Baseball pitching arm 3-D inertial parameter calculations from body composition imaging and a novel overweight measure for youth pitching arm kinetics

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Many baseball pitching studies have used inverse dynamics to assess throwing arm kinetics as high and repetitive kinetics are thought to be linked to pitching injuries. However, prior studies have not used participant-specific body segment inertial parameters (BSIPs) which are thought to improve analysis of high-acceleration motions and overweight participants. This study's objectives were to 1) calculate participant-specific BSIPs using DXA measures, 2) compare inverse dynamic calculations of kinetics determined by DXA-calculated BSIPs (full DXA-driven inverse dynamics) against kinetics using the standard inverse dynamics approach with scaled BSIPs (scaled inverse dynamics), and 3) examine associations between full DXA-driven kinetics and overweight indices: body mass index (BMI) and segment mass index (SMI). Eighteen participants (10-11 years old) threw 10 fastballs that were recorded for motion analysis. DXA scans were used to calculate participant-specific BSIPs (mass, center of mass, radii of gyration) for each pitching arm segment (upper arm, forearm, hand), BMI, and SMI. The hypotheses were addressed with t-tests and linear regression analyses. The major results were that 1) DXA-calculated BSIPs differed from scaled BSIPs for each pitching arm segment; 2) calculations for shoulder, but not elbow, kinetics differed between the full DXA-driven and scaled inverse dynamics analyses; and 3) full DXA-driven inverse dynamics calculations for shoulder kinetics were more often associated with SMI than BMI. Results suggest that using participant-specific BSIPs and pitching arm SMIs may improve evidence-based injury prevention guidelines for youth pitchers.

Keywords: baseball, biomechanics, pitching, motion analysis, body mass index.

1 Introduction

Over the past few decades, pitching-related injury and surgery rates increased dramatically for youth baseball players [1-2]. Although youth baseball organizations have recently implemented pitch count recommendations and other injury prevention guidelines, injury rates for youth baseball players are not decreasing [3]. Pitching arm injuries are thought to begin during youth play and result from overuse as high and repetitive shoulder and elbow joint kinetics lead to progressive soft tissue damage [2, 4-5]. Common shoulder pitching injuries, for pitchers of all ages, include labrum and rotator cuff strains and tears where higher shoulder internal rotation torque, horizontal abduction torque, and compression force likely lead to increased risk for these injuries [6–8]. Another common shoulder injury found primarily in youth pitchers is proximal humeral epiphysiolysis (also known as little leaguer’s shoulder) which has been linked to shoulder internal rotation torque [4]. An increasingly common elbow injury in youth pitchers is ulnar collateral ligament strain in the elbow joint; high and repetitive elbow varus torques likely lead to increased UCL strain and increased injury risk [9-10]. Thus, improving calculations of injury-related pitching arm kinetic calculations may benefit the continued development of evidence-based injury prevention strategies.

Pitching arm kinetics are commonly calculated using a two-step process. First, kinematic data is collected using motion capture cameras. Second, inverse dynamics is used to calculate elbow and shoulder joint kinetics during the throwing motion. For the inverse dynamics analysis, researchers must provide body segment inertial parameters (BSIPs) for each pitching arm segment (upper arm, forearm, and hand) including masses, centers of mass, and radii of gyration. Prior youth and adult pitching analyses [7-8] used scaled inverse dynamics with BSIPs scaled from total body mass and arm lengths with parameters based on studies of adults with normal physiques [11]. However, prior studies using scaled BSIPs for youth pitchers likely have two major sources of error in their calculated kinetics. First, BSIPs have been shown to differ, on average, between adults and youths (e.g. see [12]). Second, since the pitching arm experiences relatively high accelerations, inverse dynamics calculations of pitching arm kinetics are likely more sensitive to BSIPs than has been found in gait analysis where the legs experience relatively low accelerations. Indeed, prior gait studies reported that participant-specific BSIPs become more important to use when calculating kinetics during the swing phase of gait [13] and running [14] as compared to the stance phase of gait. Therefore, use of BSIPs scaled from adults may introduce considerable errors in inverse dynamics calculations of youth pitching arm kinetics, especially in a participant-specific manner.

