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Between-limb difference in peak knee flexion angle can identify persons post-stroke with Stiff-Knee gait

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ABSTRACT

Background: Stiff-Knee gait affects 25–75 % of individuals with post-stroke gait impairment and is typically defined as reduced swing phase knee flexion. Different studies use various measures to identify Stiff-Knee gait, such as peak swing knee flexion angle, timing of peak knee flexion, knee range of motion, and ankle push-off acceleration, leading to inconsistent results.

Methods: This study used univariate cluster analysis to examine the independence, consistency, validity, and accuracy of different definitions in 50 post-stroke individuals (24 with and 26 without Stiff-Knee gait), as determined by a physiatrist. Spearman's rank correlation was used for correlation analysis, and five clustering techniques along with clinician evaluations were used for validity analysis.

Findings: Correlation analysis showed that peak knee flexion timing and knee hyperextension are poorly correlated with reduced swing-phase knee flexion angle ($\rho = -0.09$ and $\rho = -0.26$ respectively). Validity analysis indicated that the between-limb difference in peak swing knee flexion angle and peak swing knee flexion angle at self-selected gait speeds were the most valid differentiators. At the fastest comfortable gait speed, the between-limb difference of peak knee flexion angle had the highest sensitivity, lowest specificity, and highest F1 scores.

Interpretation: We determined thresholds of less than 44.3° for peak swing knee flexion angle and greater than 17.0° for the between-limb difference of peak knee flexion angle identify Stiff-Knee gait during self-selected walking. We recommend using the difference in peak swing knee flexion angle between limbs to diagnose post-stroke Stiff-Knee gait due to its robustness to changes in gait speed.

1. Introduction

Stiff-Knee gait (SKG) is defined as reduced knee flexion during the swing phase of walking (Kerrigan et al., 1991). The term has been in use since the 1800s in reference to how knee flexion appeared in children with cerebral palsy (Abercrombie, 1887), and was then later applied to adults, primarily those post-stroke. People with post-stroke SKG have difficulty with foot clearance and often walk with frontal plane compensations such as limb circumduction (some combination of pelvic obliquity and hip abduction). The additional frontal plane motion of the limb is energetically costly (Doke et al., 2005; Royer and Martin, 2005; Shorter et al., 2017), and it is not surprising that people with SKG are hypothesized to have low endurance, be more susceptible to joint pain (Hsu et al., 2003), and have greater risk of falls (Burpee and Lewek, 2015).

SKG has most often been identified by knee flexion kinematics. The knee undergoes the largest range of motion during gait, so knee motion may be most sensitive to detection of gait abnormalities. Previous efforts at defining SKG have suggested a peak knee flexion angle of 45° (Kerrigan et al., 1991) of the paretic limb. However, knee flexion angle is highly dependent on gait speed (Campanini et al., 2013), using the same threshold at different walking speeds may confound accurate classification. To address this concern researchers have defined SKG by the difference in peak knee flexion angle with the non-paretic limb, either at

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16° (Sulzer et al., 2010) or 20° (Akbas et al., 2020) difference, or based on combinations of peak knee flexion during the swing phase, knee range of motion during the early swing phase, total knee range of motion, and timing of peak knee flexion during the swing phase (Böhm et al., 2014; Fujita et al., 2020; Goldberg et al., 2003; Goldberg et al., 2006; Jonkers et al., 2006; Lewerenz et al., 2019; Reinbolt et al., 2008) compared to healthy individuals. While there may be overlap between these definitions, it is plausible that the variance in definition of SKG between studies produces heterogeneity in results, which is what is commonly observed in interventional studies such as the effect of chemodenervation (Tenniglo et al., 2023). With so many different characterizations of SKG, it is difficult to compare results between studies, let alone obtain a standard threshold value for diagnosis.

The goal of this study was to determine the best single parameter biomechanical definition of post-stroke SKG. We conducted a univariate analysis approach to examine the independence, consistency, validity, and accuracy of the most common biomechanical metrics of SKG based on clinical judgement at two different gait speeds. We then created threshold values of the best performing parameters for suggested clinical diagnosis.

2. Methods

2.1. Participants

Retrospective data for 50 individuals post-stroke (31 left hemiparesis, 31 males, 57 ± 13.46 years) were extracted from a research database maintained by the NIH Center of Biomedical Research Excellence (COBRE) in Stroke Recovery at the Medical University of South Carolina (MUSC). The database is approved by the MUSC Institutional Review Board. All persons provided informed written consent for their data to be included in the database. Participants were included if motion capture and electromyography was collected during one or more trials of self-selected walking on a split-belt treadmill. Data collected during fastest-comfortable walking on a split-belt treadmill was extracted when available. Only data collected on start date of the individual study a participant was enrolled in was used to minimize the effect of subsequent study sessions and study protocol variability. All data were collected using the same equipment and deidentified to meet the definition of secondary research per the NIH Common Rule.

