PFJ models were then joined with the MAP-Client generated  
234 model (Model 1) yielding multiple candidate personalised OpenSim models, i.e., one Model 2  
235 per TFJ solution.

236 The final personalised TFJ-PFJ solution was chosen based on MTU kinematic evaluation  
237 metrics. Selected MTU (rectus femoris, vastus medialis, vastus lateralis, semimembranosus,  
238 biceps femoris long head, and medial gastrocnemius) kinematics were tested using the

239 objective functions employed in the MTU wrapping surface optimisation (see above and  
240 Appendix 2). Evaluation metrics were summed for each model, and the TFJ-PFJ solution  
241 selected based on the lowest summed value, theoretically representing the most physiological  
242 MTU kinematics. MTU wrapping surface optimisation was then run to generate the final  
243 personalised model (Model 4).

#### 244 **Model comparisons and muscle tendon unit kinematic evaluation**

245 After creation, each model's (Table 2) MTU kinematic evaluation metrics were calculated: (i)  
246 number of moment arm polarity penalties, (ii) normalised MTU moment arm gradient error,  
247 (iii) number of MTU bone penetration penalties, and (iv) MTU length and moment arm  
248 smoothness. Metrics were calculated for each MTU, model, and participant. For comparison,  
249 MTU were grouped: (i) quadriceps (left and right rectus femoris, vastus lateralis, vastus  
250 intermedius, and vastus medialis), (ii) hamstrings (left and right biceps femoris long and short  
251 head, semitendinosus, and semimembranosus), and (iii) extras (left and right medial and lateral  
252 gastrocnemius, sartorius, and gracilis). For each MTU metric, frequency count (i.e., penalties)  
253 or mean  $\pm$  standard deviation (i.e., smoothness and error) were calculated.

254 For each comparison, the superior model was determined by magnitudes of the evaluation  
255 metrics, with smaller values indicating more physiologically/anatomically plausible MTU  
256 pathways or kinematics. Each comparison was marked (i) improved, (ii) worse, or (iii) no  
257 change, and the count (i.e., number of occurrences) summed for each MTU group and all MTU.  
258 Metric counts were compared using proportion tests to determine statistically significant  
259 differences (Wessa P.; 2016, Testing Population Proportion (v1.0.3)). To calculate z-scores, a  
260 null hypothesis of 50% was assumed and significance set at  $p < 0.05$ . Dominant outcome (i.e.,  
261 improved, worse, or no change) was identified and tested for statistical significance.

#### 262 **Results**

263 The total time to produce the entire set of four models for each subject was approximately 13.5  
264 hours on a standard computer (2.4 GHz Intel i5 Processor, 8 GB of RAM) plus 2 hours of HPC  
265 for the optimisation (Table 3).

#### 266 **[Table 3]**

#### 267 **Effect of tuning in models with generic joint mechanisms**

268 When using generic TFJ and PFJ models, wrapping surface optimisation (i.e., Model 3)  
269 produced improved results compared to non-optimised models (i.e., Model 1) (Table 4, Fig 1

270 and 2). The only MTU metric which showed a statistically significant improvement was MTU  
271 moment arm gradient error, which improved following optimisation (Model 3). All remaining  
272 metrics showed either a significant proportion of no change cases (i.e., moment arm polarity  
273 penalties, MTU bone penetration penalties with the exception of the extras MTU group, and  
274 MTU length smoothness), or no significant proportions (i.e., MTU moment arm smoothness,  
275 and MTU bone penetration in the extras MTU group). Despite this, moment arm polarity  
276 penalties, MTU bone penetration penalties, and MTU length smoothness showed a higher  
277 number of improved cases compared to worse cases in all MTU groups. Similarly, MTU  
278 moment arm smoothness showed a higher number of improved cases in all MTU groups except  
279 the quadriceps group which showed an equal distribution of improved and worse cases.

280

281 **[Table 4]**

282 **[Fig 1]**

283 **[Fig 2]**

#### 284 **Effect of tuning in models with personalised joint mechanisms**

285 Comparison of models with personalised joint kinematic models with non-optimised (Model  
286 2) and optimised (Model 4) wrapping surfaces showed similar results to the previous  
287 comparison (Table 5). Again, the only metric which showed a statistically significant  
288 improvement was MTU moment arm gradient error which improved in the optimised model  
289 (Model 4). A significant proportion of no change cases was shown in moment arm polarity  
290 penalties (except the hamstrings MTU group), MTU bone penetration penalty (except the  
291 extras MTU group), and MTU length smoothness. No significant proportion was identified for  
292 moment arm polarity penalty in the hamstrings MTU group, MTU bone penetration penalty for  
293 the extras MTU group, and MTU moment arm smoothness. Excluding no change cases, MTU  
294 moment arm smoothness showed a higher number of improved cases compared to worse cases.  
295 Additionally, a higher number of improved compared to worse cases was shown with respect  
296 to moment arm polarity penalties, MTU bone penetration penalties and MTU length  
297 smoothness for the All, and extras MTU group.

298 **[Table 5]**

299

## 300 **Comparison of optimised models**

301 The final comparison, between optimised models with generic (Model 3) and personalised  
302 (Model 4) joints showed inconsistent results (Table 6; Fig 3 and 4). Across subjects, a  
303 significant proportion of cases for all MTU, quadriceps, and hamstrings groups showed no  
304 change between models for MTU moment arm polarity penalties. Likewise, MTU bone  
305 penetration penalties showed no change between models for the all MTU, quadriceps, and  
306 hamstrings groups. For all remaining comparisons, no dominant case was identified, as well as  
307 no trend in either improved or worse cases.

308 **[Table 6]**

309 **[Fig 3]**

310 **[Fig 4]**

## 311 **Discussion**

312 This study aimed to develop and test a framework, built atop the MAP-Client, for automated  
313 tuning of personalised OpenSim musculoskeletal models, with a particular focus on the knee  
314 joint. The presented workflow automated tasks previously performed manually or semi-  
315 manually but was also based on statistical shape modelling that used MOCAP and medical  
316 imaging to morph bones from which muscle origins, insertions, and pathways were created.  
317 This was achieved by representing the traditionally manually performed quality checks as  
318 mathematical algorithms formulated as an optimisation problem. This optimisation process  
319 automatically detected errors and adjusted the model to minimise these errors without the need  
320 for time consuming and subjective manual interventions. Generally, following the  
321 optimisation, the majority of MTU evaluation metrics showed improvements in models with  
322 both generic and personalised joint mechanisms. Importantly, this framework presents an  
323 approach for tuning model muscle pathways that could be extended from the present  
324 application (i.e., the knee joint) to other regions of the body.

## 325 **Comparison of non-optimised and optimised models**

326 The first hypothesis ( $H_1$ ), that, compared to non-optimised models, optimisation of wrapping  
327 surfaces would improve similarity of model MTU kinematics to those measured in cadavers  
328 was confirmed. With and without personalised knee mechanism, optimised wrapping surfaces  
329 resulted in a clear reduction in moment arm gradient error for all MTU groups (Tables 3 and

330 4). Although unsurprising, since moment arm gradient error was included as an optimisation  
331 objective function, the consistent improvements provided confidence in the developed  
332 framework and indicates that optimised muscles have a similar pattern of moment arms.

333 The second and third hypothesis ( $H_2$  and  $H_3$ ) that compared to non-optimised models,  
334 optimised models would show reduced instances of MTU penetration of bone and moment arm  
335 polarity errors, and improve MTU kinematic smoothness could not be confirmed. For both  
336 generic and personalised joints, MTU moment arm polarity, bone penetration, and length and  
337 moment arm smoothness showed no significant change in frequency of occurrence when  
338 wrapping surfaces were optimised. The likely reason behind the limited changes following  
339 wrapping surface optimisation was the design of the final weighted value. Considering the  
340 evaluation metrics combined for each subject and model (Appendix 3, Tables 6-9), despite  
341 normalising both smoothness and gradient errors, the magnitude of each objective functions is  
342 vastly different. Specifically, the moment arm gradient error is much larger, potentially  
343 explaining why this was the only metric to show consistent and statistically significant  
344 improvement. Implementing a different normalisation method could potentially result in more  
345 consistent and statistically significant changes for other metrics found recalcitrant to our efforts  
346 in this paper. Additionally, the different terms in the objective function may have competed  
347 with each other, which may also provide partial explanation as to why each MTU penalty (bone  
348 penetration and polarity) were not effectively minimised by the optimiser in the models. Future  
349 work should investigate new methods of normalisation or potentially objective weightings to  
350 determine if further improvements can be achieved. Despite the lack of statistical significance,  
351 most cases resulted in improvements in MTU kinematics and pathways (Fig 5) following  
352 optimisation.

353 **[Fig 5]**

#### 354 **Comparison of optimised models**

355 The final hypothesis ( $H_4$ ), that models with personalised joint mechanisms following  
356 optimisation would produce more physiological and anatomically plausible MTU kinematics  
357 was not uniformly supported. These results suggest the designed optimisation framework can  
358 produce MTU kinematics of similar quality (assessed using the suite of evaluation metrics we  
359 presented) irrespective of implemented joint mechanisms. Due to the additional data and  
360 processing time required to include these personalised joint mechanisms, models with generic  
361 TFJ and PFJ may be adequate in supporting muscle driven simulations, provided

362 physiologically and anatomically plausible MTU kinematics are established. Although  
363 evaluation metrics showed similar results, it should be noted that the magnitudes of MTU  
364 kinematics, joint kinematics, and pathways are different (Appendix 4). As these parameters  
365 (MTU lengths and moment arms) cannot be feasibly measured throughout the joints range of  
366 motion, no conclusions can be made about which of the models are more representative of *in-*  
367 *vivo* MTU kinematics or pathways.

### 368 **Comparison to previous methods**

369 The framework we present for automatic creation and tuning of MTU pathways has similarity  
370 to previous studies (Scheys et al. 2009; Nolte et al. 2016, 2020; Modenese et al. 2018;  
371 Modenese and Renault 2020), particularly its focus on automation. Our approach to incorporate  
372 data from an anatomical atlas to define MTU origins and insertions is consistent with a previous  
373 study (Nolte et al. 2016), and can be supplemented by additional medical imaging (Scheys et  
374 al. 2009). However, our method for defining intermediate MTU pathways differs from previous  
375 approaches. In past studies, cadaveric specimens were used for experiments and MTU  
376 pathways were discretised into path points through direct measurement and registration to the  
377 underlying skeleton. This approach is used for both generic (Delp et al. 2007) and subject-  
378 specific (Scheys et al. 2009) models. More recent studies have opted for wrapping surfaces  
379 instead of path points, because they produce smoother MTU kinematics (Garner and Pandy  
380 2000; Hammer et al. 2019). However, sizing, positioning and, in cases of non-spherical objects,  
381 orientation, of these wrapping surfaces is typically achieved manually by the human operator  
382 (Garner and Pandy 2000; Rajagopal et al. 2016; Lai et al. 2017; Catelli et al. 2019; Hammer et  
383 al. 2019). Automated methods for defining MTU pathways have also been presented for  
384 muscles crossing the hip joint (Modenese and Kohout 2020), relying on full segmentations of  
385 the muscles of interest. The advantage of the methods in this present study is they do not rely  
386 on explicit knowledge of the shape, size, or other morphological features of each muscle,  
387 acquired through expensive medical imaging and segmentation of muscles. Although the  
388 current study's framework did rely on imaging and segmentation of bones, these can be  
389 replaced by different morphing methods using either incomplete bone segmentations  
390 (Suwarganda et al. 2019) or 3D locations of optical motion capture markers (Nolte et al. 2016,  
391 2020; Davico et al. 2020a).

