A Parametric Thoracic Spine Model Accounting for Geometric Variations by Age, Sex, Stature, and Body Mass Index
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ABSTRACT
In this study, a parametric thoracic spine (T-spine) model was developed to account for morphological variations among the adult population. A total of 84 CT scans were collected, and the subjects were evenly distributed among age groups and both sexes. CT segmentation, landmarking, and mesh morphing were performed to map a template mesh onto the T-spine vertebrae for each sampled subject. Generalized Procrustes Analysis (GPA), Principal Component Analysis (PCA), and linear regression analysis were then performed to investigate the morphological variations and develop prediction models. A total of 13 statistical models, including 12 T-spine vertebrae and a spinal curvature model, were combined to predict a full T-spine 3D geometry with any combination of age, sex, stature, and body mass index (BMI). A leave-one-out Root Mean Square error (RMSE) analysis was conducted for each node of the mesh predicted by the statistical model for every T-spine vertebra. Most of the RMSEs were less than 2 mm across the 12 vertebral levels, indicating good accuracy. The presented parametric T-spine model can serve as a geometry basis for parametric human modeling or future crash test dummy designs to better assess T-spine injuries accounting for human diversity.

INTRODUCTION
Vertebral fractures are among the most common fractures in adults and are a major public health problem in the United States (Kaze et al., 2018; Szulc, 2018). Thoracic spine (T-spine) vertebral fractures are common in motor-vehicle crashes, and yet they are not considered in current regulatory and consumer-information vehicle crash tests. As autonomous driving technology is becoming more popular, T-spine injuries may draw more attention from the injury biomechanics field. Since occupants no longer need to drive, more reclined sitting posture may become more common in self-driving cars, which could subsequently increase the risks of T-spine injuries. Studies have shown that the reclined position is associated with increased occupant mortality (Dissanaike et al., 2008) and spinal cord injuries in frontal crashes (Thorbole, 2015).

Studies have shown that vertebral geometry has significant effects on vertebral fracture risks. For example, Bouxsein and Karasik (2006) reported that bone geometry is a key determinant of vertebral strength, and three-dimensional imaging is needed to better define the relationship between bone geometry and skeletal fragility. Ruyssen-Witrand et al. (2007) also demonstrated that vertebral size is an important risk factor for vertebral fracture.

Studies have also shown that age, sex, and BMI may affect T-spine vertebra geometry, and may have contributed to the increased risks of spinal injuries in female, older, and obese occupants compared to mid-sized, young males in motor-vehicle crashes (Hu, 2018). Oura et al.
(2019) found that the lifelong BMI not only has a positive effect on midlife vertebral size among both sexes but also had a significant positive association with the vertebral cross-sectional area (CSA) in midlife. Kolta et al. (2012) measured vertebral body dimension changes in women over 6 years and found a decrease in vertebral body anterior height, depth, and width in postmenopausal women. Kim et al. (2013) measured the spinal canal diameter and vertebral body height at T5, T6, L4, and L5, and found that vertebral height decreased with age, but spinal canal diameter did not change in patients with either lumbar spinal stenosis or herniated cervical disc. Peters et al. (2015) observed significant differences in vertebral geometry between men and women. All those studies indicated that subject covariates may have significant impact on T-spine vertebral geometry. Therefore, a better understanding of human T-spine vertebral geometry and the associated variations in the population are important to accurately estimate T-spine injuries and design countermeasures for future safety equity.

However, a parametric 3D T-spine model that can account for the morphological variations in the diverse population is not currently available in the literature. A previous study by Masharawi et al. (2008) used direct measurements of 240 normal spines of adult subjects and conducted vertebral shape analysis, but no statistical model was built to analyze the T-spine geometry. Laporte et al. (2000) conducted a quantitative morphometric study on T-spine using 50 cadaveric subjects, but the sex, age, and origin of the used subjects were unknown. Tan et al. (2004) developed a three-dimensional anatomy model of T-spine for Chinese Singaporeans but only involved 10 cadaveric subjects. Kunkel et al. (2011) developed prediction model for thoracic and lumbar articular facet joints using 2D X-ray images, but the validation data indicated a relatively large mean percent error. All these previous studies did not develop a statistical 3D T-spine geometry model that can account for the morphological variations among the population.