2.2. Data collection

Participants walked on a split-belt instrumented treadmill (Bertec, Columbus, Ohio, USA) at their self-selected speed. Of those, 41 individuals post-stroke also walked at their fastest possible gait speed. Prior to data collection, participants practiced treadmill walking to get comfortable with the experimental setup. Participants walked for at least 10 s to reach a steady-state walking pattern before each 30-s trial. Motion capture marker data were collected at 120 Hz using a 12-camera motion capture system (PhaseSpace, San Leandro, CA, USA) with a modified Helen Hayes marker set using 65 active markers. Ground reaction force (GRF) data were measured by an embedded force plate in a split-belt treadmill and low-pass filtered at 15 Hz. Using the kinematics and dynamics solver within OpenSim 4.3 (Delp et al., 2007), joint kinematics, body kinematics, and joint kinetics were obtained. All synchronized time-series biomechanical gait data were divided into strides by a paretic limb heel-strike event using vertical GRFs and expressed as a percentage of the gait cycle time. Eight strides per participant were randomly selected from 30-s treadmill walking trials since it was the highest number of strides shared by all participants. The 8 strides were averaged into one mean trajectory per feature and individual for use in cluster analysis.

2.3. Data analysis

Cluster analysis is a statistical method that objectively and quantitatively classifies individuals by grouping them into homogeneous clusters based on specific input parameters. This statistical method has been applied to aid in classifying patients based on clinical and laboratory observations for tailored medical treatment (McLachlan, 1992). In this study, we performed a clustering technique to assess the gait features commonly employed in distinguishing between those with and without SKG.

2.4. Gait parameters associated with post-stroke SKG

SKG in persons post-stroke has previously been differentiated by the most visible disability-specific kinematics in the sagittal plane. We selected biomechanical gait variables which are used as common inclusion criteria from previous literature, including: the peak knee flexion angle during the swing phase, the difference in peak knee flexion angle between limbs during the swing phase, the peak knee flexion velocity in the pre-swing phase, the knee range of motion in the initial swing phase measured from toe-off to the first half of the swing, and the total knee range of motion during gait (Goldberg et al., 2006; Kerrigan et al., 1998; Sulzer et al., 2010). In addition to these characteristics, we included the peak knee extension during the stance phase, assuming a potential causal relationship between hyperextension and SKG, given the possible presence of knee hyperextension during the stance phase (Perry and Burnfield, 2010; Riley and Kerrigan, 1999). Regarding the spatiotemporal characteristics of SKG, we assessed the timing of peak knee flexion during the swing phase to discern any indications of delayed knee flexion (Sutherland et al., 1990). Lastly, we examined the peak vertical acceleration of the lateral malleolus during the pre-swing phase, proposed as a means to distinguish insufficient push-off linked with post-stroke SKG (Campanini et al., 2013). In summary, we initially chose eight gait parameters related to post-stroke SKG, as outlined in Fig. 1.

Within the gait characteristics depicted in Fig. 1, we subsequently screened out associated features of post-stroke SKG by using a correlation analysis. This process primarily centered on the reduced paretic knee flexion kinematics, a prominent symptom of post-stroke SKG. Specifically, features exhibiting a poor correlation (< 0.75) with the paretic pre-swing phase peak knee flexion angle were excluded in further validity analysis. Since body parameters, such as a participant's height, can affect gait kinematics, we conducted the additional correlation analysis using parameters normalized by height.

2.5. Univariate clustering

We employed four clustering methods to avoid method-specific results. We choose a bisecting K-means (Banerjee et al., 2015), a ward hierarchical clustering (Ward Jr., 1963), a spectral clustering (Ng et al., 2001), and a Gaussian mixture model (Bishop, 2006). Each algorithm tackles the clustering problem using a distinct approach. The bisecting K-means clustering algorithm combines aspects of K-means clustering with divisive hierarchical clustering, resulting in reduced sensitivity to random initializations. Hierarchical clustering arranges data points into a hierarchy of clusters by iteratively merging or splitting based on their similarity or distance, providing interpretable results that unveil the data's hierarchical structure. We specifically used Ward's linkage method to form hierarchical clustering. Spectral clustering is a graph-based clustering method that leverages the eigenvectors of a similarity matrix to partition data into clusters. A Gaussian mixture model is a probabilistic model that posits that data points arise from a blend of a finite number of Gaussian distributions with unspecified parameters. In a clustering problem, a Gaussian mixture model represents the data as a mixture of several Gaussian distributions, each associated with a particular cluster. In this study, we utilized *scikit-learn* (version 1.3.0) in conjunction with Python 3.8.10 to implement the clustering methods