392 Instead, our methods rely on testing the behaviour of the MTU within a model generated  
393 through standard MAP-Client processes, and can be easily extended to other muscles and

394 joints. Although we focused our optimisation efforts on subject-specific models, their nature  
395 means they can also be applied to generic models to remove non-physiological and/or non-  
396 anatomical MTU pathways. Furthermore, wrapping surfaces were implemented in this  
397 research, but the extension of this optimisation approach to models consisting of via points is  
398 possible and is currently being tested.

399 There are limitations to this study that should be considered. First, we only considered MTU  
400 kinematics with respect to a single DOF, i.e., TFJ flexion/extension despite some MTU  
401 crossing two joints (e.g., rectus femoris). For the considered DOF, MTU kinematics may well  
402 follow the pattern from literature, however, when multiple DOFs are mobilised the MTU  
403 kinematics may present errors. Although we acknowledge this as a limitation, the framework  
404 was the first of its kind and can be extended to multiple DOFs in future work. Second, the  
405 resulting joint kinematics from the personalised joint mechanisms used in this study have not  
406 been directly validated using dynamic medical imaging. The tuning of these personalised joint  
407 mechanisms ensures physiologically and anatomically plausible solutions (Appendix 4) that  
408 track the cadaveric literature. Here we define physiologically and anatomically plausible  
409 kinematics as those which respect joint geometry (i.e., no bone into bone penetration) and tissue  
410 characteristics (i.e., ligament length changes). However, there is no guarantee the resulting  
411 kinematics represent subject-specific TFJ and PFJ kinematics. In support of this method,  
412 previous research has shown agreement in an unloaded position for 8 children (Barzan et al.  
413 2019), while another using a similar optimisation approach, for a single subject, joint  
414 kinematics were comparable to those measured from fluoroscopy (Nardini et al. 2020).

415 In its current implementation our method does not guarantee modelled pathways of each MTU  
416 matches those measured from medical imaging. Although each subject underwent lower-limb  
417 MRI, these were inadequate for segmenting individual MTUs. Therefore, we cannot comment  
418 on whether the optimised MTU pathways match those measured from MRI. However, the  
419 intention of our method was to ensure physiologically and anatomically plausible MTU  
420 kinematics using morphed bones and joints within the MAP-Client, rather than a fully  
421 personalised representation of each MTU. Indeed, a greater level of personalisation would be  
422 possible if there was availability of segmented muscles from either MRIs for single or multiple  
423 posture(s), or reconstructions from statistical shape modelling (currently being developed), in  
424 which their 3D centroids could be used as additional optimisation criteria to enforce tracking  
425 of personalised the MTU centroids. Thus, the lack of 3D MTU representations in the current

426 model's incarnation does not limit the generalisability of the approach, nor validation of the  
427 approach by other means.

428 Indirect validation is possible by examining improvements in the predictions from a  
429 neuromusculoskeletal model (e.g. joint moments and/or joint contact forces) into which the  
430 optimised MTU pathways model is inserted. Although our group (Gerus et al. 2013; Davico et  
431 al. 2020b) and others (Serrancolí et al. 2020) have used this approach, it was beyond the scope  
432 of the current study. Our current main aim was to establish criteria and an automated framework  
433 to create musculoskeletal models of different levels of personalisation and examine their ability  
434 to produced anatomically and physiologically plausible MTU pathways and kinematics (MTU  
435 lengths and moment arms). Interestingly, previous research (Serrancolí et al. 2020) has  
436 presented a framework where MTU moment arms were directly calibrated by optimising  
437 performance of the neuromusculoskeletal model in predicting joint contact forces. However,  
438 this method introduced a mechanistic disconnect between MTU moment arms and MTU  
439 lengths (i.e. mathematically, moment arms are differential of MTU length with respect to joint  
440 angle), and MTU lengths are inputs to the MTU force generation models. Furthermore,  
441 calibrating MTU moment arms to attain better neuromusculoskeletal model predictions (e.g.,  
442 joint contact forces, or joint moments) does not ensure a valid musculoskeletal model because  
443 of interdependences between musculoskeletal models and MTU models and their design  
444 variables. Instead, the current approach, by optimising the MTU pathways in the model,  
445 mechanistic validity, as well as anatomically and physiologically plausibility, is maintained  
446 between the model and the resulting MTU kinematics. Nevertheless, future research should  
447 examine if using this approach improves predictions of the overall neuromusculoskeletal  
448 models.

449 The framework developed in this study represents a significant contribution to the field of  
450 personalised musculoskeletal modelling. This was the first study which used the MAP-Client  
451 to automatically develop and tune personalised models and assess their suitability for  
452 subsequent musculoskeletal simulations. Several improvements and additions were made to  
453 the MAP-Client, most prominently, the definition of MTU intermediate pathways without the  
454 need to explicitly collect MRI at single or multiple joint angles. Several processes which have  
455 previously been performed manually were automated within this framework, reducing the  
456 subjectivity associated with generating these personalised models. These processes include  
457 manual landmark definitions, defining joint positions, and the definition of both MTU origin  
458 and insertion and muscle intermediate pathways. Future work will focus on improving the



459 MTU intermediate pathway definitions and optimisation. Specifically, an analysis of the  
460 optimisation formulation will be undertaken to minimise terms and their potential competition.  
461 Additionally, the application of these optimisation methods to via points rather than wrapping  
462 surfaces and extending the number of muscles and joints considered will also be undertaken.

#### 463 **Declarations**

#### 464 **Funding**

465 The authors would like to acknowledge the funding from a PhD scholarship from Griffith  
466 University.

#### 467 **Conflicts of interest**

468 The authors declare no conflict of interest relating to the presented work.

#### 469 **Availability of code, data, and material**

470 The pre-existing MAP-Client is freely available here: [https://map-](https://map-client.readthedocs.io/en/latest/)  
471 [client.readthedocs.io/en/latest/](https://map-client.readthedocs.io/en/latest/) with additional information provided here  
472 <https://simtk.org/projects/map>. Note the framework is currently only available in Python 2, an  
473 updated version for Python 3 is currently being produced by the original developers. Updates  
474 regarding the status of this update will be provided on the above SimTK link.

475 The developed frame generated as part of this research are available upon reasonable request  
476 from the corresponding author. The models generated as part of this research are available upon  
477 reasonable request

