A Novel Multiple-Cue Observational Clinical Scale for Functional Evaluation of Gait After Stroke – The Stroke Mobility Score (SMS)

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Background: For future development of machine learning tools for gait impairment assessment after stroke, simple observational whole-body clinical scales are required. Current observational scales regard either only leg movement or discrete overall parameters, neglecting dysfunctions in the trunk and arms. The purpose of this study was to introduce a new multiple-cue observational scale, called the stroke mobility score (SMS).

Material/Methods: In a group of 131 patients, we developed a 1-page manual involving 6 subscores by Delphi method using the video-based SMS: trunk posture, leg movement of the most affected side, arm movement of the most affected side, walking speed, gait fluency and stability/risk of falling. Six medical raters then validated the SMS on a sample of 60 additional stroke patients. Conventional scales (NIHSS, Timed-Up-And-Go-Test, 10-Meter-Walk-Test, Berg Balance Scale, FIM-Item L, Barthel Index) were also applied.

Results: (1) High consistency and excellent inter-rater reliability of the SMS were verified (Cronbach's alpha >0.9). (2) The SMS subscores are non-redundant and reveal much more nuanced whole-body dysfunction details than conventional scores, although evident correlations as e.g. between 10-Meter-Walk-Test and subscore "gait speed" are verified. (3) The analysis of cross-correlations between SMS subscores unveils new functional interrelationships for stroke profiling.

Conclusions: The SMS proves to be an easy-to-use, tele-applicable, robust, consistent, reliable, and nuanced functional scale of gait impairments after stroke. Due to its sensitivity to whole-body motion criteria, it is ideally suited for machine learning algorithms and for development of new therapy strategies based on instrumented gait analysis.

MeSH Keywords: Gait Disorders, Neurologic • Stroke • Symptom Assessment • Treatment Outcome

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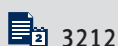
Background

Stroke is a leading cause of severe long-term disabilities in industrialized countries [1]. In the USA, about 7.2 million adults are currently living with post-stroke disabilities, while an additional 3.4 million adults yearly are estimated to have a stroke until 2030 [2]. A common impairment after stroke is limited walking ability [3,4]. Since walking is essential for performing many activities of daily living and good quality of life, gait recovery is a primary goal for stroke survivors [5]. Due to high interindividual variance in stroke severity as well as neurologic regeneration capacity, the rehabilitation of walking ability requires a personalized therapy that coordinates the application of physical therapy, robot-assisted therapy, specific medication and orthotic devices [6–8]. In this context, machine learning is being more and more integrated in the future of medical diagnostics and therapeutics [9,10]. However, the data base has to be carefully developed and controlled by human experts in order to furnish reliable machine learning techniques for reproducing or even improving current medical decisions [11]. In order to accomplish effective adjustments of the therapy program during treatment and application for machine learning, a refined assessment of patients' individual gait dysfunction is necessary.

For stroke rehabilitation, a broad spectrum of established medical scores is available, but their usefulness for functional evaluation of gait after stroke remains limited. On the one hand, neurological scales such as the National Institutes of Health Stroke Scale [6] or the Modified Ashworth Scale [12] are useful for the assessment and documentation of neurologic deficits and motor function after stroke. But since they are based on a medical examination of the patient – in part in lying position – they lack parameters for patients' dynamic movement performance, which are essential for the evaluation of gait ability.

On the other hand, observational assessments of activities of daily living like the Barthel Index [13], the Functional Independence Measure [6], and the Functional Ambulation Categories [14] or patient questionnaires such as ABILOCO ("ABILOCO: A Rasch-Built 13-Item Questionnaire to Assess Locomotion Ability in Stroke Patients") [15], ACTIVLIM-Stroke ("A Cross-cultural Rasch-Built Scale of Activity Limitations in Patients With Stroke") [16], and the Modified Rankin Scale [12] provide an indicator of activity as well as participation after stroke. However, these scores only assess overall gait performance. This also applies to conventional functional tests for mobility, balance, and motor function such as the 10-Meter-Walk-Test [17], the Timed-Up-And-Go-Test [12], and the Berg Balance Scale [18].

Other common observational gait assessment techniques such as the Edinburgh Visual Gait Score [19] and the Rivermead Visual Gait Assessment [20] assess gait movement in detail and thus provide a general picture of gait impairment. However, since they do not include any stroke-specific context, their practical benefit in stroke rehabilitation is limited. Recent review papers [17,21,22] show that the only currently existing scale for gait disorders after stroke is the Wisconsin Gait Scale (WGS) [23]. The WGS is based on a subdivision of the gait cycle of the affected leg in 4 phases and the rating of 14 items describing the leg motion during these phases. However, this approach is complex and focuses solely on leg motion, while the rest of the body is neglected. This contrasts with recent studies that show the movements of the arms and trunk are important aspects of gait pattern after stroke [24,25].

