MVN white paper: Enhancing motion tracking accuracy with novel gender-specific models

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***Abstract*—Inertial motion capture (IMC) technology has evolved rapidly, driven by advances in sensor miniaturization, computing power, and data processing. Xsens has leveraged these advancements to refine its optimization engine, integrating sensor data with biomechanical models. Traditionally, many of these models were based on outdated, male-biased cadaver templates. To address this, Xsens developed Biomech 2.0: two new gender-specific models based on *in-vivo* templates, tailored to accurately capture the physical characteristics of both male and female biological sexes. This integration, alongside refinements made to the spine modeling, has significantly improved the precision, accuracy and consistency of the Xsens MVN motion capture system.**

Our validation study reveals substantial gains in arm dimension accuracy, enhanced upper-body kinematics, and greater accuracy in ground-reaching tasks especially when filling in body dimensions, due to improved spinal flexibility. While changes in lower-body kinematics were minimal, significant improvements were observed in step width accuracy, particularly for females.

Despite the current reliance on a predominantly Caucasian dataset, the introduction of gender-specific models marks a major step forward in creating more inclusive biomechanical models. These advancements not only enhance the performance and reliability of Xsens MVN but also pave the way for more personalized and accurate assessments in health, sports, and ergonomics.

Fig. 1: Xsens MVN new Female model.

I. Introduction

Digitization of human motion has a long history, and motion capture technologies have evolved with increase in the digital computing power. Most of these technologies, if not all, limit their usage to a pre-designated motion capture space with a fixed infrastructure, which is prohibitive in terms of flexibility, usability and portability. The miniaturization of inertial sensors has transformed the way we analyze moving objects. The combination of the sensors with sensor fusion algorithms and biomechanical models has led to the development of inertial motion capture (IMC) technology. Over the past two decades, IMC has been used by a growing community in a wide range of applications; in the health and sports market, IMC has been put to use for injury prevention [29], sports performance [32], [34], and workplace ergonomics [28], [31]; whereas in the entertainment market, it is extensively used for character animation [33], and augmented and virtual reality applications such as the Meta's project Aria [54].

Inertial and magnetic measurement units (IMMUs) measure the magnetic field, linear acceleration, and angular velocity over time, rather than the absolute position and orientation in global space. Since heading of a body segment relies on measurement of the earth's magnetic field, IMC is generally very susceptible to magnetic disturbances. Furthermore, the computation of position from double-integration of acceleration is extremely unreliable due to accumulation of positional drift. In the last decade, Xsens has made substantial progress in addressing these challenges and overcoming the errors associated with inertial and magnetic sensors technologies. This effort has resulted in a state-of-the art optimization engine that combines advanced biomechanical models with the information from all the sensors, achieving immunity to magnetic distortion and resistance to positional drift [3]. The Xsens biomechanical model not only contains information about the kinematic chain but also about body segment properties such as segment lengths, segment center of mass (CoM) positions and segment mass ratios. These body segment parameters are crucial when digitizing motion and posture, especially in health, sports and ergonomics applications [11]. In fact, such a model relates the IMU and magnetic data to the positions and orientations of human body segments in global space, via a sensor-to-segment calibration procedure. In addition, precise sensor placement and careful model scaling are critical to fully leverage the capabilities of the system, ensuring accurate, objective and reliable analyses [35].

The development of biomechanical and musculoskeletal models has a rich history spanning more than a century. While Borelli's work in the 17^{th} century initially laid down foundational principles [41], it was not until the late 19th and early 20th centuries that significant developments occurred with the application of mathematical models to human movement. In particular, a major leap came in the middle of the last century with the advent of computer technology and advanced imaging, which greatly increased the precision and accuracy of these models [42], [43]. Today, biomechanical models are categorized into two main types: generic models and subject-specific models derived from medical imaging [39], [40]. As opposed to subject-specific models, generic models are based on template anatomies representing specific populations (e.g., elderly males, athletic young males, or women). Unfortunately, these templates often rely on data from male cadavers [4], [13], [14], [17] or a limited number of female subjects [15], with few studies focusing exclusively on women [16]. Consequently, most commonly used generic biomechanical models describe a typical young Caucasian male [8].

However, as pointed out in [22], males and females are not just scaled versions of each other. The physiological differences do impact amongst others the skeletal structure. This is confirmed in early research, which highlighted that model generalizations, particularly when applied to individuals of the other biological sex, can lead to significant errors in estimating body segment lengths and inertial properties [4]. These inaccuracies can impact outcome parameters such as joint biomechanics during walking [18] and drop landings [19], affecting both kinematic and kinetic analyses. For instance, recent studies showed that gender differences significantly influence lower extremity biomechanics during running and landing tasks [45], [46]. Moreover, gender-specific discrepancies in biomechanical models can affect upper- and lower-body ergonomic assessments and diagnoses of musculoskeletal disorders [49], [50]. Although the scientific community gain greater awareness of the differences and its impact, there is still a bias towards male-participants in studies, referred to as 'Biasmechanics' in [22]. This underscores the importance of developing and validating biomechanical models that accurately represent both sexes to ensure more reliable and objective results in various applications [44], [47], [48].

