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Association between Self-reported Sleep Quality and Single-task Gait in Young Adults: A Study Using Machine Learning

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Abstract

Objective The objective of the present study was to find biomechanical correlates of single-task gait and self-reported sleep quality in a healthy, young population by replicating a recently published study.

Materials and Methods Young adults ($n = 123$) were recruited and were asked to complete the Pittsburgh Sleep Quality Inventory to assess sleep quality. Gait variables ($n = 53$) were recorded using a wearable inertial measurement sensor system on an indoor track. The data were split into training and test sets and then different machine learning models were applied. A post-hoc analysis of covariance (ANCOVA) was used to find statistically significant differences in gait variables between good and poor sleepers.

Results AdaBoost models reported the highest correlation coefficient (0.77), with Support-Vector classifiers reporting the highest accuracy (62%). The most important features associated with poor sleep quality related to pelvic tilt and gait initiation. This indicates that overall poor sleepers have decreased pelvic tilt angle changes, specifically when initiating gait coming out of turns (first step pelvic tilt angle) and demonstrate difficulty maintaining gait speed.

Discussion The results of the present study indicate that when using traditional gait variables, single-task gait has poor accuracy prediction for subjective sleep quality in young adults. Although the associations in the study are not as strong as those previously reported, they do provide insight into how gait varies in individuals who

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report poor sleep hygiene. Future studies should use larger samples to determine whether single task-gait may help predict objective measures of sleep quality especially in a repeated measures or longitudinal or intervention framework.

Introduction

It is estimated that 50 to 70 million Americans experience poor sleep quality which interferes with daily functioning and adversely affects overall health.[1] Current recommendations are that adults obtain 7 to 9 hours of sleep per night;[2] however, many adults do not meet the minimum recommendation for hours of sleep per night and as a results experience poor sleep quality.[3] A large body of scientific evidence supports that sleep duration and quality is extremely important for overall health as it can have a significant impact on neurophysiological[4] and cognitive function.[5] Walking gait is the coordinated pattern of movement between body segments in order for the body to translate forward in space.[6] Gait is a basic motor skill that is sensitive to mild cognitive impairment.[7] Moreover, it is common to perform gait while concurrently performing cognitive tasks (that is, talking, counting) which is referred to as dual-task gait.[8] It has been reported that poor sleep quality leads to decline in single-task gait speed[9,10] and dual-task gait speed and gait variability (that is, increased variance in gait measures such as stride time, step length, etc.) in older adults,[11] which are gait parameters usually associated with increased fall risks.[12,13] However, little is known about the impact of sleep quality on gait parameters in young adults.

Recently, Liu et al.[14] reported that using machine learning models, single-task gait could predict self-reported sleep quality scores on the Pittsburgh Sleep Quality Index (PSQI) in healthy, young adults. The authors of that study reported that the strongest gait variables predicting sleep quality were the head, spine, shoulder, left wrist, right hand, left and right thumb, left hand tip, left hip, and left foot,[14] measures not traditionally used in gait literature. Their regression models reported high predictive values for self-reported overall subjective sleep quality, sleep duration, habitual sleep efficiency, sleep duration, and daytime dysfunction.[14] Despite prediction performance of their models, none of the reported variables that predicted overall sleep quality or any of the components were measures commonly reported in gait literature. For example, the study reported that the head, shoulder, wrist, thumb, and hand tip were variables with strong weightings in the prediction,[14] which provides no useful biomechanical information regarding the influence of subjective sleep quality on typically measured gait measures. However, their study brings up interesting questions as to how poor sleep quality may influence commonly measured gait parameters which may have clinical utility, as improper gait mechanics in young adults have been associated with increased risk for injuries.[15,16]

In a study in young runners, it was reported that runners who demonstrated greater contralateral pelvic drop and forward trunk lean at midstance and a more extended knee and dorsiflexed ankle at initial contact were more likely to report injuries.[15] In another study, duration of loading response was a significant predictor of lower-extremity injuries in young soldiers.[16] While these studies provide evidence that poor gait mechanics lead to increased risk for injuries in young adults, we are unaware of any literature that examines the association between sleep quality and gait parameters that may be associated with increased injury risks.