In summary, despite a wide range of scales currently available in neurology and gait analysis, there is still a need for a simple nuanced functional assessment of gait after stroke including arm movement and trunk posture based on standard video recordings. The objective of this study was to introduce a new multiple-cue observational scale, called the stroke mobility score (SMS), to fulfil these requirements.

Material and Methods

Population

Inclusion criteria for the study population were: (1) proven recent stroke (ischemia or haemorrhage) as verified in a computer tomography (CT) or magnetic resonance imaging (MRI) of the head; (2) medical history of only 1 stroke; (3) time since stroke ≤3 months (time period within 3 months after stroke onset was defined as subacute stroke time, as we wanted to exclude chronic stroke patients in the validation phase of this study to avoid secondary complications due to hip, knee, or spinal pain effected by the walking disability); (4) ability to walk 30 meters without help from an assistant or use of a walking frame; (5) age ≥18 years; and (6) written informed consent. Exclusion criteria were: (1) any surgery within the last year; (2) any neurological or orthopedic symptoms of the stroke interfering with walking during clinical examination; (3) known peripheral artery disease with a restriction of gait or other reasons for limiting walking prior to the stroke; and (4) participation in another study.

The authors obtained Institutional Review Board approval for instrumental gait analysis and clinical examination of stroke patients from the Ethics Committee of the University Duisburg-Essen (application number 18.7988).

Medical examination

All patients received a standard neurological examination and were assessed with the following scores:

10-Meter-Walk-Test [17], Timed-Up-And-Go-Test [12], Modified Rankin Scale [12], National Institutes of Health Stroke Scale [6], Berg Balance Scale [18], Barthel Index [13], and FIM-Item L [6]. Results were documented in a case record file (CRF) and reviewed by an independent study nurse.

Video recordings

The SMS is based on standardized whole-body video recordings of gait while walking at a self-selected pace in underwear. The recordings were conducted using 2 video cameras (Basler 602fc, 100 Hz) aligned along and perpendicular to a straight 10-meter indoor walkway, capturing front, back, and left/right side views. Patients were instructed to stand at the beginning of the walkway and to start walking when prompted. At the end of the walkway, the patients had to stop, turn 180 degrees and stand in an upright position, lifting the arms to horizontally as possible. Afterwards, the arms were lowered again, and the patient walked back. The videos were saved on a standalone PC and stored for offline analysis. All recordings were carried out by the same technician.

Score development

The Stroke Mobility Score was developed based on the Delphi method by an interdisciplinary team of neurologists, orthopedic surgeons, physiotherapists, study nurses, orthotics specialists, and biomechanical engineers over a period of 5 years within 2 multidisciplinary research projects: "ReHabX-Stroke: Personalized therapy planning of gait disorders based on the example of stroke" (2012-2015) [26] and "RehaBoard: A computer assistance system for the interdisciplinary treatment planning of gait impairments after stroke" (ongoing project 2017-2020) [27]. In a first run (development run), video recordings of the gait of 131 patients were discussed, and essential whole-body movement properties relevant to diagnosis and therapy planning were identified. This led to the following 6 principal functional criteria: (1) trunk posture, (2) leg movement of the most affected side, (3) arm movement of the most affected side, (4) gait speed, (5) gait fluency, and (6) stability of walking on flat ground/risk of falling. For each criterion, a set of 4 simple brief scoring descriptions from 0 (no pathological finding) to 3 (significant pathological findings) was developed and iterated until convergence of the assessment was achieved. The total score is thus the sum of the 6 SMS subscores, giving a number between 0 (no findings) and 18 (most critical). This scale is based solely on observation of videos with only 4 answer options per item, taking about 2–3 minutes for completion. In a second run (validation run), 6 independent medical raters (2 neurologists, 2 physiotherapists, an orthopedic surgeon, and a sports scientist) scored anonymized videos of 60 additional, randomly selected patients according to the SMS manual and an initial calibration step involving supervised

scoring of 3 patients not included in the group. None of the raters participated in the score development and thus were novice to the rating system.

