



Prediction models for the cross-sectional areas of lower lumbar intervertebral discs and vertebral endplates

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ABSTRACT

Current approaches to obtain lumbar morphometry data usually require expensive medical imaging technology, long processing time, and are often limited by small sample size. This study develops regression models for the cross-sectional areas (CSAs) of the lower lumbar (i.e., from L3/L4 to L5/S1 level) intervertebral discs (IVDs) and vertebral endplates (EPs) using both simple and complex anthropometric variables. CSAs were measured using OsiriX[®] software, based on 3T magnetic resonance imaging (MRI) scans from a sample of 13 females and 22 males, aged between 20 and 40, and asymptomatic of low back disorders. Comprehensive body anthropometry data were collected and included in the regression analyses. Several multiple regression models were developed with varying levels of complexity. Subject stature, elbow dimensions, and ankle dimensions were statistically significant predictors for the CSAs of IVDs and EPs. Gender exhibited a more predictive relationship with the CSAs when compared to body weight and age. In general, regression models using newly proposed best subset procedure resulted in smaller prediction errors, compared to the models using easy-to-measure variables (i.e., gender, age, height, and weight). However, simple regression models are still worthy of investigation given the low cost, ease of data collection, and satisfactory model performance.

1. Introduction

One of the most challenging issues for ergonomics practitioners in workplaces has been the reliable estimation of the risk of work-related low back pain (WLBP) (Andersson, 1979, 1998; Garg and Moore, 1992). To date, a number of ergonomic evaluation tools have been developed to pinpoint manual jobs with elevated risk (NIOSH, 1981; Waters et al., 1993; Moore and Garg, 1995; Blosswick and Villanve, 2000; Waters et al., 2015; Garg and Kapellusch, 2016; Gallagher et al., 2017), primarily relying on biomechanical models of the human spinal musculoskeletal structure to characterize the influence of various body postures and external loadings (Chaffin, 1969; Schultz et al., 1982a,b; Chaffin, 1988; Marras and Sommerich, 1991a,b). Biomechanical models need to employ human models of trunk musculature and structure (McGill and Norman, 1985; Németh and Ohlsén, 1986; Jorgensen et al., 2001; Marras et al., 2001) as well as mathematical representations of the human spine (Fisher, 1967; Chaffin, 1969; Sicard and Gagnon, 1993; Chen, 1999; Campbell-Kyureghyan et al., 2005) in

order to comprehensively and accurately translate the influence of body postures and external loadings into the internal response/loading of the lumbar spine. The model output, as muscle induced compressive forces, is then related to the physiological responses and the ultimate strength of the lumbar motion segments (Evans and Lissner, 1959; Sonoda, 1962; Eie, 1966; Hutton and Adams, 1982; Jäger and Luttmann, 1989), which leads to the estimation of the WLBP risk.

Contrary to the well-developed models of human trunk musculature (Gungor et al., 2015a,b), the significance of the spinal morphometry has not yet been thoroughly investigated and incorporated into the development of biomechanical models (Tang et al., 2016). As a major component of a single-level spinal motion segment, the intervertebral disc (IVD) connects two vertebral bodies together, forming the main joints of the spinal column and providing spine the mechanical properties necessary to perform complex movements, such as flexion and rotation (Ferguson and Steffen, 2003; Raj, 2008). The mechanical properties of a lumbar motion segment are largely determined by its structural integrity in terms of the mode and magnitude of loading

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transmitted from one segment to another (Adams et al., 1980; Adams and Hutton, 1981). A number of studies have reported that for a lumbar motion segment, its bone mineral content (BMC), as a function of the bone mineral density (BMD) and the cross-sectional area (CSA) of the load-bearing surface, can be used to predict its ultimate compressive strength (Biggemann et al., 1988; Brinckmann et al., 1989; Singer et al., 1995; Gallagher et al., 2007). Using animal specimens, some researchers reported a linear relationship between the CSAs of the vertebral endplate (EP) and the ultimate compressive strengths of the spinal segments (Parkinson et al., 2005). Such evidence suggests that biomechanical models that account for the influence of the lumbar load-bearing surface size (primarily the IVD and EP) on the mechanical capacity of the motion segment may improve the WLBP risk estimation. More importantly, it may be feasible to estimate the risk on an individual basis (Barim et al., 2019), rather than on a population basis, which may alter the WLBP risk evaluation paradigm by providing more personalized models (Sesek et al., 2014; Tang, 2013).

Unfortunately, morphometry of the human lumbar spine in transverse section has typically been obtained, via cadaveric specimens (Nachemson, 1960; Hansson et al., 1980; Hutton and Adams, 1982; Postacchini et al., 1983; Berry et al., 1987; Brinckmann et al., 1989; Panjabi et al., 1992) and in vivo primarily using medical images, including radiographs (Nissan and Gilad, 1984; Amonoo-Kuofi, 1991; Aydinlioglu et al., 1999; Wang et al., 2012), computed tomography (CT) scans (van Schaik et al., 1985; Colombini et al., 1989; Zhou et al., 2000; van der Houwen et al., 2010; Chen et al., 2011), and magnetic resonance imaging (MRI) scans (Aharinejad et al., 1990; Tang et al., 2016). Although these techniques can provide accurate morphometric assessment, they are expensive to use. In addition, they require restrictive measurement protocols and long processing time. Therefore, it is typically financially impractical to rely on these techniques to determine an individual's specific spinal morphometry when evaluating the personalized risk of WLBP.

In the literature, few studies have attempted to develop regression models using anthropometric variables to estimate the sizes of the lower lumbar IVDs, as a non-invasive and indirect method (Colombini et al., 1989; Turk and Celan, 2004), while others have failed to establish any predicative relationships for the lumbar EPs (Seidel et al., 2008). This inconsistency may be explained by the fact that these studies were limited to relatively small sample sizes and employed different and non-standardized measurement protocols to obtain the spinal morphometry data (Tang et al., 2016). In addition, some of these anthropometric characteristics (e.g., knee and ankle diameter) may require special anatomical knowledge and technique to obtain and may not be straightforward enough for many ergonomics practitioners to reliably measure. Therefore, the present study included a larger sample size and used a more reliable and repeatable measurement protocol to obtain geometric data for the predictions of the CSAs of the lower lumbar IVDs and EPs (Tang et al., 2016). The aim of this study was to perform morphometric analyses of the CSAs of lower lumbar IVDs and EPs, develop regression models using both simple and complex anthropometric variables, and compare the performances of these models.

2. Material and methods

2.1. Subjects

A total of 35 subjects (22 males and 13 females) were included in the present study. All subjects were in good health and between 20 and 40 years of age. At the time of study, no subjects had any self-reported episodes of low back pain (LBP) for the previous two years and no previous medical treatment for low back pain (i.e., surgical procedures). In addition, subjects with chronic leg or foot pain were also excluded, since these symptoms might be related to nerve compression in the lower lumbar region. The Institutional Review Board (IRB) approved the study protocol.

2.2. Acquisition of MRI scans

Lower lumbar MRI scans (L3/L4 to L5/S1) of the subjects were performed using a 70 cm Open Bore 3T scanner (MAGNETOM Verio, Siemens AG, Erlangen, Germany) at the Auburn University MRI Research Center. All subjects were examined in head-first-supine position (HFS) with arm and leg supports available upon request. The imaging protocols included:

1. A standard morphological T2-weighted turbo-spin-echo (TSE) sequence in the mid-sagittal plane, including at least from L2 to S1, with a repetition time (TR) of 4400 ms, an echo time (TE) of 100 ms, and a matrix of 384×288 . The section thickness was 4.5 mm and the voxel size was $0.78 \text{ mm} \times 0.78 \text{ mm} \times 4.5 \text{ mm}$.
2. A standard morphological T2-weighted TSE sequence of the lower lumbar intervertebral discs and vertebral endplates in the axial plane, with a TR of 7880 ms, a TE of 94 ms, and a matrix of 320×240 . The section thickness was 3 mm and the voxel size was $0.69 \text{ mm} \times 0.69 \text{ mm} \times 3 \text{ mm}$. The axial slicing planes were manually adjusted according to the orientation of the structures of interest (Fig. 1) to minimize errors and distortions in spinal structure reconstruction. For each lower lumbar level, at least three MRI scans were obtained with respect to the IVD and the cranial (CrEP) and caudal (CaEP) endplates (Fig. 1).

All MRI scans were anonymized and stored in the picture archiving and communication system (PACS; Siemens Healthcare Global), and then transferred to a local workstation through a secure file sharing system: Auburn University Network (AUNET) (Auburn University, Auburn, AL, USA).