478

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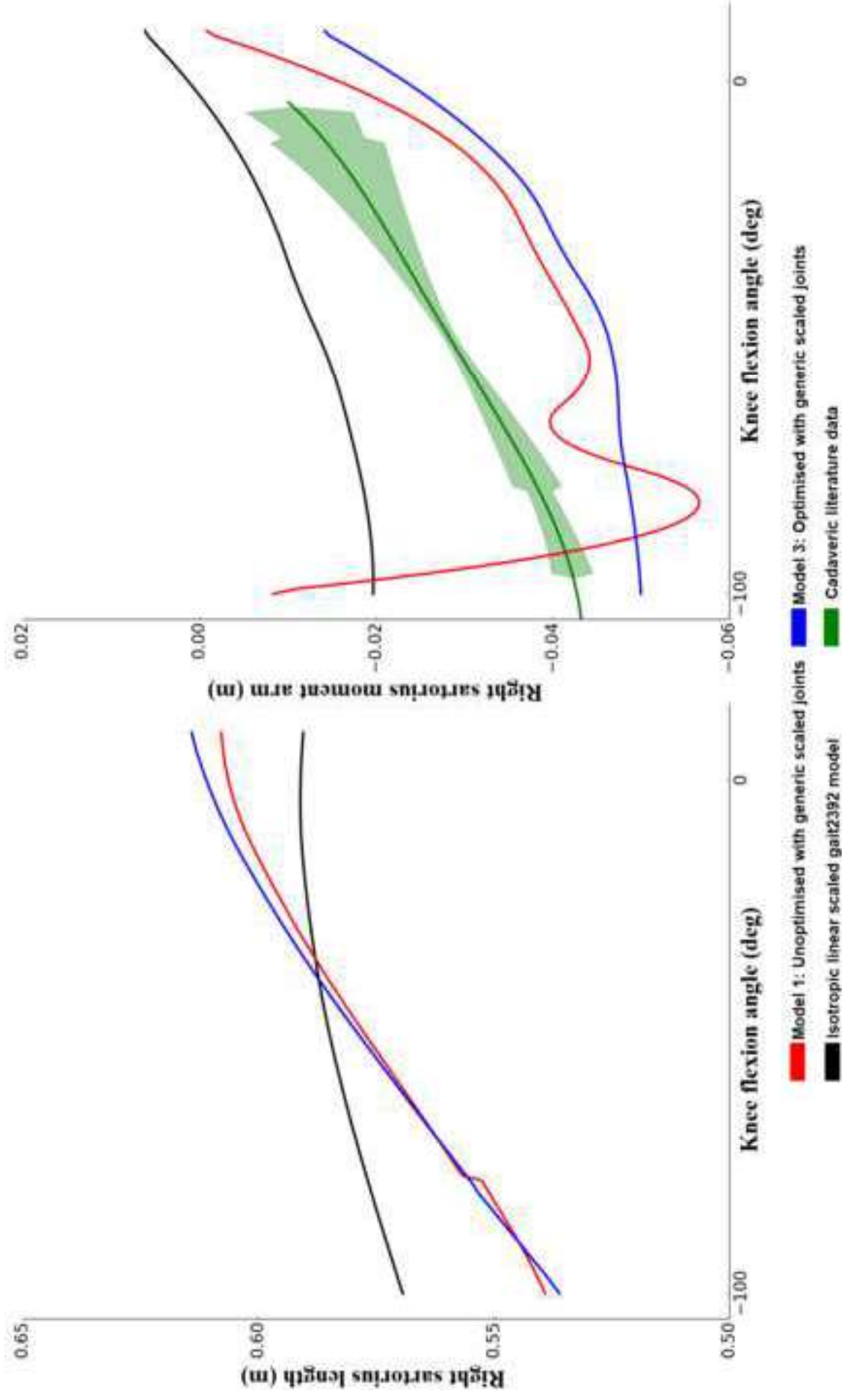
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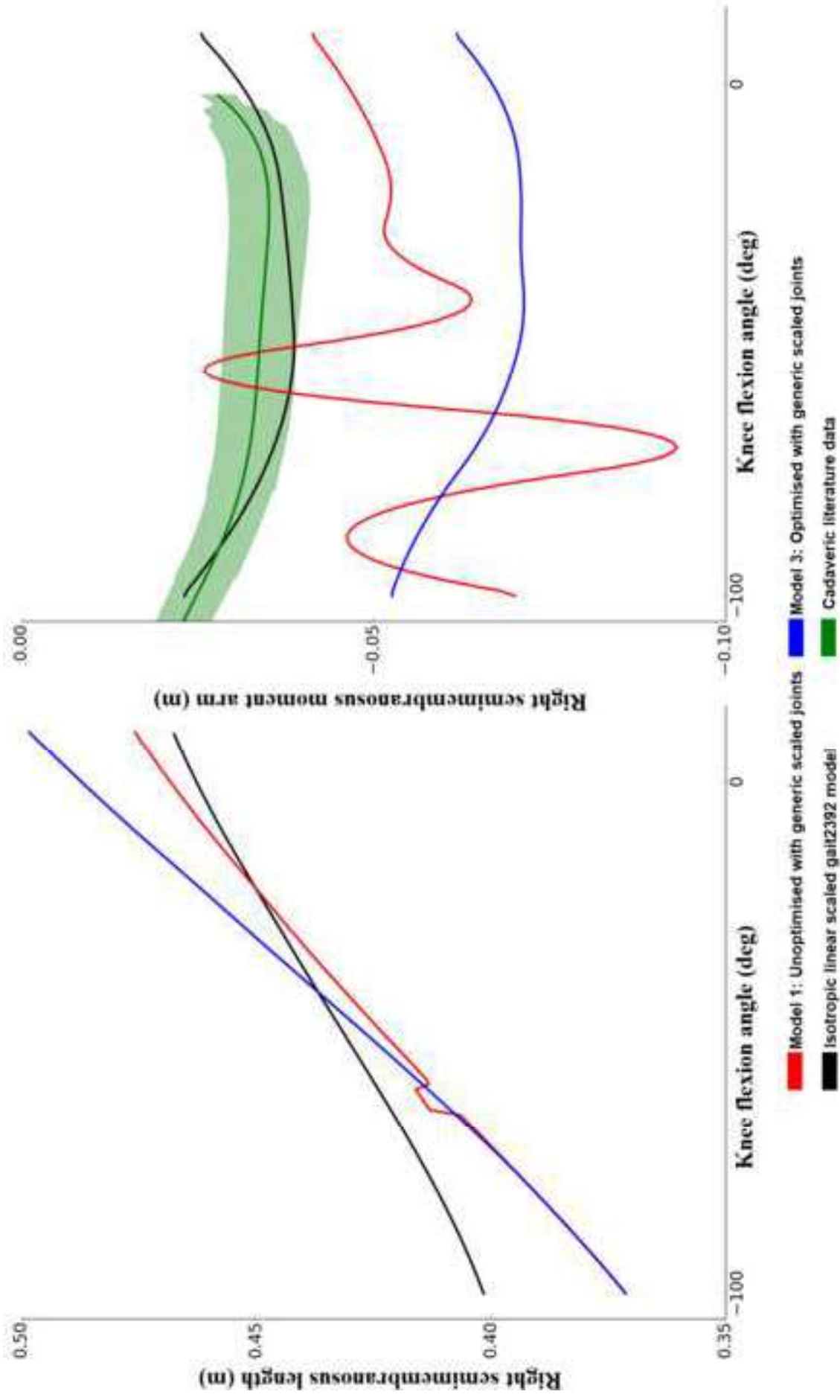
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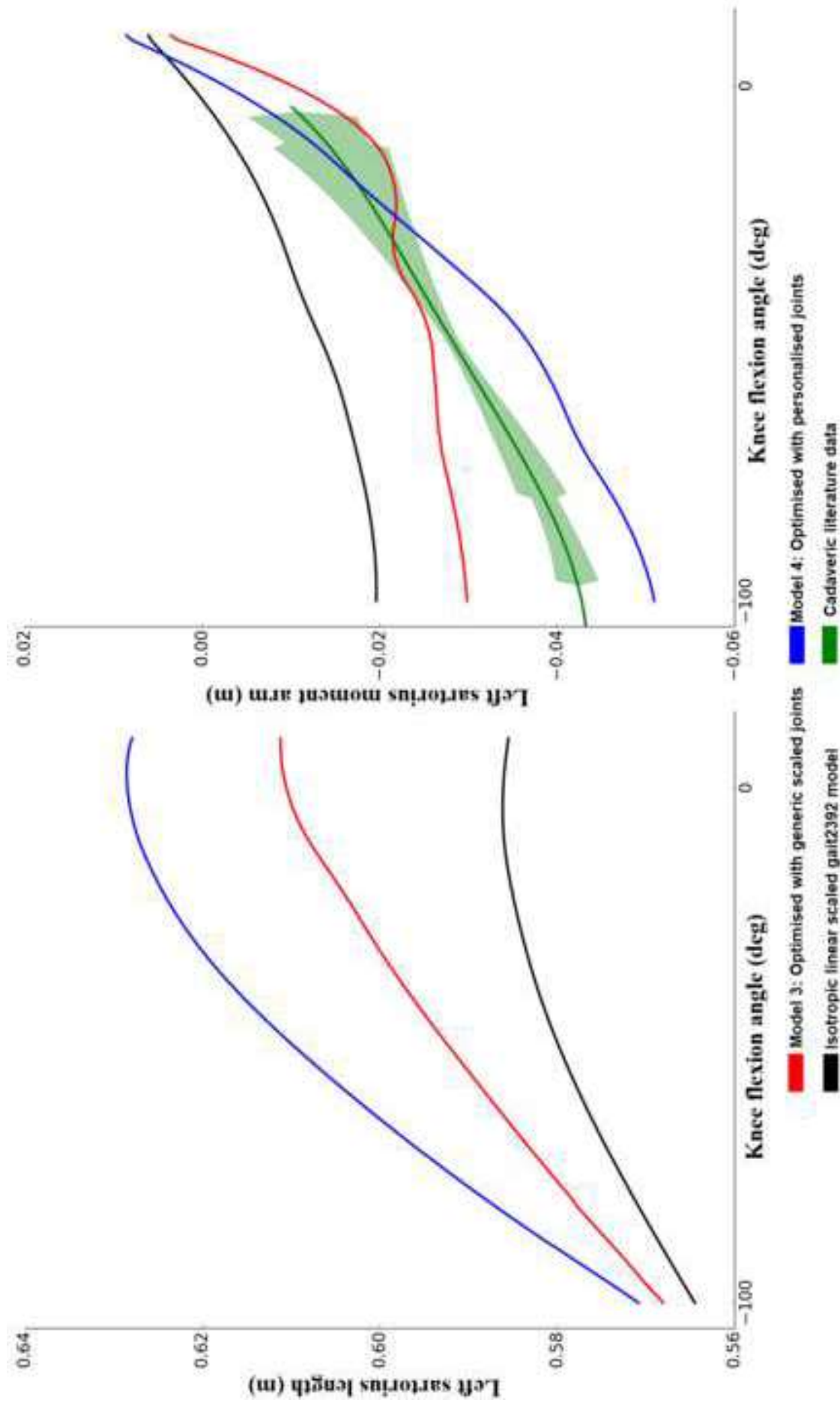
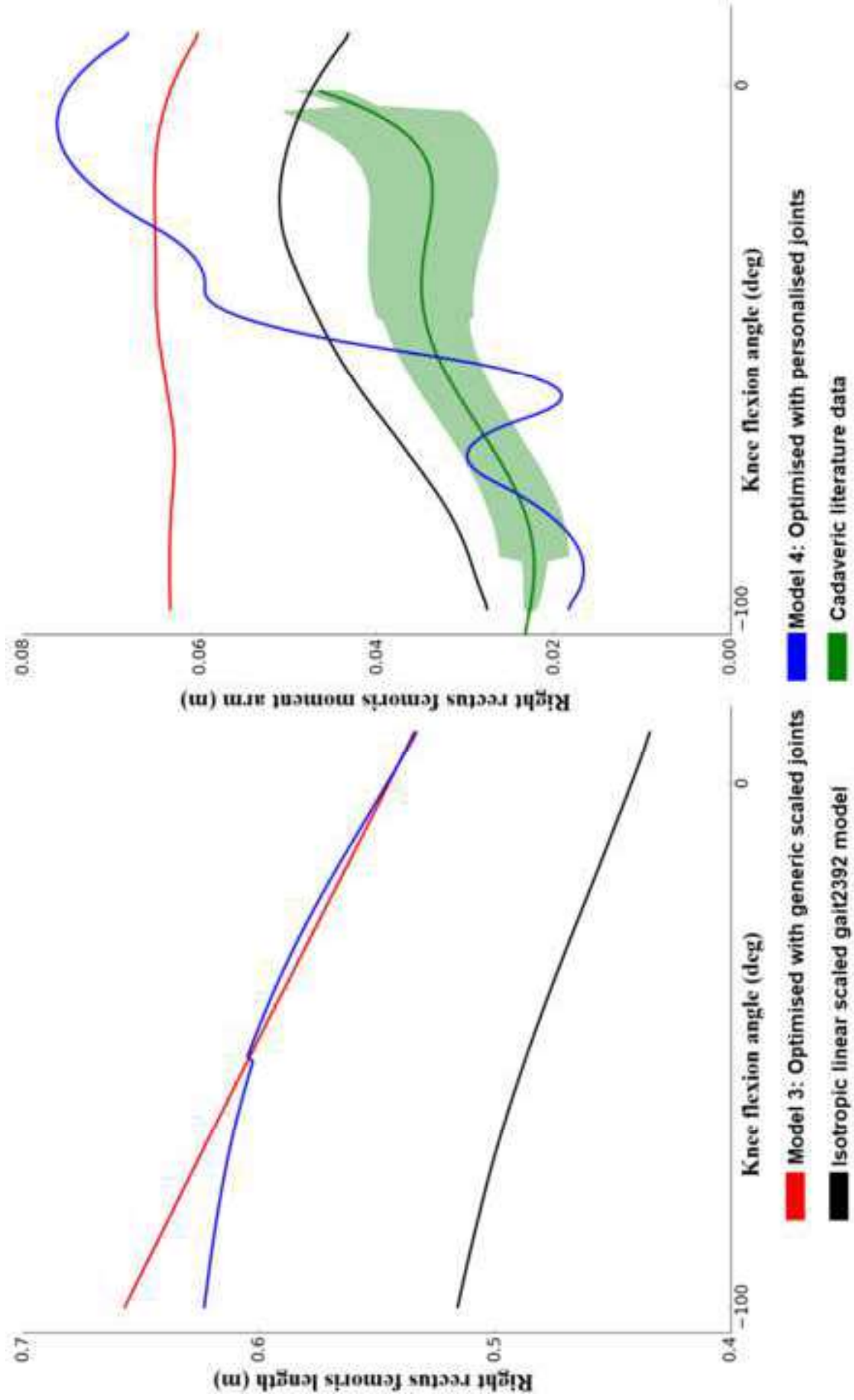
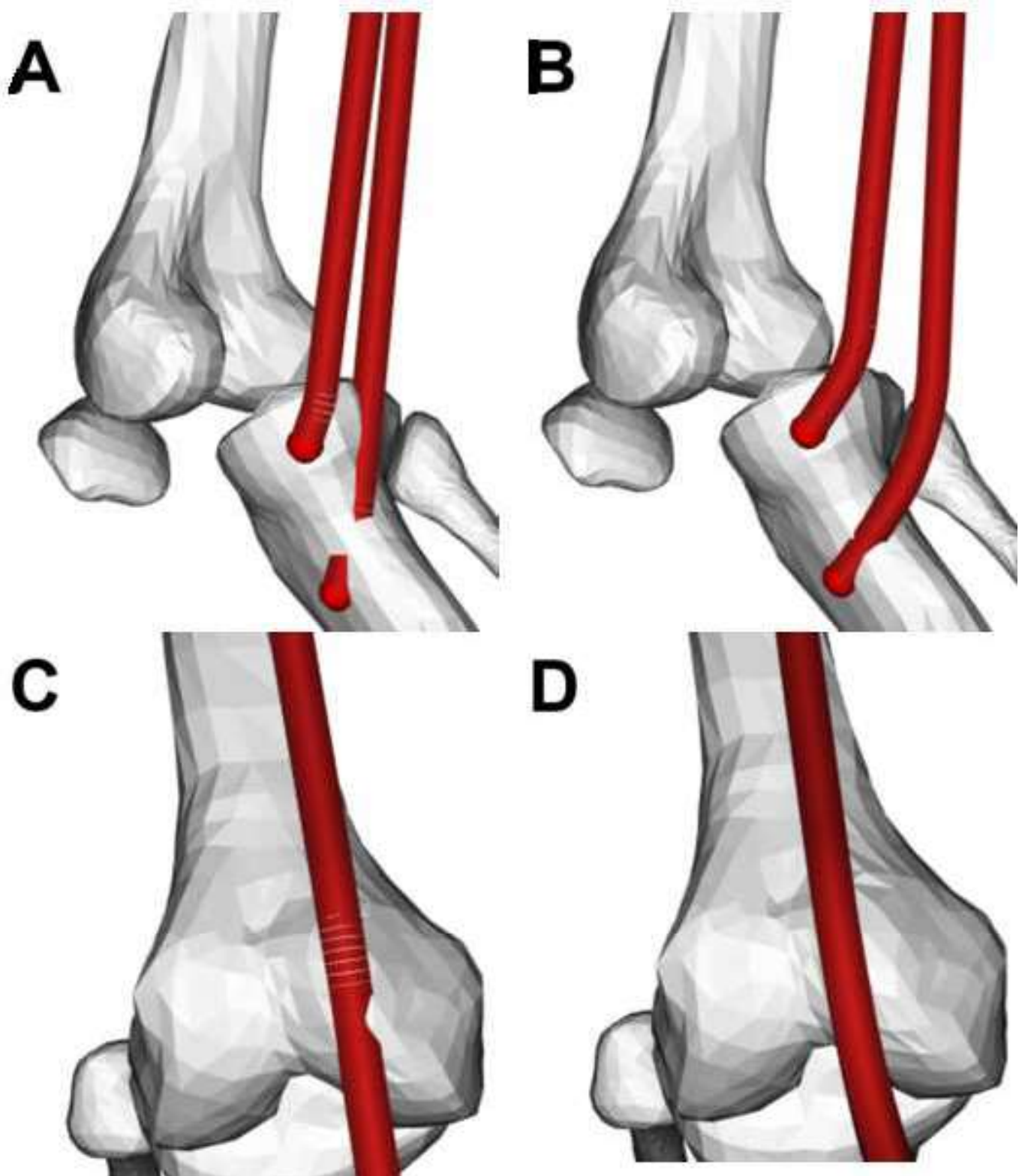