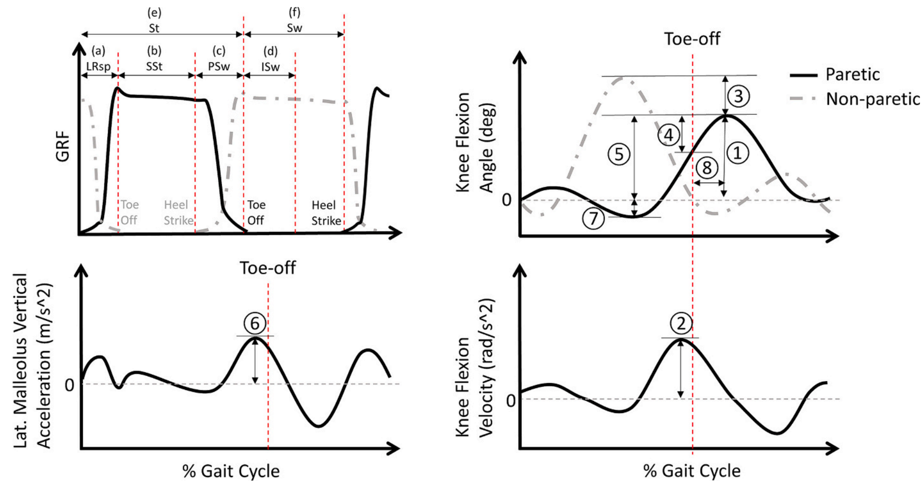

Fig. 1. Gait phases and features associated with post-stroke SKGs. Gait phases (top left) are divided into a) Loading response (LRsp), b) Single-limb support stance (SSt), c) Pre-swing (PSw), d) Initial Swing - 50 % of swing, (ISw), e) Stance (St), and f) Swing (Sw). Gait features from paretic side relevant to post-stroke SKG are 1) peak knee flexion in swing, 2) peak knee flexion velocity in pre-swing, 3) between-limb difference of peak knee flexion in swing), 4) knee range of motion in initial swing, 5) knee range of motion in full cycle, 6) peak push off acceleration in pre-swing, 7) timing of peak knee flexion in swing, and 8) peak knee extension in stance.

described above.

2.6. Cluster validity analysis

The univariate clustering was used to separate the sample into two groups (SKG and non-SKG) based on each parameter. We used external cluster validation (Jain and Dubes, 1988), which employs a priori knowledge of dataset information, such as gold standard labels. It enables evaluation of the goodness of clusters (Wu et al., 2009). In this study, our baseline labels were clinical diagnosis by an expert physiatrist (RKL). The expert viewed 3D animations of the data from four different camera view angles based on the motion capture data using OpenSim software (Delp et al., 2007). The expert clinician then reviewed these de-identified animated videos to diagnose whether participants exhibited post-stroke SKG.

Next, we computed external measures to determine the optimal univariate input feature resulting in the best clusters with the clinical diagnosis labels. These included F1 score (Wu et al., 2009), Purity (Wu et al., 2009), Adjusted Rand Index (Steinley, 2004), Adjusted Mutual Information (Vinh et al., 2010), V-measure (Rosenberg and Hirschberg, 2007), and Jaccard index (Jaccard, 1901). The F1 score measures accuracy as the harmonic mean of precision and recall. Purity measures how many objects belong to the majority class in a cluster. The Adjusted Rand Index is based on how often two different clusters agree or disagree on pairs of objects. Adjusted Mutual Information measures the shared information between two clusters. The V-measure is the harmonic mean of homogeneity and completeness, where homogeneity indicates how much each cluster contains elements from only one class, and completeness indicates how much each class's elements are assigned to the same cluster. The Jaccard Index shows how much two sets of data overlap, calculated by dividing the number of shared items by the total number of items in both sets. Higher values for all these measures indicate better cluster quality. In addition to the external validity measures, we also evaluated the sensitivity and specificity for each clustering method using a confusion matrix. Sensitivity, the probability of accurate positive diagnosis, is the number of true positives compared to the sum of true positives and false negatives. In contrast, specificity, the probability of an accurate negative diagnosis, is the number of true negatives compared to the sum of true negatives and false positives. Since gait parameters vary with gait speed (Fukuchi et al., 2019), we performed sensitivity and specificity analyses at both the comfortable self-selected and the fastest comfortable gait speed.

We additionally assessed the effect size of the cluster output, quantifying the degree of separation or differentiation between clusters using Cohen's d (Cohen, 1992). Cohen's d values between 0.2 and 0.3 are considered small, 0.5 is considered medium, and values of 0.8 or higher are considered large (Sullivan and Feinn, 2012).