The objective of this study is to develop a statistical thoracic spine model accounting for morphological variations by age, sex, stature, and BMI, based on the data extracted from CT scans. To the best of our knowledge, this is the first study that a whole T-spine 3D model can accurately predicted for any given age, sex, stature, and BMI. Our study also revealed the statistical significance of each subject covariate. This model could serve as the geometric basis for parametric human modeling for better assessing T-spine injuries and other pathological analysis.

METHODS

Fig 2 shows the method overview for developing the statistical T-spine geometry model. It started with data collection, including CT acquisition and segmentation, followed by data extraction, including landmarking and template mesh mapping, and concluded with statistical analyses for developing a model to predict T-spine 3D geometry using subject covariates.
Fig 1. Method overview for developing statistical thoracic spine model.

Data collection and data extraction

Anonymous clinical CT scans (N=84) with a resolution of 512x512 and a slice thickness of 1.25 mm were obtained from the University of Michigan Health System using a protocol approved by an institutional review board at the University of Michigan. All subjects used for this study were without skeletal pathology and were evenly distributed over both sexes with ages of 17-93 years, the stature of 1.5-2.0 m, and BMI values of 17-55 kg/m². Fig 1. shows the distribution of subject covariates. No significant correlation was found among the four subject covariates except between stature and sex.
Fig 2. Age, sex, stature, and BMI distributions of all sampled subjects.

All CT scans were imported into Mimics (Materialise NV, Belgium) for segmentation. A semi-automated thresholding method was used to segment the 3D geometries of 12 T-spine vertebrae from each subject, and STL files were output. The STL files cannot be directly used for statistical analysis because they process different numbers of vertices for different subjects. Therefore, data extraction was conducted subsequently to create homologous mesh for each subject. To do so, the STL files were imported into HyperMesh for landmarking. The landmarks served as targets for morphing a baseline model (template mesh) into the target geometry. In this study, 19 landmarks were defined for each vertebra (shown in Fig. 3) and a total of 228 landmarks were collected for the whole T-spine for each subject. The same set of landmarks were also identified on the baseline model for facilitating the mesh morphing process. A landmark-based mesh morphing method using radial basis function (RBF) was used in this study to morph the baseline model into the geometry of each sampled subject. The same RBF mesh morphing method has been widely applied to many of our previous studies (Tang et al., 2022; Wang et al., 2016; Wei et al., 2022). After mesh morphing, a set of homologous meshes for all sampled subjects were created for statistical analyses.

Fig 3. Definitions of landmark locations and T-spine curvature

Statistical analysis

The statistical methods used to develop the predication model are similar to our previous study on the lumbar spine (Tang et al., 2022), which include Generalized Procrustes analysis (GPA), principal component analysis (PCA) and linear regression. GPA was used to align all the subjects into the same location and orientation; PCA was used to re-organize the geometric variations in a more effective way; and linear regression was used to predict the 3D vertebral
geometry based on subject covariates, such as age, sex, stature, and BMI. Separate statistical models were developed for each T-spine vertebra, which led to 12 vertebral models. An additional T-spine curvature model was also developed to combine all the vertebral models together.

As shown in Fig 3, two landmarks at the center of the superior and inferior surfaces of each vertebral body were used to define the vertebra location, which resulted in a total of 24 points to define the full T-spine curvature. The center of the inferior center of T12 vertebral body was used as the global reference point of all the subjects, and the inferior plane of T12 vertebral body was considered as the reference X-Y plane.

In this study, PCA decomposes the aligned vertebra geometry data into the product of two smaller matrices, namely PC scores and PC coefficients, as shown in Eq. 1.

\[ A = U \times V^T \quad \text{(Eq. 1)} \]

where \( A \) is the data matrix stores the nodal coordinates of all sampled subjects. Each subject served as an observation, and nodal coordinates served as a feature column. Since each node has three coordinate (X, Y, and Z) values, all nodal coordinates were reshaped to have the format of \( x_1, y_1, z_1, \ldots, x_m, y_m, z_m \), where \( m \) is the total number of nodes of each vertebra. Thus, \( A \) has the size of \( N \times M \), where \( N \) is the total number of subjects (84 in this case), and \( M=3m \) is the number of feature columns. \( U \) is the PC score matrix, which has the size \( N \times k \), where \( k \) is the number of selected principal components. \( V \) is the PC coefficient matrix, which has the size of \( M \times k \).