A promising tool for obtaining participant-specific BSIPs is Dual energy X-ray absorptiometry (DXA). Indeed, DXA scans have been used in two prior pitching studies. In one study with pitchers aged 10-16 years, DXA-calculated composition measures of the total pitching arm were associated with injury-related pitching kinetics; however, that study appeared to use scaled BSIPs to calculate kinetics [15]. In a second study with pitchers aged 10-11 years, inverse dynamics analyses using DXA-calculated pitching arm segment masses ratios calculated significant increases in shoulder kinetics (up to 15%) when compared to scaled inverse dynamics analyses [16]. However, no prior study of youth baseball pitching kinetics has attempted to calculate a full set of participant-specific BSIPs, which is an objective of this study.

The use of participant-specific BSIPs may be especially important for overweight pitchers, as one study suggested that participant-specific BSIPs are more important to consider for overweight participants [14]. One-third of youths in the United States are overweight or obese [17], and similar trends have been observed in youth baseball players [18]. According to Pitch Smart guidelines [19], overweight measures including body mass and body mass index (BMI) have not been identified as risk factors for pitching injuries. However, there is evidence that being overweight increases injury risk for youth baseball players [20] and other youth athletes [21-22]. Thus, improving our understanding of how overweight or obesity affect pitching arm kinetics through use of participant-specific BSIPs may also benefit the continued development of evidence-based injury prevention strategies.

In a recent study with pitchers aged 10-11 years, pitching arm kinetics were correlated with BMI and total body mass [16]. In earlier studies with pitchers aged 9-16 years, pitching arm kinetics were correlated with total body mass, BMI, and/or total fat and lean arm masses [4, 15, 23]. An advantage to considering BMI is that it is relatively easy to calculate and, thus, highly accessible to players, parents, and coaches. However, BMI may not be the most accurate overweight measure to use because it is the masses (including both lean and fat masses) of only the pitching arm segments that inverse dynamics uses to calculate kinetics. To address that concern, this study introduces a novel overweight measure termed segment mass index (SMI) for investigating relations between body mass and pitching arm kinetics. SMI is defined by the segment mass divided by segment length (kg/m), and thus only depends on the arm segment mass (as opposed to BMI which depends on total body mass).

Thus, this study’s objectives were to 1) calculate participant-specific BSIPs using DXA measures; 2) compare inverse dynamic calculations of joint kinetics determined by those DXA-calculated BSIPs (full DXA-driven inverse dynamics) against kinetics using the standard inverse dynamics approach with scaled BSIPs (scaled inverse dynamics); and 3) examine associations between full DXA-driven kinetics and two overweight indices: body mass index (BMI) and a novel segment mass index (SMI).

The hypotheses were that, for baseball pitchers aged 10-11 years, (1) DXA- calculated and scaled pitching arm BSIPs would differ, on average; (2) injury-related pitching arm kinetics (shoulder compressive force, shoulder internal rotation torque, shoulder horizontal adduction torque, elbow varus torque) calculated by full DXA-driven inverse dynamics and scaled inverse dynamics would, on average, differ; and (3) injury-related pitching arm kinetics calculated by full DXA-driven inverse dynamics would be significantly associated with BMI and/or SMI.

2 Methods

Protocols were approved by our Institutional Review Board and were designed to minimize risks. Youth participants and a parent came to the motion analysis lab on the day of the experiment. Informed consent and participant assent were obtained from the parent and youth participant, respectively. DXA scans and motion analysis data were obtained in conjunction with a prior study [1] and are briefly summarized below.

Participants. Eighteen male participants (age: 10.6 ± 0.5 years, height: 147.8 ± 7.4 cm, body mass: 39.6 ± 7.3 kg, BMI: 18.0 ± 2.2 kg/m^2) with no recent history of pitching-related injuries participated. Only participants who self-reported regular pitching experience in the preceding Little League season were included in the study. Twelve participants were normal weight, five participants were overweight, and one participant was obese (as determined from age-specific BMI charts [24] where 5th percentile to 85th percentile is normal weight, 85th to 95th percentile is overweight, and above 95th percentile is obese). Thus, 33% of participants were overweight which is representative of the target population [18]. Four of the participants were left-handed pitchers.