2.7. Cutoff value

The cutoff value to distinguish between individuals with SKG and without SKG was determined by the average of the means of two clustered groups by each clustering method. The receiver operating characteristic (ROC) curve analysis was performed based on each clustering method and each biomechanical variable. The cutoff value from the method with the highest area under the curve (AUC) was reported.

2.8. Statistics

Statistical analyses were performed using *scipy* (version 1.14.0) in conjunction with Python 3.8.10. Shapiro-Wilk normality test confirmed the normality of gait parameters, and accordingly, Spearman's rank correlation coefficient used in correlation analysis. 95 % Confidence intervals for cutoff value and AUC were estimated by bootstrapping since clustering methods do not inherently provide confidence intervals on outcomes. We sampled 10,000 times in bootstrapping.

3. Results

Participant demographics, walking speed and their classification with respect to SKG are included in supplementary materials (Table S1). There were 24 participants with SKG and 26 without SKG. Gait features had various levels of agreement with each other and did not have a normal distribution ($p < 0.05$ in Shapiro-Wilk test). Fig. 2 shows Spearman's rank correlation coefficient (ρ) across gait features depicted in Fig. 1 and gait speed. Five knee joint kinematic gait features demonstrated a statistically significant correlation with the swing-phase peak knee flexion: the pre-swing peak knee flexion velocity ($\rho = 0.80$, $p < 0.001$), the between-limb difference of peak knee flexion angle during swing ($\rho = 0.85$, $p < 0.001$), the initial-swing knee flexion range of motion ($\rho = 0.60$, $p < 0.001$), the full gait cycle knee flexion range of motion ($\rho = 0.78$, $p < 0.001$), and the pre-swing peak push-off acceleration ($\rho = 0.81$, $p < 0.001$). Except for the initial-swing knee flexion range of motion, the other four parameters exhibited a strong correlation ($\rho > 0.75$). In contrast, the peak knee extension in the stance phase, representing hyperextension (genu recurvatum), and the peak knee

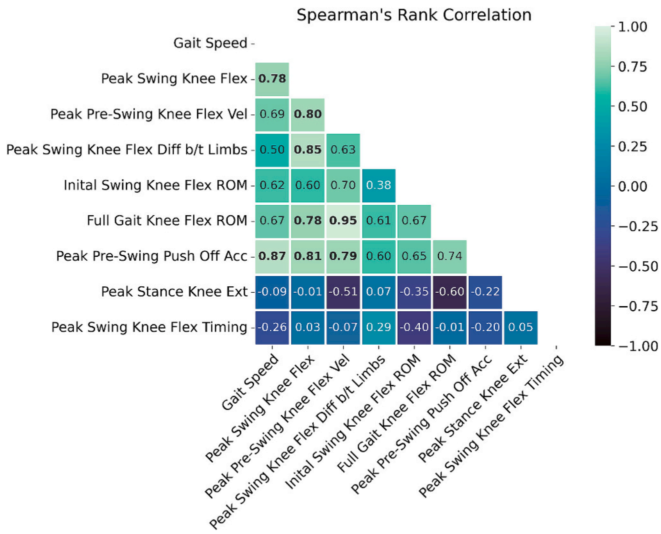

Fig. 2. Spearman's rank correlation coefficient across input variables and gait speed. Coefficients above 0.75, indicating strong relationships, are in bold font.

flexion timing, accounting for a temporal characteristic, exhibited poor correlation coefficients: $\rho = -0.09$, $p = 0.96$, and $\rho = -0.26$, $p = 0.86$, respectively. The height normalized gait parameters showed the same correlations across each other (Fig. S1).

For those variables exhibiting a correlation with peak knee flexion angle of 0.75 or above, we evaluated the validity scores using five gait parameters: the swing-phase peak knee flexion, the pre-swing peak knee flexion velocity, the between-limb peak knee flexion difference in swing, the full gait cycle knee flexion range of motion, and the pre-swing peak push-off acceleration. The between-limb peak knee flexion difference during the swing phase demonstrated the highest validity scores across all clustering methods, indicating the most accurate differentiation of the post-stroke SKG group (Table 1). Similarly, the peak knee flexion in the swing phase exhibited comparable scores. This finding was consistent with all clustering techniques. All effect sizes for the clusters, across each variable and method, indicated large effects ($d > 0.8$).