Figure 3







**Table 1:** Demographic data pertaining to study participants.

Participant	Gender	Limb	Age (years)	Height (cm)	Weight (kg)
M01	M	R	24	182.0	82
M02	F	R	22	172.0	63
M03	M	R	23	180.0	88
M07	M	L	32	185.0	89
M09	M	L	31	161.0	45
M11	F	L	21	160.5	55
(n or means±sd)	4M & 2F	3L & 3R	25.5±4.8	173.4±10.7	70.3±18.6

M-males, F-females; L-left , R-right; sd-standard deviation.

**Table 2:** Explanations of each of the four models developed as part of this study.

Model 1	MAP-Client generated model containing personalised: bone geometry, joint positions, MTU origin and insertions, and non-optimised wrapping-surfaces
Model 2	Model 1, but scaled generic TFJ and PFJ have been replaced with personalised joint mechanisms (Brito da Luz et al. 2017; Barzan et al. 2019)
Model 3	Model 1 following MTU wrapping-surface optimisation
Model 4	Model 2 following MTU wrapping-surface optimisation

MTU – muscle-tendon unit.

**Table 3:** Time required for each task in model creation.

Task	Time (hours)
MRI Segmentations (pelvis and bilateral lower limb)	3
MAP-Client bone morphing (pelvis and bilateral lower-limb)	3
TFJ MRI Segmentation (bone, cartilage, and ligaments)	3
MAP-Client OpenSim creation	0.5
TFJ and PFJ mechanism optimisation	4
Wrapping-surface optimisation	2*
<b>Total</b>	<b>15.5 hours</b>

\*The optimisation was run on the high-performance computer cluster and run in parallel. The specifications of the clusters used were 2-4GB RAM

MRI – magnetic resonance imaging; TFJ – tibiofemoral joint; PFJ – patellofemoral joint.

**Table 4.** Summary of the comparisons between the MAP-Client model with fitted wrapping-surfaces (Model 1) and the MAP-Client model with optimised wrapping-surfaces (Model 3). Displayed is the number of instances, for each MTU group and all combined MTU, where the MTU quality evaluation metric was either (+) improved, (-) worse, or ( $\pm$ ) no change. For each MTU group, sample size was 48 (8 MTU x 6 subjects). For all combined MTU, sample size was 144 (8 per group x 3 groups x 6 subjects). Statistically significant differences are denoted using coloured cells, where green indicates improvement, red indicates worsening, and yellow indicates no change. In cases of no statistically significant difference between any of the three types of results, cells were left unshaded.

Polarity penalty		Muscle penetration		Length smoothness		Moment arm smoothness		Moment arm gradient						
+	$\pm$	+	$\pm$	+	$\pm$	+	$\pm$	+	$\pm$					
All MTUs														
23, 16%	5, 3.5%	116, 80.6%	48, 33.3%	3, 2.1%	93, 64.6%	28, 19.4%	9, 6.3%	107, 74.3%	62, 43.1%	37, 25.7%	45, 31.3%	141, 97.9%	3, 2.1%	0, 0%
Quadriceps MTU group														
0, 0%	0, 0%	48, 100%	5, 10.4%	2, 4.2%	41, 85.4%	13, 27.1%	0, 0%	35, 72.9%	14, 29.2%	14, 29.2%	20, 41.7%	48, 100%	0, 0%	0, 0%
Hamstrings MTU group														
9, 18.8%	4, 8.3%	35, 72.9%	16, 33.3%	1, 2.1%	31, 64.6%	9, 18.8%	4, 8.3%	35, 72.9%	27, 56.3%	13, 27.1%	8, 16.7%	46, 95.8%	2, 4.2%	0, 0%
Extras MTU group														
14, 29.2%	1, 2.1%	33, 68.8%	27, 56.3%	0, 0%	21, 43.8%	6, 12.5%	5, 10.4%	37, 77.1%	21, 43.8%	10, 20.8%	17, 35.4%	47, 97.9%	1, 2.1%	0, 0%

Where, +, represents improvement from models 1 to 3, - represents worsening from models 1 to 3, and,  $\pm$  represents no change between models 1 and 3.

**Table 5.** Summary comparison between MAP-Client model with fitted wrapping-surfaces and personalised joint mechanisms (Model 2) and MAP-Client model with optimised wrapping-surfaces and personalised joint mechanisms (Model 4). Displayed is the number of instances, for each MTU group and all combined MTU, where the MTU quality evaluation metric was either (+) improved, (-) worse, or ( $\pm$ ) no change. For each MTU group, sample size was 48 (8 MTU x 6 subjects). For all combined MTU, sample size was 144 (8 per group x 3 groups x 6 subjects). Statistically significant differences are denoted using coloured cells, where green indicates improvement, red indicates worsening, and yellow indicates no change. In cases of no statistically significant difference between any of the three types of results, cells were left unshaded.

	Polarity penalty			Muscle penetration			Length smoothness			Moment arm smoothness			Moment arm gradient		
	+	-	$\pm$	+	-	$\pm$	+	-	$\pm$	+	-	$\pm$	+	-	$\pm$
All MTUs															
25, 17.4%	4, 2.8%	115, 79.9%	45, 31.3%	10, 6.9%	89, 61.8%	26, 18.1%	18, 12.5%	100, 69.4%	71, 49.3%	29, 20.1%	44, 30.6%	135, 93.8%	9, 6.3%	0, 0%	
Quadriceps MTU group															
1, 2.1%	1, 2.1%	46, 95.8%	9, 18.8%	4, 8.3%	35, 72.9%	6, 12.5%	7, 14.6%	35, 72.9%	21, 43.8%	9, 18.8%	18, 37.5%	46, 95.8%	2, 4.2%	0, 0%	
Hamstrings MTU group															
12, 25%	2, 4.2%	34, 70.8%	15, 31.3%	1, 2.1%	32, 66.7%	7, 14.6%	7, 14.6%	34, 70.8%	21, 43.8%	11, 22.9%	16, 33.3%	43, 89.6%	5, 10.4%	0, 0%	
Extras MTU group															
12, 25%	1, 2.1%	35, 72.9%	21, 43.8%	5, 10.4%	22, 45.8%	13, 27.1%	4, 8.3%	31, 64.6%	29, 60.4%	9, 18.8%	10, 20.8%	46, 95.8%	2, 4.2%	0, 0%	

Where, +, represents improvement from models 2 to 4, - represents worsening from models 2 to 4, and,  $\pm$  represents no change between models 2 and 4.

