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Association of Pulmonary Function and Foot Biomechanics: A Multimodal Analysis

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Abstract
Chronic respiratory impairment necessitates systemic adaptations as well; however, this relationship is poorly understood. There are a few studies indicating the association between pulmonary function, and the study was designed to investigate associations between pulmonary function and foot biomechanics using multimodal statistical and machine learning approaches, with the Chippaux Smirak Index (CSI) as the primary outcome. Subject-level demographic, pulmonary, and biomechanical data were analysed without reporting descriptive tables of variables. Baseline (demographic + pulmonary) and multimodal (demographic + pulmonary + biomechanical) models were evaluated using linear regression, Random Forest regression, canonical correlation analysis, and structural pathway analysis. Multimodal integration improved CSI prediction, with Random Forest regression indicating near-complete variance (R^2=0.9988). Biomechanical indices dominated model performance, while pulmonary variables contributed indirectly via cross-domain interactions. Canonical and structural analyses reveal interactions between pulmonary and foot biomechanics and indicate that foot indices may be complementary markers for respiratory analysis.

Keywords: Respiratory Function; Foot Biomechanics; Correlation; Machine Learning

1. Introduction

Chronic respiratory diseases affect hundreds of millions of individuals worldwide and reduce the quality of life [1]. More than 500 million people are suffering from chronic respiratory disease, imposing a financial burden on healthcare systems [1]. In respiratory disease, the body's adaptation mechanisms to inefficient gas exchange and persistent exertional dyspnea may also trigger systemic physiological responses [2]. On-time diagnosis and appropriate management of these conditions may reduce the burden. Spirometry and other pulmonary tests are noninvasive techniques to provide vital information. Studies suggest that respiratory dysfunction is beyond the thoracic system that may influence musculoskeletal integrity and locomotion [3]. Individuals with respiratory impairment usually demonstrate postural changes, reduced physical activity, and altered movement patterns therefore contributes to secondary adaptations in lower-limb biomechanics [3]. The foot plays an important role as the primary interface between the body and the ground for weight transmission, shock absorption, balancing and gait [4]. Previous studies supporting the association between COPD and dyspnea have attributed it to dyspnea-related movement compensation, plantar pressure asymmetry, shortened step length, and modified stride patterns [5]. Studies indicate influence of postural alterations on gait cycle, step variability, stride length, balance, and ankle stabilisation in respiratory disease patients [3–5]. These changes arise to minimise ventilatory demand due to reduced tolerance, respiratory muscle dysfunction, deconditioning, and adaptive strategies [6]. Over time, such changes may contribute to differences in foot structure and functional indices measured by footprint analysis. Associations between foot arch, lower-limb strength, and functional performance indicate that musculoskeletal activity and foot morphology are activity-dependent in the ageing population [7]. However, the relationship between pulmonary function and static foot structure remains poorly understood and poorly defined. Machine learning advances, such as logistic regression and Random Forest methods, enable the integration of pulmonary, demographic, and biomechanical variables to improve predictive modelling of health status [8]. Therefore, the objective of this study is to evaluate correlations among respiratory and foot-related indicies using multimodal logistic regression and Random Forest.

2. Methodology:

This study used a cross-sectional dataset of demographic, pulmonary function, and foot biomechanics of individuals. The analysis was carried out using the original dataset, without summarising descriptive statistics to explore the association of pulmonary health and basic anthropometric factors relate to foot biomechanics. Both conventional statistical techniques and machine-learning methods were applied to capture these relationships. The Chippaux–Smirak Index (CSI) is used as the main outcome variable, as it reflects midfoot contact proportion in relation to forefoot width and is commonly used as a static arch characteristic. The remaining variables were organised into three broad groups 1. Demographic variables (age, height, weight, and body mass index) 2. Pulmonary variables of spirometric measurements, along with blood pressure, and 3. Biomechanical variables included static foot indices other than CSI.