2.3. Measurements of the CSAs of the IVDs and EPs

Axial MRI scans were analyzed using an open-source, digital imaging and communications in medicine (DICOM) software, OsiriX[®] (version 4.1.1, 32-bit) (Rosset et al., 2004). At each level, CSA measurements were taken for each IVD and its adjacent CrEP and CaEP by manually identifying and tracing the actual contour of the structures (Tang et al., 2016). Measurements were taken only in oblique slices to minimize distortions.

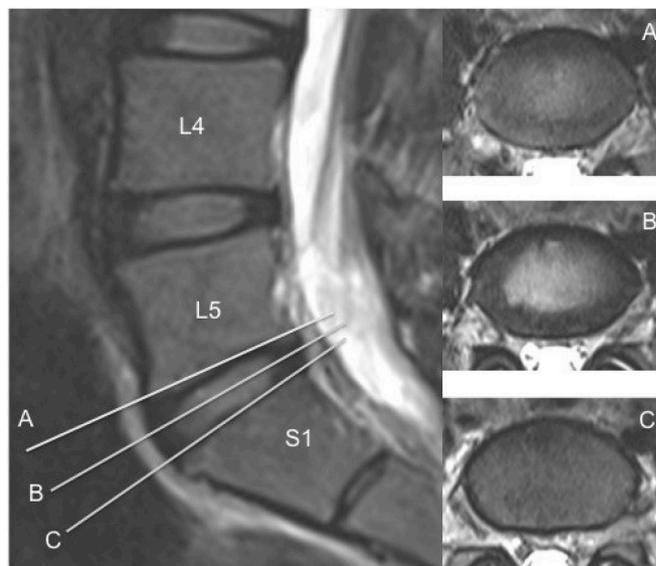


Fig. 1. T2 weighted MRI scan of the anatomical structures of interest: A) cranial endplate, B) intervertebral disc, and C) caudal endplate.

2.4. Disc degeneration

The Pfirmann grading system (Pfirmann et al., 2001) was applied to assess all IVDs for health status to exclude geometric data associated with Grade V IVDs from the final analysis due to the collapsed intradiscal space.

2.5. Anthropometric measurements

Anthropometric variables were measured while subjects were wearing sports clothing (e.g., shorts, t-shirts, or compression clothing). Subject weight (Wt) was measured using metric (kg) units. Other anthropometric variables were measured using an anthropological instrument kit (GPM, Switzerland). An anthropometer was used to measure subject height (Ht), sitting height (H_{sitting}), chest breadth (B_{chest}), chest depth (D_{chest}), shoulder width (W_{shoulder}), head depth (D_{head}), and arm length (L_{arm}). Sliding (Martin type) and spreading calipers were used to measure the widths (W) of the head, elbows, wrists, hands, and knees as well as the lengths (L) of both hands. Circumferences (C) of the head, elbows, wrists, hands, knees, and ankles were measured using a Gulick anthropometric tape. Subject head dimensions as well as H_{sitting}, B_{chest}, and D_{chest} were measured while subjects were seated with both feet flat on the floor and knees flexed at 90°. The remaining variables were measured while subjects were in an erect position (i.e., standing upright). Fig. 2 illustrates the anthropometric measurement protocol.

Subject body composition was estimated using a calibrated Lange Skinfold Caliper (Beta Technologies, Santa Cruz, CA, USA) in accordance with the American College of Sports Medicine three-site protocol (ACSM, 2009), resulting in estimations of subject body fat percentage (BFP), lean body mass (LBM), and fat weight (FW).

Based on preliminary analyses, small differences were found

Table 1
Definitions of anthropometric composite index measures.

Index	Combining Variables
I _{Head} (cm ³)	= W _{head} × C _{head} × D _{head}
I _{Chest} (cm ²)	= B _{chest} × D _{chest}
I _{Elbow} (cm ²)	= W _{elbow} × C _{elbow}
I _{Wrist} (cm ²)	= W _{wrist} × C _{wrist}
I _{Hand} (cm ³)	= W _{hand} × C _{hand} × L _{hand}
I _{Knee} (cm ²)	= W _{knee} × C _{knee}
I _{Ankle} (cm ²)	= W _{ankle} × C _{ankle}

between the right and left limb anthropometric variables. However, none of these differences were greater than 2%, nor were they statistically significant (P > 0.05). Therefore, to minimize multicollinearity issues in the regression analyses, the average values of right and left limb variables were used. Since multiple dimensions were measured at the same site, composite *index* measures (Table 1) were proposed as combinations of these variables to represent the anthropometric characteristics of the corresponding body joints and segments in the final regression analyses, while LBM was selected to represent subject body composition.

As proposed by Matiegka (1921) (Equations (1) and (2)) and Turk and Celan (2004) (Equation (3)), three additional composite measures were considered: the average square thickness of bony structures (AST), the bony structure weight (SW), and the modified AST (AST_{Turk}). These were calculated using the average limb variables as shown in Equations (1)–(3).

$$AST = \left(\frac{W_{wrist} + W_{elbow} + W_{knee} + W_{ankle}}{4} \right)^2 \tag{1}$$

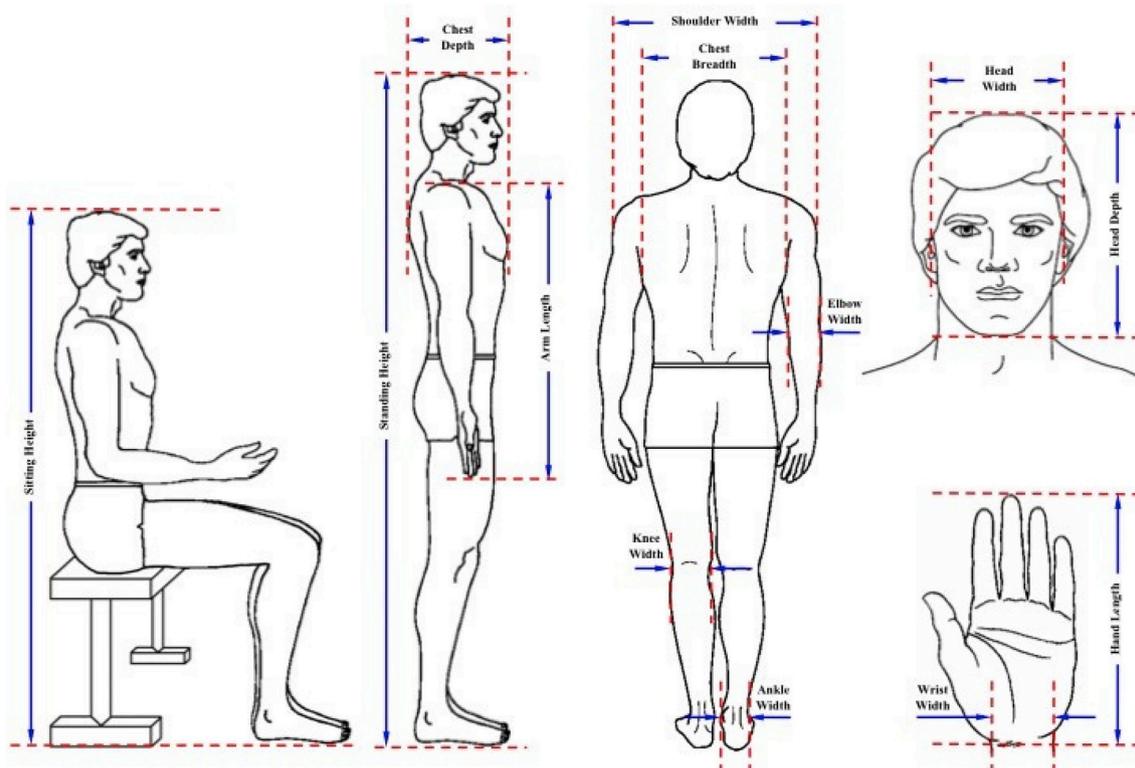


Fig. 2. Anthropometric variables.

$$SW = AST \times Ht \times 1.1 \tag{2}$$

$$AST_{Turk} = \left(\frac{W_{wrist} + W_{elbow} + W_{knee}}{3} \right)^2 \tag{3}$$

