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Sensor-Based Balance Measures Outperform Modified Balance Error Scoring System in Identifying Acute Concussion

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Abstract

Balance assessment is an integral component of concussion evaluation and management. Although the modified balance error scoring system (mBESS) is the conventional clinical tool, objective metrics derived from wearable inertial sensors during the mBESS may increase sensitivity in detecting subtle balance deficits post-concussion. The aim of this study was to identify which stance condition and postural sway metrics obtained from an inertial sensor placed on the lumbar spine during the mBESS best discriminate athletes with acute concussion. Fifty-two college athletes in the acute phase of concussion and seventy-six controls participated in this study. Inertial sensor-based measures objectively detected group differences in the acutely concussed group of athletes while the clinical mBESS did not ($p < 0.001$ and $p = 0.06$, respectively). Mediolateral postural sway during the simplest condition of the mBESS (double stance) best classified those with acute concussion. Inertial sensors provided a sensitive and objective measure of balance in acute concussion. These results may be developed into practical guidelines to improve and simplify postural sway analysis post-concussion.

Keywords

Concussion; mTBI; Balance; BESS; Postural sway; Brain injury; Inertial sensors

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CONFLICT OF INTEREST

The authors have no conflicts of interest to disclose.

INTRODUCTION

Approximately 1.6–3.8 million sports-related concussions occur annually in the United States.^{8,52} Since many concussions are unreported,³⁸ reliable and objective tools are essential for accurately evaluating an athlete with a suspected concussion. Assessment of balance post-concussion was formally recommended in the Zurich Consensus Statement on Concussion in Sport.⁴⁰ While self-reported symptom scores are the most commonly used tools for concussion assessment, balance assessment is also common.²⁶ Recently, the National Collegiate Athletic Association (NCAA) required baseline balance assessments for athletes who participate in sports at risk for concussion.⁵¹ However, the modest sensitivity and reliability of current clinical tests greatly limits the information that can be gained from them.

The most commonly used clinical balance assessment tool following concussion is the Balance Error Scoring System (BESS).⁴⁸ During the administration of the BESS, the clinician subjectively identifies and counts errors in body position while the patient attempts to maintain balance with eyes closed in three stance conditions: double stance (DS), single limb stance (SLS) and tandem stance (TS), which are each performed on two surfaces (hard ground, foam pad).⁴⁸ The modest and widely ranging sensitivity (34–64%) reported for the BESS is likely due to the subjective nature of the scoring, in which errors are identified by the examiner, as well as the floor effect of the simple DS condition.^{11,17} After concussion, athletes exhibit, on average, 7 more errors during the BESS than at baseline.² Yet, Finnoff *et al.*¹¹ reported the minimum detectable change of the BESS was 7.3 errors when judged by the same rater and 9.4 errors across different raters. Additionally, fatigue^{14,56} and practice effects⁴³ are known to influence the sensitivity of the BESS. The modest sensitivity of the BESS may also be explained by the large variance in performance during the stances on foam. Over 53% of the variance in errors can be attributed to the SLS and TS conditions on foam.²⁴ Recently, an abbreviated version entitled the modified BESS (mBESS), eliminating the foam pad condition, is used as part of the sport concussion assessment tool (SCAT-3).^{25,48} Yet, the mBESS has shown greater sensitivity to chronic post-concussive syndrome (PCS) when instrumented with a sensor.²⁸

Objective assessment of postural sway has the potential to demonstrate higher sensitivity to balance deficits than subjective scoring by counting perceived errors as performed in the mBESS.^{6,13,16,19,53} Although postural sway has traditionally been quantified using force plates, recent advances in wearable technology have yielded portable and accurate instruments that have been validated against the gold standard of force platforms.^{34,55} We previously reported that postural sway measures from a single inertial sensor over the lumbar spine were able to better discriminate between those with and without PCS than the standard clinical mBESS error count.²⁸ A similar approach using multiple sensors has also been validated against motion capture during the mBESS on healthy adults.³ Taken together, these studies suggest that an inertial sensor-based mBESS, (hereafter, instrumented mBESS), which produces objective results of postural sway, is a valid and sensitive measure of balance. However, as these studies are limited to chronic PCS and healthy subjects who have never sustained a concussion; the usefulness of instrumented balance measures in the

acute stage after concussion remains unknown. Further, the metrics generated by an instrumented approach are numerous and complex.

