applied sciences

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Wearable Sensors Technology as a Tool for Discriminating Frailty Levels During Instrumented Gait Analysis

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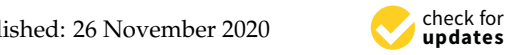
Received: 22 October 2020; Accepted: 24 November 2020; Published: 26 November 2020



Abstract: Background and objectives: One of the greatest challenges facing the healthcare of the aging population is frailty. There is growing scientific evidence that gait assessment using wearable sensors could be used for prefrailty and frailty screening. The purpose of this study was to examine the ability of a wearable sensor-based assessment of gait to discriminate between frailty levels (robust, prefrail, and frail). Materials and methods: 133 participants (≥60 years) were recruited and frailty was assessed using the Fried criteria. Gait was assessed using wireless inertial sensors attached by straps on the thighs, shins, and feet. Between-group differences in frailty were assessed using analysis of variance. Associations between frailty and gait parameters were assessed using multinomial logistic models with frailty as the dependent variable. We used receiver operating characteristic (ROC) curves to calculate the area under the curve (AUC) to estimate the predictive validity of each parameter. The cut-off values were calculated based on the Youden index. Results: Frailty was identified in 37 (28%) participants, prefrailty in 66 (50%), and no Fried criteria were found in 30 (23%) participants. Gait speed, stance phase time, swing phase time, stride time, double support time, and cadence were able to discriminate frailty from robust, and prefrail from robust. Stride time (AUC = 0.915), stance phase (AUC = 0.923), and cadence (AUC = 0.930) were the most sensitive parameters to separate frail or prefrail from robust. Other gait parameters, such as double support, had poor sensitivity. We determined the value of stride time (1.19 s), stance phase time (0.68 s), and cadence (101 steps/min) to identify individuals with prefrailty or frailty with sufficient sensitivity and specificity. Conclusions: The results of our study show that gait analysis using wearable sensors could discriminate between frailty levels. We were able to identify several gait indicators apart from gait speed that distinguish frail or prefrail from robust with sufficient sensitivity and specificity. If improved and adapted for everyday use, gait assessment technologies could contribute to frailty screening and monitoring.

Keywords: frailty; wearable sensors; gait parameters; accelerometer; aging

1. Introduction

According to the 2015 EU Ageing Report, the percentage of citizens aged over 65 years is predicted to rise from 18% to 28% by 2060. One of the greatest challenges facing the healthcare of the aging

population is frailty. In Europe, 15% of older people aged 65 and over are considered as frail [1]. Frailty is defined as a syndrome of decreased reserve and resistance to stressors, resulting from cumulative declines across multiple physiologic systems and causing vulnerability to adverse outcomes, such as worsening mobility, disability, incident falls, hospitalizations, and mortality [2]. There is much potential for frailty to be reversed, particularly in its early stages [3–5]. For that reason, the early identification and management of frailty is an important priority for both healthcare providers and healthcare policy makers [6–8].

One of the most accepted definitions of frailty is the classification proposed by Fried et al. using five criteria: weight loss, exhaustion, inactivity, slow gait speed, and weakness [2]. However, its use may have limited feasibility and reliability in a routine care setting [9,10]. The criteria of weight loss, exhaustion, slowness, and low energy expenditure are usually self-reported measures and may be prone to bias [9,11,12]. An objective frailty screening tool may be more appropriate for routine assessment.

Slow gait speed has been reported as the most easily identifiable feature of physical frailty [2,13]. Moreover, slow gait speed is a good predictor of future physical disability, falls and fractures, requirement for a caregiver, hospitalizations, and death [13]. Gait speed evaluated by the 4-m walking test could be used for frailty screening [14]. Regarding recent studies, other temporal-spatial gait characteristics may have a strong association with frailty [15,16]. A systematic review reported that frailty is associated with some temporal-spatial gait parameters beyond speed, including high stride time variability, reduced step length, and increased double support time [15]. However, most studies are conducted in the laboratory environment using camera systems [17,18], force platforms [18], or computerized walkways [19] that, due to the high costs related to acquisition and application in everyday clinical practice, are not available in every healthcare institution. Therefore, more accessible alternatives could be used, such as wearable sensors, which are easier to use, more practical, and require fewer resources. There is growing scientific evidence that gait assessment using wearable sensors could be used for prefrailty and frailty screening [20–23]. Simple and easy-to-use sensors (such as those incorporated into a smartphone) could be used to investigate gait at home and offer advantages in frailty evaluations where the full application or interpretation of Fried criteria is impracticable. There is currently a lack of data regarding which gait indicators are sensitive and specific for determining frailty and the appropriate thresholds for distinguishing between prefrailty and frailty.