2.6. Regressions

Best Subsets Linear Regression (BSLR) analyses were performed to determine the best subsets of predictors for the cross-sectional areas of the intervertebral disc (CSA_{IVD}) and endplates (CSA_{CrEP} and CSA_{CaEP}). In total, there were 15 parameters (14 independent variables and 1 intercept) proposed in this study. This generates a total of 32,767 different regression models when considering each of the three outcomes (i.e., CSAs) at each lower lumbar spinal level. To simplify, this paper presents the five best models for each model size (i.e., number of parameters), from size 2 (one independent variable and one intercept) to size 14, along with the full model (i.e., all 15 parameters). The five best models were determined based on the Akaike Information Criterion (AIC). At each lower lumbar spinal level, there were 66 models developed, corresponding to CSA_{CrEP}, CSA_{IVD}, and CSA_{CaEP}, respectively (see Appendices A through I). These regression models were then evaluated based on their specific model statistics (i.e., adjusted R², residual mean square, Mallows' C_p). In general, a better BSLR model should have a greater adjusted R², a smaller residual mean square, and a Mallows' C_p closer to the model size. In addition to these quantitative metrics, a subjective approach was employed for the purpose of investigating the biological plausibility of regression models and providing more general models for all outcomes. Based on the tendency and/or frequency a variable to appear in the model, variable(s) that were often included in the 66 models were preferred even though the quantitative metrics might suggest otherwise (Tang, 2013). Meanwhile, models with smaller size were preferred over the ones with more variables. In the end, two “optimal” BSLR models were selected and presented for each outcome. For every regression model developed, the corresponding model statistics and coefficients were determined. Linear regression models using only easy-to-measure anthropometric variables (i.e., gender, age, height, and body weight) were also developed using a *stepwise* method with backward elimination approach (i.e., Easy models). In the table, for each regression model, statistically significant predictor(s) and the intercept were highlighted with *italic* and **bold** fonts. Individual regression model performance was evaluated based on mean absolute error (MAE) and root mean squared error (RMSE) calculated by comparing predicted values to the MRI-derived values for all 35 subjects.

Best subset regression analyses were performed using Minitab (version 15, Minitab Inc., State College, PA, USA). Other statistical analyses were performed using SPSS (version 19.0, IBM SPSS Statistics, Armonk, NY, USA). An alpha level of 0.05 was established for all statistical tests.

3. Results

3.1. Descriptive statistics

In total, 315 MRI scans were obtained for this study (105 IVDs and 210 EPs) and no IVDs were scored as Grade V. Tables 2 and 3 present descriptive statistics for the anthropometric variables.

There was not a statistically significant age difference between genders. Female subjects were significantly shorter and lighter than male subjects (P < 0.001). Female subjects, on average, were

Table 2
Descriptive statistics for subject anthropometric variables.

	Gender	N	Mean	SD	Min	Max	P-value
Age (years)	Female	13	25.5	3.6	21	34	0.075
	Male	22	27.8	3.7	22	35	
Ht (cm)	Female	13	160.9	7.8	149.8	180.2	< 0.001
	Male	22	177.1	7.7	162.1	191.0	
Wt (kg)	Female	13	57.2	10.2	45.2	75.4	< 0.001
	Male	22	82.7	10.8	66.8	107.8	
BMI (kg/m ²)	Female	13	22.0	2.6	19.7	27.1	< 0.001
	Male	22	26.3	2.6	21.2	31.6	
BFP (%)	Female	13	25.6	6.7	16.8	34.9	0.002
	Male	22	19.4	4.2	8.9	24.6	
FW (kg)	Female	13	15.1	5.9	8.2	24.6	0.589
	Male	22	16.0	4.1	7.8	26.5	
LBM (kg)	Female	13	42.1	5.7	36.0	55.2	< 0.001
	Male	22	66.7	9.4	53.8	86.6	
H _{sitting} (cm)	Female	13	125.4	4.6	120.6	136.9	< 0.001
	Male	22	131.7	4.0	125.4	140.7	
W _{shoulder} (cm)	Female	13	39.0	3.2	35.3	45.2	< 0.001
	Male	22	46.3	2.5	42.8	51.1	
W _{head} (cm)	Female	13	14.5	0.6	13.7	15.4	< 0.001
	Male	22	15.5	0.7	14.3	17.1	
C _{head} (cm)	Female	13	55.0	2.1	52.2	58.5	< 0.001
	Male	22	57.5	1.6	53.6	60.6	
D _{head} (cm)	Female	13	20.2	0.9	17.9	21.1	< 0.001
	Male	22	22.8	1.3	20.1	24.8	
B _{chest} (cm)	Female	13	28.1	2.0	25.8	32.3	< 0.001
	Male	22	33.2	3.4	29.2	45.4	
D _{chest} (cm)	Female	13	18.4	2.2	14.4	23.5	< 0.001
	Male	22	21.8	2.0	17.5	24.6	

Table 3
Descriptive statistics for the limb variables for both genders.

	Gender	N	Mean	SD	Min	Max	P-value
W _{elbow} (cm)	Female	13	7.5	0.7	6.3	9.0	< 0.001
	Male	22	9.1	0.8	7.1	10.8	
C _{elbow} (cm)	Female	13	22.6	1.6	20.5	25.3	< 0.001
	Male	22	27.4	1.7	24.2	31.3	
W _{wrist} (cm)	Female	13	5.0	0.2	4.5	5.5	< 0.001
	Male	22	5.8	0.3	5.2	6.3	
C _{wrist} (cm)	Female	13	14.6	0.8	13.8	16.2	< 0.001
	Male	22	17.1	0.8	15.4	18.1	
L _{arm} (cm)	Female	13	70.1	4.5	63.6	78.8	< 0.001
	Male	22	79.9	4.6	72.9	89.2	
L _{hand} (cm)	Female	13	16.7	0.8	15.4	18.0	< 0.001
	Male	22	19.3	1.3	16.9	21.9	
W _{hand} (cm)	Female	13	7.3	0.3	6.9	7.8	< 0.001
	Male	22	8.6	0.4	7.9	9.3	
C _{hand} (cm)	Female	13	17.8	0.7	16.9	18.8	< 0.001
	Male	22	21.0	1.0	19.6	22.9	
W _{knee} (cm)	Female	13	9.4	1.1	7.8	11.2	0.002
	Male	22	10.3	0.6	9.4	11.6	
C _{knee} (cm)	Female	13	34.7	3.2	30.4	40.6	0.003
	Male	22	37.5	2.0	33.4	41.3	
W _{ankle} (cm)	Female	13	6.3	0.4	5.8	7.3	< 0.001
	Male	22	7.4	0.3	6.9	7.9	
C _{ankle} (cm)	Female	13	22.4	1.6	20.5	25.1	< 0.001
	Male	22	26.1	1.3	23.4	28.9	

“normal”, compared to male subjects being “overweight” according to the World Health Organization (WHO) body mass index (BMI) classification. Female subjects had significant higher BFP and less LBM, compared to males (P < 0.05). However, the actual body fat weight

Table 4
Descriptive statistics for the composite anthropometric measures.

	Gender	N	Mean	SD	Min	Max	P-value
I _{Head} (cm ³)	Female	13	16164.2	1452.2	14148.8	18828.8	< 0.001
	Male	22	20261.4	1706.7	17393.0	23101.2	
I _{Chest} (cm ²)	Female	13	521.0	91.1	396.0	728.5	< 0.001
	Male	22	727.7	122.5	530.3	1116.8	
I _{Elbow} (cm ²)	Female	13	171.3	25.2	141.4	227.7	< 0.001
	Male	22	250.0	33.1	188.2	338.0	
I _{Wrist} (cm ²)	Female	13	73.0	7.4	62.1	89.1	< 0.001
	Male	22	98.8	9.5	80.1	113.1	
I _{Hand} (cm ³)	Female	13	2172.1	253.7	1790.5	2571.0	< 0.001
	Male	22	3508.2	492.8	2677.2	4434.2	
I _{Knee} (cm ²)	Female	13	329.3	65.0	237.2	434.4	0.002
	Male	22	389.1	38.6	325.7	460.5	
I _{Ankle} (cm ²)	Female	13	142.5	18.7	118.6	178.9	< 0.001
	Male	22	193.5	16.0	164.6	225.4	
AST (cm ²)	Female	13	50.2	7.1	40.8	62.2	< 0.001
	Male	22	66.6	5.0	57.0	75.7	
AST _{Turk} (cm ²)	Female	13	53.7	8.2	42.0	65.3	< 0.001
	Male	22	70.8	6.3	59.6	85.0	
SW (cm ³)	Female	13	8919.1	1641.4	6884.6	12331.8	< 0.001
	Male	22	12996.9	1300.3	10418.0	15677.7	

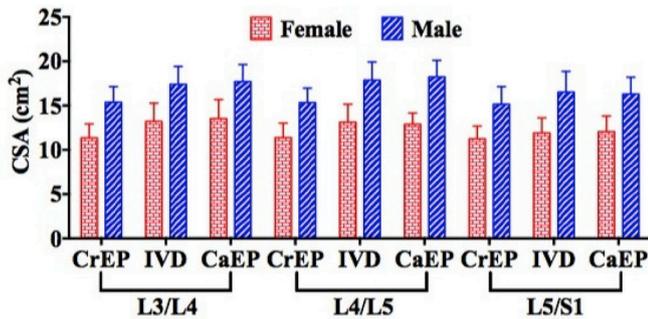


Fig. 3. Mean values of measured CSA_{CrEP}, CSA_{IVD}, CSA_{CaEP} for each gender group.