Both the peak swing knee flexion and the between-limb peak knee flexion angles exhibited the most consistent definition of SKG as compared with a clinical diagnosis. However, we hypothesized that gait speed may alter the performance of these parameters, so we examined the sensitivity and specificity of these parameters at both comfortable gait speed and the fastest comfortable gait speed conditions (Table 2). At comfortable gait speed, across all clustering methods the average sensitivity and specificity for the peak knee flexion angle parameter was 0.88 and 0.74, respectively, about the same as the between-limb difference in peak knee flexion angle (0.85 and 0.81). However, at the fastest comfortable speed, the sensitivity values diverged, with peak knee flexion angle resulting in sensitivity and specificity of 0.73 and 0.83, respectively. The average sensitivity and specificity across methods of the between-limb difference in peak knee flexion angle values were 0.90 and 0.83, respectively. The confusion matrices can be found in supplemental materials (Figs. S2 and S3). Further evaluation of performance under the fastest comfortable gait speed shows a marked superiority in the external validity measures of the between-limb

Table 2
Sensitivity/Specificity of peak swing knee flexion and between-limb differences in peak knee flexion at different gait speeds. While both outcome measures perform similarly at a comfortable gait speed, at a fast gait speed the sensitivity improves while we observe a decrement in sensitivity during comfortable gait speed. Note that only 41 persons completed the fastest comfortable walking data collection.

	Comfortable Speed (Sensitivity / Specificity)		Fast Speed (Sensitivity / Specificity)	
	Peak Swing Knee Flex	Peak Swing Knee Flex Diff b/t Limbs	Peak Swing Knee Flex	Peak Swing Knee Flex Diff b/t Limbs
Bisecting K-means	0.83/0.81	0.83/0.85	0.67/0.85	0.90/0.85
Hierarchical Clustering	0.96/0.58	0.92/0.73	0.86/0.75	0.90/0.80
Spectral Clustering	0.79/0.85	0.83/0.81	0.67/0.85	0.90/0.80
Gaussian Mixture	0.92/0.73	0.83/0.85	0.71/0.85	0.90/0.85

Table 1
External validity measures and the effect size for each univariate clustering output. Bold font values denote the outcome measure with the highest validity within each clustering algorithm. All external validity measures were computed based on clinical diagnosis labels. The effect size is based on Cohen's d, where values between 0.2 and 0.3 are considered small, 0.5 is medium, and values of 0.8 or higher are considered large.

Clustering Algorithms	Features	F1 score	Purity	Adj. Rand Index	Ad. Mutual Information	V-measure	Jaccard Index	Effect Size (Cohen's d)
Bisecting K-means	Peak Swing Knee Flex	0.82	0.82	0.40	0.31	0.32	0.69	2.79
	Peak Pre-Swing Knee Flex Vel	0.62	0.66	0.08	0.06	0.07	0.45	3.08
	Peak Swing Knee Flex Diff b/t Limbs	**0.83**	**0.84**	**0.45**	**0.36**	**0.37**	**0.71**	2.80
	Full Gait Knee Flex ROM	0.71	0.70	0.14	0.11	0.12	0.55	3.30
	Peak Pre-Swing Push Off Acc	0.77	0.78	0.30	0.23	0.24	0.62	2.92
Hierarchical Clustering	Peak Swing Knee Flex	0.79	0.76	0.26	0.28	0.29	0.66	2.83
	Peak Pre-Swing Knee Flex Vel	0.62	0.66	0.08	0.06	0.07	0.45	3.08
	Peak Swing Knee Flex Diff b/t Limbs	**0.83**	**0.82**	**0.40**	**0.34**	**0.35**	**0.71**	2.75
	Full Gait Knee Flex ROM	0.71	0.70	0.14	0.11	0.12	0.55	3.30
	Peak Pre-Swing Push Off Acc	0.74	0.76	0.26	0.19	0.21	0.59	2.91
Spectral Clustering	Peak Swing Knee Flex	0.81	0.82	0.40	0.31	0.32	0.68	2.71
	Peak Pre-Swing Knee Flex Vel	0.71	0.72	0.18	0.13	0.14	0.55	3.02
	Peak Swing Knee Flex Diff b/t Limbs	**0.82**	**0.82**	**0.40**	**0.31**	**0.32**	**0.69**	2.80
	Full Gait Knee Flex ROM	0.71	0.70	0.14	0.11	0.12	0.55	3.30
	Peak Pre-Swing Push Off Acc	0.74	0.76	0.26	0.19	0.21	0.59	2.91
Gaussian Mixture	Peak Swing Knee Flex	**0.83**	0.82	0.40	0.34	0.35	**0.71**	2.74
	Peak Pre-Swing Knee Flex Vel	0.65	0.68	0.11	0.08	0.10	0.48	3.07
	Peak Swing Knee Flex Diff b/t Limbs	**0.83**	**0.84**	**0.45**	**0.36**	**0.37**	**0.71**	2.80
	Full Gait Knee Flex ROM	0.71	0.70	0.14	0.11	0.12	0.55	3.30
	Peak Pre-Swing Push Off Acc	0.71	0.74	0.21	0.16	0.18	0.55	2.78

difference in peak knee flexion angle (Table S2). Specifically, between-limb difference in peak knee flexion angle had an average F1 score of 0.87 (0.81 at comfortable speed), whereas peak knee flexion was 0.77 (0.83 at comfortable gait speed). The visualization of outcomes from each clustering method according to gait parameters are shown in Fig. 3.