Statistical analysis

The statistical analysis of the SMS was based on the sample of the 60 validation-run patients. Descriptive statistics were compiled for age, sex, impaired side, and time period since the occurrence of the stroke. All statistics were calculated using IBM SPSS Statistics version 23. A critical level of $p<0.05$ was considered significant for all statistics except for Tukey's test of additivity and Levene's test, for which a progressive critical level of $p<0.25$ was used according to Wirtz's recommendation [28].

The consistency of the ratings of the 6 raters was evaluated by corrected item-total correlation and Cronbach's alpha coefficient. Since the ratings were not normally distributed (Shapiro-Wilk-Test: $p_i=0.000–0.024$), the relationship between the SMS subscores and established clinical scores was assessed by nonparametric rank correlation applying Spearman's rho. Interrater reliability was analysed using the interclass correlation coefficient (ICC) of type 2,1 (two-way random effects model). Tukey's test of additivity and Levene's test for equality of variances were calculated as quality criteria of the ICC. The application of the parametric ICC-analysis can be regarded as valid, since it is robust with respect to the normality assumption as long as 50 or more observations are analysed [29].

Results

As a result of the Delphi process, the SMS scoring manual shown in Table 1 was developed. Patients' demographic data are presented in Table 2. In the random sample used for score development, age ranged from 20 to 80 years (mean 53.1 years, standard deviation 12.6 years). There were 100 males and 31 females. Side of hemispheric lesion was balanced (left n=51, right n=51) and 29 patients with other stroke localizations were included as well (brainstem n=17, inconclusive n=8, no lesion n=4). In the control sample used for score validation, age ranged from 31 to 80 years (mean 56.9 years, standard deviation 10 years). Fifty patients were male and 10 were female. Stroke occurred up to 3 months prior to a patient's evaluation. Side of hemispheric lesion was balanced (left n=26, right n=25). Nine patients with a brainstem stroke were included as well. Scoring using SMS proved to be simple, consistent, and reliable, requiring only 2–3 minutes per evaluation. Moreover, the SMS subscores provided functional insight into the gait impairment properties, as shown by a differentiated correlation with conventional scores. Details of the statistical analysis for the SMS sample rating of the 60 validation-run patients are discussed in the following sections.

Table 1. SMS manual.

_____
Patient Name or ID

_____
Rater

Manual

- To be rated are patients dressed in underwear, who walk unsupported on a straight, marked walkway with a regular levelled surface.
- The walkway should be at least 10 meters in length and one meter in width.
- The observed motion sequence consists of start-walk-stop and a 180° turn at the end of the walkway.

Notes

- If a patient is using a walking aid or a mechanical device for gait (e.g., cane, orthosis, shoes) the gait has to be rated as it is. It should not be rated as the assumed gait without the walking aid or without the mechanical device.
- Patients using a walking frame are excluded from the SMS.
- Version: 1/2019

Trunk posture	
No pathological findings	0
Mild trunk bending (lateral or frontal) AND/OR mild vertical trunk rotation	1
EITHER significant trunk bending (lateral or frontal) OR significant vertical trunk rotation	2
BOTH significant trunk bending (lateral or frontal) AND significant vertical trunk rotation	3

Leg movement (most affected side)	
No pathological findings	0
Mild leg movement abnormality (slightly impaired motions at hip, knee and/or foot)	1
Significant leg movement abnormality (strongly impaired motions at hip, knee, and/or foot) AND/OR mild knee hyperextension (genu recurvatum)	2
Leg nearly rigid (flexed or extended) AND/OR significantly affected leg with knee hyperextension (genu recurvatum)	3

Arm movement (most affected side)	
No pathological findings	0
Mild arm movement abnormality (slightly impaired motions at shoulder, elbow and/or hand)	1
Significant arm movement abnormality (strongly impaired motions at shoulder, elbow and/or hand)	2
Rigidity of the entire arm OR no active arm movement (plegia)	3

Gait speed	
No pathological findings	0
Mild walking speed abnormality (walking speed is slightly reduced compared to healthy subjects)	1
Significant walking speed abnormality (walking is seemingly achieved only with full concentration)	2
Extremely slow and exhausting walking (end of the 10-meter walkway is reached only with great effort)	3

Gait fluency	
No pathological findings	0
Mild asymmetric gait (left and right steps are slightly unequal)	1
Significant asymmetric gait (left and right steps appear to be disconnected movements)	2
Severe asymmetric gait (body motion for left and right steps is controlled individually and interrupted by breaks, leading to a "staccato" motion)	3

Stability of walking on flat ground/risk of falling	
No pathological findings	0
Mild postural instabilities, but no visible risk of falling	1
Significant risk of falling due to stumbling AND/OR tumbling at turning	2
The patient is using a cane	3

Total score	
Sum of the 6 subscores	

Table 2. Demographical data of rated patients during score development and score validation.