Therefore, the purpose of the present study was twofold. The first purpose was to identify gait biomechanical characteristics (such as. gait speed and step variability), including upper body movement patterns (such as neck, trunk, and arm movement), to determine which clinically relevant variables[17,18] best predict self-reported subjective measures of sleep quality in healthy, young adults. Identifying gait variables associated with poor sleep quality could be useful to screen individuals at greater risk of injury. Based on the evidence provided by Liu et al.,[14] we hypothesize that poor sleepers will have significantly different gait patterns compared with good sleepers. The second purpose of the present study was to attempt to replicate the findings of Liu et al.[14] Given that the variables reported to predict poor sleep by Liu et al. were primarily of the upper extremity, it would be valuable to identify lower extremity variables, more commonly assessed in gait analyses, that are influenced by sleep quality.

Materials and Methods

Participants

The participants for the present study were college-age adults (age: 18 to 36 years) sampled locally from a small college town. Recruitment was conducted using flyers, word of mouth, and announcements in large classes (> 30 students) at the local university. The inclusion criteria for the study included the ability for participants to stand and ambulate for two minutes without an assistive device. Exclusion criteria included any impairment such as inability to walk or stand independently, or if they were unable to walk for up to two minutes without any pain or discomfort. In addition, participants with any neurological conditions (for example, stroke), lower extremity orthopedic surgery within the last six months, wounds, or absence of sensation to the plantar surface of their feet or any visual impairment were excluded from the present study. The study was approved by the institutional review board (approval #18.39.1), and all participants signed an informed consent prior to participating in the study.

Data Collected

Demographics

Data was collected for age, sex, height (cm), and weight (kg). The height of the participants was measured using a stadiometer (SECA model 220, SECA Corporation, Chino, CA, United States). Weight was measured using the Tanita Bioelectrical Impedance Analysis Scale (TBF-410, Tanita Corporation, Tokyo, Japan).

Sleep

The PSQI was administered to assess sleep quality. The survey includes 19 questions that yield 7-component scores.[19,20] These scores include: subjective sleep, sleep latency, sleep duration, sleep efficiency, sleep disturbance, use of sleep medication, and daytime dysfunction.[19] A total sum is then reported as an overall PSQI global score. For the present study, participants were further classified based on their PSQI global score. Participants were categorized as 'good' and 'poor' sleepers. Good sleep was quantified as a PSQI global score $\leq$ 5, while poor sleep is a PSQI global score $>$ 5.[19] The PSQI survey has demonstrated acceptable test-retest reliability (r = 0.87), high sensitivity (98.7%), and specificity (84.4%).[20] The Cronbach alpha for the PSQI for the present study is 0.71.

Gait Data

Gait data was collected using APDM's Mobility Lab (APDM Wearable Technologies, Portland, OR, United States), which is a system of small body-worn inertial sensors used to assess gait during a 2-minute walk test. The Mobility Lab consists of a set of wireless, body-worn Opal inertial sensors, each with a docking station; an access point for wireless data transmission and sub-millisecond synchronization of the independent sensors. The sensors were attached to the body in seven locations (sternum, lower back, forehead, left foot, right foot, left wrist, and right wrist) using Velcro straps. Participants performed a 2-minute walk test for gait assessment wearing these monitors. While the APDM website suggests using a 7 m track to conduct a 2-minute walk test, in order to replicate the study by Liu et al.,[14] and find biomechanical variables associated with self-reported sleep quality, we utilized their protocol and had participants walk for 2 minutes at a self-selected pace around a 6m x 1 m track. The APDM has been used in a 6-m walk to measure gait in multiple studies.[21–23] The gait variables were exported from APDM's Mobility Lab for analysis. The complete list of variables is available in ►**Supplementary Table S1**. The validity and reliability of the APMD's ability to measure gait has previously been established.[24]

Study Procedures

After the initial screenings, participants were scheduled for a 1-day session in a noiseless lab lasting approximately 75 minutes. Participants were instructed not to consume alcohol, caffeine, non-prescription medications or illicit drugs at least 24 hours prior to testing. First, height and weight were measured using a stadiometer. Participants were asked to complete a series of questionnaires regarding their activities over the last 24 hours to verify that they had followed instructions. Afterwards, participants were asked to walk for two minutes at a pace that was comfortable for them. After the completion of the walk, participants completed a series of surveys regarding their lifestyle, one of which was the PSQI. If participants had any questions regarding the surveys, they were provided further instruction as needed.