Table 3 illustrates the cutoff values and AUC from ROC curve at comfortable gait speed that differentiate between SKG and non-SKG cohorts using both peak knee flexion angle and between-limb difference in peak knee flexion angle parameters. Cutoff values were derived from the average of the means of two clustered groups. The cutoff value for identifying SKG through peak swing-phase knee flexion angle was determined to be 43.1° according to a clinical expert. The bisecting K-means showed the largest AUC from ROC curve analysis, such that 44.3° (95 % confidence interval: [37.7°, 50.2°]) was the best cutoff value to distinguish post-stroke SKG by using the peak swing-phase knee flexion angle. Similarly, the cutoff value for SKG identification using the between-limb difference in peak knee flexion angle was found to be 17.0° [11.2°, 22.5°] with bisecting K-means clustering and 17.0° by a clinical expert.

4. Discussion

In this work, we systematically investigated different definitions of SKG on a sample of 50 post-stroke individuals walking at self-selected gait speed. We used univariate cluster analysis of these definitions to first quantify the level of agreement between them. We found that peak knee extension and peak knee flexion angle timing poorly correlated with other definitions of SKG. We then compared the level of agreement of the other definitions with a clinical expert opinion using 4 different clustering methods. Based on 6 different biomechanical gait variables illustrating validity, we found that the difference between limbs of the peak knee flexion angle was the most valid parameter for diagnosis of SKG. Thus, we recommend that future studies using univariate selection criteria should base selection of SKG on peak knee flexion angle differences between limbs.

Typically, peak knee flexion angle has been used to diagnose post-stroke SKG. The majority of modern studies utilize a peak knee flexion angle of 40° to 45°, or knee flexion below two (or three) standard deviations from the mean of a sample population as an inclusion criterion (Campanini et al., 2013; Goldberg et al., 2006; Kerrigan et al., 1991; Mazzoli et al., 2018). Indeed, our work found that peak knee flexion angle was highly correlated to other definitions and one of the most valid definitions of SKG. However, because knee flexion angle changes with gait speed (Fig. 1), we hypothesized that the between-limb symmetry of peak knee flexion angle would be a more reliable definition. Our dataset was composed of post-stroke individuals walking at different comfortable gait speeds (0.10–0.90 m/s), yet the performances of peak knee flexion angle and between-limb difference of peak knee flexion angle parameters were similar (Table 1). This result is not entirely unexpected, as Kim and Eng (2004) (Kim and Eng, 2004) observed that compensatory motions can help improve gait speed without improving swing phase knee flexion. This suggests that peak knee flexion angle may be sufficient to determine SKG at comfortable walking speed.

The threshold value of peak knee flexion angle at comfortable gait speed we observed of 45° (Table 3) is consistent with other work (Kerrigan et al., 1991), although slightly higher than the threshold of 40° reported by Chantraine et al. (2022). This discrepancy, although small, could be due to the heterogeneity of the datasets or differences between analytical methods. It is notable that 5° is the clinically minimal significant difference of a goniometer measurement typically used to measure joint range of motion (Hancock et al., 2018).

While paretic peak knee flexion angle may be practical and sufficient, it is not the most robust and accurate single-parameter indicator of SKG. While the differences between individuals at different gait speeds may not consistently result in differences in knee flexion patterns (Kim and Eng, 2004), within individuals we found that changes in gait speed did affect the diagnostic capacity. Specifically, the between-limb difference in peak knee flexion angle was slightly more robust at comfortable gait speed than peak knee flexion (Table 1), but when considering walking at faster gait speeds, the between-limb difference in peak knee flexion angle had greater sensitivity and specificity (Table 2) as well as greater external validity scores across the board (Table S2) compared to the peak swing knee flexion angle. The between-limb difference of peak knee flexion angle is the highest performing single parameter diagnostic of SKG. The threshold value of 17.0° [11.2°, 22.5°] is also consistent with inclusion criteria from previous work (e.g., greater than 16°) (Akbas et al., 2020; Sulzer et al., 2010).

Given the directionality of the relationship between speed and peak knee flexion angle, impaired ankle plantarflexion push-off may be the underlying cause of post-stroke SKG (Campanini et al., 2013). For this reason, we included ankle plantarflexion kinematics in our list of possible SKG definitions. Indeed, ankle plantarflexion push-off acceleration was highly correlated with other definitions of SKG (Fig. 2). While this analysis cannot make any conclusions on causality, it does suggest a relationship between knee flexion angle and ankle push-off in those with post-stroke SKG.