DXA scans and experiments. After obtaining informed consent and participant assent, each participant completed measurements of body weight and height followed by a DXA scan using a Lunar iDXA scanner (GE Healthcare, Madison, WI, USA). Then, the participant went through a warm-up regimen (including jogging and stretching) and played catch (~25 non-pitching throws) for ~20 minutes in an outdoor area adjacent to the motion analysis lab. In the motion analysis lab, 38 retroreflective markers were placed on the participant based on the Cortex/PitchTrak software marker set (Version 7.4.6, Motion Analysis, Santa Rosa, CA, USA). The markers were separated into two groups: anatomical markers that were placed on specific landmarks and tracking markers that were arbitrarily placed on a segment. For a right handed pitcher the marker set consisted of the following anatomical markers: left acromium, right acromium, right medial scapula, right inferior scapula, left medial scapula, left inferior scapula, left lateral humeral epicondyle, left medial humeral epicondyle, left radial styloid process, left ulnar styloid process, right lateral humeral epicondyle, right medial humeral epicondyle, right radial styloid process, right ulnar styloid process, right asis, sacral, left asis, right lateral femoral epicondyle, right lateral malleolus, right calcaneus, left lateral femoral epicondyle, left lateral malleolus, left calcaneus, right medial femoral epicondyle, right medial malleolus, left medial femoral epicondyle, and left medial malleolus. The tracking markers were the top head, front head, back head, right clavicle, right hand, right thigh, right shank, right toe, left thigh, left shank, and left toe.

Participants pitched off a portable mound (height = 6 in) in the room's center and into a net 23 feet away with a scaled strike zone. Each participant threw 10 fastball warm up pitches followed by 10 fastball pitches at maximum effort that were recorded. Marker trajectories were captured using a motion analysis system (Fig. 1) with 12 cameras and recorded in Cortex analysis software (Motion Analysis) at 200 Hz, interpolated (third-order spline), and filtered (4th order Butterworth filter, cutoff frequency 12 Hz) [25]. Markers fell off the participants during ~15% of the pitches; those pitches were repeated after re-attaching the markers and not counted in the required 10 pitches.

<u>Scaled BSIPs.</u> Scaled inverse dynamics analyses were conducted with PitchTrak's default values for scaled mass ratios, centers of mass, and radii of gyration. Those default parameters were based on values for young adult males from a prior study [11], and which are similar to most prior pitching studies.

<u>DXA-calculated BSIPs.</u> DXA software (GE Healthcare) adds pixel composition measures over a default segmented region (e.g., the total arm) and reports total segment composition parameters (bone mineral content, adipose mass, lean mass). DXA images were manually segmented into the pitching upper arm, forearm, and hand segments with segment boundaries defined as in a previous youth anthropometry study [12] (Fig. 2). The upper arm segment was defined from the shoulder joint center at the humeral head with its surrounding tissue to the elbow joint center at the humeral epicondyle. The forearm segment was defined from the humeral epicondyle to the styloid process. The hand segment was defined from the styloid process to the third metacarpal.

The DXA software's pixel information was exported for further analysis in MATLAB (MathWorks, Natick, MA, USA). DXA scan files contained an array of pixels (0.24 by 0.32 mm) for both bone mineral density and soft tissue content. For this study, a custom MATLAB code was written to calculate arm segment lengths (as distances between the joint centers defined above), mass, center of mass, and radii of gyration for each arm segment. The coordinate system was defined with X as the mediolateral axis, Y as the longitudinal axis, and Z as the anteroposterior axis. The custom code is outlined below for the upper arm (Fig. 3).

1) Each pixel P_i was modeled as a point mass and its mass m_{P_i} was calculated using raw DXA values and packing factors [26]. The packing factors describe the needed conversions to give a two-dimensional pixel density ρ_{p_i} for each pixel in the array. Using the pixel width and height ($P_w,\ P_h$), the pixel mass was calculated using

$$m_{pi} = \rho_{pi} * (P_w * P_h). \tag{1}$$

2) The segment mass M was calculated by summing all pixel masses in the segment using

$$M = \sum m_{pi}. \tag{2}$$

3) The coordinates ($x_{p_{i/0}}, y_{p_{i/0}}$) of each pixel P_i relative to the pixel array origin O (which defaults to the upper left of the array at the first non-zero value) were used to calculate coordinates (x_G, y_G) of the center of mass (G) relative to O using

$$x_G = \sum(m_{Pi} * x_{P_{i/o}})\,/M\ ,\ y_G = \sum(m_{Pi} * y_{p_{i/0}})\,/M. \tag{3}$$

The center of mass was assumed to lie in the X-Y plane ($z_G = 0$) due to the DXA scans 2-D array output. These (x_G, y_G) coordinates defined the origin G of a segment coordinate system with XYZ axes (Fig. 3).