The purpose of this study was to examine the ability of wearable sensor-based assessments of gait to discriminate between frailty levels (robust, prefrail, and frail). Firstly, we sought to determine which sensor-derived gait parameters are able to discriminate between the three frailty levels. Secondly, we aimed to determine the cut-offs of the most sensitive gait parameters that separated the frailty levels. We hypothesized that we could separate the frailty groups (robust, prefrail, and frail) using a sensor-based assessment of gait. We also hypothesized that frailty is associated not only with slow gait speed, but also with longer stride time, stance phase, and double support time.

2. Materials and Methods

2.1. Study Population

Participants in this cross-sectional study were recruited from two secondary health care institutions and from the population who lived independently in the community. A convenience sample of older adults was utilized for this study. All participants were community-dwelling adults and were eligible to participate if they were aged 60 and older and reported being able to ambulate 12 m without an assistive device. Exclusion criteria were a Lithuanian version of the Mini-Mental State Examination (MMSE) [24] score <21, Parkinson's disease, recent stroke, terminal illness, or unwillingness to participate. Eligible subjects provided signed written informed consent based on the principles expressed in the Declaration of Helsinki [25]. Ethical approval was obtained from the Vilnius Regional Ethics Board for Biomedical Research. Data collection occurred between

May 2019 and February 2020. Initially, 165 subjects were invited, of whom 7 met the exclusion criteria (Parkinson's disease = 2, recent stroke = 5), and 25 were rejected due to incomplete measurement. The G-power statistics software package [26] was used to calculate the required total sample size (for two-group comparison) with a significance level of 0.05, power of 0.95, and effect size of 0.4. The sample is considered sufficient for the study purposes; therefore, data from 133 participants (86 women and 46 men) with an average age 75.1 $\pm$ 8 years were analyzed.

2.2. Data Collection

The research team conducted face-to-face interviews using structured questionnaires to record the required characteristics, such as age, gender, years of formal education, self-reported chronic diseases, number of prescribed and over-the-counter medications, self-reported history of falls in the previous 12 months, and use of an assistive device (yes/no). Height was obtained using a tape measure, weight was measured using a bathroom scale (Clatronic PW 3368, Clatronic®, Kempen, Germany), and BMI was calculated based on height and weight. Interviewer-administered questionnaires included MMSE and the Falls Efficacy Scale-International (FES-I) [27].

2.3. Assessment of Frailty Criteria

Frailty was assessed using the five components, consisting of weight loss, weakness, exhaustion, slowness, low physical activity, as proposed by Fried et al. [2]. Self-reported weight loss of >4.54 kg was used to determine unintentional weight loss over the past year. Weakness was evaluated by a grip strength measurement using a hydraulic hand dynamometer (Jamar®, Sammons PrestonRolyan, Bolingbrook, IL, USA). Three measures were performed, and the arithmetic mean was used to identify this criterion. Weakness was defined according to gender and the BMI cut-offs used by Fried et al. Exhaustion was evaluated by two statements of the Centre for Epidemiologic Studies Depression Scale (CES-D) questionnaire [28]: 'I felt everything I did was an effort' and 'I could not get going'. The frequency of 'occasionally' or 'most of the time' as a reply to either of these statements was considered as an indication of exhaustion. Slowness was defined by a walking speed of 4 m distance at the usual pace measured by a stopwatch and stratified by gender and height using the cut-offs defined by Fried et al. Low physical activity was determined using the Physical Activity Scale for Elderly (PASE) [29]. PASE scores less than 64 for men and less than 52 for women were used to indicate a positive response of low physical activity. Participants were scored one point for each criterion found, totaling a score that could range from 0 to 5. Frailty level was categorized following Fried et al. [2]: robust = no criteria; prefrail = one or two criteria, and frail = three or more criteria.