Statistical Analysis

Data Preprocessing

Data for demographics, sleep quality, and gait were initially compiled into a Microsoft Excel (Microsoft Inc., Redmond, WA, United States) database. Data was then further processed in the Python (Python Software Foundation, Wilmington, DE, United States) software, version 3.8.5. Due to the data collecting environment, some data may be missed during the data collecting process. For example, if $>$ 5% of participants missed a certain feature during the collecting process, we deleted this feature. If $<$ 5% of participants missed a certain feature for some reason during the collecting process, we filled in missing values with the mean of this feature in the dataset.[25] After preprocessing, we had 123 participants (72 good sleepers, 46 male), with 53 valid gait characteristics (features). Additional details may be found in ►**Supplementary Data File**.

Model Training

When recording high dimensional features, not every feature is equally important, and there may be redundant features that are of less importance. A random forest was used to sort features according to their relative importance.[26] The Scikit-learn (Sklearn, Python, https://www.python.org/) library default setting of 100 trees was implemented. After sorting the features, we used the dataset to train the model through regressors and classifiers respectively. For the classifier, we classified the records whose sleep quality was $\leq$ 5 as good sleepers, and the rest as poor sleepers.[19] We used all features and top 12 features (using 0.03 as a cutoff for feature importance) to train each model. Using the Monte Carlo method, we randomly split the training set (90%) and test set (10%) and ran each of the ML models 10,000 times with the training and test set varying for each iteration. Mean absolute errors (MAE) were used to assess the regressors and accuracy, to evaluate classifier models. We also assessed correlation coefficients (R^2) between the predicted PSQI and the self-reported PSQI on the regressor models.[14]

Post-hoc Analysis

A post-hoc analysis of covariance (ANCOVA) was used to determine statistically significant differences between poor sleepers and good sleepers for each of the gait values. The ANCOVA controlled for sex, age, height, and weight. An additional post-hoc re-analysis of the data publicly provided

Table 1 Characteristics of the study sample.

	PSQI global score: mean ± SD	Height (cm): mean ± SD	Weight (kg): mean ± SD	Age (years): mean ± SD	Sex (male: female)
Good sleepers (n = 72)	3.42 ± 1.32***	173.60 ± 8.81	71.95 ± 7.95*	23.92 ± 3.92	27:45
Poor sleepers (n = 51)	7.80 ± 1.76***	172.87 ± 8.52	77.34 ± 16.56*	24.61 ± 4.19	18:33

Abbreviation: PSQI, Pittsburg Sleep Quality Index; SD, standard deviation.
Notes: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

by Liu et al.[14] using the same methods described above was also performed.

Results

There were 51 participants categorized as poor-quality sleepers (41.5%) and 72 as good sleepers (58.5%; ►**Table 1**). While most participants was classified as good sleepers, the mean global PSQI of all participants was 5.26 ± 2.6, which was above the cutoff of 5 used to categorize participants as poor-quality sleepers. Weight was the only variable found to be significantly different ($p < 0.05$) between good and poor sleepers, with poor sleepers having a significantly higher mean weight (►**Table 1**).

Feature Importance

The most important feature was the first step lumbar transverse range of motion (relative importance = 0.0683), which was 58% more important than the second highest predictor (first step lumbar left frontal bending maximum). The least important variable was the gait cycle duration variance (relative importance = 0.003). All correlation coefficients for the top 12 features were < 0.65, suggesting that the top 12 features had low linear dependence. Variables with their importance and their means for each category can be found in ►**Table 2**.