**Table 6.** Summary comparison between MAP-Client model with optimised-wrapping surfaces (Model 3) and MAP-Client model with optimised wrapping-surfaces and personalised joint mechanisms (Model 4). Displayed is the number of instances, for each MTU group and all combined MTU, where the metric was either (+) improved, (-) worse, or ( $\pm$ ) no change. For each MTU group, sample size was 48 (8 MTU x 6 subjects). For all combined MTU, sample size was 144 (8 per group x 3 groups x 6 subjects). Statistically significant differences are denoted using coloured cells, where green indicates improvement, red indicates worsening, and yellow indicates no change. In cases of no statistically significant difference between any of the three types of results, cells were left unshaded.

Polarity penalty		Muscle penetration		Length smoothness		Moment arm smoothness		Moment arm gradient	
+	-	+	-	+	-	+	-	+	-
27,	13,	3,	25,	20,	27,	43,	48,	66,	78,
18.8%	9%	2.1%	17.4%	13.9%	18.8%	29.9%	33.3%	45.8%	54.2%
0,	1,	0,	11,	3,	16,	14,	16,	24,	24,
0%	2.1%	0%	22.9%	6.3%	33.3%	29.2%	33.3%	50%	50%
6,	4,	2,	4,	6,	6,	15,	15,	19,	29,
12.5%	8.3%	4.2%	8.3%	12.5%	12.5%	31.3%	31.3%	39.6%	60.4%
21,	8,	1,	10,	11,	5,	14,	17,	23,	25,
43.8%	16.7%	2.1%	20.8%	22.9%	10.4%	29.2%	35.4%	47.9%	52.1%

All MTUs

Polarity penalty		Muscle penetration		Length smoothness		Moment arm smoothness		Moment arm gradient	
+	-	+	-	+	-	+	-	+	-
27,	13,	3,	25,	20,	27,	43,	48,	66,	78,
18.8%	9%	2.1%	17.4%	13.9%	18.8%	29.9%	33.3%	45.8%	54.2%
0,	1,	0,	11,	3,	16,	14,	16,	24,	24,
0%	2.1%	0%	22.9%	6.3%	33.3%	29.2%	33.3%	50%	50%
6,	4,	2,	4,	6,	6,	15,	15,	19,	29,
12.5%	8.3%	4.2%	8.3%	12.5%	12.5%	31.3%	31.3%	39.6%	60.4%
21,	8,	1,	10,	11,	5,	14,	17,	23,	25,
43.8%	16.7%	2.1%	20.8%	22.9%	10.4%	29.2%	35.4%	47.9%	52.1%

Quadriceps MTU group

Polarity penalty		Muscle penetration		Length smoothness		Moment arm smoothness		Moment arm gradient	
+	-	+	-	+	-	+	-	+	-
27,	13,	3,	25,	20,	27,	43,	48,	66,	78,
18.8%	9%	2.1%	17.4%	13.9%	18.8%	29.9%	33.3%	45.8%	54.2%
0,	1,	0,	11,	3,	16,	14,	16,	24,	24,
0%	2.1%	0%	22.9%	6.3%	33.3%	29.2%	33.3%	50%	50%
6,	4,	2,	4,	6,	6,	15,	15,	19,	29,
12.5%	8.3%	4.2%	8.3%	12.5%	12.5%	31.3%	31.3%	39.6%	60.4%
21,	8,	1,	10,	11,	5,	14,	17,	23,	25,
43.8%	16.7%	2.1%	20.8%	22.9%	10.4%	29.2%	35.4%	47.9%	52.1%

Hamstrings MTU group

Polarity penalty		Muscle penetration		Length smoothness		Moment arm smoothness		Moment arm gradient	
+	-	+	-	+	-	+	-	+	-
27,	13,	3,	25,	20,	27,	43,	48,	66,	78,
18.8%	9%	2.1%	17.4%	13.9%	18.8%	29.9%	33.3%	45.8%	54.2%
0,	1,	0,	11,	3,	16,	14,	16,	24,	24,
0%	2.1%	0%	22.9%	6.3%	33.3%	29.2%	33.3%	50%	50%
6,	4,	2,	4,	6,	6,	15,	15,	19,	29,
12.5%	8.3%	4.2%	8.3%	12.5%	12.5%	31.3%	31.3%	39.6%	60.4%
21,	8,	1,	10,	11,	5,	14,	17,	23,	25,
43.8%	16.7%	2.1%	20.8%	22.9%	10.4%	29.2%	35.4%	47.9%	52.1%

Extras MTU group

Where, +, represents improvement from models 3 to 4, - represents worsening from models 3 to 4, and,  $\pm$  represents no change between models 3 and 4.

[Click here to view linked References](#)

**Fig 1:** Right leg sartorius MTU kinematic curves for participant M02 where left plot is MTU length and right plot is TFJ flexion moment arm. Black lines are for the isotropic linearly scaled gait2392 model, green lines are combined cadaveric literature data, red lines represent Model 1, and blue lines represent Model 3. MTU – muscle-tendon unit; TFJ – tibiofemoral joint.

**Fig 2:** Right leg semimembranosus MTU kinematic curves for participant M03 where left plot is MTU length and right plot is TFJ flexion moment arm. Black lines are for the isotropic linearly scaled gait2392 model, green lines are combined cadaveric literature data, red lines represent Model 1, and blue lines represent Model 3. MTU – muscle-tendon unit; TFJ – tibiofemoral joint.

**Fig 3:** Left leg sartorius MTU kinematic curves for participant M01 where left plot is MTU length and right plot is TFJ flexion moment arm. Black lines are for the isotropic linearly scaled gait2392 model, green lines are combined cadaveric literature data, red lines represent Model 3, and blue lines represent Model 4. MTU – muscle-tendon unit; TFJ – tibiofemoral joint.

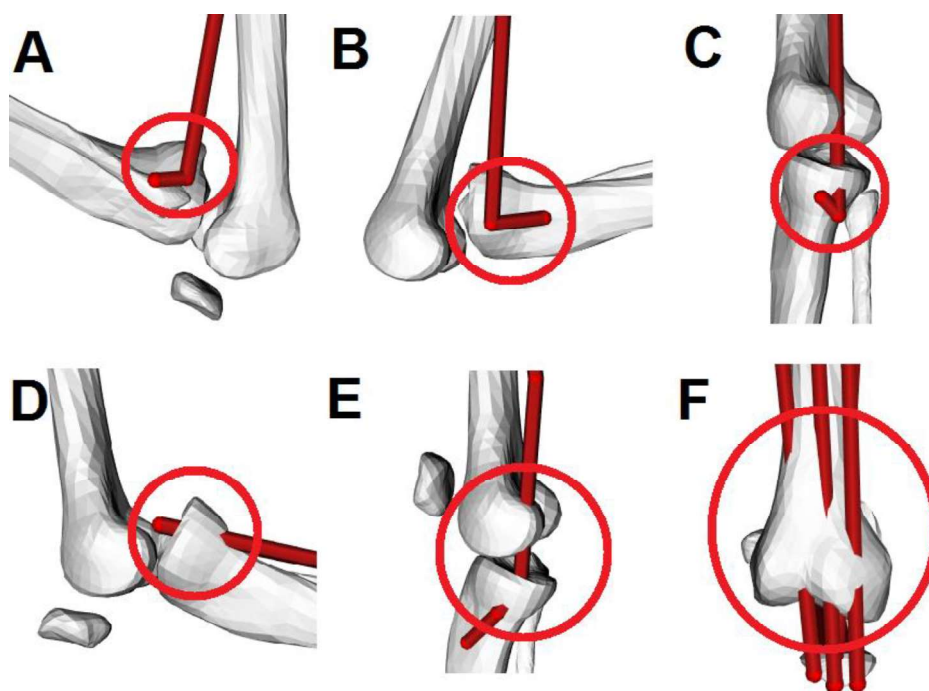
**Fig 4:** Right leg rectus femoris MTU kinematic curves for participant M01 where left plot is MTU length and right plot is TFJ flexion moment arm. Black lines are for the isotropic linearly scaled gait2392 model, green lines are combined cadaveric literature data, red lines represent Model 3, and blue lines represent Model 4. MTU – muscle-tendon unit; TFJ – tibiofemoral joint.

**Fig 5:** An example of MTU bone penetration for participant M09 in Model 1 (A, C) in the semitendinosus (A, B) and vastus lateralis (C,D) which are removed following model optimisation, i.e., Model 3 (B, D).

[Click here to view linked References](#)