4) The moment of inertia with respect to G about the anteroposterior Z axis (I_z) was calculated using

$$I_Z = \sum(m_{Pi} * d_{Pi/G}^2), \tag{4}$$

where $d_{p_{i/G}}$ was the distance of each pixel from G.

5) The anteroposterior axis radius of gyration (k_z) was calculated using

$$k_Z = (I_Z/M)^{1/2}. \tag{5}$$

The mediolateral axis radius of gyration (k_x) was assumed from symmetry about the Y-axis to be $k_x = k_z$.

6) The longitudinal axis radius of gyration about the Y axis (k_y) for each segment was assumed from previously reported scaling ratios [27] using the relations

$$k_y = 0.55 * k_z \text{ (upper arm)}, k_y = 0.47 * k_z \text{ (forearm)}, k_y = 0.63 * k_z \text{ (hand).} \tag{6}$$

7) The custom code's output variables were formatted per PitchTrak specifications [11]. Segment masses were converted to mass ratios by dividing by total body mass. The mass of the ball (147 grams) was accounted for in the hand mass ratio. Centers of mass were calculated relative to the proximal joint center, and radii of gyration were converted to ratios by dividing by segment length.

Code verification. The custom MATLAB code was verified using an alternative code developed independently by another research group (represented as co-authors on this study). That research group had previously developed a similar pixelated 2-D MATLAB approach to post-process raw iDXA data to calculate one moment of inertia of a body segment for a study published on BSIPs of Paralympic athletes [28]. For code verification, the other research group used both their alternative code and the code developed for this study to obtain upper arm segment BSIPs for four of their participants.

Kinetics. The range of motion analyzed was from front foot contact to ball release. Foot contact and ball release were determined from visual inspection of the video frames to be the time points when the heel stops moving in an anterior direction and when the throwing arm wrist initiates a sudden and large pronation, respectively. Those methods were validated for a prior study [16] using pilot experiments with a force plate (to identify foot contact) and a reflective ball (to identify ball release). All kinetics were calculated in PitchTrak, with the pitching arm BSIPs dependent on the specific inverse dynamics analysis. Since processing the kinematic data is very time consuming, only the last 3 pitches with usable data were analyzed independently to obtain averaged kinetic values. Analyzed kinetic parameters included maximum values of shoulder compressive force, shoulder internal rotation torque, shoulder horizontal adduction torque, and elbow varus torque (Fig. 4). Kinetic parameters were expressed as internal joint loads (e.g., an external elbow valgus torque produces an internal varus torque generated by tissues including the ulnar collateral ligament [29]).

Statistics. All statistical analysis was performed in MiniTab 19.2 (Minitab, United Kingdom). To assess differences between DXA-calculated and scaled BSIPs, one-sample t-tests were performed after investigating normality assumptions using the Shapiro-Wilks test. The full DXA-driven longitudinal radius of gyration for the forearm and the full DXA hand mass ratios were found to be non-normal distributions and were analyzed using Wilcoxon Signed Rank Tests with a significance level of 0.05. Since there were six parameters (one mass, two center of mass coordinates, three radii of gyration) for each of the three arm segments, resulting in 18 separate tests, a Bonferroni adjusted significance level of 0.0028 was used for each one sample t-test. To assess differences between upper arm BSIPs calculated from the alternative code and the code developed for this study, paired t-tests were performed with a significance level of 0.05.

All kinetic data normality assumptions were investigated using Shapiro-Wilks tests and found to be normal. Thus, to assess differences between kinetics calculated by the full DXA-driven and scaled ID analyses, paired t-tests were performed for each kinetic parameter. Since there were four kinetic parameters, resulting in four separate tests, a Bonferroni adjusted significance level of 0.0125 was used for each paired t-test.

Linear regression models were performed to examine the associations between each of three shoulder kinetic parameters calculated by full DXA-driven inverse dynamics and BMI (three models) and Total Arm SMI (three models). Total arm SMI was defined by total arm mass divided by total arm length (kg/m). Several other SMI formulae were considered (see Discussion for more details). Also, linear regression models were performed to examine associations between elbow varus torque calculated by full DXA-driven inverse dynamics and BMI (one model) and Lower Arm SMI (one model). Lower Arm SMI was defined similarly to Total Arm SMI but using only lower arm plus hand mass and length. 8 total linear regressions were run, and regression model significance was determined if the F-test p-value was less than 0.006.