Model Evaluation

As the MAE showed (►**Table 3**), although the predicted values deviated greatly from the true values (accuracy ranging from 2.05 to 3.08), the predicted values were positively correlated to the true values, as the correlation coefficients (R^2) showed (►**Table 4**). Overall, the best performance of the regressors was achieved by AdaBoost on the top 12 features, with an R^2 of 0.77. The best performance of the classifiers was achieved by support-vector classifiers on the top 12 features (►**Table 3**).

Post-hoc

Post-hoc ANCOVA revealed that in the top 12 features, poor sleepers had greater circumduction variance, terminal double leg support variance and a smaller first step lumbar minimum sagittal angle (►**Table 2**). Of the features not in the top 12 features used in the machine learning models, good sleepers had greater first step lumbar maximum sagittal movement angles, greater foot strike variance, and lower gait speed variance. Although not statistically significant based on mean differences of the top 12 features, poor sleepers had greater mid-swing elevation, greater stride length variance and greater first step transverse maximum angle on the right side (see ►**Table 2**).

Discussion

The findings in the present study build upon the work of Liu et al.,[14] who reported a 0.78 correlation coefficient between gait characteristics and self-reported sleep quality. As previously mentioned, Liu et al.[14] focused on gait characteristics that are not typically included in routine clinical gait assessments, such as thumb and neck movements. However, our study provides insight on variables more commonly reported in clinical gait measurements such as circumduction, pelvic tilt, and double leg support time.[27] Thus, our hypothesis that good and poor sleepers would display significantly different gait patterns were not supported by our results. The models in the present study demonstrated a relatively low association between sleep quality and gait. However, the post-hoc ANCOVA analyses did suggest that overall poor sleepers have decreased pelvic tilt angle changes, specifically when initiating gait coming out of turns (first step pelvic tilt angle), and they demonstrate difficulty maintaining gait speed. These findings are important to consider relative to the purpose of the study to predict changes in gait patterns due to poor sleep as these findings are potentially useful to screen individuals at increased risk of injury.

The results of our feature selection and post-hoc ANCOVA analyses suggest poor sleepers have an overall decrease in pelvic tilt range coming out of turns. However, while our post-hoc analysis only reported statistically significant differences between poor and good sleepers for first step pelvic tilt, machine learning allowed for a better understanding of predictors. Machine learning identified that pelvic tilt, pelvic drop/hike, and trunk motion were all predictors of sleep quality (7 of top 12 features), with poor sleepers demonstrating increased movements in the sagittal plane (see relative importance column of ►**Table 2**). Good sleepers, conversely, had increased pelvic drop/hike, as well as a slightly lower amount of trunk rotation. Taken together, these results suggest that poor sleepers could be identified by differences in pelvic and trunk motion, especially when coming out of a turn. The results of our machine learning models should be interpreted with caution as the low kappa suggests poor fitting of the overall models.

Interestingly, several studies have reported altered trunk motion during gait to be characteristic of diseased populations.[28,29] While pelvic tilt ranges are typically

Table 2 Feature importance and descriptive statistics.

