FALLS are a serious and costly problem, with over one third of individuals older than the age of 65 years sustaining a fall each year (1,2). Postural instability, as evident by excessive or uncontrolled sway, has been identified as one of the key risk factors that lead to falls (1,3–6). As such, evaluating postural instability in healthcare settings is important so that patients at risk for falls may be identified and referred for appropriate interventions.

The majority of clinical tests to assess balance have limitations including time and space requirements, subjective scoring, and ceiling/floor effects (7,8). Posturography, though not commonly used clinically, is a quick-to-administer and quantitative test that could serve as a possible alternative to overcome these limitations. This method utilizes a force-measuring platform and has the patient stand quietly on the platform surface for 10–60 seconds, similar to having their weight taken (9–11). While the patient stands on the force platform, the center of pressure (COP) is recorded, which provides an indication of the effort to control the center of gravity from swaying excessively (12).

One barrier to widespread adoption of posturography has been a lack of standardization in testing methodology and data reporting. Prior studies have addressed this issue by demonstrating the variation used in the testing protocols, reporting many differences in methodology related to visual conditions and foot placement. Even studies aimed at improving standardization by establishing the reliability of posturographic measures have differed in their required stance (13,14).

There is also little consensus as to which of over 55 sway measures should be calculated from the COP data to describe and characterize the degree of postural instability (9,11,15). The choice of the postural sway parameter is important because different types of measures are thought to reflect not only different aspects of postural sway but also different aspects of underlying physiological control (12,15). For example, sway velocity, which appears to be very reliant on an individual’s proprioception, is indicative of the effort of the postural control system to maintain equilibrium and may be used for feedback for both anticipating...
and correcting postural instability (16). In comparison, fractal measures are based on underlying trends and persistence in the data that are not observed when only traditional sway measures are studied (17,18). These findings have been used to discuss probable control strategies of postural sway and include both open-loop and closed-loop feedback (17,18).

Although much work has focused on determining which individual sway measures differentiate between participant groups, there has been limited work to determine whether grouping postural sway measures in combination might improve differentiation (6,12,19). Those who have grouped postural sway parameters have mostly done so based on correlations or through principal component analysis, but these works have not tended to target healthy older fallers (3,20,21). Some of these efforts were additionally limited in that newer fractal measures were not included in their analyses. For example, a study by Brauer and colleagues (22) performed logistic regression to determine how well a group of postural sway measures could differentiate recurrent fallers and nonfallers; however, the study only considered a few traditional time-domain measures in the analysis.

For posturography to be a feasible screening tool, physicians must know how to best test patients and must be able to interpret patient’s results quickly and easily. This study, therefore, aimed to determine which of four testing conditions (eyes open and closed in comfortable and narrow stance) best differentiated recurrent fallers from nonrecurrent fallers and which postural sway measure, or group of measures, in that condition should be used to maximize discrimination. To translate these findings to maximize their clinical potential, this study used logistic regression to create an equation that weighted each of the identified measures, calculating an overall probability of an older adult’s likelihood of having fallen.

**Methods**

A convenient sample of 150 older adults aged 65 years or more recruited from local senior centers and independent living facilities participated in this study. Participants who reported undergoing physical therapy focused on balance rehabilitation or fall prevention in the past 6 months were excluded from participation. All participants gave written informed consent according to the Ohio State University Institutional Review Board.

Information on age, height, shoe size, living arrangement, and health history were collected from participants. Participants were then asked questions about how many falls they had sustained in the past year. A fall was defined as “an event that results in a person coming to rest inadvertently on the ground or other lower level regardless of whether an injury was sustained” (23). Participants were classified as “recurrent fallers” if they self-reported having fallen at least twice in the year prior to testing. All other participants were classified as “nonrecurrent fallers.” Using at least two falls to define fallers was used to help mitigate memory recall issues and strengthen the likelihood that older adults being classified as fallers had sustained falls due to balance-related problems and not a single accidental fall associated with activity or environmental hazards (6). Recurrent fallers may also benefit most from intervention (22).

Participants removed their shoes and completed a posturography test on a force-measuring platform (Model BP 5050; Bertec Corporation, Columbus, Ohio). Participants stood as quiet and still as possible in four randomized testing conditions: eyes open comfortable stance, eyes closed comfortable stance, eyes open narrow stance, and eyes closed narrow stance. For the comfortable stance conditions, foot placement was unconstrained because it was viewed as more feasible for eventual clinical screening adoption than protocols that required rigorous alignment of the feet or adjustment of stance to the patient’s height. For the narrow stance condition, Participants were asked to stand with feet together, heels, and toes touching. This condition has been identified as discriminating well between fallers and nonfallers and also easily accommodates the participant’s feet on the platform surface (6).