Parameter	Score development	Score validation
Sample size	131	60
Age [years]: mean, median (SD) min–max	53.1, 54.0 (12.6) 20–80	56.9, 57.8 (10.0) 31–80
Gender: Male/Female	100/31	50/10
Months since stroke:		
0 to 1	42	29
1 to 2	24	23
2 to 3	15	8
>3	46	0
– (no stroke)	4	0

Parameter	Score development	Score validation
Affected hemisphere:		
Left	51	26
Right	51	25
Brainstem	17	9
Inconclusive	8	0
None (no stroke)	4	0

Table 3. Corrected item-total correlation and Cronbach's alpha for SMS subscores and total score for 6 sample medical raters.

SMS item	Corrected item-total correlation						Cronbach's alpha coefficient
	Rater 1	Rater 2	Rater 3	Rater 4	Rater 5	Rater 6	
Total score	.951	.943	.962	.938	.961	.948	.983
Trunk posture	.750	.787	.806	.706	.834	.767	.919
Leg movement	.797	.930	.898	.889	.890	.873	.962
Arm movement	.702	.831	.872	.802	.849	.861	.931
Gait speed	.888	.893	.878	.737	.883	.830	.949
Gait fluency	.815	.848	.801	.772	.839	.847	.939
Stability/risk of falling	.900	.903	.920	.911	.922	.932	.974

0.8	≤ Corrected item-total correlation ≤	1	High
0.6	≤ Corrected item-total correlation <	0.8	Good
0.4	≤ Corrected item-total correlation <	0.6	Moderate
0.2	≤ Corrected item-total correlation <	0.4	Weak
	Corrected item-total correlation <	0.2	Poor

0.9	< Cronbach's alpha ≤	1	Excellent
0.8	< Cronbach's alpha ≤	0.9	High
0.7	< Cronbach's alpha ≤	0.8	Acceptable
0.6	< Cronbach's alpha ≤	0.7	Disputable
0.5	< Cronbach's alpha ≤	0.6	Low
	Cronbach's alpha ≤	0.5	Unacceptable

Consistency

Consistency between raters was analysed using corrected item-total Cronbach's alpha coefficient between each rater's scorings and the average of the other raters for each SMS subscore and the SMS total score, respectively, over all patients. Table 3 displays the corresponding results. For all raters and for all SMS items, a correlation >0.7 was achieved. The lowest correlations were found for "trunk posture", while SMS total score and "stability" subscore showed the highest correlation. Only 2 raters (rater 1 and 4) differed moderately from the others in some subscores.

Inter-rater reliability

SMS inter-rater reliability according to interclass correlation coefficient ICC type 2,1 (two-way random effects model) following Fleiss' guideline [30] proved to be good-to-excellent. Excellent reliability scores (>0.75) were obtained for "leg movement", "stability of walking on flat ground/risk of falling" and total score, and good reliability scores (>0.6) were achieved for "trunk posture", "arm movement", "gait speed", and "gait fluency" (Table 4).

Table 4. Inter-rater reliability $ICC_{2.1}$ of SMS subscores and SMS total score for 6 sample medical raters.

SMS item	$ICC_{2.1}$	Reliability
Total score	.894	Excellent
Trunk posture	.601	Good
Leg movement	.796	Excellent
Arm movement	.688	Good
Gait speed	.726	Good
Gait fluency	.714	Good
Stability/risk of falling	.842	Excellent

Inter-subscore cross-correlation

SMS subscore cross-correlation was evaluated by computing the rank correlation according to Spearman's rho values between each pair of items (15 pairs) over all 60 patients for each rater (6 raters). Then, the average was taken for each item pair over the 6 raters. Table 5 shows the obtained average values for all item pairs. It can be observed that no SMS item pair correlates high, but that all SMS item pair correlations range on a level of good to moderate. "Leg movement" and "stability/risk of falling" displayed the highest item-total correlation (Cronbach's alpha coefficient 0.962 resp. 0.974) and inter-rater reliability ($ICC_{2.1}$ 0.796 resp. 0.842), while "trunk posture" and "arm motion" yielded the lowest (Cronbach's alpha coefficient 0.919 resp. 0.931/$ICC_{2.1}$ 0.601 resp. 0.688).