Xsens MVN software partially addresses gender differences by allowing users to customize the generic model into a subject-specific one, specifically by providing individual body dimensions such as segment lengths. This process, however, is time-consuming, requires knowledge of anatomical landmarks, and is susceptible to human error and variability between operators, which can affect the accuracy of joint kinematics and its objectivity [36], [37]. To mitigate these issues, Xsens facilitates the user by offering a generic model that is scaled based on the body height and foot length, designed to approximate the participant's anthropometry. Unfortunately, this model — referred to as Biomech 1.0 (BM1) — is based on data from predominantly male subjects [52]. To account for gender diversity, Xsens has put efforts into developing Biomech 2.0 (BM2): two generic models to better reflect anatomical variability. In addition, refinements were made to the spine to further improve accuracy of upper-body kinematics.

This paper presents and evaluates BM2, the two newly developed biomechanical models designed to portray the physical characteristics of male and female biological sexes. The performance of these models is assessed by comparing their results with data obtained from an optical motion capture system. Additionally, BM2 models are compared to the current BM1 model to investigate the performance both in terms of accuracy and consistency.

II. Model

The biomechanical model within Xsens MVN software has evolved from its male-centric biomechanical model to one that accounts for both male and female biological anatomy separately. Building on the same model basics as BM1, the BM2 models include two-fold adjustments. First, some generic changes were made to the spine function, which are present in both models. The second set of adjustments were gender-specific, and related to body segment parameters such as segment lengths, segment mass and CoM ratios.

This section is organized as follows: the commonality is detailed in subsection A; the two-fold adjustments are discussed in subsection B and C respectively; finally, in subsection D, the expected impacts of the adjustments on the outcome parameters are discussed.

A. Model basics

As it is the case with BM1, the BM2 models have 23 segments, and a kinematic chain with 22 ball-joints with similar constraints, contact models and scaling algorithm. Motion trackers are placed on 17 of the segments. Those are the feet, lower legs, upper legs, pelvis, shoulders, sternum, head, upper arms, forearms and hands. The remaining six segments are the toes, neck, and spine segments – L5, L3, and T12. The motion of those segments is estimated based on information of connected segments combined with the biomechanical model. As previously mentioned, to estimate segment kinematics through sensor measurements, it is necessary to determine the alignment between sensors and segments. To do so, all motion trackers have to be mapped onto the right segment via the so-called sensor-to-segment calibration. Since the orientation of the motion trackers in the global space is unknown, the orientations of the segments are assumed to be known via a reference pose. In Xsens MVN the calibration procedure starts with the subject in an N-pose (recommended) or T-pose, after which the subject has to walk a few meters back and forth. For more information on the model basics, we refer to the Xsens MVN white paper by Schepers et al. [3].

B. Generic changes

Common to both of the new BM2 models, the generic changes aim to gain accuracy in estimating the upper body kinematics. First, the spine function is refined to improve the accuracy of estimated motion and provide a better physiological representation of the spine curvature during standing and bending.

The human spine is curved like an S-shape during standing, while it takes on a C-shape during bending. Each spine segment contributes in a different amount during bending, known as the lumbopelvic rhythm [2]. With only one motion tracker located at the pelvis, shoulders and sternum, it is unfeasible to track the shape of the spine solely with sensor data. Hence, a theoretical approach, known as spherical linear extrapolation (SLERP), is adopted to interpolate the shape of the spine segments. More specifically, each segment is being allocated a weight contribution to take into account the lumbopelvic rhythm. This results in more flexibility during bending, increasing the range of motion, and a more realistic capture of the S- to C-shape of the spine physiology.

In addition to refining the spine function, the lengths of spine segments are also adjusted (see subsection C). Moreover, the changes in segment lengths induced a shift in the point of attachment of the shoulders to the torso, which had to be adjusted accordingly.

C. Gender-specific model changes

Gender-specific adjustments are made to the segment properties, which are based on anatomy templates of living subjects. The BM2 male model is now based on data from 31 healthy Caucasian male adults, with an average age of 27.5 years, a mean weight of 80.5 kg and an average stature of 1.77 m [17]. The BM2 female model is based on a database that consists of 46 healthy Caucasian female adults with an average age of 31.2 years, a mean weight of 63.9 kg and an average stature of 1.61 m [16]. From there, all body dimensions of both male and female model are linearly scaled to a 1.70 m default model in Xsens MVN.

The parameters such as segment lengths and ratios for both the segment mass and CoM locations are based on Dumas et al. [5], who adjusted the work of McConville et al. [17] and Young et al. [16], to express the parameters in the conventional coordinate system [24]–[26]. As a result, in both new models, the dimensions of all body segments are updated, with the most noticeable adjustments being in shoulder and hip widths, having broader shoulders and narrower hips for male compared to female.