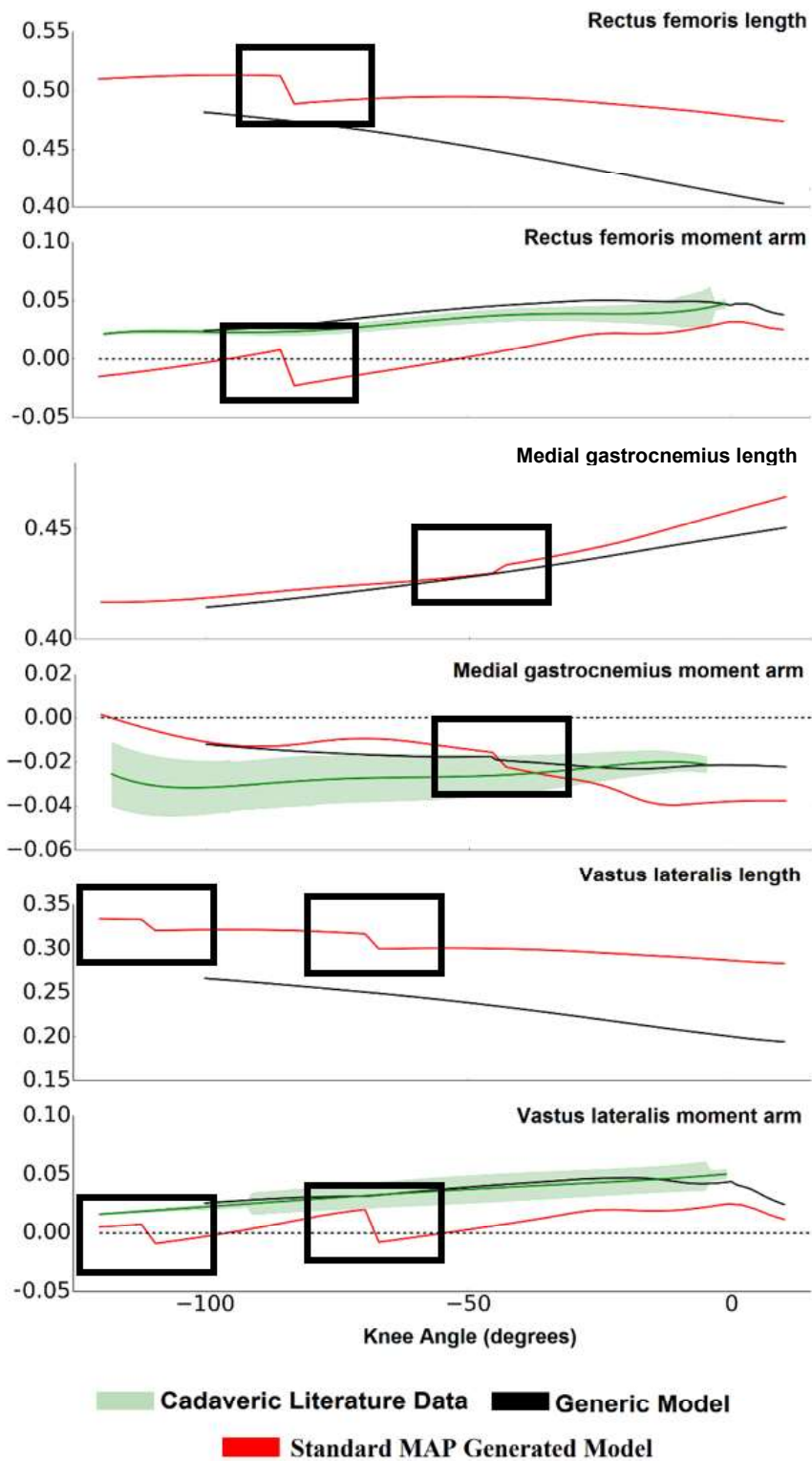
## 1 **Appendix 1: Common non-physiological MTU kinematics and non-physical MTU** 2 **pathways**

3 In most generic OpenSim models, MTU intermediate pathways are predominantly defined  
4 using a combination of fixed and conditional (“via”) path points. The use of via points allows  
5 users to define MTU pathways conditional to the behaviour of the model (e.g., becoming active  
6 when the model reaches a specific configuration). Although this approach may work in generic  
7 models, transferring these via points to personalised models through linear or deviatic scaling  
8 is a non-trivial task. Previous researchers (Scheys et al. 2009; Modenese et al. 2018), as well  
9 as the MAP-Client developers have used non-rigid morphing methods to fit via points to  
10 personalised bone geometries. Although these methods can be implemented in a  
11 straightforward manner within the MAP-Client, they often introduce non-physical pathways  
12 (Fig S1) and non-physiological MTU kinematics (Fig S2). Non-physical pathways refer to  
13 pathways which contain 90° turns and penetrate bones. Non-physiological MTU kinematics  
14 refer to MTU lengths which are not smooth and/or do not follow the patterns (represented as  
15 the change in moment arm magnitude with respect to joint angle) from previously published  
16 literature developed through cadaveric experiments.



17  
18 **Fig S1:** Examples of non-physiological MTU shapes (A, B, C) and MTU bone penetration (C,  
19 D, E, F) in a standard MAP-Client generated model with morphed via points. MTU – muscle-  
20 tendon unit.





21

22 **Fig S2:** The MTU lengths and moment arms from a standard MAP-Client generated model  
 23 (red), generic gait2392 model (black), and cadaveric literature (green) for the rectus femoris,  
 24 medial gastrocnemius, and vastus lateralis where discontinuities are highlighted in black boxes.  
 25 MTU – muscle-tendon unit.

26

## 27 **Appendix 2: Detailed optimisation and evaluation criteria**

28 The optimisation method was written using open-source Python packages and deployed on the  
29 Griffith University High-Performance Computing Cluster “Gowonda” (<https://conf-ers.griffith.edu.au/display/GHCD/Gowonda+HPC>) enabling massive parallelisation. The  
30 optimisation method used within this framework is referred to as particle swarm optimisation  
31 (PSO) (*pyswarm: A Python package for particle swarm optimization (PSO) with constraint support*, Abraham D. Lee, <https://pythonhosted.org/pyswarm/>). The PSO simultaneously  
32 searches different regions of the solution space using different “particles”. During each  
33 iteration, MTU length and moment arms were calculated and tested against various objective  
34 criteria and penalty functions.  
35

37 The MTU moment arms calculated using OpenSim are highly sensitive to small changes in  
38 MTU length. To overcome this and increase computational speed, previously published  
39 methods for accurate estimations of MTU moment arms were implemented. This  
40 implementation uses cubic B-splines fit to MTU lengths (Sartori et al. 2012) across the  
41 TFJ flexion/extension range of motion. The MTU moment arms are then calculated as the  
42 partial derivatives of these splines with respect to joint degree of freedom, i.e., changes in  
43 length divided by changes in joint angle. To ensure this process was not artificially increasing  
44 the calculated MTU length smoothness (covered below), the normalised error (*splineNormErr*)  
45 between the OpenSim calculated and cubic B-splined MTU lengths was calculated and  
46 minimised within the optimisation framework.

47 Patterns of MTU kinematics were represented as gradients with respect to joint angle (change  
48 in MTU moment arm/length divided by the change in joint angle), therefore pattern similarity  
49 was assessed using the normalised error between the gradients (*maGradErr*) of the modelled  
50 (MAP-Client personalised model) and target data (cadaveric literature data). Further objective  
51 functions were created to measure and control curve smoothness to ensure smooth and  
52 continuous MTU kinematics. The smoothness measure relied on three assumptions. First, MTU  
53 kinematic curves were primarily monophasic with no significant peaks or troughs, which is  
54 correct when the joints are moved through physiological ranges. Second, the gradient of the  
55 curves was constant with respect to MTU length or slowly changing in the case of MTU  
56 moment arms. The third and final assumption was that if MTU kinematic curves were a  
57 perfectly straight line, the second derivative of this line would be zero. Consequently, if the  
58 MTU kinematics had only slightly changing gradients the second derivative would  
59 approximate zero. Therefore, kinematic smoothness was defined as the number of modelled

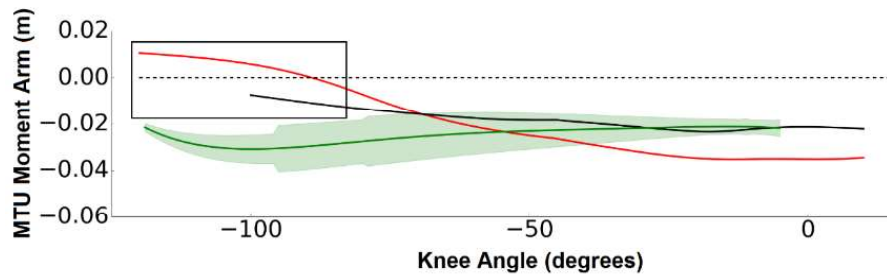
60 curve (MAP-Client personalised model) derivatives required for the differentiated curve's  
61 range, mean, and maximum to fall below predefined thresholds. The smoothness measure of  
62 the tested curve was then normalised to the smoothness measure of the target data. It should be  
63 noted that only the generic OpenSim model data were used to normalise the smoothness  
64 measure whereby the average smoothness measure of the two generic OpenSim models (see  
65 below) was used. As mentioned above, the objective criteria used several targets within the  
66 optimisation.

67 Target data were taken from multiple sources but can be divided into two distinct categories:  
68 model and literature data. Model data were obtained from two generic OpenSim models:  
69 gait2392 model (Delp et al. 2007), on which MAP-Client models are based, and the more recent  
70 Fullbody Model (Rajagopal et al. 2016). Unlike model data, literature data were taken from a  
71 wide range of different studies carried out on cadavers (Fick 1879; Draganich et al. 1987;  
72 Visser et al. 1990; Spoor and van Leeuwen 1992; Buford et al. 1997; Pal et al. 2007; Wilson  
73 and Sheehan 2009; Arnold et al. 2010; Navacchia et al. 2017). **Note that selected original  
74 cadaveric data was not directly available for each of the aforementioned studies. However, we  
75 used cadaveric data that were reproduced and published elsewhere (Arnold et al. 2010;  
76 Rajagopal et al. 2016). These values were combined for each MTU, and the mean and standard  
77 deviation calculated.**

78 Optimisation criteria and penalty functions were employed to mathematically detect various  
79 errors commonly observed in MTU kinematics and pathways. Each MTU's moment arm was  
80 required to have a mechanical action about a joint DOF (e.g., flexion or extension) consistent  
81 with target data (Fig S3). This was termed "polarity of the moment arm" and a penalty was  
82 defined to ensure these were physiological (moment arm polarity penalty). At each TFJ flexion  
83 angle, the polarity of the tested model (i.e., MAP-Client personalised model) and the generic  
84 gait2392 model was compared. If the polarity was the same, no penalty was applied, else a  
85 secondary test was performed. Specifically, the adjacent 20 angles (i.e.,  $\pm 10^\circ$ ) were checked. If  
86 the polarity of the tested model within this range matched the target data, the discrepancy was  
87 no longer considered a polarity error. When this condition was not met, a penalty was applied  
88 to the final weighted value.

89

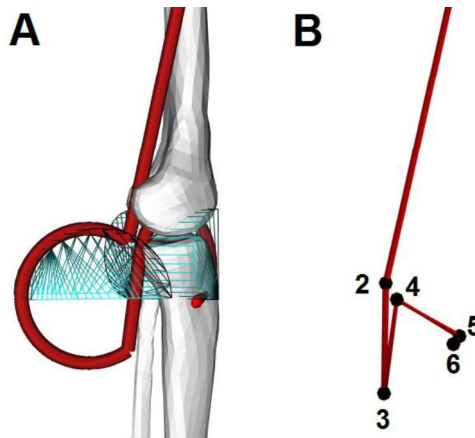
90



91

92 **Fig S3:** Example of MTU moment arm polarity error in the MAP-Client generated model (red)  
 93 compared to both generic model (black) and literature (green) data.

94 Depending on where an MTU intersects an associated wrapping cylinder, it may wrap entirely  
 95 around it, i.e., complete a full circumferential loop before continuing to the insertion point (Fig  
 96 S4A). To avoid these non-physical MTU pathways, the MTU path points in the neutral position  
 97 were queried. These points represent the origin, insertion, and via points as well as the points  
 98 where the MTU starts and finishes wrapping (Fig S4B). With the assumption that each MTU  
 99 path point is inferior compared to the previous path point (which is true in the neutral position),  
 100 the superior/inferior coordinate of each path point is tested. If the superior/inferior coordinate  
 101 of a path point was greater than the superior/inferior coordinate of the previous path point this  
 102 was indicative of a wrapping error.