A single parameter to diagnose or identify post-stroke SKG has several clinical implications. First, a single parameter would provide a means for reconciling the variety of definitions for post-stroke SKG (Campanini et al., 2013; Goldberg et al., 2006; Kerrigan et al., 1991; Sulzer et al., 2010) under a universal method for diagnosis thereby reducing variation across practice. Second, a universally adopted single parameter for post-stroke SKG provides a theoretical framework for testing causal hypotheses and expose theories to falsification (Popper, 2005). For example, the relationship between knee flexion angle and push-off. Third, it would provide a potential biomarker for clinical use to inform and guide treatment planning (*FDA-NIH Biomarker Working Group*, 2016). As noted above, there are many definitions of SKG. At the same time, there is a large variance in outcomes from interventions (Tenniglo et al., 2023). We undertook this study to come up with a simple, single-parameter definition of post-stroke SKG that could help homogenize recruitment and allow comparisons between studies. In other words, by better defining the problem, we can find a more precise solution.

This study has several limitations. Data was extracted from a research database where the data was initially collected by separate research studies. There may have been variability in the study aims and protocols. We attempted to minimize any influences of interventions or treatments on participants by only using data from the initial data collection time point in a study. While SKG is often considered a simple single parameter definition, clinical diagnosis is not solely focused on the knee. For instance, our clinical expert examined whole body motion, including frontal plane compensations commonly found in SKG (Kerrigan et al., 2000; Stanhope et al., 2014), to provide a diagnosis. As such, it should be expected that a single-parameter definition would not fully overlap with clinical expert opinion. We acknowledge that a multi-parameter definition of SKG may have greater agreement with clinical expert opinion. It may be that such a grouping may find different phenotypes of SKG. Another limitation of this study is the dataset. We examined 50 participants, which is a relatively large number, but still may be insufficient to generalize findings to the entire population. We also used a single clinical expert instead of a group of experts. While the SKG diagnosis may have differed using more experts, because there is no true gold standard, the differences in diagnosis may not significantly vary. Given the propensity of approaches towards crowdsourcing and artificial intelligence strategies of scouring multiple sources without credence to the quality of those sources, the benefit of including a group of clinicians over a single experienced one is a topic for future investigation.

