A comprehensive approach to assess walking ability and fall risk using the Interactive Walkway

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Chapter 7

Walking adaptability for targeted fall-risk assessments

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Background. Most falls occur during walking and are due to trips, slips or misplaced steps, which suggests a reduced walking adaptability. The objective of this study was to evaluate the potential merit of a walking-adaptability assessment for identifying prospective fallers and risk factors for future falls in a cohort of stroke patients, Parkinson's disease patients, and controls (n = 30 for each group). Research question. Does an assessment of walking-adaptability improve the identification of fallers compared to generic fall-risk factors alone? Methods. This study comprised an evaluation of subject characteristics, clinical gait and balance tests, a quantitative gait assessment and a walking-adaptability assessment with the Interactive Walkway. Subjects' falls were registered prospectively with falls calendars during a 6-month follow-up period. Generic and walking-related fall-risk factors were compared between prospective fallers and non-fallers. Binary logistic regression and Chi-square Automatic Interaction Detector analyses were performed to identify fallers and predictor variables for future falls. Results. In addition to fall history, obstacle-avoidance success rate and normalized walking speed during goal-directed stepping correctly classified prospective fallers and were predictors of future falls. Compared to the use of generic fall-risk factors only, the inclusion of walking-related fall-risk factors improved the identification of prospective fallers. Significance. If cross-validated in future studies with larger samples, these fall-risk factors may serve as quick entry tests for falls prevention programs. In addition, the identification of these walking-related fall-risk factors may help in developing falls prevention strategies.

Introduction

The incidence of falls increases with age, but is particularly high in patients with neurological disorders, such as stroke and Parkinson's disease (PD) [1,2]. Falls can occur as a result of both intrinsic factors (i.e., subject characteristics and gait impairments) and extrinsic factors (e.g., slippery floor, uneven walking surface) [3]. For the latter, it is important to be able to adapt walking to the environment, an aspect of walking that is difficult to assess with clinical tests [4]. Most falls occur during walking and are due to trips, slips or misplaced steps [5-7], suggesting a reduced walking adaptability. An evaluation of walking adaptability could potentially improve the identification of fallers and may help in developing falls prevention strategies [8]. The Interactive Walkway (IWW; Figure 7.1) can be used to perform quick and unobtrusive quantitative gait assessments [9] and to quantify various aspects of walking adaptability [10].

The aim of this study is to evaluate the potential merit of the IWW for identifying prospective fallers and risk factors for future falls in a composite cohort with stroke patients, PD patients and controls. First, we will examine differences in walking ability between fallers and non-fallers. Second, two methods will be used to identify fallers and risk factors for future falls; one extensive method and one easily interpretable method fit for use in the clinic. We expect that walking-adaptability assessments improve the classification of prospective fallers compared to generic fall-risk factors alone (i.e., subject characteristics, clinical gait and balance tests, quantitative gait assessments) and that a poor walking adaptability is a risk factor for future falls.

Methods

Subjects

30 stroke patients, 30 PD patients and 30 controls participated in this study (Table 7.1). Groups were age- and sex-matched. Patients were recruited from the outpatient clinics of neurology and rehabilitation medicine of the Leiden University Medical Center and from a list of patients who were discharged from

the Rijnlands Rehabilitation Center. Controls were recruited via advertisement. Subjects were 18 years or older and had command of the Dutch language. Patients had to be able to stand unsupported for more than 20 seconds and walk independently. Stroke patients had to be more than 12 weeks post stroke. PD patients had to fulfill clinical diagnostic criteria according to the UK Parkinson's Disease Society Brain Bank [11] and could have a Hoehn and Yahr stage of 1-4 [12]. PD patients were measured in the ON state. Controls had to have unimpaired gait, normal cognitive function (Montreal Cognitive Assessment score ≥ 23; [13]) and normal or corrected to normal vision. Exclusion criteria were (additional) neurological diseases and/or problems interfering with gait function. All subjects gave written informed consent, and the study was approved by the local medical ethics committee (P15.232).

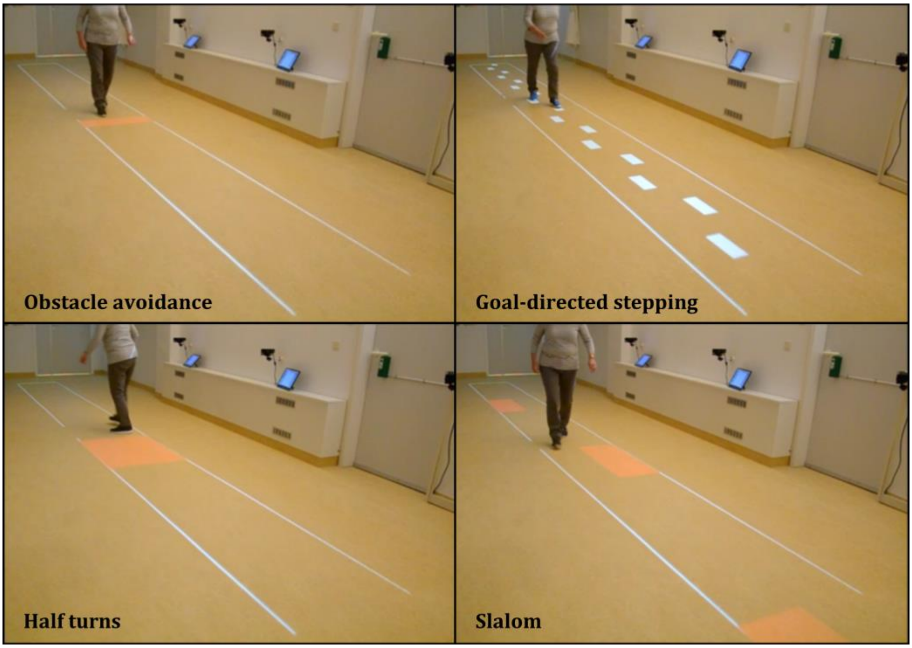

Figure 7.1 The Interactive Walkway for an assessment of walking adaptability, which may unveil potential fall-risk factors.

Table 7.1 Group characteristics of stroke patients, Parkinson's disease patients and controls.