Two analytical strategies: 1. a model focused on demographic and pulmonary variables, and 2. a second model incorporating biomechanical variables with demographic and pulmonary. Linear association was examined using multiple linear regression analysis, and model performance was evaluated using the coefficient of determination and mean squared error. Whereas nonlinear patterns and interactions were evaluated using Random Forests. Further feature importance, and canonical correlation were also performed.

3. Results:

Baseline linear regression represents limited predictive power (R^2 = 0.062; MSE = 102.29) for CSI using demographic and pulmonary variables, compared with the multimodal linear model (R^2 = 0.514; MSE = 52.99) incorporating biomechanics variables also. In Random Forest regression, the baseline Random Forest model achieved an R^2 of 0.866 (MSE = 14.64), whereas the multimodal Random Forest model achieved near-complete variance (R^2 = 0.9988; MSE = 0.126), therefore indicating strong nonlinear cross-domain interactions (Table 1).

Table 1: Regression Performance for CSI Prediction

Model	R^2	MSE
Linear Baseline	0.062	102.29
Linear Multimodal	0.514	52.99
RF Baseline	0.866	14.64
RF Multimodal	0.9988	0.126

Figure 1 represents bar plot R^2 values for baseline, multimodal linear and Random Forest models, illustrating the superior performance of multimodal nonlinear modelling.

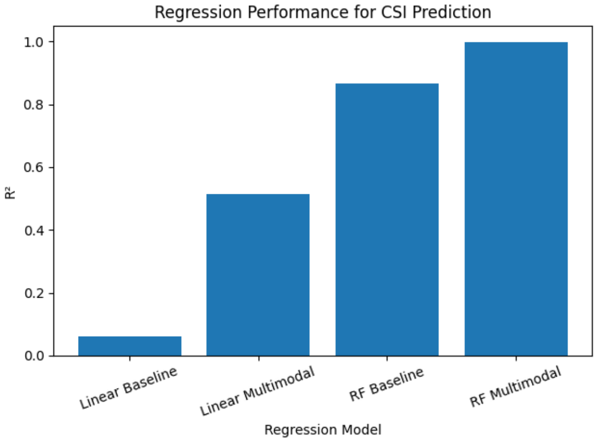

Figure 1: Performance Analysis for CSI Prediction

In the multimodal linear regression model, positive and negative coefficients were predicted for CSI. It shows positive associations with the Staheli Index (β = 16.266), heel–forefoot ratio (β = 7.886), body weight (β = 0.448), %FEV_1 (β = 0.459), and diastolic blood pressure (β = 0.267); negative associations were observed with foot length to width ratio (β = −14.377), age (β = −1.117), % FEV_3 (β = −0.186), % FEF25–75 (β = −0.121), and %FVC (β = −0.101) whereas height (β = 0.039) and body mass index (β = −0.033) showed less contributions (Figure 2A). In the multimodal Random Forest regression model feature importance analysis identified Staheli Index as the dominant contributor to CSI prediction (importance = 0.7488), followed by heel–forefoot ratio (0.2250) and foot length–width ratio (0.0217), whereas therewas very less contribution of pulmonary importance values as 0.00063 for %FEV_1 and 0.00041 for %FVC. Demographic variables accounted for minimal importance, with values of 0.00034 for age and 0.00031 for BMI (Figure 2 B)

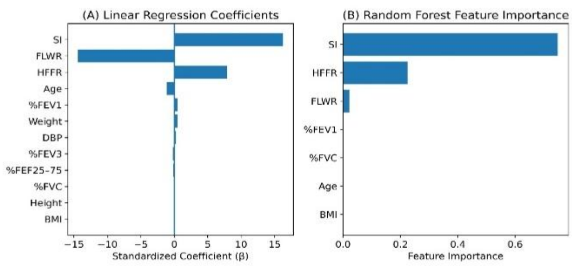

Figure 2: (A) Linear Regression Coefficient (B) RF features importance

Canonical correlation (Table 2) indicates a moderate relationship between pulmonary and biomechanical variables (r = 0.382). The first canonical function represents the correlation of expiratory pulmonary parameters (%FEV_1, %FEF25–75) and midfoot-related biomechanical indices (SI and FLWR). Loadings indicated dominant contributions from %FEV_1 (0.897) and %FEF25–75 (0.526) on the pulmonary side (Table 3) and SI (0.854) and FLWR (0.773) on the biomechanical side (Table 4).