3 Results

Code verification found averaged upper arm masses calculated by the alternative code to be 2.980 ± 0.430 kg while masses calculated from the code developed for this study were 2.975 ± 0.452 kg. Also, upper arm moments of inertia about the anteroposterior axis were 0.022 ± 0.004 N-m as calculated by the alternative code and 0.020 ± 0.005 N-m by the code developed for this study. Paired t-tests indicated that the two codes did not calculate different upper arm masses (p=0.73) or moments of inertia (p=0.16).

DXA and scaled BSIP ratios differed for each arm segment (Table 1). For the upper arm, DXA mass ($p<0.001$), longitudinal and sagittal center of mass coordinates ($p<0.001$), and transverse, longitudinal, and sagittal radii of gyration ($p<0.001$) were greater than their respective scaled parameters. For the forearm, DXA mass ($p<0.001$) and sagittal center of mass coordinate ($p<0.001$) were greater than their respective scaled values. For the hand, DXA mass ($p<0.001$), longitudinal and sagittal center of mass coordinates ($p<0.001$), and sagittal and longitudinal radii of gyration were less than their respective scaled parameters ($p<0.001$).

Shoulder kinetic parameters (Table 2) varied between full DXA-driven inverse dynamics and scaled inverse dynamics for compressive force ($p<0.001$), internal rotation torque ($p<0.001$), and horizontal adduction torque ($p<0.001$). For all three shoulder kinetic parameters, full DXA-driven inverse dynamics calculated higher mean values as compared to scaled inverse dynamics: 14% higher for shoulder compressive force, 31% higher for shoulder internal rotation torque, and 47% higher for horizontal adduction torque. Elbow varus torque calculations did not differ between the inverse dynamics models.

For the four kinetic parameters, only shoulder internal rotation torque ($p=0.005$) was positively associated with BMI (Table 3). Also, only shoulder compressive force ($p=0.002$) and internal rotation torque ($p=0.004$) were positively associated with total arm SMI. For all four kinetic parameters, the correlations (represented by the R^2 values) were higher in models with SMI than with BMI.

4 Discussion

There were several novel features of this study. First, DXA scan data were used to calculate a complete set of participant-specific pitching arm BSIPs. Second, those BSIPs were used with a full DXA-driven inverse dynamics analysis to calculate pitching arm kinetics. Third, the inverse dynamics results were used to analyze associations between injury-related pitching arm kinetics and a novel overweight measure, SMI, which was proposed as a new overweight-related measure for investigating relations between body mass and pitching arm kinetics.

The results supported the first hypothesis as DXA-calculated BSIPs differed from standard scaled BSIPs. One explanation for that result is that scaled values were based on adults and it has been previously reported that child and adult anthropometric parameters differ [16]. Upper-arm BSIPs presented the greatest differences, presumably due to the DXA segment definition of the upper arm, which agrees with some previous studies [12, 16] (but not others [11, 27]) that included upper arm mass proximal to a transverse plane through the shoulder joint center. Including the additional upper arm mass resulted in several changes relative to scaled BSIPs. First, the upper arm's DXA mass was higher than its scaled mass. Second, the DXA center of mass shifted toward the proximal endpoint and was likely the cause of the lower longitudinal center of mass ratio. Third, the DXA center of mass shifted off the longitudinal axis in a medial direction. Fourth, the DXA upper arm radii of gyration were higher than scaled values, due to the fact that the additional upper arm mass shifts the mass concentration away from the origin. For the forearm, the mediolateral center of mass locations differed as the DXA calculations did not assume they lie along the longitudinal axis. For the hand, the DXA mediolateral and longitudinal center of mass locations and mediolateral and longitudinal radii of gyration were less than their respective scaled values.