After PCA, linear regression was then performed to use subject covariates to predict PC scores as shown in Eq. 2.

\[ U = F \times C \quad \text{(Eq. 2)} \]

where \( F \) is the subject covariate matrix that has the size of \( N \times 6 \) (Age, Stature, BMI, Sex, and Stature×Sex) and \( C \) is the regression coefficient matrix which has the size of \( 6 \times k \). \( C \) can be obtained by multiplying \( U \) with the Moore-Penrose pseudo-inverse matrix of \( F \). The interaction term Stature×Sex was added to account for different stature distributions between males and females. For each regression model, the predicted nodal coordinate matrix \( \hat{A} \) of a vertebra can be predicted by Eq. 3.

\[ \hat{A} = F' \times C \times V^T \quad \text{(Eq. 3)} \]

where \( F' \) is a given set of subject covariates.

By combing the 12 regression models for the vertebrae and one regression model of the T-spine curvature, the final model can use any combination of age, sex, stature, and BMI to predict a full T-spine geometry.

**RESULTS**

**PCA Results**

Fig 4. shows the geometric variations in the first 3 PCs for four (T1, T4, T8, and T12) T-spine vertebrae with PC scores of means ± 2 standard deviations for each PC. Although different vertebrae show slightly different trends, the geometric meanings from the top three PCs are consistent across different T-spine levels. Specifically, the first PC mainly represents the size variation, and accounts for about 40% to 50% of the vertebral geometric variations. The second and third PCs mainly represent the shape variations as well as the orientation variations of spinous/transverse processes, which account for 6% to 18% of the vertebral geometric variations. Multiple regression analyses were conducted to evaluate the significance of each subject covariate.

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on each PC scores, and statistically significant covariates are highlighted with asterisk in Fig. 4. Age, stature and sex are statistically significant for the first PC in all vertebrae, while BMI are significant for some of the vertebrae in the second and third PCs.

**Fig 4.** Predicted T-spine vertebral geometry with varied PC scores.

### Vertebral Body Dimension

Box plots of the depth, height, and width of the vertebral bodies from T1 to T12 vertebra are shown in Fig 5. Both vertebral depth and height monotonically increase from T1 to T12, but with different trends. From T1 to T12, vertebral depth reaches a plateau around the T8 vertebra, but vertebral height increases faster after the T8 vertebra. In contrast, vertebral width shows a clear necking effect around T3 and T4. Specifically, the vertebral width decreases from T1 to T3 and starts increasing after the T4 vertebra. The wedging ratio in Fig. 5 is defined as the ratio between anterior vertebral height and the posterior vertebral height, which does not vary significantly among the 12 vertebrae. The anterior and posterior disc heights are also measured as shown in Fig 5. The anterior disc height is consistently larger than the posterior disc height. From T1 to T12, the anterior disc height shows a similar trend as that in vertebral width. All these geometric trends are important since they can have a significant impact on T-spine injury predictions and pathologic analysis.
Fig 5. Trends in vertebral body dimensions and disc height in T-spine
Effects from Subject Covariates

Exemplary effects of different subject covariates on T-spine geometry are shown in Fig 6. Age has a significant effect on the T-spine curvature, with older subjects having a more kyphotic T-spine. Stature dominates vertebral height with taller subjects having longer T-spine. Sex and BMI effects are relatively small compared with age and stature effects.

Model Error Analysis

Leave-one-out cross-validation was performed for the regression model, and the distributions of the root mean square errors of all the nodes on each vertebra are shown in Fig. 7. Most of the errors are within 3 mm with the average errors generally less than 2 mm, which indicates good model accuracy. As the heat map suggested, most errors are below 2.5 mm, especially in the vertebral body areas. The errors in the transverse processes and the tip of the spinous process are slightly higher likely due to the difficulty associated with segmenting and landmarking these sub-regions and subject variations.