(FW) was not statistically different between genders ($P = 0.589$). Female anthropometric variables for body segments (Table 2) and limbs (Table 3) were statistically smaller than the corresponding male segments and limbs ($P < 0.05$). As shown in Table 4, female composite anthropometric measures were statistically smaller than the corresponding male ones ($P < 0.05$). Fig. 3 illustrates the mean values of measured CSA_{IVD}, CSA_{CrEP}, and CSA_{CaEP} across all three lower lumbar levels for both genders. Female lower lumbar geometric data were significantly smaller than the corresponding male data ($P < 0.001$).

Table 5
Regression models for the lower lumbar CSA_{IVD}.

Level	Size	Equations for the CSA _{IVD}	ANOVA	R ²	Adj-R ²	S.E.	C _p	AIC
			P-value					
L3/L4	4	$= -18.124 + 0.160 * Ht - 0.022 * I_{Elbow} + 0.065 * I_{Ankle}$	< 0.001	0.862	0.848	1.12	-0.3	11.52
	5	$= -24.434 + 0.110 * Ht - 0.020 * I_{Elbow} + 0.063 * I_{Ankle} + 0.115 * H_{Sitting}$	< 0.001	0.872	0.855	1.09	-0.2	10.83
L4/L5	3	$= -26.782 + 0.253 * H_{Sitting} + 0.058 * I_{Ankle}$	< 0.001	0.850	0.841	1.22	1.0	17.00
	4	$= -25.356 + 0.248 * H_{Sitting} + 0.037 * I_{Ankle} + 0.001 * I_{Hand}$	< 0.001	0.866	0.853	1.17	-0.3	15.00
L5/S1	5	$= -26.736 + 0.254 * H_{Sitting} + 0.054 * I_{Ankle} - 0.029 * I_{Elbow} + 0.002 * I_{Hand}$	< 0.001	0.863	0.844	1.22	3.4	18.52
	6	$= -26.591 + 0.180 * H_{Sitting} + 0.057 * I_{Ankle} - 0.032 * I_{Elbow} + 0.001 * I_{Hand} + 0.062 * Ht$	< 0.001	0.867	0.844	1.22	4.5	19.36

3.2. BSLR models

At each lower lumbar level, two BSLR models were developed to predict the CSA_{IVD} (Table 5), CSA_{CrEP} (Table 6), and CSA_{CaEP} (Table 7), respectively. ANOVA tests (Tables 5–7) revealed that all regression models were significant ($P < 0.001$).

For the CSA_{IVD}, Ht, I_{Elbow}, and I_{Ankle} were statistically significant predictors in both the 4-variable (three independent variables and one intercept) and 5-variable BSLR models at the L3/L4 level. H_{sitting} was not a statistically significant predictor in the 5-variable model. However, the 5-variable model performed better than the 4-variable model, given that R² and adjusted R² values increased from 0.862 to 0.872 and from 0.848 to 0.855, respectively, and the standard error decreased from 1.12 to 1.09. At the L4/L5 level, Ht and I_{Ankle} were statistically significant predictors in both the 3-variable and 4-variable models. The inclusion of the statistically insignificant predictor I_{Hand} slightly improved the performance of the 4-variable model. At the L5/S1 level, H_{sitting}, I_{Ankle}, I_{Elbow}, and I_{Hand} were statistically significant predictors in both the 5-variable and 6-variable models. Both models had relatively equal predictive performance.

For the CSA_{CrEP}, both the 6-variable and 7-variable models included Gender, Ht, I_{Chest}, I_{Ankle}, and I_{Hand} as statistically significant predictors at the L3/L4 level. The 7-variable model slightly outperformed the 6-variable model when I_{Elbow}, a statistically insignificant predictor, was included. At the L4/L5 level, both the 5-variable and 6-variable models shared statistically significant predictors, Gender, Ht, I_{Chest}, and I_{Ankle}. The inclusion of the statistically insignificant predictor H_{sitting} slightly improved model performance. At the L5/S1 level, the inclusion of I_{Wrist}, a statistically insignificant predictor, improved the performance of the 5-variable over the 4-variable model which included statistically significant predictors, Ht, I_{Elbow}, and I_{Ankle}.

For the CSA_{CaEP}, both the 4-variable and 5-variable models included H_{sitting} and I_{Ankle} as the statistically significant predictors and I_{Chest} as a statistically insignificant predictor at the L3/L4 level. I_{Wrist} was not significant alone but was included in the 5-variable model, which outperformed the 4-variable model. At the L4/L5 level, Gender, Ht, and I_{Knee} were statistically significant predictors in both the 4-variable and 5-variable models. With the inclusion of I_{Chest}, a statistically insignificant predictor, the 5-variable model exhibited increases in R² and adjusted R² values and decreased standard error. At the L5/S1 level, the inclusion of additional statistically significant predictor, I_{Elbow}, the 5-variable outperformed the 4-variable model with the same remaining significant predictors, H_{sitting}, I_{Ankle}, and I_{Hand}.

3.3. Easy models

Table 8 lists the regression models developed using only easy-to-measure anthropometric variables to predict the CSA_{IVD}, CSA_{CrEP}, and

Table 6
Regression models for the lower lumbar CSA_{CrEP}.

Level	Size	Equations for the CSA _{CrEP}	ANOVA	R ²	Adj-R ²	S.E.	C _p	AIC
			P-value					
L3/L4	6	= -17.630 + 1.969*Gender + 0.176*Ht - 0.005*I _{Chest} + 0.049*I _{Ankle} - 0.002*I _{Hand}	< 0.001	0.880	0.860	0.97	2.7	3.11
	7	= -18.718 + 2.017*Gender + 0.185*Ht - 0.004*I _{Chest} + 0.052*I _{Ankle} - 0.001*I _{Hand} - 0.010*I _{Elbow}	< 0.001	0.887	0.863	0.96	3.2	3.03
L4/L5	5	= -13.845 + 1.159*Gender + 0.148*Ht - 0.005*I _{Chest} + 0.026*I _{Ankle}	< 0.001	0.864	0.846	0.99	2.0	4.00
	6	= -21.066 + 1.312*Gender + 0.097*Ht - 0.005*I _{Chest} + 0.025*I _{Ankle} + 0.126*H _{sitting}	< 0.001	0.880	0.859	0.95	0.8	1.59
L5/S1	4	= -17.842 + 0.153*Ht - 0.020*I _{Elbow} + 0.056*I _{Ankle}	< 0.001	0.841	0.825	1.09	-2.8	10.02
	5	= -16.224 + 0.136*Ht - 0.025*I _{Elbow} + 0.041*I _{Ankle} + 0.055*I _{Wrist}	< 0.001	0.850	0.830	1.08	-2.2	9.99

Gender: 0 for female, 1 for male.

Table 7
Regression models for the lower lumbar CSA_{CaEP}.

Level	Size	Equations for the CSA _{CaEP}	ANOVA	R ²	Adj-R ²	S.E.	C _p	AIC
			P-value					
L3/L4	4	= -24.405 + 0.248*H _{sitting} + 0.062*I _{Ankle} - 0.004*I _{Chest}	< 0.001	0.858	0.843	1.12	-1.5	11.72
	5	= -21.986 + 0.222*H _{sitting} + 0.038*I _{Ankle} - 0.004*I _{Chest} + 0.063*I _{Wrist}	< 0.001	0.873	0.855	1.08	-2.1	9.84
L4/L5	4	= -10.812 + 2.427*Gender + 0.126*Ht + 0.011*I _{Knee}	< 0.001	0.851	0.834	1.24	1.0	17.18
	5	= -11.070 + 2.929*Gender + 0.134*Ht + 0.014*I _{Knee} - 0.004*I _{Chest}	< 0.001	0.864	0.843	1.21	0.8	16.23
L5/S1	4	= -22.889 + 0.224*H _{sitting} + 0.037*I _{Ankle} + 0.001*I _{Hand}	< 0.001	0.861	0.846	1.09	0.3	9.47
	5	= -25.462 + 0.249*H _{sitting} + 0.045*I _{Ankle} + 0.001*I _{Hand} - 0.018*I _{Elbow}	< 0.001	0.884	0.867	1.02	-1.8	5.64

Gender: 0 for female, 1 for male.