Cross-correlation of average SMS subscores with conventional scores

Table 6 shows the cross-correlation between the averaged SMS subscores and the conventional scores used for gait impairment assessment. For better interpretation, columns and rows are ordered such that higher values are displayed in the upper left and the lower values are displayed in the bottom right. The highest correlation results were between the SMS subscores "gait speed"/"gait fluency" and the conventional Ten-Meter-Walk- and Timed-Up-And-Go-Tests. This is not surprising, as both assess velocity, which is quite easy to determine. What was surprising is that the observational SMS assessment based on a simple video was as good in velocity assessment as the measurement with a clock. Reading this result in inverse direction shows that a simple remote observational scale can replace complex instrumented walking speed analysis settings with almost the same clinical information. The table also shows that specific SMS subscores rating localized functional impairments are not reflected by the conventional scores, as seen for the 3 SMS subscores "trunk posture", "leg movement", and "arm movement", which have only weak to moderate correlation with the conventional scores (the lowest being "arm movement"). The results also display that all existing conventional scales, such as Barthel Index, FIM-Item L and Berg Balance Scale, correlate only weakly to moderately with the functional SMS subscores.

Table 5. Mean Spearman's cross-correlations between SMS subscores over 6 sample medical raters.

SMS subscore	Trunk posture	Leg movement	Arm movement	Gait speed	Gait fluency	Stability/ risk of falling
Trunk posture	–	.588	.529	.562	.568	.496
Leg movement	.588	–	.686	.726	.759	.715
Arm movement	.529	.686	–	.608	.625	.606
Gait speed	.562	.726	.608	–	.765	.700
Gait fluency	.568	.759	.625	.765	–	.719
Stability/risk of falling	.496	.715	.606	.700	.719	–

All correlations are significant at the 0.01 level (2-tailed).

0.8	≤ |rho| ≤	1	High
0.6	≤ |rho| <	0.8	Good
0.4	≤ |rho| <	0.6	Moderate
0.2	≤ |rho| <	0.4	Weak
	|rho| <	0.2	Poor

Table 6. Spearman's cross-correlation between the average SMS subscores and average SMS total score and established scores in stroke rehabilitation.

SMS subscore	Ten-Meter-Walk-Test	Timed-Up-And-Go-Test	National Institutes of Health Stroke Scale	Berg Balance Scale	FIM – Item L	Barthel Index
Gait speed	.63	.60	.53	.45*	.48*	.45*
Gait fluency	.63	.56	.51	.46*	.46*	.44*
Stability/risk of falling	.54	.50	.52	.44*	.44*	.39*
Total score	.59	.52	.53	.46*	.43*	.42*
Trunk posture	.51	.46	.48	.40*	.41*	.40*
Leg movement	.56	.47	.41	.44*	.40*	.43*
Arm movement	.42	.33	.41	.33*	.28*	.37*

* Negative correlation. All correlations are significant at the 0.01 level (2-tailed).

0.8	≤ |rho| ≤	1	High
0.6	≤ |rho| <	0.8	Good
0.4	≤ |rho| <	0.6	Moderate
0.2	≤ |rho| <	0.4	Weak
	|rho| <	0.2	Poor

Discussion

In summary, the results show 3 major findings: (1) the presented SMS measures the disability of walking after stroke; (2) a high consistency and excellent inter-rater reliability of the SMS were verified (Cronbach's alpha >0.9); and (3) the SMS subscores are non-redundant and reveal much more nuanced whole-body dysfunction details than conventional scores, although evident correlations such as between 10-Meter-Walk-Test and subscore "gait speed" are verified.

The main findings can be further discussed as follows:

1) Efficacy of the score for assessing walking disability

Clinical scores are developed for diagnosis or as risk factors [31]. They are widely used for therapeutic decision-making, benchmarking, and clinical trials. A clinical score should be a valuable tool for measuring patient condition and should be highly reliable. Thus, for clinical and scientific application, high inter-rater reliability and validity are required. The presented SMS was developed to measure the disability of walking after stroke. The score included the walking speed and the main factors influencing the walking ability after stroke (leg and arm movement, body control). Thus, it is not surprising that tools like the 10-Meter-Walk-Test are partially compatible with the

SMS. In contrast, global scores like the Barthel Index or the National Institutes of Health Stroke Scale, which are examined while the patient is lying down, have very low correlation. For example, "Arm movement" correlates most with "leg movement" (rho=0.686), displaying an interlimb coupling between the two, typical for stroke hemiparesis. "Leg movement" again correlates most strongly with "gait fluency" (rho=0.759), showing that "walking speed" is not the only the primary factor of walking quality. Also, the highest correlation of "trunk posture" appears in the pair with "leg motion" (rho=.588), showing the influence of upper-body motion on lower-body motion. This underscores the importance of upper-body assessment for gait improvement in patients after stroke.