		Stroke	Parkinson's disease	Control
Age (years)	**mean ± SD**	62.5 ± 10.1	63.1 ± 10.0	62.9 ± 10.3
Sex	**male/female**	18/12	18/12	18/12
MOCA [0-30]*	**mean ± SD**	22.5 ± 6.3	-	27.7 ± 1.4
FMA lower extremity [0-34]*	**mean ± SD**	19.7 ± 7.4	-	-
Bamford classification	**PACS/TACS/ POCS/LACS/unk**	16/2/2/8/1	-	-
SCOPA-COG [0-43]*	**mean ± SD**	-	30.4 ± 7.1	-
MDS-UPDRS motor score [0-132]**	**mean ± SD**	-	36.9 ± 18.0	-
Hoehn and Yahr stage [1-5]**	**mean ± SD**	-	2.3 ± 0.7	-

Abbreviations: MOCA = Montreal Cognitive Assessment; FMA = Fugl-Meyer Assessment; PACS = partial anterior circulation stroke; TACS = total anterior circulation stroke; POCS = posterior circulation syndrome; LACS = lacunar syndrome; unk = unknown; SCOPA-COG = Scales for Outcomes in Parkinson's Disease – Cognition; MDS-UPDRS = Movement Disorder Society version of the Unified Rating Scale for Parkinson's disease.

* Higher scores represent better outcomes.

** Higher scores represent worse outcomes.

Experimental set-up and procedure

Before performing the experimental tasks, the Montreal Cognitive Assessment [14] and Scales for Outcomes in Parkinson's Disease – Cognition [15] were administered to assess cognitive abilities. In stroke patients, sensorimotor impairment was assessed using the Fugl-Meyer Assessment - lower extremity [16]. Higher scores on these clinical tests reflect better outcomes (Table 7.1). In PD patients, the Movement Disorder Society version of the Unified Rating Scale for Parkinson's disease [17] and Hoehn and Yahr stage [12] were administered to assess disease severity, with higher scores reflecting worse outcomes (Table 7.1). All subjects completed the Falls Efficacy Scale - International [18] to assess fear of falling, the Modified Survey of Activities of Fear of Falling in the Elderly Scale [19] to assess activity avoidance due to fear of falling (higher scores indicate more fear of falling) and were asked about their fall history in the year prior to the experiment.

Commonly-used clinical gait and balance tests included the Timed-Up-and-Go test and the 10-meter walking test at comfortable and maximum walking speed to assess mobility (longer completion times indicate worse mobility), the Tinetti Balance Assessment for an evaluation of gait and balance performance of which the combined score of the two sections was used in this study (higher scores indicate better performance), the 7-item Berg Balance Scale to measure static and dynamic balance during specific movement tasks (lower outcome indicates worse balance) and the Functional Reach Test to determine the maximal distance one can reach forward from a standing position (smaller distance indicates worse balance). The order of these commonly-used clinical tests was randomized.

The validated IWW [9,10,20] was used for quantitative gait and walking-adaptability assessments. The IWW set-up, using multiple Kinect sensors for markerless 3D motion registration, is described in detail in Supplement 7.1. The quantitative gait assessment was performed using an 8-meter walking test. In addition, subjects performed various walking-adaptability tasks under varying levels of difficulty: obstacle avoidance, sudden stops-and-starts, goal-directed stepping (symmetric and irregular stepping stones), narrow walkway (entire walkway and sudden narrowing), speed adjustments (speeding up and slowing down), slalom, turning (half and full turns) and dual-task walking (plain and augmented), yielding a total of 36 trials (Figure 7.2; see Supplement 7.1 for more details and Supplement 7.2 for a video). Dual-task walking was assessed using an auditory Stroop task in which the words high and low were pronounced at a high or low pitch (i.e., congruent and incongruent stimuli) simultaneously with the 8-meter walking test (plain dual-task walking) and obstacle-avoidance task (augmented dual-task walking), respectively. Subjects had to respond with the pitch of the spoken word, which was different from the spoken word in case of an incongruent stimulus. Stimuli were presented with a fixed interval of 2 s. Subjects were instructed to complete each trial at a self-selected walking speed, while also responding to the Stroop stimuli in case of dual-task walking.

Half of the subjects in each group started with the clinical tests, the other half with the IWW assessment. With regard to the latter, subjects always started with the 8-meter walking test, which enabled us to adjust the settings of the walking-adaptability tasks to one's own gait characteristics in an attempt to obtain a similar level of difficulty for each subject (see Supplement 7.1). For example, available response times for suddenly appearing obstacles were controlled by self-selected walking speed during the 8-meter walking test and available response distance (ARD in Figure 7.2). Subsequently, the 8-meter walking test was performed with the dual task (i.e., plain dual-task walking), preceded by a familiarization trial in which the auditory Stroop task was practiced while sitting. The remaining IWW tasks (as specified in Table 7.2) were randomized in blocks.

After the experiment, subjects were asked to register falls during a 6-month follow-up period using a falls calendar. Subjects had to report every day whether they had fallen. A fall was defined as an unexpected event in which the subject comes to rest on the ground, floor, or lower level [21]. Subjects were asked to send back their falls calendar every month and were contacted on a monthly basis to ask about the falls that occurred.

Data pre-processing and analysis

Data pre-processing followed Geerse et al. [9,10], as reproduced in more detail in Supplement 7.1. 111 trials (3.4% of all trials) were excluded since subjects did not perform the tasks or trials were not recorded properly (i.e., incorrect recording or inability of sensors of the IWW to track the subject). These excluded trials only concerned stroke and PD patients. IWW outcome measures were calculated from specific body points' time series, estimates of foot contact and foot off and step locations, as detailed in Table 7.2 and Supplement 7.1. Outcome measures of dual-task performance were success rate, response time and a composite score that represents the trade-off between these two outcome measures (Table 7.3; [22-24]). The average over trials per IWW task per subject was calculated for all outcome measures.