D. Expected effect on outcome parameters

By implementing gender-specific models, we expect the BM2 models to better approximate the participant's anthropometry when scaled based on the body height and foot length of the participant. In addition, with the specific changes regarding the spine function and shoulder attachment points, we also expect an increase in accuracy regarding the whole upper body kinematics. This should be observable in motion capture of hand clapping and spine range of motion. Regarding the lower body, we expect the changes to minimally affect the joint angles, but it would be more pronounced in the estimation of the spatio-temporal parameters, such as step length and step width, due to the changes in the pelvis dimensions.

III. Method

To objectively assess the performance of the new gender-specific models, a comparative evaluation is performed between the BM2 models and BM1. In addition, the models – BM1 and both BM2 versions – are compared to an optical marker-based reference system combined with an OpenSim model.

A. Setup

A group of 11 young adults participated in the study: 6 males (avg. height: 185.1 cm) and 5 females (avg. height: 166.0 cm). Each participant was instructed to perform activities that would independently mobilize their upper and lower bodies. The activities include walking at a self-chosen pace, performing squat jumps, flexion of the trunk, and lifting the arms, with a hand clap occurring both above the head and in front of the body of the participant.

Motion capture data was collected using the full body Xsens MVN Awinda system (17 sensors) and an optical marker-based system (Qualisys optical system with 15 Miqus M3 cameras set), with both systems recording at a frequency rate of 60 Hz. For the marker-based system, the sports marker set was used, which includes 43 reflective markers. To avoid errors due to motion artefacts, the reflective markers were placed on bony landmarks on the skin as illustrated in Figure 2. Furthermore, to avoid inter-operator variability in the output, anthropometric values were measured by the same operator for all subjects. The body height and foot length were provided as inputs for the scaling of the Xsens MVN biomechanical models. Regarding the sensor-to-segment calibration, the recommended (N-Pose + Walk) protocol of Xsens MVN was followed. In addition to the result of the calibration provided by the software, the quality was further assessed and confirmed by ensuring sound representation of inter-hand and inter-feet distances. Only after calibration, Qualisys and Xsens MVN were synchronized using the vendor-supported integration protocol [6].

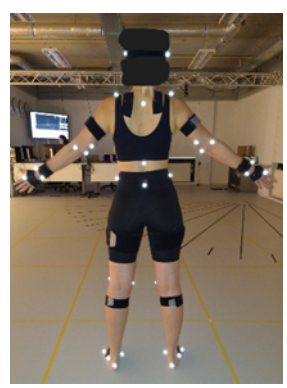

Fig. 2: Subject wearing Xsens MVN trackers and optical markers.

B. Data analysis

Kinematics data were extracted from Xsens MVN Analyze after performing HD reprocessing. Optical motion capture data were processed and low-pass filtered using a zero-lag fourth-order Butterworth filter with an 8 Hz cut-off frequency to reduce noise [51]. Gender-specific OpenSim models were scaled for each subject [9], [10], and joint kinematics were calculated using the Inverse Kinematics tool [27]. The analysis was divided into three main sections: full-body, upper-body, and lower-body evaluations.

The full-body analysis evaluated the automatic scaling of BM2 models against measured body dimensions, with a comparison made to BM1. Scaling errors were expressed as percentages, and a paired Student's two-tailed t-test ($\alpha = 0.05$) assessed statistical significance in differences between both Biomech models [36], [37].

The upper-body analysis assessed model improvements through inter-hand distances during clapping events and trunk flexion performance. First the effects of the new segment lengths were assessed by evaluating the hand positions, representing the end of the kinematic chain, between Xsens MVN models and optical marker data. Specifically, the Euclidean distances between the hands at clapping instants were calculated for each system, with errors defined as differences between these distances. The analysis excluded hand thickness effects since markers were consistently placed on hand surfaces. Accuracy was assessed using Root Mean Square Error (RMSE), and statistical significance was evaluated with a paired t-test. Second, the performance of the new spine model was assessed during a trunk flexion analysis by comparing wrist marker distances to the ground at the lowest point of the motion, between the Xsens MVN models and optical marker data. Accuracy was assessed using RMSE (as absolute error) across all trials and subjects.

The lower-body analysis evaluated the impact of model changes on joint kinematics and spatial gait parameters during walking at a self-chosen pace and squat-jump trials. Estimates of the hip, knee and ankle joint angles (Flexion/Extension as F/E, Adduction/Abdution as A/A, and Internal/External rotation as I/E) by applying BM2 models were compared to that of BM1 and those from the OpenSim IK tool [7], [27]. The RMSE assessed accuracy, while the standard deviation of errors (STDE) provided insight into within-cycle variability and consistency across subjects. The spatial parameters - step width and length during gait cycles - were derived from heel markers and compared between Xsens MVN estimates and optical data. Errors were expressed as absolute differences, with statistical significance evaluated using a paired t-test.

For all upper- and lower-body analyses, errors were reported as mean $\pm$ standard deviation. The RMSE quantified accuracy relative to optical markers, or optical markers with OpenSim models. Statistical significance was evaluated using a paired Student's two-tailed t-test ($\alpha = 0.05$).

IV. Performance Evaluation

A. Estimation of body dimensions

Regardless of the model used, measured body height and foot length are essential inputs for Xsens MVN as they are required to scale all other body dimensions. These dimensions were therefore excluded from the analysis. Errors in other scaled body dimensions relative to measured dimensions are shown in Figure 3.