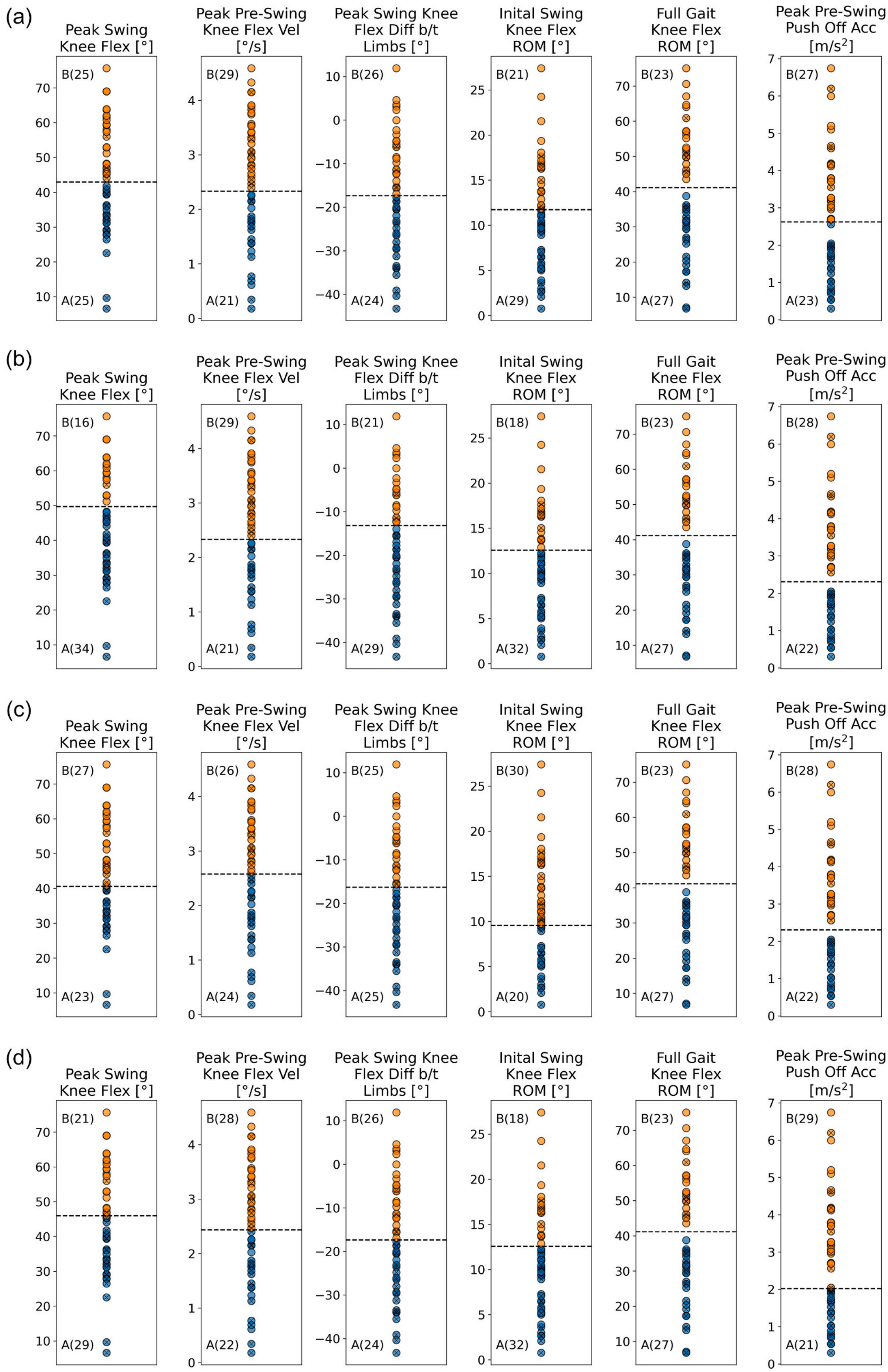

Fig. 3. Visualization of clustering by each method: a) bi-sectioning K-means, b) hierarchical clustering, c) spectral clustering, and d) gaussian mixture.

Table 3
Cutoff values distinguishing SKG and non-SKG cohorts through clustering methods. Cutoff values were derived from the average of group means. The cutoff value with the largest AUC from ROC curve analysis on each method is highlighted as bold font.

	Peak Swing Knee Flexion		Peak Swing Knee Flex Diff b/t Limbs	
	Cutoff [95 % CI]	AUC [95 % CI]	Cutoff [95 % CI]	AUC [95 % CI]
Bisecting K-means	**44.3° [37.7°, 50.2°]**	**0.536 [0.115, 0.909]**	**17.0° [11.2°, 22.5°]**	**0.560 [0.099, 0.924]**
Hierarchical Clustering	45.2° [38.0°, 51.5°]	0.525 [0.133, 0.897]	17.0° [9.6°, 24.4°]	0.548 [0.114, 0.917]
Spectral Clustering	43.5° [38.6°, 50.0°]	0.504 [0.117, 0.907]	16.6° [12.1°, 22.0°]	0.498 [0.096, 0.924]
Gaussian Mixture	43.2° [25.0°, 52.5°]	0.499 [0.139, 0.883]	17.6° [8.1°, 25.9°]	0.552 [0.115, 0.917]

5. Conclusions

Stiff-Knee gait (SKG) is one of the most common gait disabilities in people after stroke, but it lacks an agreed upon definition. The novel approach in this work was to compare commonly used diagnostic single parameters for SKG in terms of their accuracy and validity based on clinical expert diagnosis. We examined gait kinematics and kinetics in a group of 50 individuals post stroke (24 with SKG and 26 without SKG). We found that the between-limb difference in peak knee flexion angle was the highest performing single parameter. However, at comfortable gait speed, paretic peak knee flexion alone performed nearly as well. We found single parameter thresholds of less than 44.3° peak knee flexion angle and greater than 17.0° between-limb difference of peak knee flexion angle were appropriate thresholds for post-stroke SKG at comfortable walking speed. This systematic approach towards quantitative SKG diagnosis leads towards more clinical consistency and better homogeneity for future study.

Human ethics and consent to participate declarations

This analysis used deidentified retrospective data from a research database maintained by the NIH Center of Biomedical Research Excellence in Stroke Recovery. The research database is approved by the Medical University of South Carolina's Institutional Review Board in accordance with the Declaration of Helsinki. All participants signed an informed consent prior to study enrollment agreeing to have their data archived for future research.

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Contribution

As the primary author, JL managed the data analysis, interpretation of results, preparation of figures and tables, and writing of the manuscript. RKL provided the clinical diagnoses. SAK assisted with data analysis and interpretation of results. JS, SAK, and RAN guided the study's conceptualization and contributed to interpreting the findings. All authors reviewed and approved the final manuscript.

CRediT authorship contribution statement

Jeonghwan Lee: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Robert K. Lee:** Writing – review & editing, Resources, Conceptualization. **Bryant A. Seamon:** Writing – review & editing, Resources, Data curation. **Steven A. Kautz:** Writing – review & editing, Resources, Conceptualization. **Richard R. Neptune:** Writing – review & editing, Conceptualization. **James Sulzer:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no competing interests.

Data availability

The data used in this study are available from the NIH Center of Biomedical Research Excellence in Stroke Recovery upon reasonable request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.clinbiomech.2024.106351.

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