Falls calendars were used to classify subjects as prospective faller (i.e., those reporting at least one fall during the follow-up period) or non-faller. In the literature, fallers are classified using both retrospective and prospective falls. Therefore, non-fallers were defined as subjects that did not report a fall in the follow-up period or in the year prior to the experiment. Only walking- or balance-related falls were taken into account. A total of 88 subjects completed the entire 6-month follow-up period. One PD patient stopped prematurely with the falls calendar as it took too much time, but was not excluded from the analyses since this patient was already identified as a prospective faller based on the received falls calendars. One stroke patient who did not fill in a single falls calendar was excluded. In total, 33 (37.1%; 37.9% of stroke patients, 50.0% of PD patients and 23.3% of controls) subjects reported at least one fall in the follow-up period (i.e., prospective fallers), of which 24 (72.7% of prospective fallers; 27.0% of total) also had a history of falling. In the sample of 56 (62.9%) subjects without a prospective fall, 47 (83.9%; 52.8% of total) were actual non-fallers according to our definition; consequently, 9 (16.1%; 10.1% of total) subjects were excluded since they had a history of falling without prospective falls.

Statistical analysis

Outcome measures of prospective fallers (n = 33) and non-fallers (n = 47) were compared using chi-squared tests for categorical data and independent-samples *t*-tests for continuous variables to examine differences in walking ability. We computed *r* to quantify the effect sizes of continuous variables [25], where values between 0.10-0.29 were regarded as small, between 0.30-0.49 as medium and above 0.50 as large effect sizes [25].

Binary logistic regression analyses (forward method, Wald test) were performed on four models (Table 7.3) to identify prospective fallers and predictor variables for future falls. Model 1 included only subject characteristics (e.g., age, fall history, group) as potential predictor variables. For model 2, clinical test scores were added to subject characteristics. Model 3 consisted of subject characteristics, clinical test scores and spatiotemporal gait parameters. For model 4, also IWW walking-adaptability outcome measures were added. We calculated the sensitivity (i.e., percentage correctly classified prospective fallers), specificity (i.e., percentage correctly classified non-fallers) and overall accuracy (i.e., percentage of correctly classified prospective fallers and non-fallers) for each prediction model. We also inspected the sign and size of the coefficients (i.e., describing the relationship between predictor variable and outcome) to determine the direction of the association with falls and the relevance of a predictor variable. Receiver operating characteristic curve analyses were used to assess the predictive accuracy of each model by estimating the area under the curve (AUC). AUCs of more than 0.70, 0.80 and 0.90 are considered acceptable, excellent and outstanding, respectively [26]. Multiple imputation was performed to handle missing data (1.4%, 69 complete cases) in 23 out of 48 potential predictor variables. Five imputations were performed using chained equations including all potential predictor variables of model 4 and the outcome variable (i.e., prospective faller or non-faller).

We also used the Chi-square Automatic Interaction Detector (CHAID) analysis to identify significant predictors for inclusion in a prediction model based on a decision tree. Potential predictor variables included in our model were subject characteristics, clinical test scores, spatiotemporal gait parameters and IWW walking-adaptability outcome measures. In our model, we imposed a minimum of one subject per node, a significance level of 0.05 (with a Bonferroni correction) and a division on a maximum of two levels to keep the decision tree as simple as possible. Sensitivity, specificity and overall accuracy were calculated.

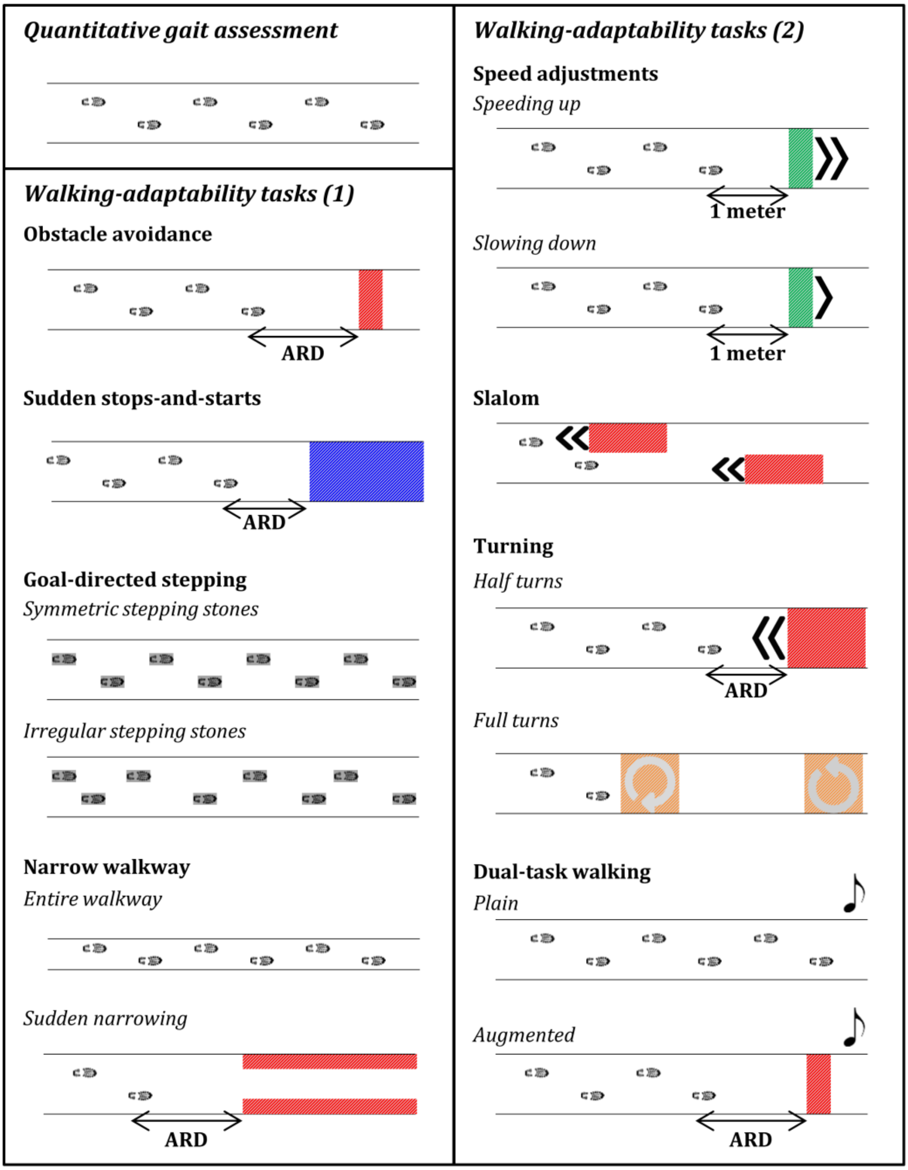

Figure 7.2 Schematic of the quantitative gait assessment and walking-adaptability tasks on the Interactive Walkway, as detailed in the main text.