Postural sway can be quantified across multiple domains such as sway amplitude, velocity, frequency and variability^{35,49} making the translation to clinical assessment daunting. Sway amplitude, which is the maximum length of sway in a given direction, has been related to the stability achieved by the postural control system.^{35,49} Sway velocity, or average speed of sway in a given direction, has been interpreted as the amount of compensatory activity associated with a given level of stability.^{23,31,32} Sway frequency is defined as the number of oscillations in a given time period, and may be reflective of axial rigidity in neurologically impaired populations.⁵⁰ Sway variability represents dispersion from the mean. In addition to multiple domains, postural sway can also be characterized by the direction in which the movements occur (anteroposterior, AP and mediolateral, ML). Therefore, although an instrumented mBESS holds promise, technical questions remain. Guided variable selection is needed in order for instrumented sway measures to be translated into a routine clinical assessment.

The primary objectives of this study were to (1) determine if inertial sensor-based measures of postural sway during the mBESS are more sensitive than the non-instrumented clinical assessment in the acutely concussed state and (2) to determine the stance condition of the mBESS that best differentiates between the acutely concussed and the non-concussed groups. Following results showing altered sway in people with chronic PCS,²⁸ we hypothesized that objective measures of postural sway will show greater sensitivity to detect balance impairments in acutely concussed athletes compared to the clinical mBESS. We also hypothesized that instrumenting the more complex conditions of SLS and TS would best differentiate concussion from control subjects.

MATERIALS AND METHODS

Study Design

This was a cross-sectional study in college athletes. This study was registered at clinicaltrials.gov (NCT01661075) and was part of a larger longitudinal study to measure balance recovery after concussion.

Participants

College-aged student athletes were recruited during their academic sports' season from six Universities: Portland State University, Lewis & Clark College, Linfield College, Pacific University, Concordia University, and George Fox University. In order to participate, interested athletes were required to be above 18 years of age, have sustained a concussion past 1–4 days (case group) or have a history of no concussion in past six months (control group). If the concussed athletes were tested more than 2 days from the concussive event, the athlete's data was excluded if no symptoms were reported. All concussed athletes were identified and managed throughout return-to-play by their team physician. Concussion diagnoses were confirmed by the team physician. Athletes were excluded if they (1) met DSM-IV criteria for substance abuse or self-reported drug use within the past 24 h, (2) had a

history of a medical condition that could impair balance or cognition other than the recent concussion, or (3) had a lower extremity injury or surgery within the past 6 months. Athletes with injuries or surgeries that occurred more than 6 months prior to testing were included in the study if the injury or surgery did not subjectively interfere with balance, as reported by the athlete. The OHSU Institutional Review Board (IRB) approved this study. All subjects signed an informed consent form approved by OHSU IRB. All work was conducted in accordance with the Declaration of Helsinki (1964).

Procedure

During a single day, balance was assessed during the mBESS test using two methods obtained simultaneously: (1) the clinical subjective mBESS error count²⁵ and (2) the instrumented mBESS producing postural sway metrics. Consenting and questionnaires were performed in a private office and the balance testing was completed indoors in an open area on a hard flat surface. All consenting and protocols took place at the host institution. Subjects were administered the mBESS test, in which they were instructed to close their eyes and stand as still as possible for 30 s in three different stance conditions: DS, SLS, and TS. Subjects were videotaped and rated later by a blinded research assistant trained in the classification criteria of the mBESS to count errors such as lifting hands off hip, opening eyes or touching the foot down. In accordance with the clinical mBESS scoring, only the first 20 s of each stance were scored.³⁹ Simultaneously, postural sway was recorded for the full 30 s with an inertial sensor (Opal, APDM Inc) containing a tri-axial accelerometer, a tri-axial gyroscope and a tri-axial magnetometer; which was placed at L5 with an elastic belt.^{27,28} All of the tests were completed in the same order, according to the clinical mBESS, and rest breaks were given to avoid fatigue (Fig. 1).