Only one trial per test condition was conducted so as to mimic the screening process that would be most feasible within the time constraints of current patient intake processes. All participants wore a safety harness attached to a safety structure during testing. Each trial was 60-second long based on recommendations of Carpenter and colleagues (24), and data was collected at 1000 Hz. COP data were recorded for the anterior–posterior (A/P) and medial–lateral (M/L) sway directions (A/P and M/L COP accuracy better than ±2 mm). Individual trials where a participant lost balance were excluded from further analysis. Only one trial per testing condition was conducted, even if a loss of balance occurred.

COP data were then used to calculate the traditional time-domain measures: A/P COP sway range, M/L COP sway range, mean sway velocity, root mean square displacement, 95% confidence ellipse area, primary direction of sway with respect to A/P, mean frequency, and M/L sway velocity. These eight measures were selected to represent the diversity of possible parameters, in particular representing both direction-specific (A/P and M/L) and resultant (2D) type measures, as well as “distance,” “area,” and “hybrid” measures as described by Prieto and colleagues (12). Medial–lateral measures of sway and sway velocity were notably included as medial–lateral stability appears important in the differentiation of recurrent fallers and nonrecurrent fallers (3,6). Calculations for each measure have been described elsewhere (12,15). Based on findings by Loughlin and colleagues (25) regarding nonstationarities in the data, fractal analysis measures were chosen for inclusion over traditional frequency-domain measures to examine
underlying patterns in the data. Fractal measures were calculated using detrended fluctuation analysis (DFA) applied to each of the A/P and M/L COP data (26). DFA is a method that has been recommended over stabiogram diffusion analysis and results in an α-scaling exponent (27). DFA has been described in detail in (28). An α-scaling exponent greater than 1.5 indicates a persistent pattern of sway, such that movement away from equilibrium is followed by continued movement away from equilibrium, which can be beneficial in exploring the base of support. An α-scaling exponent less than 1.5 indicates an antipersistent pattern, such that movements away from equilibrium are countered with movements back. This can be beneficial in preventing excessive sway without recovery. For each DFA plot, the two linear regions present were characterized by a short-term scaling exponent, a long-term scaling exponent, and a crossover point from one region to the other (28,29).

For each testing condition, a stepwise logistic binary regression using forward selection, with α = .15, was performed in PASW version 17.0 (formerly SPSS, Chicago, IL), using fall status as the response variable. Prior to determining which variables to include in the model, Pearson correlation coefficients were determined for all pairs of sway parameters so that multicollinearity was not an issue. The nine traditional sway parameters; six DFA measures; and age, height, weight, body mass index (BMI), sex, shoe length, and living condition were included in the analysis. For each regression model, the Nagelkerke $R^2$ value was calculated to determine goodness of fit of the model for differentiating recurrent fallers from nonrecurrent fallers. Sensitivity and specificity were also calculated for each model, with a cut value set to 0.500. For each parameter included in the model, the significance and the odds ratio, calculated as Exp(B), were reported to indicate the parameter’s overall contribution to the model.

To then determine how the resulting logistic regression models compared with a model containing only the single most significant postural sway parameter, an “entry” logistic regression was performed using PASW. Nagelkerke $R^2$, sensitivity, and specificity were again calculated.

### RESULTS

Table 1 summarizes the characteristics of the 150 participants participating in this study. The majority of these subjects, 110 of 150, were female. Twenty-one subjects were classified as recurrent fallers.

A total of 42 participants lost balance on at least one of the four trials, with almost 25% of participants losing balance during the eyes closed narrow stance condition. Twenty-nine of the 37 to lose balance were nonrecurrent fallers. Because of this, the eyes closed narrow stance condition was excluded from further analyses. The remaining three conditions had no more than 10 older adults who lost balance and no more than 3 of whom were recurrent fallers.

Table 2 provides a summary of the stepwise logistic regression models for each of the remaining three testing conditions. The model associated with the highest $R^2$ goodness-of-fit value was the eyes closed comfortable stance condition. This model consisted of, in order of significance, medial–lateral sway velocity, anterior–posterior short-term α-scaling exponent, medial–lateral short-term α-scaling exponent, mean frequency, BMI, and age. Using a $p$ value of .05, only medial–lateral sway velocity was identified as statistically significant within the model, with

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Sig.</th>
<th>OR Exp(B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M/L velocity</td>
<td>0.000</td>
<td>1.223*</td>
</tr>
<tr>
<td>Mean frequency</td>
<td>0.121</td>
<td>0.125</td>
</tr>
</tbody>
</table>

Table 2. Summary of Stepwise Logistic Regression Models by Testing Condition Considering All Variables