The results supported the second hypothesis as full DXA-driven inverse dynamics and scaled inverse dynamics calculated different shoulder, but not elbow, kinetics. In particular, shoulder kinetic parameters were higher when using full DXA-driven inverse dynamics. An explanation for that finding is that the scaled inverse dynamics analyses of this and previous studies [11, 26-27] used upper arm mass and radii of gyration that were lower than values used in the full DXA-driven analysis. The inverse dynamic analysis that PitchTrak uses calculates joint loads and torques by going from the distal to the proximal joint centers, where the calculated kinetics at each joint center (elbow and shoulder) are then dependent only on the BSIPs for the segments distal to that joint. Thus, the upper arm BSIPs contribute to only the shoulder joint kinetics. The additional upper arm mass included tissues surrounding the shoulder that appear to rotate around the shoulder joint center during the pitching motion. Since including that mass in the definition of the upper arm segment increased calculated shoulder kinetics values, future pitching studies of shoulder kinetics should carefully consider how the upper arm segment is defined.

The results supported the third hypothesis as shoulder, but not elbow, kinetics were associated with BMI and SMI. The positive associations between shoulder compressive force and internal rotation torque with BMI and/or SMI generally agreed with previous studies that have reported relations between kinetics and BMI [16, 30]. However, a novel feature of this study was the introduction of SMI as an overweight measure for pitching analyses. Interestingly, shoulder compressive force was significantly associated with SMI but not BMI (after Bonferroni adjustment for multiple tests). This is likely because the SMI definitions only considered the pitching arm segment masses, which are the only mass parameters used for inverse dynamics analyses. Intuitively, this finding agrees with the observation that, in the inverse dynamics approach, shoulder kinetics depend directly on upper arm, forearm, and hand masses and not total body mass. Thus, a measure of whether the arm is "overweight" such as SMI should produce stronger associations with kinetics than with BMI, especially when one considers that BMI is largely determined from other segment masses (e.g. trunk and legs) that account for ~90% of total body mass [11]. However, a higher BMI due to excessive adiposity in the trunk and legs may have altered injury-related kinematics and is currently being examined in a follow-up study. Further, it is important to note that correlations between kinetics and body fat percentage were also considered in preliminary statistical analyses for this study. No such correlations were detected and, thus, were not reported here. Those results reinforce the idea that measures based on total mass, and not lean or fat mass separately, appear to be best for predicting pitching arm kinetics – which agrees with several previous studies that have also considered relations between total, fat, and/or lean masses and pitching arm kinetics [15, 16].

This study provides several implications for youth baseball players. Common pitching injuries include shoulder rotator cuff and labrum injuries, which have been linked to high shoulder horizontal abduction torque, internal rotation torque, and compression force [6, 31–33]. Thus, a clinically relevant result was that the full DXA-driven inverse dynamics method calculated higher shoulder kinetics when compared to scaled inverse dynamics. The use of participant-specific BSIPs likely leads to more accurate calculations of injury-related pitching arm kinetics and, thus, may lead to an improved understanding of injury risk factors. Moreover, when participant-specific accuracy is the focus of a pitching biomechanics study, full DXA-driven inverse dynamics becomes more imperative as differences between full DXA-driven and scaled inverse dynamics kinetics on a participant-specific basis were as high as 76% for shoulder internal rotation torque and 25% for elbow varus torque.

Another clinically relevant result was that, for pitchers aged 10-11 years, shoulder compressive force and internal rotation torque were significantly associated with BMI and/or SMI. During the past three decades, prevalence rates of childhood and adolescent obesity have more than doubled in the United States [34]. Overweight and obesity prevalence in youth baseball is similar to the general youth population [18, 35-36], but that prevalence is higher than most other youth sports [20, 37-38] likely due to the sport containing relatively low vigorous activity and caloric expenditures [35, 39] and an unhealthy food culture [40]. While BMI appears to be a reliable predictor of injury-related kinetics in youth pitchers [15, 30], a recent study found that shoulder kinetics were much more strongly correlated with arm mass than total body mass [16]. Accordingly, SMI, which considers just the total arm mass, appears to be an overweight measure that is an even better predictor of injury-related pitching arm kinetics than BMI. Thus, pitchers with higher SMI, whether due to excessive fat or muscle mass, may be at more risk for shoulder injury.