Measures

Postural sway metrics collected by the inertial sensor were automatically calculated using the Mobility Lab software.³³ Instrumented outcome measures characterized postural sway amplitude, velocity, variability, and frequency^{34,47} for each of the 3 mBESS stance conditions in both the ML and AP directions yielding one hundred and thirty-two metrics for each stance position, including all domains of bidirectional sway. Outcome measures from the clinical mBESS consisted of the sum of errors subjectively identified by the blinded rater.²⁵

We recorded additional information about subjects, including age, gender, body mass index (BMI), sport, and number of previous concussion. Subject were then classified as either contact or non-contact sport athletes based on their respective competition sport. For the purpose of this paper, contact sports included: football, soccer, and lacrosse while non-contact sports were swimming, tennis, track, baseball, softball, volleyball and basketball.

Statistical Analysis

Descriptive methods were used to summarize characteristics of our study sample; frequencies and percentages were calculated for categorical variables; means and standard deviations were computed for continuous variables. Differences in these characteristics between groups were assessed using Chi squared or Fisher's exact test and independent

sample t-tests with or without equal variances for categorical and continuous variables, respectively. We graphically evaluated the distribution of each sway metric and all metrics were right-skewed; thus, for additional descriptive purposes, the median and interquartile range were calculated for the sway metrics considered for entry into our logistic regression models. Additionally, we used the nonparametric Mann–Whitney U test to examine the differences between concussed and control groups for these metrics. Prior to any additional analyses, we log-transformed the sway metrics to achieve normality.

In order to determine the best condition and sway metrics to differentiate subjects in the acute stage post-concussion from controls, we first used Breiman and Cutler's Random Forests for Classification and Regression as a variable selection technique, as numerous postural sway measures are produced using the inertial sensor.²⁹ Briefly, a Random Forest's building block is a decision tree, which is a tree-like model of decisions used to predict the value of a target variable. Each branch of the tree represents a decision or rule for splitting the data based on the value of a predicting variable. A decision tree also contains rules for deciding when a branch can no longer be split and rules for predicting the target variable once a terminal branch is reached. Drawing from a data set, a Random Forest builds multiple decision trees using different subsets of observations and different predicting variables. The final prediction of the target variable is an average of each decision tree's prediction. A Random Forest produces indices that represent the relative importance of a variable in the prediction of the target variable. We report the mean decrease in the Gini index, which in general measures each predicting variable's discriminative ability. Variables that have a greater discriminative ability will have a greater decrease in Gini index. In this study, instrumented mBESS measures that better discriminated between concussed and non-concussed had a higher decrease in Gini index. We visually inspected plots of the mean decrease in Gini index to choose which variables we should investigate in further analyses. Random Forests was conducted in R package *randomForest*.²⁹

We built two univariate and one multivariate logistic regression models to predict concussion versus control group membership. Our first univariate model contained the clinical mBESS score and the second model contained the instrumented measure with the highest decrease in Gini index. A forward selection procedure was used to build our multivariate model; the first variable to enter a model was the most important as determined by Random Forests and additional variables entered into the model if the area under the receiver operating characteristic curve (AUC) increased and the variable was statistically significant at an α -level of 0.05. Once a full model was produced, each variable was removed and the AUC was recalculated. The variable was retained in the model if the AUC was reduced by more than 3 points. AUC values and their responding 95% confidence intervals are reported for each model.

We tested the equality of AUCs for the two instrumented models compared to the clinical mBESS model. In addition, we calculated the sensitivity of each model given a specificity of 80%. Stata/SE13.1 was used for all analyses other than Random Forests.

RESULTS

One hundred and twenty-eight college athletes participated in the study; fifty-two subjects with concussion and seventy-six age-matched controls (Table 1). Participants were recruited with the help of the athletic training staff and were tested at their respective schools. The average post-injury duration at evaluation was 2.21 days (± 1.19). Four individuals were tested 4 days post-injury but were retained in the analysis as all reported at least one symptom (# of symptoms for each participant tested at day 4: 1, 21, 14, 15; Symptom severity score: 2, 61, 28, 41).