### Notes

- OR = odds ratio.
- *Denotes that an increase in this parameter’s value increases the odds of recurrent falling, noted by Exp(B) value greater than 1. For all others, a decrease in the parameter value would increase the odds of recurrent falling.
Table 3. Comparison of Stepwise Logistic Regression Results Upon Considering All Variables and Entry Regression Considering Only Significant Parameters (p < .05)

<table>
<thead>
<tr>
<th></th>
<th>Stepwise Regression Considering All Variables</th>
<th>Entry Regression Considering Significant Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Negelkerke R</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eyes open comfortable stance</td>
<td>0.207</td>
<td>0.117</td>
</tr>
<tr>
<td>Eyes closed comfortable stance</td>
<td>0.411</td>
<td>0.230</td>
</tr>
<tr>
<td>Eyes open narrow stance</td>
<td>0.206</td>
<td>0.206</td>
</tr>
<tr>
<td><strong>Sensitivity (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eyes open comfortable stance</td>
<td>71.4</td>
<td>15.8</td>
</tr>
<tr>
<td>Eyes closed comfortable stance</td>
<td>75.0</td>
<td>28.6</td>
</tr>
<tr>
<td>Eyes open narrow stance</td>
<td>80.0</td>
<td>23.5</td>
</tr>
<tr>
<td><strong>Specificity (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eyes open comfortable stance</td>
<td>89.7</td>
<td>98.4</td>
</tr>
<tr>
<td>Eyes closed comfortable stance</td>
<td>93.7</td>
<td>99.2</td>
</tr>
<tr>
<td>Eyes open narrow stance</td>
<td>90.3</td>
<td>99.2</td>
</tr>
</tbody>
</table>

Discussion

It was found that the eyes closed comfortable stance testing condition and its associated model best differentiated recurrent fallers from nonrecurrent fallers. The eyes closed condition likely amplifies the differences between groups as it has been suggested that individuals with postural instability can often compensate for their differences by becoming more visually reliant (30). The eyes closed narrow stance condition was too challenging, even for nonrecurrent fallers, making it inappropriate for the regular screening of older adults. Future studies should explore whether loss of balance itself could provide clinical insight into postural instability and/or fear of falling. The recommendation of the eyes closed comfortable stance testing condition is somewhat in contrast to Melzer and colleagues (6), who found that only narrow stance was able to differentiate recurrent fallers and nonrecurrent fallers. Melzer, however, did not use logistic regression to group parameters and did not include any fractal measures. Laughton and colleagues’ (31) work similarly found no differences between recurrent fallers and nonfallers in comfortable stance, despite using logistic regression and fractal measures. Their work included only the traditional measures A/P and M/L sway range, excluding M/L sway velocity from the analysis. This suggests the importance of considering a comprehensive set of parameters.

The logistic regression model for this best condition included two traditional sway measures (M/L sway velocity and mean frequency), two fractal measures (both A/P and M/L short-term α-scaling exponents), and two personal characteristics (BMI and age). This is particularly noteworthy as it suggests that differentiation is improved when relevant postural sway measures are considered jointly, rather than considering only an individual sway measure, as is often done. This has been alluded to by others, such as Prieto and colleagues (12) and Rocchi and colleagues (20), who have proposed that different postural sway parameters may describe different aspects of postural stability. The increased sensitivities observed for all three testing conditions and the improved model fits for the primary logistic regression analysis compared with the entry regression consisting of only M/L sway velocity further support the need for consideration of multiple parameters. The difference between the regression techniques is the way that the variables are treated. For the stepwise procedure, variables are added to the model one at a time based on the specified criterion. After each variable is entered, variables currently in the model are checked to see which should remain and which can be removed. Adding one variable often changes the relative contribution of another variable already in the model. This addition and subtraction of variables will change the sensitivity and specificity results from those obtained by considering only one variable in a logistic regression, even if the stepwise technique results in a model that includes only a single variable.

an odds ratio indicating that those older adults with increased medial–lateral sway velocity were more likely to be recurrent fallers. This model resulted in a sensitivity of 75%. The specificity was found to be 93.7%.

As this model was associated with the highest $R^2$ value, it was the model identified for best differentiating recurrent fallers from nonrecurrent fallers. The resulting logistic regression model equation for this condition was:

$$\text{logit}(p) = -20.6730 + 0.0775 \times \text{age}$$
$$+ 0.1355 \times \text{BMI} - 3.9006 \times \text{mean frequency}$$
$$+ 0.2044 \times \text{M/L velocity} - 12.8356 \times \text{M/L short-term \(\alpha\)-scaling exponent}$$
$$+ 16.9492 \times \text{A/P short-term \(\alpha\)-scaling exponent},$$

where $p$ is the probability of an older adult having fallen at least twice in the past year.