One limitation of the current study is that DXA data provides 3-D mass data within a 2-D image of the coronal plane by condensing the density data along the anterior-posterior axis (Fig. 3) to an average density for that specific pixel, P_i. Therefore, this study had to make assumptions about the 3-D mass distribution in the sagittal and transverse planes. However, it is likely that the DXA-calculated BSIPs were more accurate than the scaled values due to the use of participant-specific DXA data and the fact that scaled values were based on other limiting assumptions [11]. A second limitation was uncertainty regarding the exponent of the length term used in the definition of SMI. SMI was defined in a manner analogous to BMI and, thus, quantified whether the pitching arm segment was "overweight." More specifically, SMI was defined by total segment mass divided by total segment length. For BMI (body mass divided by height squared), the exponent on height is two and was chosen so that BMI is an index for excessive adiposity of the total body. In contrast, here the SMI parameter was defined to be an overweight measure of the pitching arm, including both lean and fat mass, that correlates with pitching arm kinetics. For this study, we examined three other choices of exponents, and found that an exponent of 1 was best correlated (due to lowest p-values) of pitching arm kinetics.

A third limitation is that calculating BSIPs using DXA data is challenging, time consuming, and requires a DXA scan of each participant. There are two other approaches that might be attractive for future studies with youth pitchers. One approach (referred to as DXA scaled inverse dynamics below) would be to use the new mean BSIPs reported here as scaling ratios in a standard scaled inverse dynamics approach. Another approach (referred to as DXA mass inverse dynamics below) would be to use the DXA approach, but to only calculate segment masses after the custom segmentation step while continuing to use other published values for the other BSIPs. For this study, obtaining the segment masses was relatively straightforward as the only additional step was to manually perform the custom segmentation in the DXA software; then, the DXA software automatically calculated and displayed those segment masses.

To assess those alternative approaches, we calculated the kinetic parameters using DXA scaled and DXA mass inverse dynamics analyses, and then performed paired t-tests to investigate for differences between those kinetics and the kinetics calculated using the full DXA-driven inverse dynamics approach (Table 2). Using DXA scaled inverse dynamics, the results (mean ± standard deviation) for shoulder compressive force, shoulder internal rotation torque, shoulder horizontal adduction torque, and elbow varus torque were (276 ± 82 N-m), (18.2 ± 6.5 N-m), (40.8 ± 23 N-m), and (11.7 ± 2.7N-m), respectively, and the corresponding t-test p-values were 0.976, 0.795, 1.000, and 0.619, respectively. Thus, there were no differences detected between the DXA scaled and full DXA-driven inverse dynamics analyses. Using DXA mass inverse dynamics, the results (mean ± standard deviation) for shoulder compressive force, shoulder internal rotation torque, shoulder horizontal adduction torque, and elbow varus torque were (258± 63 N-m), (15.2± 4.6 N-m), (29.1± 12 N-m), and (11.8± 2.5 N-m), respectively, and the corresponding t-test p-values were 0.004, <0.001, <0.001, and 0.794, respectively. Thus, there were differences detected between the DXA scaled and full DXA-driven inverse dynamics analyses for the shoulder, but not elbow, kinetics.

Thus, these additional analyses suggest that for studies involving groups of youth pitchers, future studies may consider utilizing the average BSIPs from Table 1 or an alternate set of BSIPs that are both age-specific and that include the shoulder joint mass in the definition of the upper arm segment. However, it is emphasized that if the focus is on individual participants, full DXA-driven inverse dynamics likely leads to greater accuracy as differences between full DXA-driven and DXA scaled inverse dynamics ranged from -30 to 89 percent depending on kinetic parameter and participant.

In summary, this study was the first to investigate youth pitching arm kinetics calculated with a complete set of 3-D participant-specific and DXA-calculated BSIPs for the pitching arm. Novel results for youth pitchers were that (1) DXA-calculated BSIPs were different from scaled BSIPS, (2) full DXA driven inverse dynamics calculated higher shoulder kinetic parameters than scaled inverse dynamics, and (3) full DXA-driven inverse dynamics calculations for shoulder kinetics were more often associated with SMI than BMI. These novel results suggest that full DXA-driven inverse dynamics more accurately calculates shoulder kinetics than scaled inverse dynamics for youth baseball pitchers. Furthermore, this study introduced a new parameter, SMI, that appears to be an overweight measure that better correlates with injury-related pitching arm kinetics than total body BMI.

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Tables

Table 1 - Scaled and DXA upper arm, forearm, and hand segment inertial parameter ratios; mean ± 1 SD values shown. One sample t-tests were run to compare the scaled and DXA inertial values.