Variable Selection

In order to investigate which stance conditions and which measures of sway could best differentiate concussed and control groups, we computed the mean decrease in the Gini impurity index for each of the 132 instrumented sway metrics, including AP and ML directions, for each of the 3 stance positions. These values are displayed for the top 25 measures with the highest mean decrease in Gini index (Fig. 2). These results show that DS stance was consistently the best stance-specific condition for discerning the concussed group from the non-concussed group. Neither the SLS nor the TS stance displayed importance values higher than the 85th percentile. As Fig. 2 displays, saturation begins to occur after 15 measures. Thus, we chose to show only the top 25 measures. In addition to DS being the most discriminating stance, the ML direction most frequently classified group membership correctly. The top sway measures also included multiple domains of sway including area, frequency and variability. Specifically, root mean square (variability), total power (frequency), and mean distance (amplitude), all in the ML direction and in DS stance were the top 3 measures that best discriminated between the groups.

Comparison Between Groups

To limit the number of group comparisons, we chose to compare the top 10 measures identified using the Random Forest approach. Table 2 presents the median values and group comparisons for these measures as well as for the clinical (non-instrumented) mBESS. We found that the total score for the clinical mBESS was not significantly different between acutely concussed and control athletes, while several measures of postural sway during DS with eyes closed showed a significant impairment in balance in subjects with concussion as compared to controls. Significant differences between groups for the 10 sway measures in DS are listed in Table 2.

Considering the top measures, we combined and built a classification model to determine if a combination of measures, rather than a single one, could better identify those people with acute concussion. Table 3 provides values of AUC and sensitivity calculations, at a specificity of 80%, for each. Figure 3 provides AUC plots for each of the models.

DISCUSSION

We compared the ability of inertial sensor-based postural sway measures and of the clinical mBESS error count to differentiate acutely concussed athletes from controls.

As predicted, we found that the instrumented measures outperformed the clinical error count when separating concussed and healthy control athletes. Additionally, our findings suggest that (1) the simplest condition of DS was the best discriminator between our group of acutely concussed and control athletes, (2) measures of postural sway in the ML direction had more utility than measures in the AP direction in discriminating the two groups.

Our results strengthen the growing evidence that current clinical tests can be improved with inertial sensor technology. While inertial sensors have been proposed for objective, clinical measures of balance²⁰ and validated with laboratory force platforms,^{34,55} there are few studies that have used inertial sensor technology to quantify balance^{10,15,28} or gait^{9,12,22} after concussion. The current evidence from these studies is relatively consistent in showing that inertial sensor-based measures can detect abnormal balance or gait when clinical tests may not. An exception is the paper from Furman *et al.*,¹⁵ where adding an inertial sensor to quantify balance did not add value over the traditional BESS protocol. However, the sway measures were obtained from balance conditions separate from the BESS and only the path length measure in the AP direction was reported. Conversely, the studies that concluded inertial measures of balance have utility for concussion balance screenings,^{10,28} including the present results, have simultaneously obtained the sway measures and the mBESS error counts, and considered both the AP and ML directions of sway.

Interestingly, inertial measures from the DS condition provided the best discrimination between groups. The clinical mBESS includes increasingly difficult conditions, such as SLS and TS, to create imbalance as the DS condition has a known floor effect.²⁴ The imbalance caused by the SLS and TS conditions, while eliciting errors, also creates large variability in inertial sway measures caused by the gross movements to regain balance.²⁸ Conversely, the baseline DS condition had minimal errors, ensuring low variability across postural sway measures that may have contributed to the DS condition's superiority in detecting the subtle but significant balance deficits post-concussion. A recent study in a small sample of concussed and healthy control athletes found consistent results: the DS condition was the only mBESS stance to detect differences when using an inertial sensor.¹⁰ Further, while the SLS and TS conditions did not differ between groups, Doherty *et al.*¹⁰ did find that sway volume from the inertial sensor during SLS and TS conditions was highly sensitive at detecting clinical errors. Thus, the instrumented mBESS may be most sensitive during the DS condition precisely because it has so few observable errors.