Table 7.2 Outcome measures of the quantitative gait assessment and walking-adaptability tasks of the Interactive Walkway.

	Outcome measure	Unit	Calculation
Quantitative gait assessment			
8-meter walking test	Walking speed	cm/s	The distance travelled between the 0-meter and 8-meter line on the walkway divided by the time, using the data of the spine shoulder.
	Step length	cm	The median of the differences in the anterior-posterior direction of consecutive step locations.
	Stride length	cm	The median of the differences in anterior-posterior direction of consecutive ipsilateral step locations.
	Step width	cm	The median of the absolute mediolateral difference of consecutive step locations.
	Cadence	steps/min	Calculated from the number of steps in the time interval between the first and last estimate of foot contact.
	Step time	s	The median of the time interval between two consecutive instants of foot contact.
	Stride time	s	The median of the time interval between two consecutive ipsilateral instants of foot contact.
Walking-adaptability tasks			
Obstacle avoidance	Obstacle-avoidance margins	cm	The distance of the anterior shoe edge (trailing limb) and posterior shoe edge (leading limb) of the step locations to corresponding obstacle borders during obstacle crossing.
	Success rate	%	Number of successfully avoided obstacles divided by the number of obstacles presented times 100%.

Sudden stops-and-starts		Sudden-stop margins	cm	The minimum distance of the anterior shoe edge to the corresponding stop cue border during the period in which the cue was visible.
		Success rate	%	Number of successful stops divided by the number of stop cues presented times 100%.
		Initiation time	s	The time between disappearance of the stop cue and the moment of first foot contact.
Goal-directed stepping	**SSS** **ISS**	Stepping accuracy	cm	The standard deviation over the signed deviations between the center of the stepping target and the center of the foot at corresponding step locations. The center of the foot was determined using the average distance between the ankle and the middle of the shoe-size-matched targets of the calibration trials (see Supplement 7.1).
		Normalized walking speed	%	Walking speed divided by walking speed of the 8MWT times 100%.
Narrow walkway	**EW** **SN**	Success rate	%	Number of steps inside the walkway or the sudden narrowing walkway divided by the total number of steps taken times 100%.
		Normalized walking speed	%	Walking speed divided by walking speed of the 8MWT times 100%.
		Normalized step width	%	Step width divided by the imposed step width by the entire walkway times 100%.
Speed adjustments	**SU** **SD**	Success rate	%	The percentage of the time spend walking faster (or slower) than the imposed speed minus (or plus) 20% during the period in which the speed cue was visible.
		Normalized walking speed	%	Walking speed divided by the imposed walking speed times 100%.

Table 7.2 Continued.

		Outcome measure	Unit	Calculation
Slalom		Success rate	%	Number of successfully avoided obstacles divided by the number of obstacles presented times 100%.
		Normalized walking speed	%	Walking speed divided by walking speed of the 8MWT times 100%.
Turning	**HT** **FT**	Success rate	%	Number of successful half turns divided by the number of half turns times 100%.
		Turning time	s	Time within the turning square (for full turns) or time from appearance of the turning cue till moment walking direction was reversed (for half turns), using the data of the spine shoulder.
Dual-task walking	**PDT**	Normalized walking speed	%	Walking speed divided by walking speed of the 8MWT times 100%.
	ADT	Normalized success rate	%	Obstacle avoidance success rate divided by success rate of the obstacle-avoidance task times 100%, excluding subjects that had an obstacle-avoidance success rate of 0% at baseline.
		Success rate dual task	%	Number of correct responses divided by the number of stimuli given times 100%. No response was classified as an incorrect response.
		Response time	s	Average time between stimulus onset and response onset.
		Composite score dual task	%	Success rate dual task divided by the response time.

Abbreviations: SSS = symmetric stepping stones; ISS = irregular stepping stones; EW = entire walkway; SN = sudden narrowing; SU = speeding up; SD = slowing down; HT = half turns; FT = full turns; PDT = plain dual-task walking (8-meter walking test with dual task); ADT = augmented dual-task walking (obstacle avoidance with dual task); 8MWT = 8-meter walking test.

Results

Prospective fallers had significantly more fear of falling (i.e., higher score on the Falls Efficacy Scale) and more often avoided activities due to fear of falling (i.e., higher score on the Modified Survey of Activities of Fear of Falling in the Elderly Scale; Table 7.3) than non-fallers. In addition, prospective fallers performed overall worse on clinical tests (significantly for the Timed-Up-and-Go test, Tinetti Balance Assessment and 7-item Berg Balance Scale) and IWW tasks (significantly for the obstacle-avoidance, sudden-stops-and-starts, goal-directed-stepping and turning tasks) and walked slower and with smaller steps than non-fallers (Table 7.3).

Binary logistic regression models

Model 1 included fall history (B = 23.11) and age (B = 0.08) as best predictor variables for prospective falls, models 2 and 3 also only included fall history and age, while model 4 included fall history (B = 24.16), obstacle-avoidance success rate (B = -0.07) and reaching distance on the Functional Reach Test (B = 0.20). Sensitivity increased from 72.7% (models 1-3) to 78.8% (model 4), specificity increased from 97.9% to 100.0% and overall accuracy increased from 87.5% to 91.3%. AUC increased from 0.926 (95% CI = [0.858 0.995]; models 1-3) to 0.943 (95% CI = [0.886 1.000]; model 4).

CHAID analysis

The CHAID analysis identified three significant predictors for prospective falls (Figure 7.3). Subjects were initially dichotomized by fall history, with retrospective falls classifying 24 of 80 subjects as prospective faller of which all were actual prospective fallers. The remaining 56 subjects without a fall history (i.e., falls-naïve cohort, including 9 prospective fallers) were split by obstacle-avoidance success rate (> 77.8% and ≤ 77.8%). 35 subjects with a success rate > 77.8% were classified as non-fallers, of which 33 subjects were non-fallers. The remaining 21 subjects with an obstacle-avoidance success rate ≤ 77.8%

were finally split by normalized walking speed during goal-directed stepping on symmetric stepping stones (> 91.9% and ≤ 91.9% or missing). The 6 subjects with a normalized walking speed > 91.9% were classified as prospective fallers, of which 5 subjects were prospective fallers. The sensitivity of this model was 87.9% (29 out of 33 prospective fallers correctly identified), while the specificity was 97.9% (46 out of 47 non-fallers correctly identified), with an overall accuracy of 93.8%.