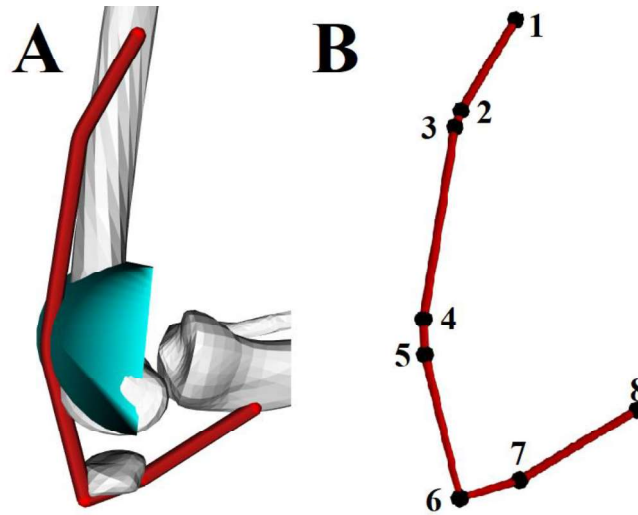


103

104 **Fig S4:** (A) Example of MTU wrapping error in an OpenSim model whereby the MTU wraps  
 105 around the circumference of the cylinder and (B) associated MTU path points numbered  
 106 sequentially where points 3 and 4 illustrate the wrap error.

107 MTU bone penetration penalty employed an automated detection algorithm. Initially, the joints  
 108 that each MTU spanned and the bodies (i.e., bones) they could penetrate were determined. Like  
 109 the wrap error penalty, each MTU path point is determined and a vector calculated between  
 110 adjacent path points. Due to limitation in the OpenSim application programming interface

111 (API), the path between wrap on/off points cannot be readily determined. As a result the penalty  
 112 only considered vectors that intersected bone surfaces between either: (i) two fixed points (e.g.,  
 113 origin or via point), (ii) a fixed point and a wrapping on point, (iii) a wrapping off and wrapping  
 114 on point (on different wrapping surfaces), and (iv) a wrapping off point and a fixed point (Fig  
 115 S5). It was assumed that if the on/off wrapping points did not penetrate, the intermediate path  
 116 also did not penetrate.



117  
 118 **Fig S5:** (A) Illustration of the vastus medialis pathway at 100° of TFJ flexion within OpenSim  
 119 and (B) each of the path points available within the OpenSim API. Where points 1, 6, 7, and 8  
 120 are fixed points, points 2 and 4 are wrapping on points, and points 3 and 5 are wrapping off  
 121 points. Using the proposed framework, tested path point pairs are: 1-2, 3-4, 5-6, 6-7, and 7-8.  
 122 Once each of the penalties had been determined, they were combined into a single penalty  
 123 value where each penalty function, if returning a positive test, attracted penalty value. The  
 124 penalty functions and objective criteria were combined into a single weighted value, which was  
 125 minimised via optimisation (Equation 1). Detailed explanations of each of the optimisation  
 126 functions and penalty functions are restated explicitly below.

127 
$$wv = splineLenN + lenN + splineNormErr + maGradErr + pen \quad (1)$$

128 where,  $wv$ , is the weighted value,  $splineLenN$ , is the smoothness measure of the splined  
 129 lengths fit to the OpenSim MTU lengths,  $lenN$ , is the smoothness measure of the OpenSim  
 130 API derived MTU lengths,  $splineNormErr$ , is the normalised error between the OpenSim  
 131 derived and cubic B-spline fit MTU lengths,  $maGradErr$ , is the normalised error between the  
 132 MTU moment arms and target data, and,  $pen$ , is the summed penalty value.

133 *splineLenN*: provided an estimation of the smoothness of the splines MTU lengths. Here the  
134 MTU lengths at each joint angle defined by the B-spline method are differentiated with respect  
135 to joint angle. This derivation was repeated (using the `numpy.gradient` function) until the mean,  
136 max, min, and range of the derivatives fell below a defined threshold which was 9 orders of  
137 magnitude smaller than the tested values. The number of derivations required for this to occur  
138 defined the *splineLenN* value.

139 *lenN*: Is identical to the above *splineLenN* measure however instead of using the lengths from  
140 the implemented B-spline method, it uses length derived directly from OpenSim's API.

141 *splineNormErr*: was designed to ensure the implemented B-spline method was not artificially  
142 increasing the smoothness of the MTU lengths. It was calculated as the root mean squared  
143 difference between the MTU length from the OpenSim API and the B-spline estimation  
144 normalise to the MTU length from OpenSim.

145 *maGradErr*: provided an estimation of the similarity between the cadaveric and model data.  
146 As mentioned above, the pattern of both cadaveric and model moment arms is represent as the  
147 gradient, i.e., change in moment arm / change in joint angle. The *maGradErr* was then  
148 calculated as the root mean squared difference between cadaveric and model values,  
149 normalised to the cadaveric value.

150 *pen*: represented the summed penalty value, as mentioned there were three penalties  
151 implemented in this framework. First the wrapping error penalty and second MTU bone  
152 penetration error, and third the MTU polarity penalty. Each of these errors, if presented were  
153 penalised with a value of 250 added to the final error.

154 **Appendix 3: Model evaluation criteria results for each model**

155 The combined evaluation metrics used within this research are shown below for Models 1 – 4,  
 156 in Table S1- S4, respectively.

157 **Table S1:** Performance criteria results for the MAP-Client model with fit wrapping surfaces  
 158 and a generic joint model (Model 1).

	Polarity penalty	Muscle penetration	Length smoothness	Moment arm smoothness	Moment arm gradient error
<b>M01</b>	7 (29.2%)	8 (33.3%)	3.5 ± 11.5	1.5 ± 0.4	1270.8 ± 1964.14
<b>M02</b>	4 (16.7%)	8 (33.3%)	1.1 ± 0.2	3.1 ± 6.5	19527 ± 72014
<b>M03</b>	7 (29.2%)	8 (33.3%)	1.4 ± 1.1	1.6 ± 1.1	1891.7 ± 4145.5
<b>M07</b>	6 (25.0%)	9 (37.5%)	1.3 ± 0.8	1.42 ± 0.9	1704.2 ± 2666.1
<b>M09</b>	5 (20.8%)	13 (54.2%)	2.1 ± 4.8	6.7 ± 20.6	55325.7 ± 182702
<b>M11</b>	8 (33.3%)	7 (29.2%)	3.4 ± 10.8	6.8 ± 23.4	42438.2 ± 20233

Where polarity penalty and muscle penetration are reported as the number and percentage of occurrences of each penalty, and the remaining metrics are reported as the average ± standard deviation across each of the 24 muscles considered in this analysis. In all cases, a lower value represents a better result.

159

160 **Table S2:** Performance criteria results for the MAP-Client model with fit wrapping surfaces  
 161 and a personalised joint model (Model 2).

	Polarity penalty	Muscle penetration	Length smoothness	Moment arm smoothness	Moment arm gradient error
<b>M01</b>	10 (41.7%)	8 (33.3%)	2.7 ± 7.6	2.8 ± 5.3	9915.8 ± 416417.7
<b>M02</b>	4 (16.7%)	12 (50%)	1.6 ± 2.1	5.7 ± 18	33246.5 ± 157718
<b>M03</b>	3 (12.5%)	10 (41.7%)	1.2 ± 0.2	1.5 ± 0.5	683.9 ± 741.9
<b>M07</b>	6 (25%)	9 (37.5%)	1.1 ± 0.2	3.7 ± 5.5	7808.9 ± 13452.1
<b>M09</b>	12 (50%)	15 (60%)	1.7 ± 1.8	7.2 ± 17.3	45440.5 ± 147443
<b>M11</b>	9 (37.5%)	11 (45.8%)	1.12 ± 0.19	3.9 ± 9.7	22362.5 ± 96077.7

Where polarity penalty and muscle penetration are reported as the number and percentage of occurrences of each penalty, and the remaining metrics are reported as the average ± standard deviation across each of the 24 muscles considered in this analysis. In all cases, a lower value represents a better result.

162

163 **Table S3.** Performance criteria results for the MAP-Client model with optimised wrapping  
 164 surfaces and a generic joint model (Model 3).

	Polarity penalty	Muscle penetration	Length smoothness	Moment arm smoothness	Moment arm gradient error
<b>M01</b>	7 (29.2%)	0 (0.0%)	1.06 ± 0.2	1.36 ± 0.9	97.88 ± 251.9
<b>M02</b>	7 (29.2%)	0 (0.0%)	1.37 ± 1.3	1.36 ± 0.8	36.46 ± 49.7
<b>M03</b>	5 (20.84%)	1 (4.2%)	1.23 ± 0.7	1.32 ± 0.4	87.62 ± 151.3
<b>M07</b>	7 (29.2%)	4 (16.7%)	1.17 ± 0.2	1.40 ± 0.6	110.94 ± 188.7
<b>M09</b>	6 (25.0%)	2 (8.3%)	1.06 ± 0.2	1.30 ± 0.6	54.42 ± 87.3
<b>M11</b>	5 (20.8%)	1 (4.2%)	1.13 ± 0.2	1.72 ± 0.6	142.36 ± 186.1

Where polarity penalty and muscle penetration are reported as the number and percentage of occurrences of each penalty, and the remaining metrics are reported as the average ± standard deviation across each of the 24 muscles considered in this analysis. In all cases, a lower value represents a better result.

165

166 **Table S4.** Performance criteria results for the MAP-Client model with optimised wrapping  
 167 surfaces and a personalised joint model (Model 4).