Similar to our finding that DS was better at discriminating concussed athletes and healthy controls than SLS or TS, we found three inertial measures were better than all other measures at discriminating the two groups. The three measures, root mean square (RMS) of the acceleration time series, total power of the acceleration time series, and the mean distance from the center of the acceleration trajectory, corresponded to variability, frequency, and amplitude characteristics of sway, respectively. This finding is interesting considering the measures chosen by other studies to examine post-concussion balance. For example, Doherty *et al.*¹⁰ used ellipsoidal sway volume, which is similar to ellipsoidal sway area but incorporates three dimensions instead of two, but our results suggest larger effects may have been seen had RMS or total power been used instead. Notably, this is a second study reporting the utility of RMS for clinical management of concussion; a previous study found

differences between a small sample of individuals with non-resolving mTBI and controls using RMS sway.²⁸

While sway is considered only in the AP direction during sophisticated balance tests after concussion, such as the Sensory Organization Test (SOT),^{18,36,37} our results suggest sway in the ML direction, when obtained during DS with eyes closed and feet together, may be more sensitive to concussion. When feet are placed close together in DS, the base of support is restricted in the ML direction, and individuals become more sensitive to ML perturbations of sensory information than to AP perturbations.⁴⁴ Notably, gait, which also places a higher demand on ML balance control, was found to be similarly sensitive to ML perturbations of sensory information,⁴⁴ and has shown both acute and persistent effects from concussion.^{5,45} While it is unclear what specific mechanism is responsible for the impaired ML sway in concussed athletes, it is possible that ML sway control poses a higher demand on sensory integration or requires greater attentional control of balance, both of which are impaired in concussed athletes during gait.^{5,18,21} The importance of ML balance control is further supported by the sensitivity of ML sway, compared to AP sway, to aging, fall risk, and balance impairments in elderly populations.^{1,30,41,54}

Our results indicating RMS was the most sensitive measure to acute concussion agrees with the results of RMS sway reported by Powers *et al.*⁴⁶ Yet, we found ML RMS sway to be most sensitive while Powers *et al.*⁴⁶ reported stronger effects for AP sway. The differing results may be due to methodological issues, including the duration of stance and the instrumentation. While Powers *et al.*⁴⁶ used a force platform and quantified the RMS of the center of pressure (COP) displacement, we quantified the RMS of the lumbar acceleration. It is possible that COP RMS from the force platform may be more representative of AP fluctuations, as balance control in the AP direction is performed predominantly at the ankle, but lumbar acceleration RMS from the lumbar mounted inertial sensor may be more representative of ML fluctuations, as ML balance is controlled through hip-related loading and unloading of the left or right limb.⁵⁷ However, it is unclear how AP and ML RMS measures differ when quantified by a force platform or from an inertial sensor at the lumbar spine. Second, Powers *et al.*⁴⁶ analyzed 45 s of sway, compared to the 30 s of sway analyzed here. Postural sway is known to be a non-stationary process with large amplitude oscillations occurring predominantly in the AP direction⁴ and at frequencies around 0.16 Hz.⁵⁸ The longer sway durations may have included non-stationary rambling in the AP direction that was different between concussed and control subjects. Similarly, longer sway recordings have indicated concussed and control athletes have different sway regularity, quantified with approximate entropy, in the AP direction,¹³ while shorter recordings have shown regularity differences in the ML direction.⁷ Such results suggest that ML measures may be superior for differentiating concussed and control athletes with shorter duration recordings, but AP measures may have utility for longer recordings.