Overall, body dimensions were better estimated with the BM2 models, with the most notable gains observed in arm dimensions. Errors in arm span were reduced by over 50%, while errors in elbow and wrist spans dropped below 2.2% ($\sim$2 cm) and 5% ($\sim$6 cm), respectively ($p<0.05$). These substantial improvements in arm-related metrics are expected to enhance the accuracy of upper-body kinematics.

Statistically significant differences were observed where the BM2 models performed slightly worse than BM1: shoulder height and hip height. For shoulder height, BM1 consistently overestimated the dimension by 1.36%, while BM2 underestimated it by 1.52% ($p<0.05$). For hip height, BM1 was more accurate by 2.5% (5.09% vs. 7.48%, $p<0.05$). This difference likely stems from the difficulty in measuring the greater trochanter, a landmark that is challenging to palpate. Importantly, despite the statistical significance, the absolute median error remained around 5 cm across subjects, falling within the range of typical human measurement error and minimizing practical impact [36].

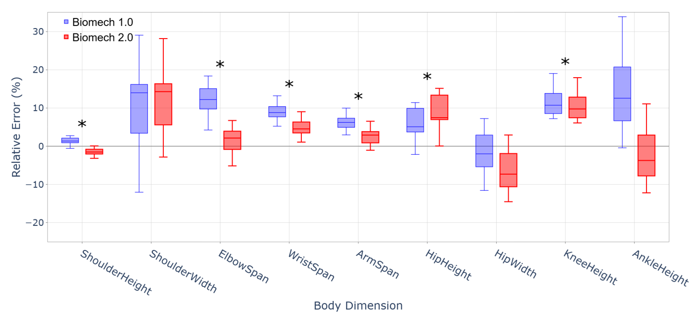

Fig. 3: Relative error (%) in body dimensions for BM1 (blue) vs. BM2 (red) models over all participants. The asterisk symbol indicates statistically significant differences ($p<0.05$)

B. Upper body

This section evaluates the performance of BM2 models for upper-body motion, focusing on inter-hand distance during hand clapping and spine flexibility during trunk flexion.

1) Inter-hand distance evaluation:

The absolute error of the inter-hand Euclidean distance is shown in Figure 4 and Figure 5 for clapping above the head and in front of the body respectively. BM2 significantly improved the accuracy of inter-hand distance for clapping in front of the body ($p<0.05$), where errors decreased by over 40%, achieving an RMSE of 8.5 ± 7.5 cm. In contrast, a slight decrease in accuracy was observed for clapping above the head, with an error increase of less than 1.0 cm.

Gender-specific analyses confirmed these trends. In males, error increased by 1.4 cm for clapping above the head, while frontal clapping error dropped by over 55% (5.6 ± 5.4 cm vs. 12.9 ± 5.0 cm). In females, error slightly increased above the head (0.5 cm), but improved by 35% when clapping in front of the body, reducing the error from 16.9 ± 8.3 cm to 11.0 ± 8.6 cm.

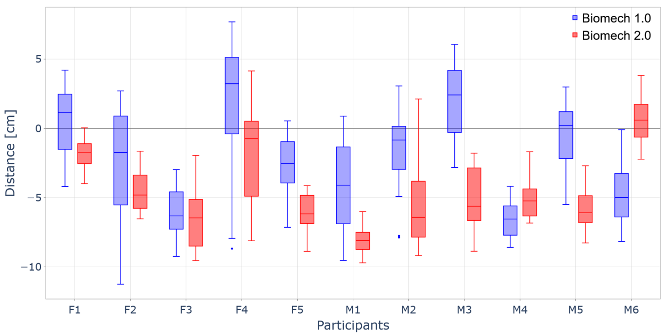

Fig. 4: Absolute error (cm) in inter-hand Eucledian distance while clapping above the head, for BM1 model (blue) and BM2 models (red). Results are shown for all participants (F for females, M for males).

Overall, these results suggest a robust improvement for clapping in front of the body, albeit, at a cost of slight decrease in accuracy when clapping above the head. While the gender-specific trends should be interpreted with caution due to the small sample sizes (5 and 6 subjects per group), the pattern held across both genders and in the full cohort indicating a meaningful trend. This discrepancy likely stems from limitations in the shoulder joint model. Clapping above the head demands substantial arm elevation which involves scapular motion according to the scapulohumeral rhythm [55]. This additional scapular motion is not fully present. While BM1 may have compensated for these limitations through overestimated arm lengths, BM2's more accurate body dimensions exposes them. By contrast, clapping in front of the body involves less shoulder elevation and falls within a more stable range for the current shoulder model. Here, BM2's refined anthropometry — particularly in arm dimensions — directly enhances accuracy.

2) Spine range of motion:

Figure 6 presents the performance of capturing full spine range of motion for both biomech models.