	Polarity penalty	Muscle penetration	Length smoothness	Moment arm smoothness	Moment arm gradient error
<b>M01</b>	3 (12.5%)	3 (12.5%)	1.41 ± 0.9	1.46 ± 0.7	422.44 ± 1126.1
<b>M02</b>	0 (0.0%)	2 (8.3%)	0.99 ± 0.2	1.33 ± 0.4	32.50 ± 35.6
<b>M03</b>	4 (16.7%)	5 (20.8%)	1.58 ± 2.1	1.83 ± 1.9	438.29 ± 1983.8
<b>M07</b>	Fig4 (16.7%)	9 (37.5%)	1.62 ± 1.6	1.71 ± 0.9	150.03 ± 302.1
<b>M09</b>	5 (20.8%)	5 (20.8%)	1.32 ± 0.2	1.29 ± 0.4	169.25 ± 321.1
<b>M11</b>	4 (16.7%)	6 (25.0%)	1.14 ± 0.2	1.68 ± 1.1	186.06 ± 353.7

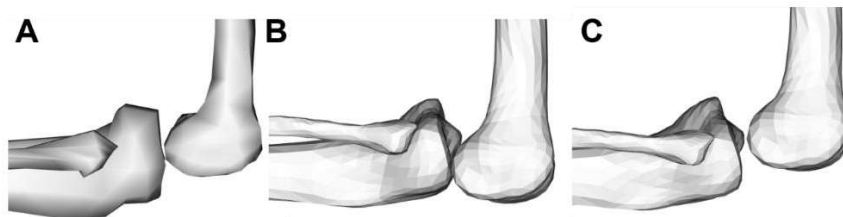
Where polarity penalty and muscle penetration are reported as the number and percentage of occurrences of each penalty, and the remaining metrics are reported as the average ± standard deviation across each of the 24 muscles considered in this analysis. In all cases, a lower value represents a better result.

168



169 **Appendix 4: Comparison of joint mechanism**

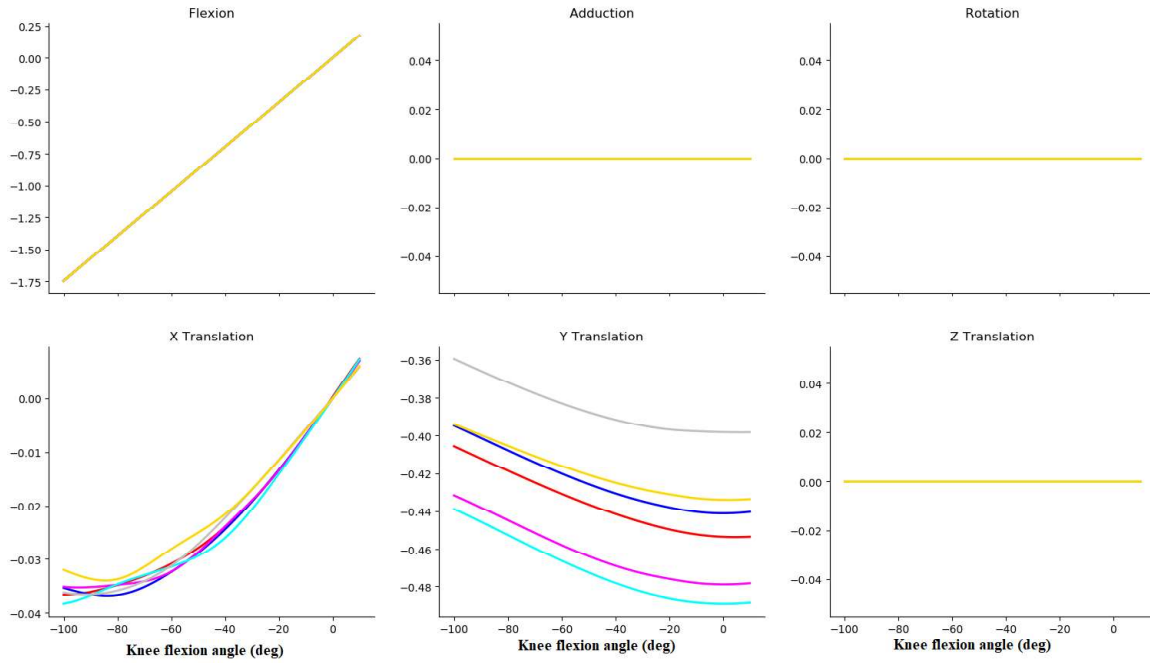
170 Two different types of joint mechanisms were implemented in this manuscript, the first a  
171 generic implementation similar to the generic gait2392 model, and second personalised joint  
172 mechanisms based on medical imaging segmentations. No direct validation between these  
173 two joint mechanisms was performed as no gold standard ground truth data was available.  
174 The personalised joint mechanisms were implemented due to observed errors in joint motion  
175 in the generic joint mechanisms, specifically, the tibia was observed to translate too far  
176 superiorly (Fig S6) at 90 degrees of knee flexion.



177

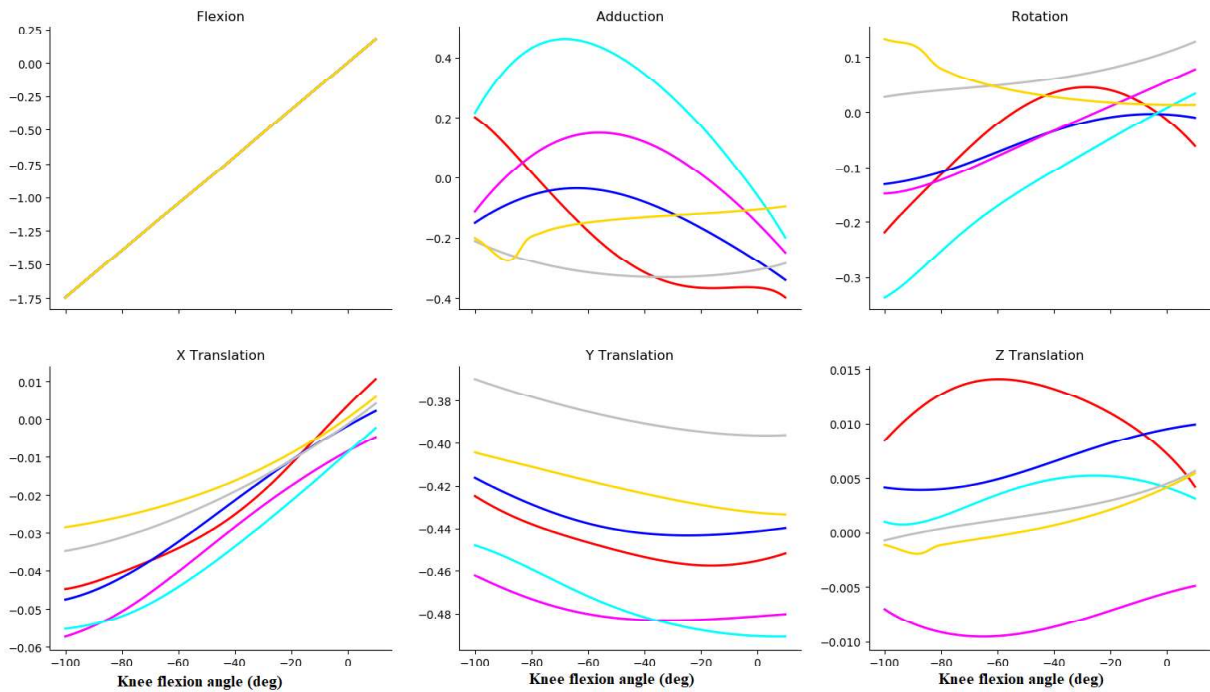
178 **Fig S6:** Comparison of the tibia position at 90 degrees of tibiofemoral flexion in the generic  
179 gait 2392 model (A), a model with the generic joint mechanism (B), and a personalised joint  
180 mechanism (C)

181 In addition to these seemingly non-physiological motions, the observed variation in the  
182 estimated secondary kinematics showed much higher variability in both tibiofemoral and  
183 patellofemoral kinematics (Fig S8, S9) especially compared to those in the generic joint  
184 mechanisms (Fig S7)



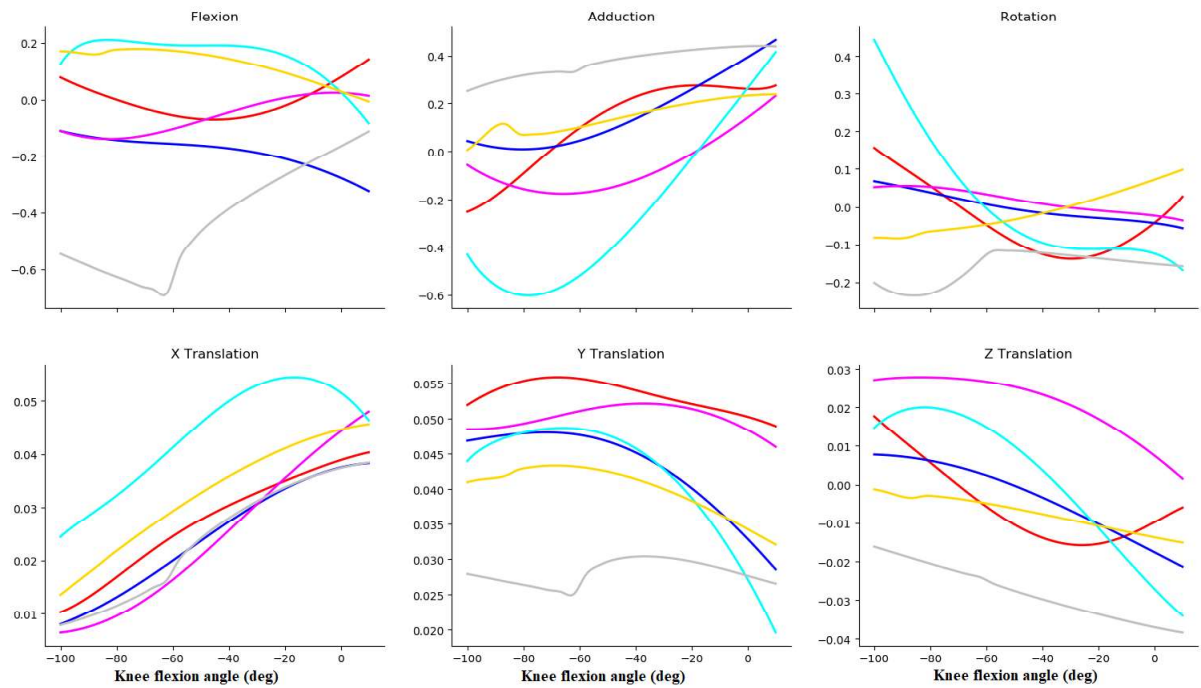
185

186 **Fig S7:** Tibiofemoral joint motion from MAP Client generated models with generic joint  
 187 mechanisms for each participant and each of the 6 DOFs where each colour represents a  
 188 different participant. Translations are reported in metres and rotations in radians. Note that  
 189 each motion is expressed relative to the TFJ flexion angle.



190

191 **Fig S8:** Personalised TFJ kinematics for each participant and each of the 6 DOFs where each  
 192 colour represents a different participant. Translations are reported in metres and rotations in  
 193 radians. Note that each motion is expressed relative to the TFJ flexion angle.



194

195 **Fig S9:** Personalised PFJ motion for each participant and each of the 6 DOFs where each colour  
 196 represents a different participant. Translations are reported in metres and rotations in radians.  
 197 Note that each motion is expressed relative to the TFJ flexion angle