			Good sleepers ($n = 51$)		Poor sleepers ($n = 72$)			
Feature	**Relative importance**	**Ranking**	**Mean**	**SD**	**Mean**	**SD**	**Significant difference**	**Finding**
First step pelvic rotation ROM (deg)	0.063	1	10.65	3.41	11.29	3.49		
First step pelvic drop/hike maximum angle (deg)	0.039	2	6.14	2.69	5.66	2.61		
Circumduction variance (%)	0.037	3	16.55	10.43	20.78	17.25	**Yes**	Bad > good
Terminal double leg support variance (%)	0.035	4	3.84	4.04	2.98	2.61	**Yes**	Good > bad
Circumduction (cm)	0.035	5	2.84	1.16	2.88	1.13		
Toe out angle (deg)	0.035	6	36.78	3.10	37.10	3.53		
Step variability	0.031	7	2.95	0.72	2.80	0.66		
Trunk transverse ROM (deg)	0.031	8	9.08	2.54	9.48	2.44		
Pelvic rotation ROM (deg)	0.031	9	8.22	2.88	8.25	2.30		
Trunk angle (deg)	0.030	10	186.56	4.13	186.96	4.50		
First step pelvic drop/hike(deg)	0.030	11	9.15	2.86	8.98	2.92		
First step pelvic tilt minimum angle (deg)	0.030	12	-1.26	4.18	-3.33	5.71	**Yes**	Good > bad
Toe out angle variance (%)	0.026	13	2.45	1.76	2.27	1.73		
First step pelvic tilt maximum angle (deg)	0.023	14	4.85	4.01	2.80	5.61	**Yes**	Good > bad
Foot strike angle variance (%)	0.023	15	4.38	3.80	3.37	3.00	**Yes**	Good > bad
Gait speed variance (%)	0.021	16	0.93	0.75	1.14	0.73	**Yes**	Bad > good
Steps in turn (#)	0.020	17	3.54	0.29	3.52	0.37		
Arm swing ROM (deg)	0.019	18	43.53	15.89	41.34	15.39		
Trunk frontal plane ROM (deg)	0.019	19	4.80	1.86	4.99	1.99		
Arm swing velocity (deg/s)	0.019	20	191.84	65.35	190.61	69.76		
Mid-swing elevation variance (%)	0.019	21	17.22	14.40	16.98	15.32		
Back transverse plane left rotation maximum angle (deg)	0.018	22	4.19	12.35	1.66	15.12		
Single leg support variance (%)	0.018	23	0.96	0.94	0.95	0.65		
Turns duration (s)	0.018	24	2.21	0.24	2.19	0.19		
Swing variance (%)	0.018	25	0.90	0.94	0.98	0.70		
Mid-swing elevation (cm)	0.018	26	1.24	0.62	1.39	0.64		
Turn velocity (deg/s)	0.018	27	182.26	29.27	181.57	27.28		

(*Continued*)

Table 2 (*Continued*)

			Good sleepers ($n = 51$)		Poor sleepers ($n = 72$)			
Feature	**Relative importance**	**Ranking**	**Mean**	**SD**	**Mean**	**SD**	**Significant difference**	**Finding**
Lumbar pelvic tilt (deg)	0.018	28	5.30	1.43	5.53	1.65		
Arm ROM variance (%)	0.016	29	13.05	11.39	14.83	11.02		
Step duration variance (%)	0.016	30	1.02	0.87	0.94	0.91		
Back right frontal plane bending angle (deg)	0.015	31	3.01	2.41	3.32	2.31		
Cadence variance (%)	0.015	32	0.21	0.18	0.25	0.23		
Stance variance (%)	0.014	33	0.60	0.61	0.65	0.46		
Stride length variance (%)	0.014	34	0.84	0.63	1.01	0.66		
Double leg support variance (%)	0.014	35	0.66	0.51	0.62	0.53		
Gait speed (m/s)	0.013	36	1.06	0.13	1.06	0.13		
Step variability variance (%)	0.013	37	10.32	7.13	10.96	7.87		
Back transverse plane right rotation maximum angle (deg)	0.011	38	6.47	12.89	9.62	14.73		
Foot strike angle (deg)	0.011	39	24.12	4.36	24.30	4.58		
Swing phase (% gait cycle)	0.010	40	39.88	1.39	39.63	1.78		
Stride length (m)	0.010	41	1.20	0.10	1.20	0.11		
Trunk sagittal plane ROM (deg)	0.010	42	5.50	1.60	5.46	1.56		
First step lumar sagittal plane ROM (deg)	0.010	43	6.11	2.27	6.14	1.92		
Stance (% gait cycle)	0.009	44	60.12	1.39	60.37	1.78		
Cadence (step/min)	0.009	45	105.58	8.14	105.40	8.85		
Number of turns	0.007	46	17.14	2.31	16.82	2.26		
Double leg support (% gait cycle)	0.007	47	20.29	2.76	20.81	3.47		
Step duration (s)	0.007	48	0.57	0.04	0.57	0.05		
Gait cycle duration (s)	0.005	49	1.14	0.09	1.15	0.10		
Single leg support (% GCT)	0.005	50	39.83	1.38	39.56	1.70		
Terminal double leg support (%GCT)	0.005	51	10.21	1.37	10.46	1.71		
Gait cycle duration variance (%)	0.003	52	0.19	0.24	0.22	0.29		