Table 8
Regression models using only easy-to-measure predictors.

Prediction Equation			R ²	Adj-R ²	S.E.	P-value
CSA _{CrEP}	L3/L4	= -10.047 + 0.152*Ht + 1.839*Gender - 0.119*Age	0.808	0.789	1.19	< 0.001
	L4/L5	= -13.823 + 0.157*Ht + 1.417*Gender	0.813	0.801	1.13	< 0.001
	L5/S1	= -21.073 + 0.203*Ht	0.731	0.723	1.38	< 0.001
CSA _{IVD}	L3/L4	= -22.394 + 0.224*Ht	0.736	0.728	1.50	< 0.001
	L4/L5	= -16.525 + 0.184*Ht + 1.750*Gender	0.782	0.769	1.47	< 0.001
	L5/S1	= -16.959 + 0.179*Ht + 1.700*Gender	0.730	0.713	1.66	< 0.001
CSA _{CaEP}	L3/L4	= -10.709 + 0.176*Ht + 1.723*Gender - 0.159*Age	0.784	0.763	1.38	< 0.001
	L4/L5	= -12.581 + 0.159*Ht + 2.634*Gender	0.827	0.815	1.31	< 0.001
	L5/S1	= -14.807 + 0.167*Ht + 1.608*Gender	0.772	0.756	1.38	< 0.001

CSA (cm²); Gender (0 for female, 1 for male); Ht: height (cm); Age: age (years).

CSA_{CaEP} across the three lower lumbar levels.

ANOVA revealed that all regression models were significant (P < 0.001). Ht was a significant predictor in all models. Wt was insignificant and not included in any models. Gender was also a significant predictor, except for L3/L4 CSA_{IVD} and L5/S1 CSA_{CrEP}. Age was only significant in models for CSA_{CrEP} and CSA_{CaEP} at the L3/L4 level. In general, models for the L4/L5 level had the largest R² and adj-R² values and smallest standard error, compared to the models for L5/S1 level, which had the smallest R² and adj-R² values and the largest standard error.

3.4. Comparison with regression models reported in the literature

Table 9 compares the regression models for the CSA_{IVD} with previous ones reported in the literature.

Compared to Colombini et al. (1989), the present models using SW yielded larger R² value at the L4/L5 level, but smaller values at the L3/L4 and L5/S1 levels. Colombini et al. (1989) reported the largest R² value for the L3/L4 CSA_{IVD} model and the smallest value for the L4/L5 CSA_{IVD} model. In this study, the largest R² value was reported for the L4/L5 model, while the smallest value was found for the L5/S1 model. The present study also found that, based on the current study sample, regression models using SW outperformed the models using AST and AST_{Turk} across all three lower lumbar levels.

3.5. Comparison of model performance

Regression models presented in this study were used to predict the CSAs for the current sample of subjects. Prediction errors associated with models using the BSLR method and Easy method are listed in

Table 9
Comparison with regression models for CSA_{IVD} reported in the literature.

		Prediction Equation	R ²	Adj-R ²	S.E.	P-value
L3/L4	Colombini et al. (1989)	= 0.95 + 0.002*SW	0.706	–	–	< 0.001
	This study	= 4.651 + 0.001*SW	0.693	0.684	1.61	< 0.001
	This study	= 3.544 + 0.191*AST _{Turk}	0.525	0.510	2.01	< 0.001
L4/L5	Colombini et al. (1989)	= 2.234 + 0.225*AST	0.609	0.597	1.82	< 0.001
	This study	= 2.7 + 0.002*SW	0.624	–	–	< 0.001
	This study	= 3.657 + 0.001*SW	0.749	0.742	1.56	< 0.001
L5/S1	Turk and Celan (2004)	= 2.11 + 0.29*AST _{Turk}	–	–	–	–
	This study	= 2.074 + 0.218*AST _{Turk}	0.596	0.584	1.98	< 0.001
	This study	= 0.824 + 0.253*AST	0.670	0.660	1.79	< 0.001
L3/L4	Colombini et al. (1989)	= 2.57 + 0.002*SW	0.672	–	–	< 0.001
	This study	= 3.069 + 0.001*SW	0.655	0.645	1.84	< 0.001
	Turk and Celan (2004)	= 3.55 + 0.25*AST _{Turk}	–	–	–	–
L4/L5	Colombini et al. (1989)	= 2.078 + 0.197*AST _{Turk}	0.483	0.467	2.26	< 0.001
	This study	= 2.078 + 0.197*AST _{Turk}	0.483	0.467	2.26	< 0.001
	This study	= 0.592 + 0.235*AST	0.570	0.557	2.05	< 0.001

Table 10. Prediction errors associated with the models reported in the literature and the newly developed ones using the same variables are listed in Table 11.

In terms of MAE and RMSE, BSLR models generally outperformed the corresponding Easy models. BSLR models produced smaller errors with the exception of the CSA_{CrEP} at the L3/L4 level. For the BSLR models, absolute differences between the predicted values and the measured values were on average 6.2% for the IVDs, 6.5% for the CrEPs, and 6.3% for the CaEPs. MAEs for the Easy models were 8.2% for the IVDs, 7.0% for the CrEPs, and 6.9% for the CaEPs. The newly developed IVD models using the composite variables proposed in the literature produced smaller errors, compared to the models reported in the literature. On average, the application of models proposed by Colombini et al. (1989) overestimated the size of L3/L4, L4/L5, and L5/S1 discs by 51.0%, 60.0%, and 74.2%, respectively. Similarly, models proposed by Turk and Celan (2004) overestimated the L4/L5 and L5/S1

Table 10
Comparisons of prediction errors between the regression models using BSLR method* and the ones using easy-to-measure variables (Easy).

	Model	Absolute Error				RMSE		
		Mean	SD	Min	Max	%		
L3/L4	CSA _{CrEP}	BSLR	1.09	0.67	0.06	2.52	7.7	1.28
		Easy	0.95	0.60	0.16	2.49	6.8	1.12
	CSA _{IVD}	BSLR	0.87	0.62	0.00	2.22	5.5	1.06
		Easy	1.19	0.85	0.06	3.92	7.7	1.45
L4/L5	CSA _{CaEP}	BSLR	0.85	0.71	0.04	3.37	5.1	1.10
		Easy	1.04	0.79	0.00	2.77	6.6	1.30
	CSA _{CrEP}	BSLR	0.78	0.63	0.01	2.33	5.7	1.00
		Easy	0.89	0.62	0.01	2.39	6.7	1.08
L5/S1	CSA _{IVD}	BSLR	0.94	0.71	0.09	3.02	6.0	1.17
		Easy	1.19	0.77	0.11	3.21	7.6	1.41
	CSA _{CaEP}	BSLR	0.97	0.64	0.04	2.64	6.1	1.16
		Easy	0.98	0.78	0.08	3.66	6.2	1.25
L3/L4	CSA _{CrEP}	BSLR	0.81	0.64	0.01	2.43	6.2	1.03
		Easy	1.00	0.90	0.00	3.75	7.5	1.34
	CSA _{IVD}	BSLR	1.01	0.64	0.09	2.67	7.3	1.19
		Easy	1.34	0.87	0.25	3.61	9.3	1.59
CSA _{CaEP}	BSLR	1.02	0.78	0.02	2.84	7.6	1.28	
	Easy	1.08	0.75	0.01	2.73	7.9	1.31	

*The smaller-sized BSLR model was applied in the comparison.

discs by 30.9% and 35.9%, respectively. When compared to the corresponding BSLR models and Easy models, IVD models using the composite variables proposed in the literature produced greater error across the lower lumbar region.

4. Discussion

The present study explored the relationships between an individual's anthropometry and the CSAs of the lower lumbar IVDs and EPs in healthy (i.e., LBP asymptomatic) subjects and developed regression models to predict these CSAs. This information may be valuable for the development of improved biomechanical models of the lower lumbar spine to better estimate its load-bearing capacity by incorporating individual specifics in anthropometry. In the literature, the ultimate compressive strength of a lumbar motion segment has been critical input for biomechanical analyses of lifting and lowering tasks to determine the associated tissue damage and injury risk (Chaffin and Park, 1973; Jäger and Luttmann, 1989; Waters et al., 1993). For a lumbar motion segment, the size of its load-bearing surface and bone mineral density help determine its bone mineral content (BMC), which

Table 11
Comparisons of prediction errors between the regression models reported in the literature and the newly developed models using the same variables.