2) Consistency and excellent inter-rater reliability

Our results revealed good-to-excellent ICC regardless of being used by specialists or trained students. Excellent reliability scores were achieved for subscores, especially for falling risk. Thus, the SMS fulfils all conditions for clinical application and trials as a score. For example, as shown in Table 4, the SMS shows a high consistency to detect "risk of falling" (ICC2,1=0.842). It is evident that "risk of falling" correlates to a poorer outcome after stroke and is a relevant traumatic complication [32]. A meta-analysis revealed a low risk prediction by single-test systems based on questionnaire assessment [33].

In the present study, it was well-detected in the videos and allowed identifying patients at risk by learning algorithms based on a short video sequence.

3) Non-redundancy of SMS

For development of a scoring system, it is important how many items are needed. For example, the body mass index is calculated by 2 items, but the quality of life questionnaire has 36 items [34]. Driven by the functionality of walking, we designed 7 items with various functional properties. The broad distribution of the classification points (0–18) allows a very fine differentiation of disability, in contrast with existing standard scales. For example, the results of Table 6 show that, out of the 6 standard scales, only the 10-Meter-Walk-Test and Timed-Up-And-Go-Test show a strong correlation with the SMS subscores gait speed and gait fluency (rho=0.56 to 0.63), while the other standard scores such as Barthel Index, FIM-Item L, Berg Balance Scale, and National Institutes of Health Stroke Scale were only moderately correlated (Table 6 rho=0.44 to 0.53). This is of importance not only because low-cost measuring environments (based on only 2 to 4 video cameras and a walking room) can be used for movement analysis, but also because the presented multiple-cue observational scale can be used in the future for training machine learning algorithms.

Outlook

Due to its observational nature and the empirical evidence that all test raters scored consistently after a short video training on calibration patients and that the results of the different raters from different disciplines were interchangeable, the SMS score is ideal for later training of machine learning algorithms.

Moreover, the SMS score proves to be a consistent, reliable, tele-assessable, and easy-to-learn clinical observational scale for multiple-cue functional evaluation of gait dysfunctions after stroke, which can be used as a bedside test without access to instrumented gait analysis. Thus, the SMS is also suitable for monitoring of the stroke course.

A limitation of this study is that the sample patient database was not balanced between male and female patients. This is due to the situation that a database of patients in normal treatment was used that contained more males than females, and that the random selection from the complete database used in this setting yielded the given male/female distribution. Future studies might use broader test groups. However, it is believed that these will not influence the main findings of this paper, as the observational score is independent of gender differences, in contrast to instrumented gait analysis, in which physiologic differences in geometry and muscle and mass distribution must be considered.

Conclusions

A novel observational clinical scale for multiple-cue functional evaluation of gait after stroke – the Stroke Mobility Score (SMS) – is presented. The score is easy to learn and to apply and is based solely on video recordings of patients' gaits on a 10-meter walkway, allowing for fast evaluation in just 2–3 minutes, and can also be used in tele-assessment. The SMS can measure aspects of walking that are not part of existing scores, enabling, despite its simplicity, a nuanced functional assessment of gait after stroke, including arm and leg movement as well as trunk posture. Statistical evaluations show that the SMS subscores and its total score have excellent consistency and good-to-excellent inter-rater reliability after a short period of self-study. The analysis of SMS subscore cross-correlations unveils new functional interrelationships for stroke gait profiling. Due to its sensitivity to whole-body motion criteria, it is ideally suited for machine learning algorithms and for development of new therapies based on instrumented gait analysis. Therefore, the SMS meets all relevant requirements for a useful clinical tool for assessment of gait dysfunctionality after stroke and for training of machine learning algorithms. The SMS manual and 6 anonymized patient calibration videos can be downloaded as supplementry materials.

Conflicts of interest

None

Supplementary Material

T{01, 03, 08, 10, 12, 17}.mp4 and Ratings of SMS training videos.pdf
Material for self-study of SMS: Six videos of impaired gaits and corresponding SMS ratings
https://figshare.com/articles/
Material_for_self-study_of_SMS_zip/10048982

SMS scoresheet.pdf
SMS scoresheet as a blank form (DIN A4)
https://figshare.com/articles/SMS_scoresheet_pdf/10048913

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