Abbreviations: deg, degrees; GCT, ground contact time; ROM, range of motion.
Notes: Variance was computed as the difference in percentages between the left and right sides. Differences between good and bad sleepers were tested with independent samples *t*-tests. Trunk and upper extremity variables are shaded light gray. Lower extremity kinematic and gait variance variables are shaded dark gray.

Table 3 Model evaluation results.

Regressors: R^2	Rank	Mean	SD	Minimum	25%	50%	75%	Maximum
AdaBoost top 12	1	0.35	0.25	- 0.73	0.19	0.38	0.54	0.94
Random forest top 12	2	0.26	0.26	- 0.71	0.09	0.28	0.46	0.91
Linear top 12	3	0.17	0.27	- 0.83	- 0.01	0.18	0.36	0.90
AdaBoost full	4	0.10	0.28	- 0.78	- 0.08	0.11	0.30	0.88
Random forest full	5	0.01	0.27	- 0.90	- 0.18	0.01	0.19	0.84
Linear full	6	- 0.04	0.28	- 0.84	-0.25	- 0.05	0.15	0.89
Regressors: mean absolute error	**Rank**	**Mean**	**SD**	**Minimum**	**25%**	**50%**	**75%**	**Maximum**
AdaBoost top 12	1	2.05	0.38	0.80	1.79	2.03	2.30	3.70
Random forest top 12	2	2.11	0.38	0.74	1.84	2.09	2.37	3.65
Linear top 12	3	2.16	0.44	0.75	1.85	2.14	2.45	4.12
AdaBoost full	4	2.21	0.41	0.96	1.93	2.20	2.48	3.98
Random forest full	5	2.22	0.41	0.79	1.93	2.21	2.49	3.91
Linear full	6	3.08	0.66	0.95	2.61	3.05	3.51	5.92
Classifiers	**Rank**	**Mean**	**SD**	**Minimum**	**25%**	**50%**	**75%**	**Maximum**
Support-Vector top 12	1	0.58	0.13	0.15	0.46	0.62	0.69	1.00
Support-Vector full	2	0.59	0.13	0.15	0.46	0.62	0.69	1.00
Random forest full	4	0.56	0.13	0.08	0.46	0.54	0.62	1.00
Random forest top 12	3	0.56	0.13	0.08	0.46	0.54	0.62	1.00
AdaBoost top 12	5	0.53	0.13	0.08	0.46	0.54	0.62	1.00
AdaBoost full	6	0.52	0.13	0.08	0.46	0.54	0.62	1.00
Cohen Kappa	**Rank**	**Mean**	**SD**	**Minimum**	**25%**	**50%**	**75%**	**Maximum**
Random forest top 12	1	0.07	0.25	- 0.81	- 0.10	0.06	0.24	1.00
Random forest full	2	0.04	0.24	- 0.81	- 0.13	0.03	0.20	1.00
AdaBoost top 12	3	0.03	0.25	- 0.86	- 0.13	0.03	0.22	1.00
AdaBoost full	4	0.00	0.25	- 0.86	- 0.18	0.03	0.18	0.84
Support-Vector classifier top 12	5	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Support-Vector c lassifier full	6	0.00	0.00	- 0.16	0.00	0.00	0.00	0.00

Abbreviation: SD, standard deviation.
Note: Models were evaluated using a Monte Carlo method and data were randomly split into 90% training set and 10% data set. Each of the models was run 10 thousand times. Ranks were determined by 50% values and in case of same values model with fewer features was ranked higher.

small, this sagittal plane motion is considered important to economical gait patterns.[30] Limitations in pelvic tilt ranges have been found in relation to hip pathologies, such as impingement.[30] The decreased pelvic movements mentioned likely influenced the lower extremity variables reported to be predictive of sleep quality.[31] Our findings suggest that in general poor sleepers had increased variance of circumduction, decreased variance in double leg support time, and increased gait speed variance. These findings suggest that poor sleepers were spending more time loading and they had a difficult time initiating gait and sustaining a consistent gait speed. Poor sleepers are more likely to increase circumduction and decrease pelvic movements following turns, while good sleepers were found to be more likely to elevate the hip to achieve foot clearance following turns.