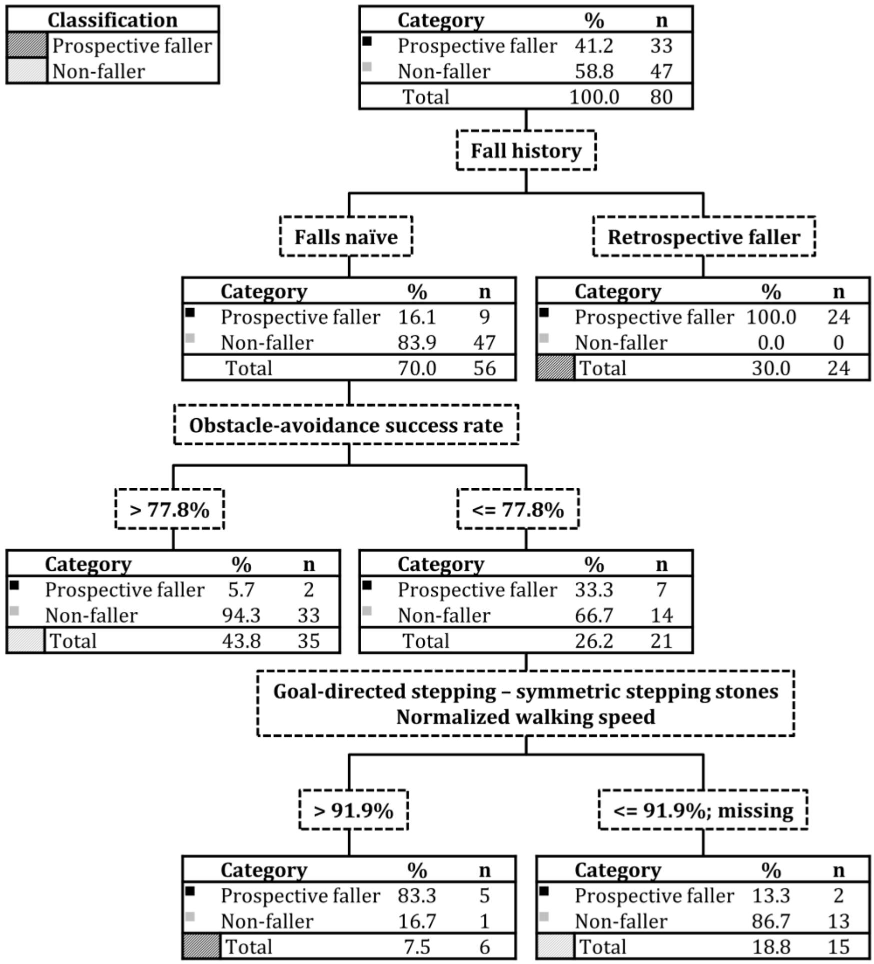

Figure 7.3 Decision tree of the CHAID analysis.

Table 7.3 Means, standard deviations and between-groups statistics of subject characteristics, clinical tests, the quantitative gait assessment and the walking-adaptability tasks for prospective fallers and non-fallers.

			Prospective faller n = 33 mean ± SD	Non-faller n = 47 mean ± SD		*p*-value	*r*-value
Subject characteristics							
Group	**S/PD/C**		11/15/7	13/13/21	$\chi^2_2 = 5.01$	0.082	-
Gender	**male/female**		18/15	31/16	$\chi^2_2 = 1.06$	0.302	-
Age	**Age (years)**		64.8 ± 10.5	60.5 ± 9.2	$t_{78} = -1.94$	0.056	0.215
Falls Efficacy Scale	**Score [0-64]***		9.5 ± 7.1	4.6 ± 6.0	$t_{61.7} = -3.27$	0.002	0.385
mSAFFE	**Score [17-51]***		24.4 ± 6.2	20.7 ± 5.6	$t_{78} = -2.80$	0.006	0.302
Clinical tests							
Timed-Up-and-Go test	**Time (s)***		14.1 ± 11.4	9.8 ± 6.1	$t_{78} = -2.15$	0.035	0.236
10-meter walking test	**Time (s)**	**CWS**	13.4 ± 12.7	9.3 ± 5.0	$t_{39.1} = -1.76$	0.087	0.271
10-meter walking test	**Time (s)**	**MWS**	10.4 ± 11.0	7.1 ± 4.3	$t_{78} = -1.83$	0.072	0.203
Tinetti Balance Assessment	**Score [0-28]***		23.4 ± 4.5	25.8 ± 4.1	$t_{78} = 2.50$	0.015	0.272
7-item Berg Balance Scale	**Score [0-14]***		10.8 ± 2.9	12.4 ± 2.3	$t_{78} = 2.80$	0.006	0.302
Functional Reach Test	**Reaching distance (cm)**		24.2 ± 8.2	27.5 ± 6.6	$t_{78} = 1.95$	0.055	0.216
Quantitative gait assessment							
8-meter walking test	**Walking speed (cm/s)***		100.1 ± 32.5	121.0 ± 34.5	$t_{78} = 2.74$	0.008	0.296
	Step length (cm)*		60.0 ± 15.4	68.9 ± 14.8	$t_{78} = 2.60$	0.011	0.283
	Stride length (cm)*		120.7 ± 30.9	138.5 ± 29.7	$t_{78} = 2.60$	0.011	0.282

Table 7.3 Continued.