The initial analysis focused on wrist-to-ground distance during maximal trunk flexion. BM2 showed a slight reduction in accuracy here (error increased by less than 0.6 cm), though a small improvement was observed for females (0.2 cm). As with the inter-hand distance evaluation, these results are sensitive to the small sample sizes (5 and 6 subjects per group), and appear driven more by changes in arm length scaling than the refined

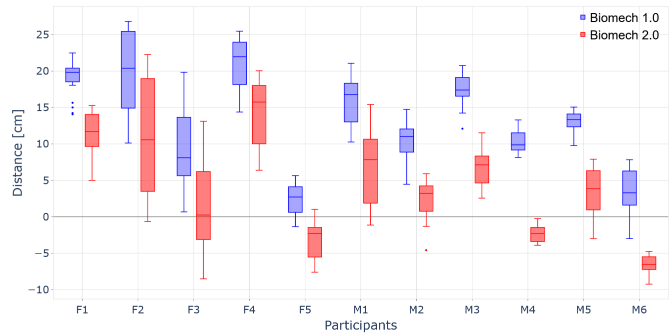

Fig. 5: Absolute error (cm) in inter-hand Eucledian distance while clapping in front of the body, for BM1 model (blue) and BM2 models (red). Results are shown for all participants (F for females, M for males).

spine mechanism (Section IV-A). Indeed, when incorporating all subject-specific dimensions, BM2 significantly improved wrist-to-ground accuracy, reducing error by over 3 cm — a 25% gain. This pattern held across both genders.

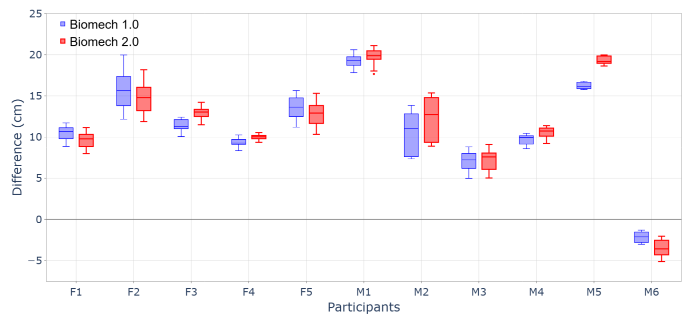

Fig. 6: Absolute error (cm) in the wrist-to-ground distance during maximal trunk flexion, for BM1 model (blue) and BM2 models (red). Results are shown for all participants (F for females, M for males).

To isolate the spine's contribution, a secondary analysis evaluated shoulder-to-ground distance during trunk flexion (Figure 7). By removing arm length influence, BM2 reduced error here from 10.3 ± 5.8 cm to 8.5 ± 6.6 cm — a gain of $\sim$2 cm ($p<0.05$) — with consistent improvements across subjects.

Overall, these findings indicate a meaningful gain in spine flexibility modeling. The small decline in wrist-to-ground accuracy for the BM2 scaled model likely results from limitations in the shoulder model and especially in shoulder translation — during bending and reaching — which can introduce 5–10 cm of variability. Thus, as with hand clapping, this highlights shoulder model limitations rather than the gender-specific updated scaling of BM2.

Together, these results demonstrate BM2's enhanced physiological representation and accuracy for upper-body motion. Substantial improvements in frontal clapping and trunk flexion accuracy confirm the benefits of gender-specific anthropometry and refined spine function. These gains are especially

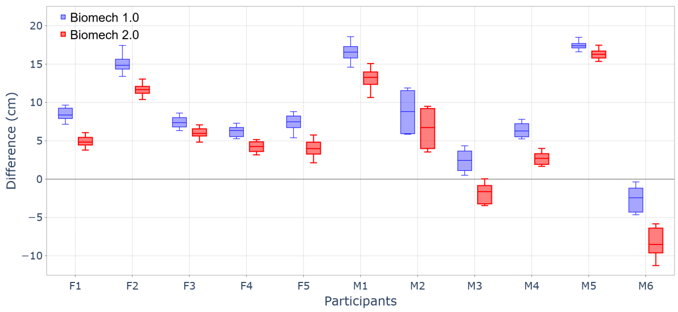

Fig. 7: Absolute error (cm) in the shoulder-to-ground distances during maximal trunk flexion, for BM1 model (blue) and BM2 models (red). Results are shown for all participants (F for females, M for males).

relevant for time-sensitive applications — where accurate scaling makes a measurable difference — or tasks requiring coordinated movements across arms, shoulders, and spine.

C. Lower body

This section evaluates the impact of model changes on lower-body kinematics and spatial gait parameters during walking at self-chosen pace and squat-jump trials.

1) Joint angles analyses:

Figure 8 and Figure 9 present the mean and standard deviation of joint angles during gait cycles and squat jump repetitions, comparing BM1 and BM2 models against marker-based OpenSim reference data.

Both Biomech models versions demonstrate excellent correspondence, with correlations ranging higher than 0.98 ± 0.03. A small but consistent offset, lower than $1°$, reflects differences in body segment properties, as both Biomech versions share the same calibration file and kinematic chain.