	Mass (%)		**Mediolateral Center of Mass (%)**	
	Scaled	**DXA**	**Scaled**	**DXA**
Upper Arm	2.71	3.34 ± 0.26[*]	0	7.65 ± 1.49[*]
Forearm	1.62	1.51 ± 0.11[*]	0	4.32 ± 1.97[*]
Hand	0.61	0.66 ± 0.05[*]	0	6.22 ± 4.14[*]
	Longitudinal Center of Mass (%)		**Mediolateral Radius of Gyration (%)**	
Segment	Scaled	DXA	Scaled	DXA
Upper Arm	57.7	41.3 ± 2.10[*]	28.5	33.8 ± 1.58[*]
Forearm	45.7	46.0 ± 2.51	27.6	27.1 ± 1.39
Hand	79.0	70.6 ± 6.17[*]	62.8	53.9 ± 4.87[*]
	Longitudinal Radius of Gyration (%)		**Anteroposterior Radius of Gyration (%)**	
Segment	Scaled	DXA	Scaled	DXA[b]
Upper Arm	15.8	18.7 ± 0.68[*]	26.9	33.8 ± 1.23[*]
Forearm	12.1	12.6 ± 0.96	26.5	27.1 ± 1.39
Hand	40.1	33.8 ± 4.39[*]	51.3	53.9 ± 4.87

Note. Segment masses are relative to body mass. Center of mass locations and radii of gyration are relative to segment length. Anteroposterior center of mass location assumed on the longitudinal axis through the center of mass. [b] Scaled from McConville et al.[27] [*] = significant difference compared against scaled value, $p<0.001$

Table 2 - Shoulder and elbow kinetics calculated using scaled and full DXA-driven inverse dynamics; mean ± 1 SD values shown. Paired t-tests were used to compare the kinetics calculations.

Shoulder	**Scaled ID**	**Full DXA-driven ID**
Compressive force (N)	245± 56	279± 74*
Internal rotation torque (N-m)	14.4± 4.1	18.9± 6.3*
Horizontal adduction torque (N-m)	27.8± 11	40.9± 22*
Elbow		
Varus torque (N-m)	11.6±2.4	11.8± 2.8

Note. *=significant difference when compared to the scaled ID value, p<0.001.

Table 3 - Simple linear regression results of full DXA-driven inverse dynamics shoulder and elbow kinetics vs. BMI and SMI; R^2 and p-values shown. Total Arm SMI was used for shoulder kinetics and Lower Arm SMI was used for elbow kinetics.

	BMI		**SMI**	
Shoulder	R^2	p-value	R^2	p-value
Compressive force (N)	0.39	0.040	0.46	0.002^*
Internal rotation torque (N-m)	0.24	0.005^*	0.41	0.004^*
Horizontal adduction torque (N-m)	0.27	0.028	0.29	0.020
Elbow				
Varus torque (N-m)	0.05	0.375	0.10	0.191

Note. *=significant correlation; $p<0.006$ defined significance.

Figures

Figure 1 - Participant pitching off portable pitching mound with retroreflective markers to capture kinematic data and 1 of 12 motion analysis cameras shown.

Figure 2 - (Left) bone mineral density (BMD) and (right) soft tissue image of a youth participant. BMD scan: higher grayscale intensity indicated higher bone density. Soft tissue scan: higher grayscale intensity indicated lower body fat percentage. Regions 1 and 4 represent hands, regions 2 and 5 represent forearms, and regions 3 and 6 represent upper arms.

Figure 3 – Axes and distances used for inertial parameter calculations of the upper arm. (Left) Axes centered at mass center (G): longitudinal Y-axis through elbow (EJC) and shoulder (SJC) joint centers, medial X-axis directed through elbow epicondyles but located at G, anterior Z-axis (not shown). O = pixel array origin, P_i = arbitrary pixel. (Right) Coordinates ($x_{p_{i/0}}, y_{p_{i/0}}$) of P_i relative to O and distance $d_{p_{i/G}}$ of P_i relative to G.

Figure 4 - Schematic of PitchTrak angle definitions used for torque directions for a right-handed pitcher. Angles of 0 degrees correspond to the neutral position. Angles of +90 degrees correspond to upper arm internal and horizontal adduction rotations and forearm varus rotation. For shoulder internal rotation and horizontal adduction torques, the circular arrows represent the directions of internal torques applied to the upper arm segment at the shoulder joint. For elbow varus torque, the circular arrow represents the direction of internal torque applied to the forearm segment at the elbow joint.