			Prospective faller n = 33 mean ± SD	Non-faller n = 47 mean ± SD		*p*-value	*r*-value
	Step width (cm)		13.5 ± 5.2	12.4 ± 5.3	$t_{78} = -0.94$	0.348	0.106
	Cadence (steps/min)		101.6 ± 18.7	108.0 ± 15.0	$t_{78} = 1.71$	0.092	0.190
	Step time (s)		0.609 ± 0.174	0.560 ± 0.097	$t_{78} = -1.59$	0.117	0.177
	Stride time (s)		1.216 ± 0.357	1.118 ± 0.196	$t_{78} = -1.58$	0.119	0.176
Walking-adaptability tasks							
Obstacle avoidance	**Margins trailing limb (cm)**		13.4 ± 8.8	17.0 ± 9.2	$t_{78} = 1.74$	0.085	0.194
	Margins leading limb (cm)*		3.9 ± 9.8	9.1 ± 6.7	$t_{52.5} = 2.66$	0.010	0.345
	Success rate (%)*		49.6 ± 37.7	77.9 ± 23.8	$t_{49.6} = 3.82$	<0.001	0.476
Sudden stops-and-starts	**Sudden-stop margins (cm)***		0.0 ± 7.6	4.3 ± 9.2	$t_{77} = 2.19$	0.031	0.242
	Success rate (%)*		59.8 ± 23.6	73.7 ± 20.1	$t_{77} = 2.82$	0.006	0.306
	Initiation time (s)		1.521 ± 0.357	1.383 ± 0.320	$t_{77} = -1.81$	0.074	0.202
Goal-directed stepping	**Stepping accuracy (cm)***	**SSS**	3.4 ± 1.6	2.7 ± 1.1	$t_{51.9} = -2.42$	0.019	0.319
	Normalized walking speed (%)	**SSS**	89.0 ± 15.8	90.4 ± 16.8	$t_{77} = 0.39$	0.697	0.045
	Stepping accuracy (cm)*	**ISS**	4.7 ± 1.8	3.9 ± 1.0	$t_{46.3} = -2.07$	0.044	0.291
	Normalized walking speed (%)	**ISS**	87.7 ± 18.6	90.1 ± 15.8	$t_{78} = 0.63$	0.531	0.071
Narrow walkway	**Success rate (%)**	**EW**	76.9 ± 25.8	78.6 ± 22.3	$t_{77} = 0.32$	0.752	0.036
	Normalized walking speed (%)	**EW**	89.1 ± 19.9	92.7 ± 16.5	$t_{77} = 0.87$	0.390	0.098
	Normalized step width (%)	**EW**	52.4 ± 26.4	46.8 ± 29.0	$t_{77} = -0.86$	0.390	0.098
	Success rate (%)	**SN**	88.0 ± 21.9	90.0 ± 23.2	$t_{74} = 0.38$	0.705	0.044

	Normalized walking speed (%)	**SN**	90.8 ± 16.0	92.1 ± 11.6	t_{74} = 0.42	0.675	0.049
Speed adjustments	**Success rate (%)**	**SU**	62.3 ± 14.6	65.5 ± 12.3	t_{75} = 1.06	0.294	0.121
	Normalized walking speed (%)	**SU**	87.9 ± 8.7	89.2 ± 7.6	t_{75} = 0.73	0.466	0.084
	Success rate (%)	**SD**	75.5 ± 6.0	77.7 ± 6.4	t_{75} = 1.57	0.121	0.178
	Normalized walking speed (%)	**SD**	100.4 ± 4.0	99.4 ± 6.6	t_{75} = -0.77	0.443	0.089
Slalom task	**Success rate (%)**		56.3 ± 24.0	50.9 ± 21.2	t_{75} = -1.04	0.301	0.119
	Normalized walking speed (%)		87.3 ± 20.3	91.5 ± 13.1	$t_{46.9}$ = 1.02	0.311	0.148
Turning task	**Success rate (%)**	**HT**	32.3 ± 37.7	50.0 ± 40.8	t_{75} = 1.93	0.058	0.217
	Turning time (s)	**HT**	1.513 ± 0.303	1.459 ± 0.309	t_{75} = -0.77	0.445	0.088
	Turning time (s)*	**FT**	5.304 ± 4.587	3.058 ± 2.038	$t_{39.8}$ = -2.59	0.013	0.380
Dual-task walking	**Normalized walking speed (%)**	**PDT**	84.0 ± 13.8	82.9 ± 15.0	t_{75} = -0.31	0.759	0.036
	Success rate dual task (%)	**PDT**	86.7 ± 18.0	88.6 ± 19.6	t_{75} = 0.42	0.679	0.048
	Response time (s)*	**PDT**	1.108 ± 0.161	0.986 ± 0.150	t_{75} = -3.41	0.001	0.139
	Composite score dual task (%)	**PDT**	81.1 ± 24.6	92.0 ± 25.0	t_{75} = 1.90	0.062	0.214
	Success rate (%)	**ADT**	91.6 ± 67.2	92.0 ± 31.8	$t_{31.6}$ = 0.03	0.977	0.005
	Success rate dual task (%)	**ADT**	77.5 ± 24.8	84.0 ± 19.9	t_{69} = 1.22	0.228	0.145
	Response time (s)	**ADT**	1.102 ± 0.147	1.040 ± 0.131	t_{69} = -1.84	0.070	0.216
	Composite score dual task (%)	**ADT**	71.7 ± 25.3	81.7 ± 21.3	t_{69} = 1.77	0.081	0.209

Abbreviations: S = stroke patient; PD = Parkinson's Disease patient; C = control; mSAFFE = Modified Survey of Activities of Fear of Falling in the Elderly Scale; CWS = comfortable walking speed; MWS = maximum walking speed; SSS = symmetric stepping stones; ISS = irregular stepping stones; EW = entire walkway; SN = sudden narrowing; SU = speeding up; SD = slowing down; HT = half turns; FT = full turns; PDT =plain dual-task walking (8-meter walking test with dual task); ADT = augmented dual-task walking (obstacle avoidance with dual task).

* Significant difference between prospective fallers and non-fallers ($p < 0.05$).

Discussion

This study evaluated the potential merit of the IWW for identifying fallers and risk factors for future falls in a composite cohort with stroke patients, PD patients and controls. Prospective fallers experienced more fear of falling, a well-known fall-risk factor [8,21,27]. Fallers also more often reported fear-induced activity avoidance than non-fallers. In addition, prospective fallers walked slower and with smaller steps, and had a poorer performance on clinical gait and balance tests. As anticipated, prospective fallers performed worse on various walking-adaptability tasks, including the obstacle-avoidance, sudden-stops, goal-directed-stepping and full-turn tasks. Since tripping is considered one of the most common causes of falls in everyday life [5-7], smaller margins of the leading limb during obstacle avoidance were expected. Overall, the ability to make step adjustments, either under time pressure demands or during goal-directed stepping, was impaired in prospective fallers and was associated with falls in [28,29]. This may point at specific underlying gait impairments that can be targeted in falls prevention strategies to reduce fall risk. No differences were found between prospective fallers and non-fallers for dual-task walking, except for response time during plain dual-task walking (Table 7.3). An explanation for this might be between-subject variation in task prioritization in both groups. In the study of Timmermans et al. [30] the amount of cognitive-motor interference did not differ between obstacle avoidance over physical obstacles compared to projected obstacles, while task prioritization did. In Timmermans et al. [30] and in the current study, subjects were instructed to perform both tasks as well as possible, affording differences in task prioritization. This likely increased between-subject variation in the performance of the walking task and the cognitive task, which might explain the lack of a clear effect of the dual task (Table 7.3). Note that response time during augmented dual-task walking and the composite scores showed trends towards poorer dual-task performance in fallers.