Overall, BM2 models demonstrate strong to excellent correlations with OpenSim estimates (from $0.57 \pm 0.46°$ for the hip A/A joint angle during the squat jump trials, to $0.98 \pm 0.01°$ for the hip and knee F/E joint angles during the walking trials). This is corroborated by RMSE values and error variability reported in Table I and Table II, which align with prior literature [38]. Only the hip I/E rotation during gait analysis exhibited a weaker correlation ($0.31 \pm 0.36°$), although RMSE values were comparable to the other joint angles over both conditions. In addition, OpenSim estimates exhibit greater variability, particularly in hip F/E angles. These discrepancies, while expected due to subject-specific variations, stem from differences in biomechanical modeling approaches.

Key sources of discrepancies between both Xsens MVN models and OpenSim include variations in local segment frame definitions, marker placement accuracy, and initialization methods, such as Xsens MVN's sensor-to-segment calibration versus OpenSim's scaling and inverse kinematic tools. Even minor errors, such as a millimeter discrepancy in the joint axis of rotation, can significantly impact output data [53]. In prior work [3], applying OpenSim's static pose during Xsens

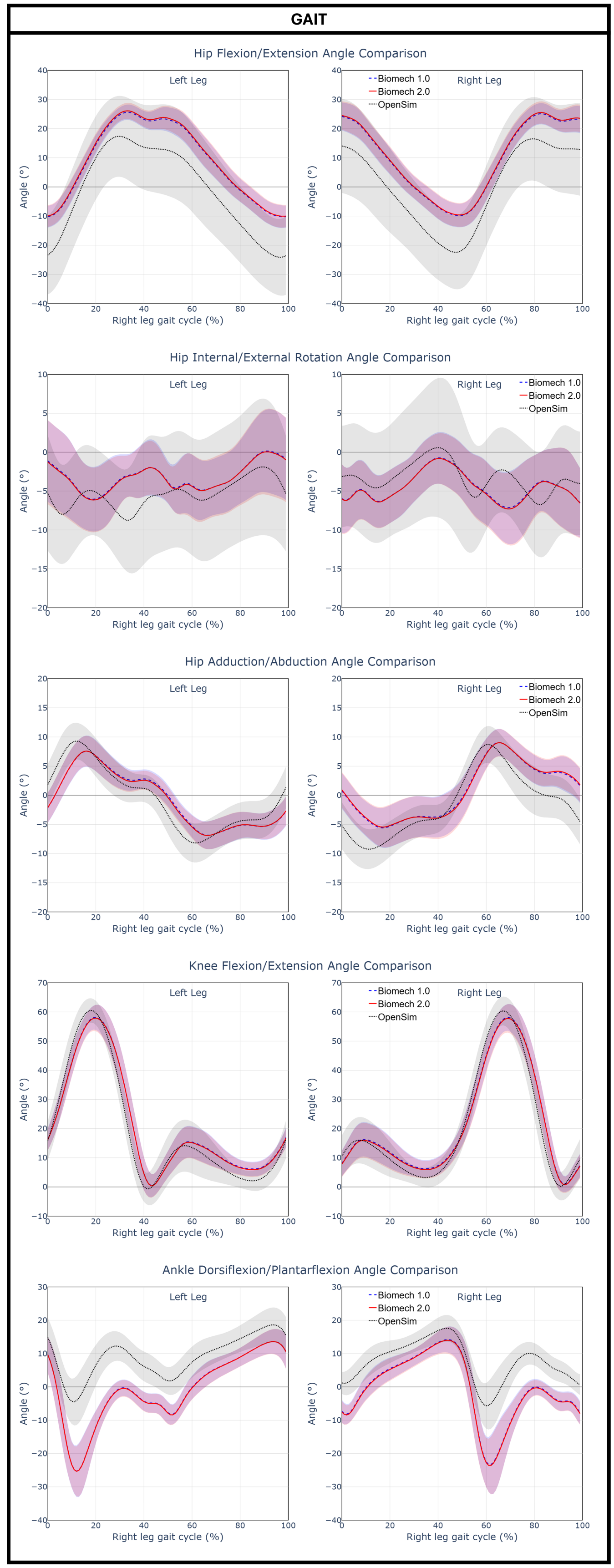

Fig. 8: Mean (line) and standard deviation (shaded area) of the joint angles of both legs for the hip (F/E, A/A, I/E), knee (F/E) and ankle (F/E) for walking estimated from BM1 (blue), BM2 (red) and optical via OpenSim [7] (black). Gait cycles are from the right legs, averaged over all subject, time-normalized and expressed as percentage of the gait cycle.