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DISCUSSION

Morphological effect from subject covariates

Ruhli et al. (2005) found that the diameters of the vertebral bodies and pedicle heights at various levels of T-spine vertebrae has age-related alterations. Kolta et al. (2012) conducted a longitudinal study on female subjects and reported that both minimal cross-sectional area and vertebral body width decrease in T-spine with increased age. The findings of our study are consistent with those previous studies that age is statistically significant variable affecting T-spine vertebral geometry. Previous studies on sex effects on the spinal geometry are largely lacking (Mohan and Huynh, 2019), while our study suggests that sex plays an important role in affecting the size of the vertebrae (Fig. 4), which is statistically significant for the first PC at all levels of T-spine. In addition, sex is also statistically significant for vertebral depth at all levels except T1, and statistically significant for vertebral width at all levels except T3. Stature is also found to be statistically significant for the first PC at all levels. In contrast, BMI has the smallest impact on the vertebral geometry compared to age, sex, and stature.

Comparison to previous T-spine geometry studies

A previous study (Masharawi et al., 2008) used direct measurements of 240 normal spines of adult subjects for vertebral shape analysis, and revealed that vertebral width decreased from T1 to T4 and then increased toward L4-L5, which is consistent with the necking effect found in this study. However, no statistical analysis was done in that study, so statistical significance levels of age, sex, stature, and BMI on vertebral geometry are not available. Tan et al. (2004) developed a 3D anatomy model of the T-spine of Chinese Singaporeans. They found that T4 vertebra has the smallest spinal canal area, and that dimension is generally smaller than that from Caucasian subjects. However, that study only involved 10 cadaveric subjects, which is somewhat limited. Our study shows that the wedging ratio decreases from T1 to T7, then increases from T8 to T10, and decreases to T11 and T12 which is consistent with the result showed in previous study conducted by Goh et al. (2000). Kunkel et al. (2011) developed a prediction model for thoracic and lumbar articular facet joints, however the model cannot predict the full T-spine geometry. In summary, previous studies either quantified part of the T-spine geometry or analyzed the effects from subject covariates of on global vertebral geometric measures. However, their models cannot predict the 3D full T-spine geometry based on the subject covariates. In the present study, a statistical thoracic spine geometry model accounting for morphological variations by age, sex, stature, and body mass index was developed. This model can predict a full 3d T-spine model given any combination of age, sex, stature, and BMI with a root mean square error less than 2.5 mm. We believe that this is a new contribution to the field, and the model developed in this study will be valuable for developing parametric human body models for injury assessment or other applications.

Limitations

In this study, all CT scans were collected while subjects were in a supine position. Therefore, the curvature model developed in this study may not be appropriate for representing other postures. The landmarking process was finished by a single person manually and followed by another person checking the landmarking quality. This may potentially introduce errors related to landmark positioning and subsequently impact the morphing results.
CONCLUSIONS

We developed a statistical T-spine geometry model that can account for morphological variations in the population by age, sex, stature, and BMI. The data set used in this study came from clinical CT scans from 84 subjects and then proceeded with data extraction, statistical analysis, and final model prediction. We found significant morphological variations in the T-spine across the sampled subjects. Dimensional trends showed that both vertebral height and depth increased consistently from T1 to T12, while vertebral width decreased from T1 to T3 and then increased from T4 to T12, indicating a necking effect around T3/T4. A wedging ratio, the ratio of the anterior to posterior height of the vertebral bodies, was observed to range from 0.9 to 0.95 for T1-T12. Statistical analyses found a significant effect of age on the T-spine curvature, as older subjects tend to have more kyphotic curvatures. Stature had a significant effect, especially on the vertical height, which also had a profound impact on the geometric differences between women and men. A leave-one-out error analysis shows that most of the RMSEs were less than 2 mm across the 12 vertebral levels, indicating good accuracy. Model accuracy decreased slightly for the tip of the spinal process and transverse processes, which is likely due to the difficulty associated with segmenting and landmarking these sub-regions and subject variations. The presented parametric T-spine model can serve as a geometry basis for parametric human modeling or future crash test dummy designs to better assess T-spine injuries accounting for human diversity.

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REFERENCES