Study Limitations

Several limitations must be noted regarding this study. The primary limitation is that baseline data was lacking on the concussed athletes. It is possible some sway differences are naturally occurring variations between our concussed and control groups. However, in an

attempt to address this limitation, a robust sample of control athletes were included. Second, we were unable to recruit any concussed subjects from non-contact sports. As such, it is possible that some of the balance deficits attributed to concussion in the current results may be due to differences from previous concussions or related to contact versus non-contact sports. Specifically, such effects, if present within this data, may be due to sub-concussive head trauma⁴² that may have exaggerated the reported differences between concussed and control subjects. Third, while the instrumented measures were based on 30 s of sway according to standard measurements of postural sway, the clinically scored mBESS was based on the standard 20 s clinical assessment. This discrepancy in data length limits a direct comparison between BESS errors and sway characteristics, as 1/3 of the instrumented sway time were not scored by the clinical assessment. While participants with recent injuries were excluded from this study, it is possible that some participants had residual, yet unperceived, balance deficits from injuries greater than 6 months prior to testing. However, such injuries are unlikely to influence the results or conclusion of this study as such injuries would likely show similar effects in both instrumented and clinical mBESS scoring. Finally, the clinical mBESS was only scored once. While typical practice similarly uses a single, cross-sectional score for clinical use, moderate to poor intra-rater reliability of the error count¹¹ suggest that the clinical error count, and therefore our comparisons between clinical and instrumented mBESS outcomes, may change if the videos were re-assessed for errors. Notably, the instrumented mBESS is not susceptible to this concern. While small differences in sensor placement can introduce intra- and inter-rater reliability concerns, re-analyzing the same data at a later date is highly unlikely to yield different sway measures.

CONCLUSION

Objective measures of balance after concussion using inertial sensor-based postural sway as a marker of imbalance may identify balance deficits suitable for diagnosing concussion and tracking recovery with or without comparison to individual baseline data. We have shown here that adding one inertial sensor to the waist during only the DS was more sensitive than the full clinical mBESS in detecting impairments after concussion in this sample of acutely concussed athletes. Our findings suggest that the inclusion of ML information may be essential to detect and characterize balance deficits after concussion. These findings provide practical guidance in simplifying and improving the testing paradigm showing evidence to select the best measures and conditions for inertial sensor-based balance assessments after concussion.

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ABBREVIATIONS

NCAA	National Collegiate Athletic Association
BESS	Balance error scoring system
mBESS	Modified BESS
DS	Double stance
TS	Tandem stance
SLS	Single limb stance
SCAT-3	Sport concussion assessment tool 3
PCS	Post-concussive syndrome
BMI	Body mass index
AUC	Area under the receiver operating characteristic curve
AP	Anteroposterior
ML	Mediolateral
SOT	Sensory organization test
COP	Center of pressure

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FIGURE 1.

Representative sway tracings from an acutely concussed (black) and control (green) individual with eyes closed in all 3 stance condition of the mBESS; double stance (a), single limb stance (b) and tandem stance (c).

FIGURE 2.

Random forest displaying the top measures for distinguishing between health controls and acutely concussed athletes. Measures from DS are shown in blue, and those from TS are shown in green. ML, AP, and two-dimensional measures are indicated with circles, squares, or hexagons, respectively.

FIGURE 3.

ROC curves for the true positive and false positive rates for the clinical mBESS error count, and instrumented mBESS models of (1) ML RMS and (2) ML RMS + ML total power. Both instrumented models used only measures obtained from the DS condition.

TABLE 1

Participant demographics and characteristics of concussed and control subjects.