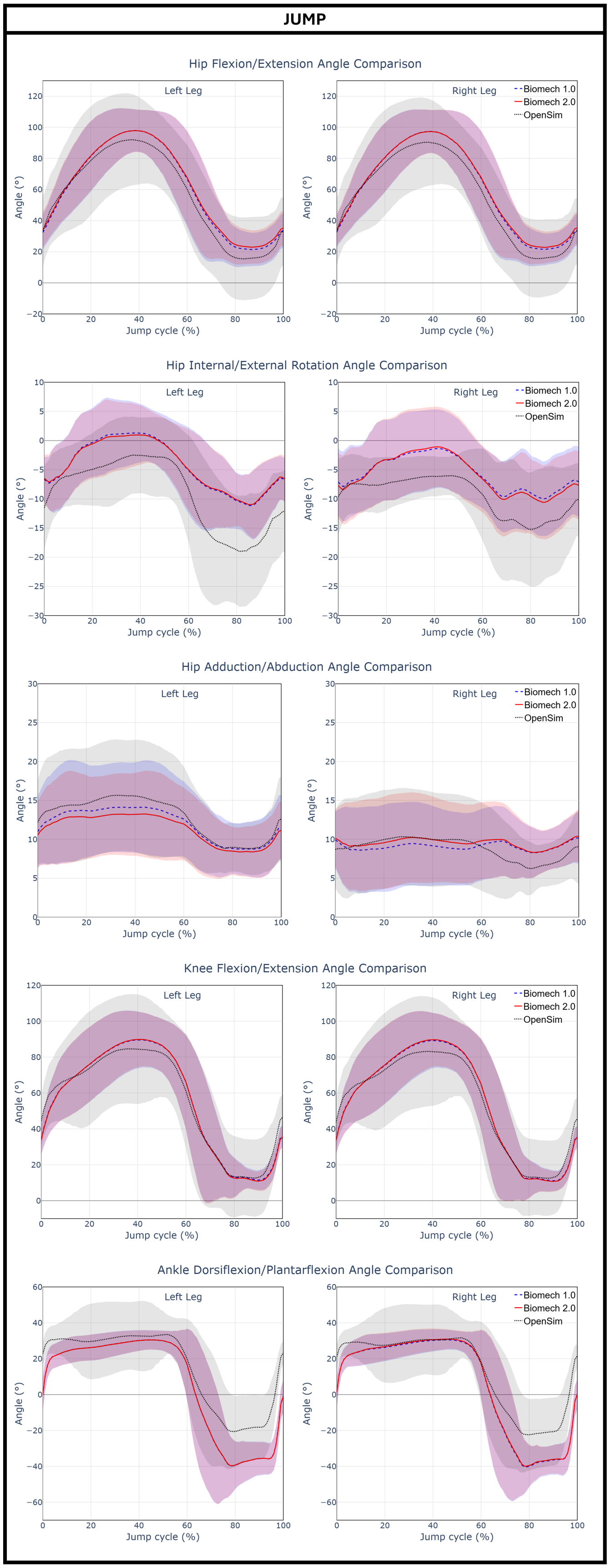

Fig. 9: Mean (line) and standard deviation (shaded area) of the joint angles of both legs for the hip (F/E, A/A, I/E), knee (F/E) and ankle (F/E) for jumping estimated from BM1 (blue), BM2 (red) and optical via OpenSim [7] (black) and expressed as percentage of the jump cycle.

MVN calibration substantially reduced RMSE and increases variability, aligning Xsens MVN outputs more closely with OpenSim estimates. We refer to [3] for more details on the influence of calibration poses on joint kinematics.

TABLE I: RMSE (mean $\pm$ std) and STDE (mean $\pm$ std) in degrees (°) between the joint angles estimated from the Xsens MVN models and OpenSim during walking trials. Each column indicates the joint angles (F/E, A/A, and I/E) of the hip, knee and ankle.

	BM1				
	Hip F/E	**Hip A/A**	**Hip I/E**	**Knee F/E**	**Ankle F/E**
RMSE	14.4 ± 9.9	3.9 ± 1.5	6.7 ± 2.9	5.4 ± 1.8	10.6 ± 3.6
STDE	2.9 ± 0.9	3.1 ± 1.1	4.3 ± 1.3	4.0 ± 1.3	5.1 ± 1.7
	BM2				
	Hip F/E	**Hip A/A**	**Hip I/E**	**Knee F/E**	**Ankle F/E**
RMSE	14.5 ± 10.0	3.8 ± 1.6	6.6 ± 2.8	5.4 ± 1.8	10.8 ± 3.5
STDE	2.8 ± 0.8	3.1 ± 1.1	4.2 ± 1.3	4.0 ± 1.3	5.1 ± 1.7

TABLE II: RMSE (mean $\pm$ std) and STDE (mean $\pm$ std) in degrees (°) between the joint angles estimated from the Xsens MVN models and OpenSim during squat jump trials. Each column indicates the joint angles (F/E, A/A, and I/E) of the hip, knee and ankle.

	BM1				
	Hip F/E	**Hip A/A**	**Hip I/E**	**Knee F/E**	**Ankle F/E**
RMSE	16.9 ± 11.7	4.6 ± 1.9	8.0 ± 4.1	11.6 ± 14.8	15.9 ± 14.0
STDE	11.6 ± 12.4	2.5 ± 1.3	4.9 ± 1.6	11.2 ± 14.9	11.7 ± 14.9
	BM2				
	Hip F/E	**Hip A/A**	**Hip I/E**	**Knee F/E**	**Ankle F/E**
RMSE	17.3 ± 11.4	4.6 ± 1.9	8.0 ± 4.1	11.6 ± 14.9	15.7 ± 13.9
STDE	11.9 ± 12.0	2.5 ± 1.3	5.0 ± 1.7	11.1 ± 15.0	11.7 ± 14.8

2) *Spatial parameters:*

Table III summarizes the accuracy of step length and step width estimates derived from heel markers data during gait cycles, analyzed across all subjects as well as male and female groups separately.