2.4. Physical Performance Tests

The timed up and go test (TUG) [30] is widely used for the identification of older adults at a high risk of falling. Savva et al. (2013) [31] proposed that the TUG test is a sensitive and specific measure of frailty. In our study, participants were told to sit on a chair (seat height, 46 cm). Participants were then instructed to stand, to walk at their normal pace for a distance of 3 m, to turn at the endpoint, to walk back the same distance, and sit on a chair. Total time starting from standing up to full sitting down was recorded. The time of one trial was taken as the TUG test score. The participants were then evaluated using the dynamic gait index (DGI) [32] for the assessment of the gait in response to changing tasks, such as turning the head while walking, stepping over the obstacle, climbing the stairs, and others. This index consists of eight tasks. Each task is scored from 0 to 3 points, with 0 being the worst and 3 being the best performance. The maximum score is 24 points. A result less than 19 points indicates impaired gait and a risk of falling.

2.5. Sensor-Based Assessment of Gait

We used a total of six wireless inertial sensors (Shimmer Research, Dublin, Ireland) attached by straps on the thighs, shins, and feet (Figure 1). Results from the data of shank and foot IMUs will be presented in this study.

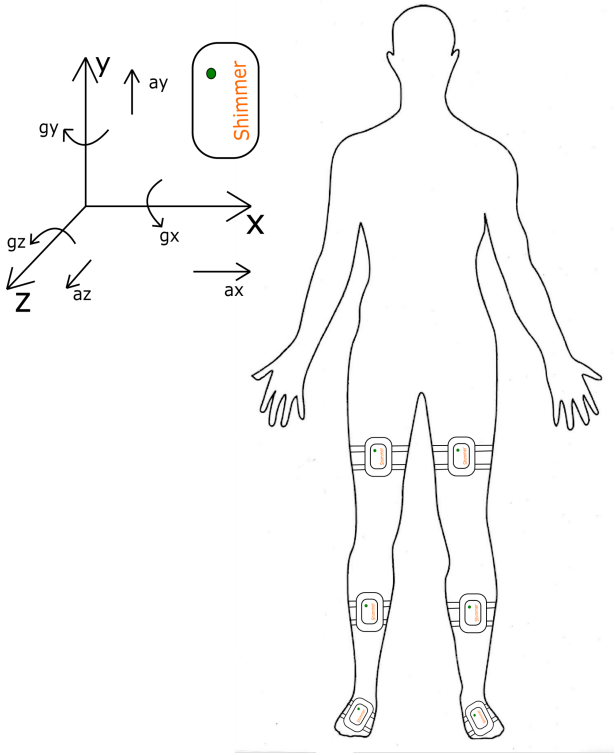


Figure 1. Wireless sensors fixed on the lower limb segments.

Each sensor includes a triaxial accelerometer, gyroscope, and magnetometer and is able to measure linear acceleration, angular velocity, and magnetic heading in three dimensions. The data from sensors were acquired via a Bluetooth wireless connection at a sampling frequency of 256 Hz.

Participant walked a distance of 4 m (13 feet) at the self-selected usual pace. The distance of 4 m for a walk test was chosen because it is a gold standard test for functional assessment in older adults, which is used in the Short Physical Performance test, gait speed test [33,34]. Data from three trials were used. From all the data obtained from the inertial sensors, we selected shank angular velocity and foot linear acceleration to determine heel-strike and toe-off characteristic points. These data were filtered using a Butterworth second order low pass filter with an 8 Hz cut-off frequency and an additional least square method 25th order filter with a 10 Hz cut-off frequency for composite foot acceleration data. A gait event detection algorithm was made by picking toe-off points from the angular velocity data [35,36] and heel strike points from composite foot acceleration data [37]. Gait parameters were calculated based on gait events determined by the toe-off (TO) and heel-strike (HS) events detected by the algorithm. Full gait cycle (also referred as stride) was defined as two consecutives HSs of the same leg, stance phase begins with the HS and concludes with TO of the ipsilateral foot, swing phase begins with the TO and ends with the HS of the same leg. Double support occurs twice in gait cycle and it starts at the beginning and end of stance phases of contralateral legs. Time calculated as number of samples between respective gait event markers divided by sampling rate. The following quantitative gait parameters were calculated: stance phase time, swing phase time, stance and swing phases normalized to a percent gait cycle, gait speed, stride time, on right and left leg accordingly, double support time, and cadence (steps/min).