Table 2: Canonical Correlation Analysis (CCA)

Canonical Function	Canonical Correlation (r)
Canonical 1	0.382
Canonical 2	0.088

Table 3: Canonical Loadings (Pulmonary Domain)

Pulmonary Variable	Canonical 1	Canonical 2
%FEV_1	0.897	0.803
%FEF25–75	0.526	−0.066
%FVC	0.469	0.552
DBP	0.607	−0.565

Table 4: Canonical Loadings (Biomechanical Domain)

Biomechanical Variable	Canonical 1	Canonical 2
Staheli Index (SI)	0.854	−0.075
FLWR	0.773	−0.492
CSI	0.437	0.426
HFFR	0.088	−0.911

4. Discussion:

This study evaluated the relationship between pulmonary and foot biomechanics using a multimodal statistical and machine learning approach with CSI as the primary outcome. Results demonstrate that pulmonary and demographic variables provide limited predictive power for CSI, whereas integrating biomechanical features improves model performance under nonlinear learning. These findings support the that respiratory impairment is associated with distal biomechanical adaptations rather than isolated pulmonary effects. Baseline linear regression showed weak predictive capacity, consistent with previous reports indicating spirometric indices inadequately explain musculoskeletal and postural adaptations associated with respiratory functioning[9-10]. Results of the multimodal linear model indicate that the contribution of foot biomechanics also contributes to pulmonary metrics. However, the near-complete variance explained by the multimodal Random Forest model highlights the importance of nonlinear interactions, increasingly recognized in physiological systems [11-12]. Feature importance analysis further indicates midfoot biomechanical indices, Staheli Index and foot length width ratio as important parameters for CSI prediction. This is supported by the studies reporting that altered plantar loading, increased midfoot contact, and modified stance strategies in individuals with reduced exercise and chronic dyspnea [13-15]. Therefore, to reduce ventilatory effort, individuals reduce physical activity, compensate with posture , and experience muscle deconditioning as mechanisms of underlying adaptation [16-17]. Pulmonary parameters, %FEV_1, influence linear models but minimal contribution in nonlinear analysis, suggesting an indirect rather than a direct effect on foot structure. Canonical correlation also supports cross domain adaptation by indicating moderate multivariate alignment between expiratory pulmonary and midfoot biomechanics variables that is in line with the studies indicating expiratory flow limitation has been associated with balance deficits, altered gait timing, and reliance on distal stabilization, particularly at the foot and ankle [18-20]. The dominance of midfoot indices in the biomechanical domain explains the foot's role as a compensatory interface between the body and the ground during chronic respiratory compromise. Although pulmonary variables showed weaker direct associations with CSI than biomechanical indices, multivariate indicate that pulmonary function influences CSI indirectly through biomechanical adaptation [21-23]. Overall, these findings suggest that biomechanical variables the foot may serve as a complementary, noninvasive tool to evaluate the functional adaptation associated with respiratory health. This study also highlights the limitations of linear modeling compared with multimodal nonlinear approaches for understanding complex physiological interactions [24-26].

5. Conclusion:

This study demonstrates that pulmonary function is associated with adaptations in foot biomechanics, affecting midfoot-related indices. While demographic and pulmonary variables alone showed limited prediction to CSI, multimodal integration substantially improved the prediction, under nonlinear modeling. The findings highlight coordinated cross domain interactions between respiratory performance and foot structure, suggesting that static foot biomechanical assessment may serve as a complementary, noninvasive tool alongside spirometry for functional evaluation in respiratory impairment.

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