	Model	Absolute Error				RMSE		
		Mean	SD	Min	Max	%		
L3/L4	Colombini et al. (1989)	8.06	2.97	2.61	16.44	51.0	8.58	
	SW	1.29	0.95	0.00	4.46	8.4	1.59	
	AST _{Turk}	1.63	1.09	0.02	3.90	10.3	1.95	
L4/L5	AST	1.47	0.99	0.06	3.68	9.4	1.77	
	Colombini et al. (1989)	9.55	2.72	2.91	16.48	60.0	9.92	
	SW	1.43	1.13	0.00	4.47	8.5	1.81	
L4/L5	Turk and Celan (2004)	4.69	2.10	0.12	9.17	30.9	5.13	
	AST _{Turk}	1.59	1.09	0.05	4.20	10.1	1.92	
	AST	1.47	0.94	0.11	4.02	9.4	1.74	
L5/S1	Colombini et al. (1989)	10.73	10.81	3.56	18.20	74.2	11.13	
	SW	1.46	1.08	0.03	3.77	9.7	1.81	
	Turk and Celan (2004)	4.86	2.30	0.17	9.06	35.9	5.36	
L5/S1	AST _{Turk}	1.81	1.25	0.08	4.83	12.2	2.19	
	AST	1.64	1.15	0.18	4.36	11.2	2.00	

has been demonstrated to be closely related to the ultimate compressive strength of the structure (Biggemann et al., 1988; Brinckmann et al., 1989; Singer et al., 1995; Gallagher et al., 2007). Spinal geometries, particularly the CSAs of the IVDs and EPs, are critical input for the state-of-the-art, comprehensive approaches to lumbar spine modeling, such as finite element analysis (FEA), that precisely model the internal loading conditions and investigate the influence of motions, postures, and forceful loadings on spinal structures (Hussain et al., 2010; Natarajan and Andersson, 1999; Robin et al., 1994). Knowing an individual's spinal geometry facilitates the development of more specific finite element models, and may improve our understandings of the influence of human spinal geometry variability on FEA models and outputs (Niemeyer et al., 2012).

In general, to achieve reliable regression models, two primary assumptions are necessary and should be satisfied. First, morphometric data regarding the lower lumbar IVDs and EPs should be as precise and accurate as possible. In this study, geometric data regarding the CSAs of the lower lumbar IVDs and EPs were obtained using a standardized and reliable measurement protocol (Tang et al., 2016). More importantly, the protocol has superior capability to handle the lumbar curvature and is able to measure the actual CSAs of the IVDs and EPs across the lower lumbar spine, particularly at the lumbosacral joint, rather than using a simple ellipsoid approximation method (Farfan, 1973; Brinckmann et al., 1989; Colombini et al., 1989; Panjabi et al., 1992) which may introduce systematic measurement error (Seidel et al., 2008; Tang et al., 2016). Second, the present sample is assumed to be a good representation of the asymptomatic young adult population without spinal pathology and abnormality. In this regard, this study is superior to the previous studies using cadavers with unknown health conditions (Seidel et al., 2008), or patients seeking medical treatments (Turk and Celan, 2004).

4.1. Regression models: performance vs. complexity

To the authors' knowledge, this study may be the first attempt to develop regression models with a comprehensive set of anthropometric variables, using the BSLR method, for both IVDs and EPs in the lower lumbar region. In the literature, previous studies used traditional stepwise approaches to develop their models with relatively few anthropometric variables (Colombini et al., 1989; Turk and Celan, 2004). Stepwise approaches are relatively straightforward and simple to employ; automatically adding or removing one predictor variable at a time based on its statistical significance to produce a single model in the end. In contrast, the BSLR method evaluates *all* possible models based on the total predictors and displays the best-fitting models in each model size (i.e., number of variables). The BSLR method explores the possibility that certain *combinations* of variables may better explain model variation than each individual variable. The BSLR method provides multiple models for each model size along with statistics, so that various model trade-offs can be assessed using qualitative criteria. For example, a predictive variable may be excluded because it does not improve model results enough relative to how difficult it is to obtain. Model simplicity and field application by practitioners are reasons that some variables may be selected over others. In this study, 25 anthropometric variables were measured and/or calculated. A total of 14 potential predictors were included for model development. For each model size (i.e., 2 to 14), 5 top models were selected based on model statistics (i.e., AIC, adjusted R^2 , and residual mean square). In addition to quantitative criteria, this study used subjective knowledge

to select more “optimal” models based on model size, complexity, and the likelihood that a variable to be included in a model. For the purpose of this study, these “optimal” models were subsequently compared with their corresponding Easy models, predicting the spinal geometry of the same group of subjects. In general, the BSLR models outperformed the Easy models, demonstrating lower mean absolute errors (MAEs). As stated earlier, model selection is a trade-off between performance (i.e., model statistics) and complexity (i.e., model size). Complex models are more likely to provide better CSA prediction statistics (e.g., lower MAE). However, more effort and resources are required to obtain a larger number of anthropometric variables. In this study, the BSLR models exhibited better model statistics and lower MAEs, compared to the Easy models. However, for many ergonomics practitioners, the Easy models might be preferred since they provide similar performance to the BSLR models, but can significantly simplify data collection and reduce analysis time. Selection of appropriate regression models is a function of the end-user's needs, expertise, and available resources. For example, for an ergonomics practitioner, a simple and easy model may be more favorable to estimate the lower lumbar geometry of 200 assembly line workers in order to evaluate the associated risk of WLBP. On the other hand, in a spinal surgery where an artificial implant of intervertebral disc is needed, the designer of the implant may prefer a more comprehensive regression model to predict the size of the IVDs and EPs in healthy conditions so that the artificial implant may better facilitate prosthesis-vertebra contact and improve spinal loading capacity (van der Houwen et al., 2010; Lakshmanan et al., 2012).

4.2. Regression models of the CSAs of the lower lumbar IVDs and EPs

Relatively few regression models predicting human lower lumbar geometry have been developed (Colombini et al., 1989; Turk and Celan, 2004) and there have been conflicting findings regarding their predictions. Colombini et al. (1989) proposed three regression models using body weight, W_{wrist} , and SW, respectively. Turk and Celan (2004) also proposed regression models using the AST to predict the CSAs of the L4/L5 and L5/S1 IVDs. SW and AST, as composite anthropometric variables, were developed to specifically characterize the overall development of the human skeletal system (Matiegka, 1921). Both Colombini et al. (1989) and Turk and Celan (2004) found that regression models using these composite measures had better capability to explain the variance within the lower lumbar geometry. On the contrary, some studies reported poor correlations between the body anthropometry and the CSAs of the lower lumbar EPs; and, therefore, failed to establish any regression models using anthropometric variables (Seidel et al., 2008). However, it should be noted that Seidel et al. (2008) collected morphometric data on cadaveric specimens, which have been susceptible to the effect of post-mortem changes (White III and Panjabi, 1990; Zhou et al., 2000). This study provided valuable evidence suggesting the feasibility of using anthropometry-derived regression models to predict the size of the human lower lumbar IVDs and EPs. Our results also confirmed that composite variables such as SW and AST can be significant predictors. However, it should be noted that these regression models were outperformed by both the corresponding BSLR models and Easy models as measured by MAE and RSME.

For the lower lumbar CSA_{IVD}, I_{Ankle} was the most predictive anthropometric variable, which was most likely to be included in the BSLR models. Subject stature, measured by standing height and seated

height were also significant predictors in CSA_{IVD} models. Subject I_{Elbow} was significant and included in models for the L3/L4 and L5/S1 CSA_{IVD}, but not for the L4/L5 CSA_{IVD}. Subject I_{Hand} was only predictive in the model for the L5/S1 CSA_{IVD}. BSLR models for the size of the EPs also revealed that I_{Ankle} and subject stature were superior to other anthropometric variables. Subject I_{Hand} was predictive in the models for the L3/L4 CSA_{CrEP} and L5/S1 CSA_{CaEP}. Subject I_{Elbow} was only predictive in the model for the L5/S1 CSA_{CaEP}. Rather than combining anthropometric variables associated with different body joints, this study proposed several composite index measures combining geometric dimensions of the same body joints or segments, which indicated superior predictive relationships with the lower lumbar geometry.