We performed two different analyses to identify prospective fallers and predictor variables for future falls, namely the binary logistic regression and CHAID analysis, which both performed very well in terms of overall accuracy. The results of the CHAID analysis are easier to interpret and implement in daily practice [31]. On the other hand, binary logistic regression models are more informative on the relevance of a predictor variable (i.e., size of coefficient). Both analyses identified fall history and obstacle-avoidance success rate as predictor variables. The CHAID analysis additionally identified normalized walking speed during goal-directed stepping on symmetric stepping stones as predictor variable, whereas age and reaching distance on the Functional Reach Test both significantly increased fall risk (i.e., positive coefficients) in the binary logistic regression models. Group (i.e., stroke, Parkinson's disease, control) was not identified as a significant predictor variable for prospective falls. This suggests that the presence of a neurological disorder does not automatically increase fall risk, a finding in line with another study on fall-risk assessments [32]. Notably, controls without specific disorders also experienced falls (23.3%). A decreased walking ability in older adults compared to younger adults has been demonstrated [33], both in steady-state walking and walking adaptability. Assessing limitations in walking ability, regardless of their cause (e.g., neurological disorders, ageing), thus likely provides a better indication of someone's fall risk. In accordance with previous studies, fall history was the best sole predictor of future falls in our study [27,34]. All subjects classified as prospective faller in models 1-3 had a history of falling and the coefficients for fall history in the models were high. The addition of obstacle-avoidance success rate and reaching distance led to the correct classification of two more fallers and one non-faller. Using the CHAID analysis, we subsequently evaluated risk factors of first falls in the falls-naïve cohort. It appeared that subjects who poorly performed the obstacle-avoidance task and who did not substantially lower their walking speed during goal-directed stepping are most at risk of falling (i.e., 5 out of 9 fallers correctly classified). Reminiscent of a speed-accuracy trade-off, subjects seem to maintain their normal walking speed (i.e., no significant group difference in normalized walking speed), at the expense of stepping accuracy (i.e., significantly less accurate in prospective fallers). However, the latter seems more important when walking in the community. There thus appears to be a discrepancy between their perceived and actual walking ability, which may be a factor contributing to falls [35]. The amount of misjudgment has been emphasized to be useful to include in fall-risk assessments [36] and allows for better personalized interventions [35]. This was confirmed by the study of Butler et al. [37]; subjects that took higher risks than their physical ability allowed were more likely to experience a fall in the upcoming year. Assessing walking adaptability in addition to asking about falls in the previous year thus seems of added value when assessing fall risk. Besides, identification of these walking-related fall-risk factors may lead to more targeted, personalized and possibly more effective falls prevention programs.

A limitation of this study was the sample size. Although 90 subjects were included and followed prospectively for falls, this was still relatively small when the distribution of fallers and non-fallers and the type of analysis are taken into account. This limits cross-validation of the models and the risk of overfitting must be considered. This study should therefore be regarded as a first step in evaluating the proposed comprehensive fall-risk assessment including generic and walking-related factors. The results, when confirmed by a larger sample, provide indications for a strategy to identify subjects that are at a high risk of falling. First, subjects should be asked about their fall history and subjects with a history of walking-related falls may be advised to follow a falls prevention program, aimed at improving balance, walking and walking adaptability. Second, subjects that are falls-naïve should perform an assessment of about five minutes, including the obstacle-avoidance and goal-directed stepping tasks and a baseline walk (to determine normalized walking speed) to identify potential fallers. Subjects with poor walking adaptability who do not reduce their walking speed accordingly, may also be advised to follow a falls prevention program. Given these walking-related predictor variables, such a program should be geared towards improving (sudden) step adjustments and creating awareness about a subject's ability to adapt walking in order to reduce their walking-related fall risk.

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Supplement 7.1

Experimental set-up and procedure

The quantitative gait assessment and walking-adaptability assessment were performed on the Interactive Walkway (IWW; Figure S7.1) using four spatially and temporally integrated Kinect v2 sensors to obtain full-body kinematics. The IWW set-up was based on a validated IWW set-up used in Geerse et al. [1,2], with improved inter-sensor distances following recommendations of Geerse et al. [3]. The sensors were positioned at a height of 0.95 m alongside a walkway of 8 by 0.75 m. The first three sensors were placed frontoparallel (i.e., with an angle of 70 degrees relative to the walkway direction) with a distance of 1.2 m from the left border of the walkway. The last sensor was positioned frontally at the end of the walkway, since this will minimize orientation-based biases [4]. The first sensor was positioned at 3 m from the start of the walkway and the other sensors were placed at inter-sensor distances of 2.1 m. The IWW was equipped with a projector (EPSON EB-585W, ultra-short-throw 3LCD projector) to augment the entire 8-meter walkway with visual context for the walking-adaptability tasks. The coordinate systems of the sensors and projector were spatially aligned to a common coordinate system using a spatial calibration grid. IWW data were sampled at 30 Hz using custom-written software utilizing the Kinect-for-Windows Software Development Kit (SDK 2.0). Details about the experimental tasks performed on the IWW can be found in Table S7.1.