Characteristic	Total (<i>n</i> = 128)	Concussion (<i>n</i> = 52)	Control (<i>n</i> = 76)	<i>p</i> value ^a
Age, mean (SD)	20.53 (1.36)	20.36 (1.30)	20.64 (1.40)	0.211
Sex, <i>n</i> (% Male)	73 (57.03)	35 (67.31)	38 (50.00)	0.052
Height, mean (SD), cm	176.52 (9.90)	177.82 (9.59)	175.64 (10.07)	0.228
Weight, mean (SD), kg	82.14 (20.56)	86.52 (20.51)	79.14 (20.18)	0.049
BMI, mean (SD)	26.07 (4.57)	27.08 (4.58)	25.37 (4.46)	0.040
Contact sport, <i>n</i> (%)	78 (60.94)	44 (84.62)	34 (44.74)	<0.001
Sport, <i>n</i> (%) ^b				
Football	51 (39.84)	32 (61.54)	19 (25.00)	
Soccer	25 (19.53)	10 (19.23)	15 (19.74)	
Basketball	11 (8.59)	3 (5.77)	8 (10.53)	
Lacrosse	2 (1.56)	2 (3.85)	–	
Volleyball	6 (4.69)	2 (3.85)	4 (5.26)	
Softball	7 (5.47)	1 (1.92)	6 (7.89)	
Baseball	5 (3.90)	1 (1.92)	4 (5.26)	
Track and field	19 (14.84)	1 (1.92)	18 (23.68)	
Tennis	1 (0.78)	–	1 (1.32)	
Swimming	1 (0.78)	–	1 (1.32)	
History of concussion, <i>n</i> (%)	46 (35.93)	24 (46.15)	22 (28.95)	0.133
Number of prior concussions (range) ^c		0–5	0–3	0.051
Average time from mTBI to test		2.22 (1.19)		
Average time from mTBI to return to play		12.72 (5.11)		

BMI Body mass index, *SD* standard deviation, *mTBI* mild traumatic brain injury.^aUnless otherwise noted, *p* values for categorical variables are from Chi squared tests and *p* values for differences in continuous variables are from *t* tests with equal variances.^bFisher's exact test.^cMann–Whitney U-test.

TABLE 2

Clinical measure (non-instrumented) significance compared to instrumented measure significance for the mBESS.

Variable	Condition	Control (<i>n</i> = 76) Median (p25, p75)	mTBI (<i>n</i> = 52) Median (p25, p75)	<i>p</i> value ^a
mBESS ^b	Total	1.5 (0, 3)	2 (1, 4)	0.064
	DS	0 (0, 0)	0 (0, 0)	
	SLS	1 (0, 3)	3 (1, 5)	
	TS	0 (0, 1)	0 (0, 1)	
Instrumented measures				
RMS ML (m s ⁻²)	DS	0.048 (0.039, 0.058)	0.065 (0.052, 0.085)	<0.001
Total power ML (m ² s ⁻⁴)	DS	1.053 (0.683, 1.421)	1.742 (1.162, 3.226)	<0.001
Mean distance ML (m s ⁻²)	DS	0.038 (0.030, 0.046)	0.051 (0.041, 0.068)	<0.001
Total power AP (m ² s ⁻⁴)	DS	1.493 (1.097, 2.211)	2.364 (1.732, 3.833)	<0.001
Range of acceleration ML (m s ⁻²)	DS	0.278 (0.238, 0.341)	0.380 (0.282, 0.466)	<0.001
Ellipse sway area (m ² s ⁻⁵)	DS	0.052 (0.036, 0.080)	0.094 (0.062, 0.133)	<0.001
95% Power frequency AP (Hz)	TS	2.682 (2.532, 2.832)	2.599 (2.283, 2.915)	0.288
Path length ML (m s ⁻²)	DS	4.742 (3.689, 5.569)	5.759 (4.393, 7.560)	<0.001
Total sway area (m ² s ⁻⁵)	DS	0.005 (0.004, 0.009)	0.008 (0.006, 0.014)	<0.001
95% Circle sway area (m ² s ⁻⁵)	DS	0.051 (0.038, 0.093)	0.098 (0.065, 0.150)	<0.001

AP anterior-posterior, ML mediolateral.

^a *p* value from Mann-Whitney U.

^b Missing *n* = 10.

TABLE 3

Summarizes details of ROC AUC per measure of balance (error count and instrumented test in double stance) and comparison of AUC.

Classification models	AUC (95% CI)	<i>p</i> value ^a	Sensitivity (%) ^b
Clinical mBESS	0.606 (0.503, 0.709)	–	35
Double stance RMS ML	0.735 (0.637, 0.833)	0.042	63
Double stance RMS ML + double stance total power ML	0.750 (0.653, 0.847)	0.023	59

AUC area under the curve, *CI* confidence interval.

^aTest of equality of AUC using the clinical mBESS model as the reference.

^bSensitivity calculated for a specificity of 80%.