Easy models developed in this study revealed that subject height and gender were the primary significant predictors. Although subject weight was significantly correlated with the size of the lower lumbar IVDs and EPs, it was not included as a significant predictor in any Easy models. In the literature, regression models using subject weight have been reported (Colombini et al., 1989). However, the relatively low R^2 values indicated that subject weight might only be able explain a small portion of the variance. In fact, the correlation between body weight and lower lumbar geometry may indeed be weak (Tang, 2013). Although one can speculate that adult spinal structures may be adaptive to the mechanical stimulation introduced by body weight as suggested by Wolff's law (Chaffin et al., 2006), the changes could only be in very small range, given that an adult's skeleton system has become mature (Raj, 2008). Therefore, it is very difficult to predict the actual size of the lower lumbar IVDs and EPs based on weight alone, since an adult individual can quickly change body weight (i.e., gain or lose). In addition, in the present study, LBM did not appear in many regression models, despite the fact that it exhibited stronger correlations with the lower lumbar geometry than body weight (Tang, 2013).

Previous studies failed to investigate whether subject age and gender can be used to predict the CSAs of the lower lumbar IVDs and EPs (Colombini et al., 1989; Turk and Celan, 2004; Seidel et al., 2008). This study noted that in the Easy models, age became a significant predictor, but only in the models for the L3/L4 CSA_{CrEP} and CSA_{CaEP} with the presence of gender and height. It may be due to the possible interactions between these three anthropometric variables at the L3/L4 level or the uniqueness of the geometric data of the present sample. For the BSLR models, age was not proposed as a potential predictor, due to its poor correlations with all measurements of CSAs. In the literature, the influence of aging has also been found to be more pronounced on the vertical displacements (e.g., disc height) (Twomey and Taylor, 1987; Amonoo-Kuofi, 1991; Aydinlioglu et al., 1999; Al-Hadidi et al., 2001; Shao et al., 2002). The present sample of subjects has a narrow range of age (from 21 to 35) and may not be diverse enough to detect the influence of age on the CSAs of the IVDs and EPs. While age may not appear significant for the current subject sample, it may be predictive for a larger sample with older subjects. Also, age may be used in subsequent studies as a weighting factor to adjust the estimate of the ultimate compressive strength of the spinal segments to account for disc degeneration and bone mineral loss associated with aging. In the literature, it is generally believed that spinal disc degeneration is an aging process (Adams et al., 2002; Pearce et al., 1991) with studies suggesting that aging has a negative effect on the integrity of the spine (Genaidy et al., 1993). However, further research is needed to develop a more complete relationship between the aging process and the mechanical properties of the spine.

This study noted that based on the BSLR models developed, the

appearance of gender was less pronounced, compared to other anthropometric variables. In this study, gender was not selected in any "optimal" BSLR models for CSA_{IVD}, due to its low frequency of being included in models across all three lower lumbar levels. The influence of gender was somewhat evident in the models for EPs, particularly in the CSA_{CrEP} models. In contrast, almost all Easy models included gender as a significant predictor. At first, it seems that this finding would corroborate previous studies reporting the influence of gender on the CSAs of the IVDs (Hansson et al., 1980; Hutton and Adams, 1982; Nachemson, 1960), the EPs (Hall et al., 1998), and the vertebral bodies (Gilsanz et al., 1994). However, it actually raises an important question, "is gender a true differentiating factor in lower lumbar geometry?" Since male and female subjects in the present sample were significantly different in nearly every anthropometric measurement, one could speculate that the influence of gender may be derived from the actual variations in human skeletal system among the general population. For example, one might expect that healthy males and females with similar body anthropometry, would have similar lower lumbar geometry. Unfortunately, the design of this pilot study was inadequate to address this issue. Future investigations are much needed, especially using size-matched gender groups, to reveal more information regarding the influence of gender on lower lumbar geometry.

There are some limitations to this study, including the relatively small sample size. The subjects represented a convenience sample recruited from the university student body. No effort was made to achieve a gender or body size matched sample. The subjects were relatively young and healthy. These limitations may help explain why gender and age did not appear more predictive. Future research should employ larger samples of subjects with greater variations in age and body anthropometry. In addition, further studies are needed to investigate the potential influence of measurement errors associated with anthropometric variables on the regression model performance. Finally, future studies should test the regression models developed in this study among different samples with various subject characteristics and verify the generalizability to apply to a larger and more general population.

5. Conclusions

The present study measured the CSAs of the lower lumbar IVDs and EPs using a sample of young healthy subjects. Using newly developed measurement protocols, precise and accurate morphometric data were obtained. A comprehensive set of anthropometric variables were taken and included in the regression analyses. This study proposed a new approach to develop the regression models using an all-possible-regressions procedure, BSLR, which facilitates the development of alternative regression models with comparable performance, based on different model selection criteria. This may provide a better understanding of the associations between the subject anthropometric variables and the lower lumbar morphometry and subsequently improve risk estimations for individuals subjected to low back spinal loadings.

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Appendix A. BSLR models for the L3/L4 CSA_{VPD}

Variables														Statistics					
Gender	Height	Weight	Sitting	Shoulder Width	Lean Body Mass	Arm Length	Head	Chest	Elbow	Wrist	Knee	Ankle	Hand	Intercept	Parameters	R ²	Adj-R ²	Mallow's C _p	s (=√MSE)
	X											X		X	2	75.3	74.6	16.7	1.4459
										X				X	2	73.6	72.8	20	1.4955
			X							X				X	2	73.4	72.6	20.4	1.5021
						X								X	2	66.1	65.1	34.4	1.6942
			X									X		X	2	64.5	63.4	37.6	1.7345
	X									X		X		X	3	83.6	82.6	2.6	1.1958
			X									X		X	3	82.7	81.6	4.4	1.2292
						X						X		X	3	80.8	79.6	8.1	1.2952
			X									X	X	X	3	80.3	79.1	9	1.3116
	X								X				X	X	3	80.1	78.9	9.4	1.3187
			X					X				X		X	4	86.2	84.8	-0.3	1.1174
	X							X				X		X	4	85.9	84.5	0.3	1.1295
	X	X										X		X	4	85.7	84.3	0.6	1.1357
	X							X				X		X	4	85.3	83.9	1.4	1.1516
	X				X							X		X	4	85.1	83.7	1.7	1.1575
			X			X						X		X	5	87.4	85.7	-0.6	1.0852
	X		X					X				X		X	5	87.3	85.6	-0.4	1.0895
	X		X			X			X			X		X	5	87.2	85.5	-0.2	1.093
			X			X		X				X		X	5	87.2	85.4	-0.2	1.0945
	X							X				X		X	5	87	85.2	0.2	1.1021
	X							X	X			X		X	6	88.2	86.2	-0.2	1.0657
	X							X	X			X		X	6	88	86	0.1	1.0749
			X			X		X	X	X		X		X	6	87.9	85.9	0.3	1.0781
			X			X		X	X	X		X		X	6	87.9	85.8	0.4	1.0798
	X						X		X	X		X		X	6	87.9	85.8	0.4	1.0809
	X					X		X	X	X		X		X	7	89	86.6	0.3	1.049
			X					X	X	X		X		X	7	88.5	86.1	1.1	1.0698
	X		X				X	X	X	X		X		X	7	88.5	86.1	1.1	1.07
	X		X				X	X	X	X		X		X	7	88.5	86	1.2	1.0716
	X		X					X	X	X		X		X	7	88.5	86	1.2	1.0723
	X		X					X	X	X		X		X	8	89.2	86.4	1.9	1.0593
	X		X				X	X	X	X		X		X	8	89.2	86.4	1.9	1.0596
	X		X					X	X	X		X		X	8	89	86.2	2.2	1.0668
X	X		X					X	X	X		X		X	8	89	86.1	2.3	1.0678
	X	X						X	X	X		X		X	8	89	86.1	2.3	1.0681
	X		X					X	X	X		X		X	8	89.3	86	3.7	1.0739
	X		X					X	X	X		X		X	9	89.2	85.9	3.8	1.0759
	X		X				X	X	X	X		X		X	9	89.2	85.9	3.8	1.0761
	X		X				X	X	X	X		X		X	9	89.2	85.9	3.8	1.0765
	X		X				X	X	X	X		X		X	9	89.2	85.9	3.8	1.0774
	X		X				X	X	X	X		X		X	10	89.4	85.5	5.5	1.0907
	X		X			X		X	X	X		X		X	10	89.4	85.5	5.6	1.0909
	X		X			X		X	X	X		X		X	10	89.4	85.5	5.6	1.0913
	X		X					X	X	X		X		X	10	89.3	85.5	5.6	1.0928
	X		X		X			X	X	X		X		X	10	89.3	85.5	5.6	1.0929
	X		X			X		X	X	X		X		X	11	89.5	85.1	7.3	1.1056
	X		X		X			X	X	X		X		X	11	89.4	85	7.4	1.1097
	X		X					X	X	X		X		X	11	89.4	85	7.4	1.1099
	X		X			X		X	X	X		X		X	11	89.4	85	7.4	1.1102
X	X		X			X		X	X	X		X		X	11	89.4	85	7.5	1.1117
X	X		X			X		X	X	X		X		X	12	89.6	84.6	9.1	1.1258
	X		X		X			X	X	X		X		X	12	89.6	84.6	9.2	1.127
	X		X		X			X	X	X		X		X	12	89.5	84.5	9.2	1.1279