Data pre-processing and analysis

The Kinect for Windows Software Development Kit (SDK 2.0, www.microsoft.com) provides 3D time series of 25 body points using inbuilt and externally validated human-pose estimation algorithms [1,5-8]. These body points are: head, neck, spine shoulder, spine mid, spine base and left and right shoulder, elbow, wrist, hand, thumb, hand tip, hip, knee, ankle and foot. For offline data analysis, the 3D positional data for these body points were first preprocessed per Kinect sensor separately. Body points labelled as inferred (i.e., Kinect's human-pose estimation software infers positions when segments are partially occluded for example) were treated as missing values. The body point's time series were linearly interpolated using Kinect's time stamps to ensure a constant sampling frequency of 30 Hz, without filling in the parts with missing values. We removed data points from the time series when they did not meet our stringent requirements for valid human-pose estimation (e.g., a minimum of 15 out of the 25 possible body points should be labeled as tracked, including the head and at least one foot and ankle, without outliers in segment lengths). In addition, a manual check of the data was added to remove errors of the algorithm due to depth occlusion of the right leg by the left leg. Subsequently, data of the four Kinect sensors were combined by taking for each sample the 3D positions of the body points of a validly estimated human pose. If, for a given sample, more than one sensor contained valid human pose data, the associated body point's 3D positions were averaged for that specific sample.

Body point's time series with more than 50% of missing values were excluded from further analyses. However, percentages of missing data for all three groups did not exceed 27.3% with an average of 5.0 ± 2.1% for the body points' time series of interest (i.e., ankles, spine base and spine shoulder). The missing values of the remaining data were interpolated with a spline algorithm. The so-obtained time series were used for the calculation of the spatiotemporal gait parameters and walking-adaptability outcome measures.

The outcome measures of the IWW assessment were calculated from specific body points' time series, estimates of foot contact and foot off and step locations, as detailed in Table 7.2. Estimates of foot contact and foot off were defined as the maxima and minima of the anterior–posterior time series of the ankles relative to that of the spine base [1,2,9]. Step locations were determined as the median anterior–posterior and mediolateral position of the ankle joint during the single-support phase (i.e., between foot off and foot contact of the contralateral foot; [1,2]). Shoe edges and center of the foot were also needed to calculate several outcome measures. Ankle-to-shoe calibration trials, in which the subject was standing in two shoe-size-matched targets at a position on the walkway in front of the last Kinect, were included to determine the average distance between shoe edges and the ankle.

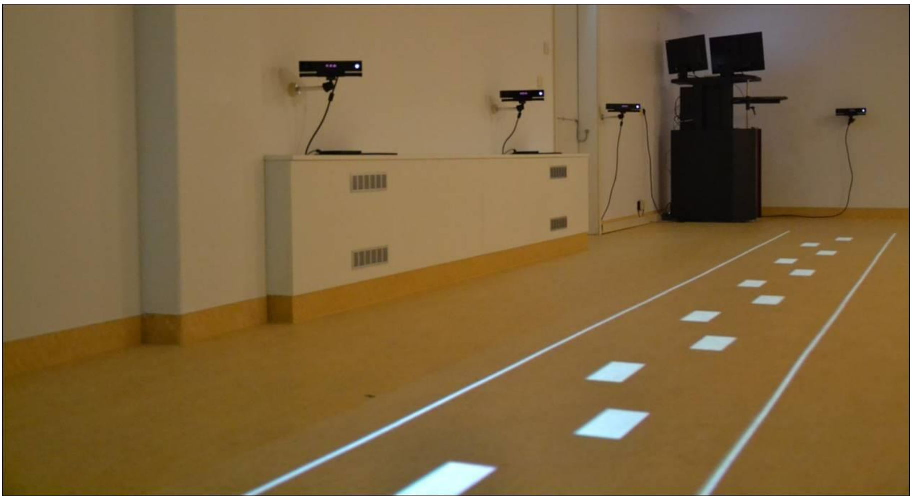

Figure S7.1 Set-up of the Interactive Walkway with visual context projected on the walkway.

Table S7.1 Quantitative gait assessment and walking-adaptability tasks on the Interactive Walkway.

Assessments		n	Level of difficulty	Characteristics
Quantitative gait assessment				
8-meter walking test		2		Walking at self-selected walking speed.
Walking-adaptability tasks				
Obstacle avoidance		5	ART = 1 s (three trials) ART = 0.75 s (two trials)	Avoiding suddenly appearing obstacles.
Sudden stops-and-starts		5	ART = 1 s (three trials) ART = 0.75 s (two trials)	Stopping behind the suddenly appearing stop cues and start walking as soon as the cues disappear.
Goal-directed stepping	**SSS**	3	Average SL 75% average SL 125% average SL	Stepping as accurately as possible onto the shoe-size-matched stepping stones.
	ISS	2	25% variation in SL left and right 50% variation in SL left and right	
Narrow walkway	**EW**	2	WW = 1.5*SW+FW WW = SW+FW	Walking between the lines of the walkway or between the blocks of the suddenly narrowing walkway.
	SN	1	ART = 1 s, WW = 1.5*SW+FW	
Speed adjustments	**SU**	2	120% SSWS 140% SSWS	When a speed cue appears one meter in front of the subjects it has to be followed at the imposed speed.
	SD	2	80% SSWS 60% SSWS	

Slalom		2	Symmetric distance between obstacles Variable distance between obstacles	Walking around the moving obstacles that approach the subjects with a speed of 50% SSWS.
Turning	**HT**	2	ART = 3 s ART = 2 s	When a turning cue approaches the subject with a speed of 100% SSWS, the subject has to turn and walk back to the start.
	FT	1		In the two presented squares the subject has to make a full turn as fast and safe as possible in the direction of the arrow.
Dual-task walking	**PDT**	2		Walking while also performing a dual task. The dual task was an auditory Stroop task.
	ADT	5	ART = 1 s (three trials) ART = 0.75 s (two trials)	Avoiding suddenly appearing obstacles while also performing a dual task. The dual task was an auditory Stroop task.
Total trials		**36**		

Abbreviations: SSS = symmetric stepping stones; ISS = irregular stepping stones; EW = entire walkway; SN = sudden narrowing; SU = speeding up; SD = slowing down; HT = half turns; FT = full turns; PDT =plain dual-task walking (8-meter walking test with dual task); ADT = augmented dual-task walking (obstacle avoidance with dual task); ART = available response time; SL = step length; WW = walkway width; SW = step width; FW = foot width; SSWS = self-selected walking speed of unconstrained walking.

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Supplement 7.2

Video of assessments on the Interactive Walkway in a patient with stroke. This video is available at https://youtu.be/k7O2kc5R-K8.