Both Biomech versions overestimate step length, but BM2 demonstrates a marginal, but statistically significant improvement, with errors decreasing from -5.4 $\pm$ 3.6 cm to -5.2 $\pm$ 4.7 cm ($p<0.05$). These improvements were consistent across all subjects. Substantial enhancements were observed in step width estimation, where errors were reduced from 4.0 cm in the BM1 model to 3.5 cm in the BM2 models. Female-specific improvements were particularly pronounced, with a gain of 1 cm (from 3.4 $\pm$ 3.7 cm to 2.4 $\pm$ 3.7 cm).

Despite methodological differences from previous studies [3] — which compared the Xsens MVN gait report with the Vicon plug-in-gait report — BM1's performance aligns with established literature. BM2, however, achieved slightly greater accuracy, particularly in step width estimation, underscoring its advancements in scaling and value of gender-specific body dimensions.

V. Conclusion

This white paper presents a comparative performance evaluation between BM1 - generalized - and BM2 - gender-specific - Xsens MVN biomechanical models, highlighting

TABLE III: Absolute distance (mean ± std) of the step lengths and widths for all three systems over both legs, absolute error (mean ± std) between the optical data and the Xsens MVN models, and the differences (mean ± std) between BM1 and BM2 models in centimeters (cm). The analysis was conducted over all subjects (All), and also for each gender: Females and Males.

Distances (cm)						
	All		**Female**		**Male**	
	Length	**Width**	**Length**	**Width**	**Length**	**Width**
Optical	62.1 ± 5.3	10.1 ± 4.4	61.2 ± 5.8	8.4 ± 4.4	63.0 ± 4.6	11.5 ± 3.8
BM1	67.6 ± 6.3	6.1 ± 2.2	66.8 ± 7.5	5.0 ± 1.6	68.2 ± 5.0	7.0 ± 2.2
BM2	67.4 ± 6.8	6.6 ± 2.1	66.5 ± 8.1	6.0 ± 1.6	68.0 ± 5.4	7.2 ± 2.2
Absolute error/Bias (cm) between optical data and Xsens MVN models						
	Length	**Width**	**Length**	**Width**	**Length**	**Width**
BM1	-5.4 ± 3.6	4.0 ± 3.5	-5.6 ± 4.0	3.4 ± 3.7	-5.3 ± 3.2	4.5 ± 3.3
BM2	-5.2 ± 4.7	3.5 ± 3.6	-5.4 ± 5.4	2.4 ± 3.7	-5.0 ± 4.1	4.3 ± 3.3
Differences between BM1 and BM2 (cm)						
	Length	**Width**	**Length**	**Width**	**Length**	**Width**
1.0 vs. 2.0	1.9 ± 1.9	0.7 ± 0.5	1.7 ± 1.7	1.1 ± 0.2	2.0 ± 2.0	0.2 ± 0.2

overall enhancements in accuracy. While a slight increase of error could be observed for a few parameters in some motions, they reflect the enhanced physiological representation of BM2. Indeed, the most substantial gains achieved by BM2 gender-specific models lie in their enhanced anatomical scaling accuracy and improved precision of upper-body kinematic modeling. By incorporating gender-specific body dimensions, the models have significantly refined arm scaling, which directly impacts accuracy and consistency of inter-hand distances as well as the overall movement precision. Furthermore, the refinement of the spine model made it more physiological correct, improving flexibility and spine range of motion, enhancing the system's ability to reliably capture complex and coordinated upper-body movements. Furthermore, incorporating all subject-specific dimensions significantly enhanced BM2 motion tracking accuracy. These advancements are especially critical for applications requiring high precision and consistency, such as physical therapy, ergonomics, robotics, and personalized motion analysis.

Despite the continued reliance on data from a primarily Caucasian population, the shift toward gender-specific models marks a pivotal advancement in our biomechanical model. While areas for further refinement remain - such as the shoulder model - these improvements represent a substantial step forward in enhancing the Xsens MVN system's performance, accuracy, and reliability. The new Xsens MVN gender-specific models provide a more robust framework, offering more objective assessments tailored to individual needs, paving the way for more precise and inclusive motion tracking in the future.

HIGHLIGHTS

With the introduction of the new BM2 gender-specific models, Xsens MVN enhanced its motion tracking accuracy and consistency with substantial gains in:

- Arm Dimension Accuracy: Arm span errors reduced to $<2.9\%$ (<5 cm) and elbow span errors to $<2.1\%$ (~ 2 cm).
- Clapping Motion Precision: inter-hand distance errors improved by over 40%, now <9 cm.
- Spine Flexibility and Accuracy: Shoulder-to-ground distance improved by ~ 2 cm - with the spine portraying a physiological lumbopelvic rhythm.
- Gait Spatial Parameters: Step width accuracy improved by 0.5 cm overall and 1.0 cm for females.

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