Appendix E. BSLR models for the L4/L5 CSA_{CREP}

Variables														Statistics					
Gender	Height	Weight	Sitting	Shoulder Width	Lean Body Mass	Arm Length	Head	Chest	Elbow	Wrist	Knee	Ankle	Hand	Intercept	Parameters	R ²	Adj-R ²	Mallow's Cp	s (=√MSE)
X										X				X	2	77.7	77	13.3	1.2114
						X								X	2	73.1	72.2	22.5	1.3305
														X	2	71.5	70.7	25.5	1.3676
												X		X	2	69.9	69	28.7	1.4066
														X	2	67	66	34.5	1.473
	X		X									X		X	3	82.4	81.3	6	1.0927
	X									X				X	3	81.3	80.1	8.1	1.1259
	X									X				X	3	81.1	79.9	8.5	1.1315
														X	3	81	79.8	8.7	1.134
						X								X	3	80.9	79.7	8.9	1.1374
						X								X	4	85.1	83.7	2.5	1.0194
	X						X					X		X	4	85	83.5	2.8	1.0251
	X							X				X		X	4	84.8	83.4	3.1	1.0299
	X							X						X	4	84.2	82.7	4.3	1.0499
	X								X			X		X	4	84.1	82.5	4.6	1.0555
						X						X		X	5	86.8	85	1.3	0.97796
	X											X		X	5	86.4	84.6	2	0.99134
	X											X		X	5	86.2	84.4	2.4	0.99829
						X						X		X	5	86.1	84.3	2.5	1.0012
	X											X		X	5	86.1	84.3	2.6	1.0021
	X											X		X	6	88	85.9	0.8	0.94676
	X											X		X	6	87.9	85.8	1.1	0.95232
	X											X		X	6	87.7	85.5	1.5	0.96096
	X									X				X	6	87.4	85.3	1.9	0.96907
	X					X						X		X	6	87.3	85.1	2.3	0.97588
	X					X						X		X	7	88.4	85.9	2	0.94668
										X				X	7	88.4	85.9	2	0.94719
												X		X	7	88.4	85.9	2	0.94727
										X				X	7	88.2	85.7	2.3	0.95453
												X		X	7	88.2	85.7	2.4	0.95589
										X		X		X	8	89	86.2	2.8	0.93915
										X		X		X	8	89	86.1	2.8	0.93993
										X		X		X	8	88.9	86	3.1	0.9449
						X				X		X		X	8	88.8	85.8	3.3	0.95031
										X		X		X	8	88.7	85.8	3.3	0.95078
										X		X		X	9	89.4	86.2	4	0.93847
										X		X		X	9	89.3	86	4.3	0.94531
						X				X		X		X	9	89.3	86	4.3	0.94608
										X		X		X	9	89.1	85.8	4.6	0.95197
										X		X		X	9	89.1	85.7	4.6	0.95359
						X				X		X		X	10	89.8	86.1	5.3	0.94121
						X				X		X		X	10	89.8	86.1	5.3	0.94121
						X				X		X		X	10	89.7	86	5.5	0.94636
										X		X		X	10	89.6	85.9	5.6	0.9497
										X		X		X	10	89.5	85.8	5.8	0.95274
										X		X		X	10	89.5	85.7	5.9	0.95596
										X		X		X	11	89.9	85.7	7.1	0.9558
										X		X		X	11	89.8	85.6	7.2	0.95996
										X		X		X	11	89.8	85.5	7.2	0.96023
							X			X		X		X	11	89.8	85.5	7.3	0.96046
						X				X		X		X	11	89.8	85.5	7.3	0.96056
						X				X		X		X	12	89.9	85.1	9	0.9756
						X				X		X		X	12	89.9	85.1	9	0.97597
						X				X		X		X	12	89.9	85.1	9.1	0.97634

Appendix H. BSLR models for the L4/L5 CSA_{CaEP}

Variables														Statistics					
Gender	Height	Weight	Sitting	Shoulder Width	Lean Body Mass	Arm Length	Head	Chest	Elbow	Wrist	Knee	Ankle	Hand	Intercept	Parameters	R ²	Adj-R ²	Mallow's C _p	s (=√MSE)
X										X				X	2	76	75.2	11.6	1.5203
	X													X	2	75.6	74.7	12.3	1.5346
												X		X	2	75	74.1	13.2	1.5534
													X	X	2	72	71	18.1	1.6437
	X			X								X		X	2	69.6	68.6	21.8	1.7108
												X		X	3	83.2	82	2	1.2938
	X		X									X		X	3	83	81.7	2.4	1.3038
													X	X	3	82.7	81.5	2.8	1.3127
	X		X							X				X	3	82.2	80.9	3.6	1.3321
											X			X	3	81.5	80.1	4.8	1.36
	X												X	X	4	85.1	83.4	1	1.2426
											X		X	X	4	85	83.3	1.1	1.2462
												X	X	X	4	84.9	83.2	1.3	1.2502
				X							X		X	X	4	84.8	83.1	1.4	1.254
X	X										X	X		X	4	84.4	82.6	2.1	1.2712
X							X				X			X	5	86.4	84.3	0.8	1.2073
X	X						X	X			X			X	5	86.4	84.3	0.9	1.2088
X		X									X		X	X	5	86.1	84	1.3	1.2215
X											X	X		X	5	86	83.9	1.5	1.2259
X	X		X							X	X			X	5	85.9	83.7	1.7	1.2328
X	X	X					X	X			X			X	6	87.3	84.8	1.4	1.1903
X	X	X					X	X		X				X	6	87.2	84.6	1.6	1.1956
X	X		X				X	X		X	X			X	6	87.2	84.6	1.6	1.1974
X	X	X					X	X		X	X			X	6	87.1	84.5	1.7	1.2007
X	X	X			X		X	X		X	X			X	6	87.1	84.5	1.7	1.2009
X		X					X	X			X			X	7	88	85.1	2.2	1.1798
X	X	X					X	X		X	X		X	X	7	87.9	84.9	2.4	1.1855
X	X	X			X		X	X		X	X		X	X	7	87.9	84.8	2.5	1.1884
X	X	X					X	X	X	X				X	7	87.8	84.8	2.6	1.1914
X	X	X			X		X	X	X	X	X			X	7	87.8	84.7	2.7	1.1937
X		X	X				X	X	X	X				X	8	88.5	85.1	3.4	1.1796
X	X	X	X				X	X	X	X	X			X	8	88.3	84.8	3.8	1.1914
X	X	X	X				X	X	X	X	X			X	8	88.3	84.7	3.8	1.1936
X	X	X	X				X	X	X	X	X			X	8	88.3	84.7	3.8	1.1937
X	X	X	X				X	X	X	X	X		X	X	8	88.3	84.7	3.9	1.1946
X	X	X	X				X	X	X	X	X		X	X	9	88.9	84.8	4.9	1.1893
X	X	X	X				X	X	X	X	X		X	X	9	88.7	84.7	5.1	1.1952
X	X	X	X		X		X	X	X	X	X		X	X	9	88.7	84.6	5.2	1.1985
X	X	X	X				X	X	X	X	X		X	X	9	88.6	84.5	5.2	1.2008
X	X	X	X		X		X	X	X	X	X		X	X	9	88.6	84.5	5.3	1.2016
X	X	X	X		X		X	X	X	X	X		X	X	10	89.1	84.4	6.5	1.2054
X	X	X	X		X		X	X	X	X	X		X	X	10	89.1	84.4	6.5	1.2056
X	X	X	X		X		X	X	X	X	X		X	X	10	89	84.3	6.6	1.2081
X	X	X	X		X		X	X	X	X	X		X	X	10	89	84.3	6.6	1.2087

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