Table 4 Correlation coefficients.

	Regressor		
	Random forest	Linear	AdaBoost
Full features	0.61	0.63	0.73
Top 12 features	0.59	0.63	0.77

In addition to analyzing our own data, we also re-ran the models using the data made available by Liu et al.[14] We find that both studies had similar correlation coefficients and similarly poor classification accuracy (~ 60 to 65%). However, we should note that ~ 0.3% of all models had 100% classification accuracy. These results suggest that while there is a relationship between gait and self-reported sleep quality, significantly more subjects would be needed for us to create machine learning models that may be able to accurately classify good and poor sleepers. The models that had 100% accuracy were "lucky" in the participants who were randomly selected for their training and test models and were perhaps over-fitting. Furthermore, we used machine learning models to predict scores on all seven sub-sections of the PSQI however, due to poor distribution of subjects on each of the subscales, the models were overfitting and could not be interpreted.

Previous research has indicated that slower gait speeds can cause altered mechanics of the pelvis.[32] Interestingly, our findings suggest that pelvic movements in all 3 planes were able to predict those who self-report poor sleep. This suggests that poor sleep may cause individuals to adopt a gait more similar to when they walk more slowly. In the present study, individuals were instructed to walk at their self-selected gait speed. A pelvic pattern more consistent with slower gait was present in those with poor sleep even though there was no difference in the average gait speed of the two groups. This is an important detail as machine learning becomes more prominent and as clinicians begin to apply findings in the clinical setting as poor sleep quality may exacerbate these gait changes in populations with diagnoses of chronic disease.[28,29]

Like most studies, the present study had several limitations, such as the use of a cross-sectional design. Additionally, although the PSQI has been found to be valid and reliable,[20] it is a subjective measure and its sensitivity in detecting poor sleep quality in young healthy adults is limited.[33] Currently, objectively monitoring chronic sleep quality is challenging in healthy populations and although many wearables are able to the monitor sleep the reliability of these devices remains limited.[34] An additional limitation of the present study is that we did not control for moods and/or eliminate any participants with a mood disorder, which have been shown to influence gait.[35,36] Lastly, we assume that gait may be affected by poor sleep and that these changes can be detected. A recent study by Umemura et al. compared the effects of acute sleep deprivation to chronic poor sleep quality to a control sample on gait.[37] Interestingly, it was reported that while poor sleep quality did affect gait, it was not to the same extent as acute sleep deprivation. Therefore, the effects of sleep quality on gait may be very subtle from a clinical perspective and make accurately modeling challenging. Due to the complexity of gait, it is advised that future research directions include investigating the effects of sleep quality on balance, as there is evidence that chronic sleep disturbance affects static postural control.[38] Additionally, future researchers may also try to apply deep learning approaches to determine whether those approaches may yield in more accurate results. Additionally, it is suggested that if single-task gait is explored in the context of self-reported sleep quality, it should be examined in older adults since older adults report greater disturbances in single task gait than their younger counterparts.[39]

Conclusion

To our knowledge, this is the first study to use machine learning to identify clinically relevant biomechanical gait characteristics predictive of self-reported sleep quality in healthy young adults. The models in our study were not as strong as previously reported by Liu et al.[14] The results of our post-hoc findings support that poor sleepers may display very subtle changes in gait normally associated with difficulty initiating and maintaining gait speed. Notably, these gait patterns are similar to individuals who are at a higher risk for lower extremity injuries[15,16,30] or walking more slowly.[32] Future research should longitudinally collect single-task gait data in larger sample sizes and use objective measures of sleep quality to further investigate the effects of sleep quality on gait.

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Conflict of Interests
The authors have no conflict of interests to declare.

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