As with eyes closed comfortable stance condition, medial–lateral sway velocity was the sway parameter also found to be the most significant parameter in both the eyes open comfortable stance and eyes open narrow stance conditions. The model for the eyes open comfortable stance condition had a lower $R^2$ value, sensitivity, and a specificity. The eyes open narrow stance condition had a sensitivity that was higher than the eyes closed comfortable stance condition, but the lower goodness of fit and specificity did not support it as the best choice.

The stepwise linear regression models were then compared with entry regression models that included only medial–lateral sway velocity, the sway parameter identified in all models as most significant ($p < .05$). Results showed that sensitivities all dramatically decreased, as summarized in Table 3. Sensitivities dropped from 71.4% to 15.8%, 75.0% to 28.6%, and 80.0% to 23.5% for the eyes open comfortable stance, eyes closed comfortable stance, and eyes open narrow stance, respectively.
Medial–lateral sway velocity was identified as the parameter that best differentiated recurrent fallers and nonrecurrent fallers in each testing condition. This is in accordance with the findings of Maki and colleagues (3) and Melzer and colleagues (6), who noted the importance of controlled sway in the medial–lateral direction. The importance of sway velocity in the control of quiet-stance postural sway has been previously suggested by Masani and colleagues (16). Though outside the scope of the current work, we hypothesize that differences in cutaneous sensation in fallers suggested by Maki and colleagues (3) and Melzer and colleagues (6) likely lead to a poorer ability to control velocity. According to Masani and colleagues (16), this inability to control velocity would lead to greater postural instability, as observed in this study. Loss of cutaneous sensation may also explain why older adults with a history of falls drifted away from equilibrium in the medial–lateral direction for short-time periods more so than nonrecurrent fallers. As this drift relates to exploration of the participant’s base of support, a loss of cutaneous sensation would likely impair the ability to determine and control the movement of the COP.

Short-term fractal measures in both the A/P and the M/L sway directions were also notable inclusions in the model. These findings suggest that fractal measures are an important component to the differentiation of participants while also suggesting that they are not alone sufficient. As work in fractals move forward, it is important that researchers focus not on whether fractal measures are better than traditional measures but whether the addition of fractal measures to other postural sway parameters may improve the usefulness of posturography. Interestingly, results showed that the odds ratio of being a recurrent faller increased as the M/L short-term α-scaling exponent became more persistent but decreased in the A/P direction for the same situation. This may be related to fundamental differences in the dimensions of the base of support, such that the M/L direction is constrained by the narrowness of the foot so that drifts from equilibrium encounter the boundary more quickly than in the A/P direction.

Mean frequency was also included in the model, and the odds ratio for recurrent falling was found to be surprisingly high. This is likely because the values of the mean frequency are traditionally quite small, which inflates the odds ratio appearance.

The findings of the current work indicate promise that a logistic regression model could be used to differentiate between a diverse group of recurrent fallers and nonrecurrent fallers. However, it is recognized that the model’s overall goodness of fit is still quite low, likely due to the large variation in health and activity of the people studied. The model’s sensitivity of 75% is also lower than desired and may in fact be overinflated because cross-validation using a separate participant group was not possible due to sample size. However, as postural instability is not the only reason people fall, the sensitivity of such a balance-related screening tool would likely never reach 100% and instead should aim to flag at least more people than would be identified during a regular exam without balance assessment.

One of the limitations of this work is the number of participants, and particularly number of recurrent fallers, in light of the number of variables considered in the logistic regression model. Had a sufficient number of participants been available, it would have been possible to cross-validate the findings of the logistic regression by using one subset to develop the model and the other subset to validate it. With so few participants, however, it was necessary to use all available for the development of the model. Retrospectively, it was calculated that a sample size of \( n = 1,049 \) would have ensured an adequate sample size with the current percentage of recurrent fallers. Future studies will need to address more equitable recruitment to ensure a higher number of recurrent fallers as well as an overall increase in participants to develop the current work further. In doing so, defining participants based on multiple falls, single falls, and no falls may be additionally advantageous to determine whether better goodness-of-fit, sensitivity, and specificity can be found based on definition.

Another limitation of this work was its retrospective nature that precluded results from translating to the prediction of future falls. Future work involving prospective fall monitoring will advance these findings. However, the retrospective nature of the developed model also meets an important clinical need to elicit fall history from patients (1).

The current work suggests that a more comprehensive approach to analyzing COP data where traditional, fractal, and even demographic information are considered jointly may be more insightful in differentiating recurrent fallers from nonrecurrent fallers than examining only a single or few selected measures. Future work is necessary to look at whether the inclusion of postural sway parameters other than those included in the current analysis may provide additional discrimination and greater sensitivity. Additionally, future work should concentrate on looking at possible improvement of the model by characterizing the optimum trial duration and number of trials required.

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