2.6. Statistical Analysis

Demographic and clinical characteristics were compared between frailty groups using one-way analysis of variance (ANOVA) for continuous variables and Pearson's chi-squared test for categorical variables. The Shapiro–Wilk normality test ($p < 0.05$) was used for a test of data normality. Normally distributed data were compared utilizing the parametric statistical method, i.e., with one-way ANOVA ($p < 0.05$) or Pearson's chi square. One-way ANOVA was used to compare the frailty group scores on physical performance tests and gait parameters derived from sensor data. The presence of overall statistically significant results in the ANOVA was followed with post-hoc Tukey analysis to identify significant pairwise associations. Effect sizes were calculated as partial eta-squared. The guidelines [38] for interpreting this value are: 0.01 = small effect, 0.06 = moderate effect, and 0.14 = large effect.

Multinomial logistic regression [39], with the robust group as the reference, was then used to investigate the gait parameters that discriminate the three frailty levels. The dependent variable was frailty, modeled as two indicator variables of prefrail and frail referenced to the category of robust. The independent variables were TUG time, DGI score, and eight different sensor-based gait parameters. The independent variables assessed had partial eta squared effect sizes $\geq$0.14 for both prefrail versus robust and frail versus robust [38]. Each of the independent variables was fitted in a separate univariate logistic regression model for a total of ten models. Each model estimated the odds ratios for prefrail relative to robust and frail relative to robust. Linear regression diagnostics were performed to evaluate multicollinearity and normality. There were no major deviations from normality and multicollinearity.

We used receiver operating characteristic (ROC) curves to calculate the area under curve (AUC) to estimate the predictive validity of each parameter. The cut-off values were calculated based on the Youden index. Sensitivity and specificity were calculated based on the cut-off values. All analyses were performed using IBM SPSS for Windows software, version 20.0. Statistical significance was set at a p-value less than 0.05.

3. Results

Frailty was identified in 37 (28%) participants, prefrailty in 66 (50%), and no criteria were found in 30 (23%) participants. Demographic and clinical characteristics are shown in Table 1.

Post-hoc comparisons using the Tukey HSD test indicated that the mean scores of age, calf circumference, PASE and FES-I scores for the frailty group were significantly different from the prefrailty and robust groups, and the number of medications between prefrailty and frail groups. We did not find any significant differences in gender (Table 2), MMSE score, BMI, comorbidities between these three groups. Frail participants were significantly older, they had a smaller calf circumference, had a higher proportion of fallers, and higher FES-I scores, while prefrail subjects had a higher fear of falling prevalence (Table 2) than in other groups. Compared to prefrail individuals, frail individuals had a significantly higher prevalence of weak hand grip strength and weight loss criteria.

The comparison of scores of physical performance tests and sensor-derived gait parameters between three frailty groups is presented in Table 3.

Table 1. Demographic and clinical characteristics.

Characteristic *	Total Sample (n = 133)	Robust (n = 30)	Prefrail (n = 66)	Frail (n = 37)	*p* Value [a] (F) Partial η^2	*p* Value [a] 95% CI [LL UL] [b]		
						R vs. P	P vs. F	R vs. F
Age, mean (±SD)	75.1 ± 8 [73.71 76.46]	73 ± 6.3 [70.69 75.38]	73.9 ± 8.5 [71.78 75.94]	78.9 ± 7.3 [76.48 81.36]	**0.002** (6.467) 0.09	1.000 [−5.15 −3.93]	**0.006** [−8.97 −1.14]	**0.020** [−10.7 −0.68]
BMI, mean (±SD)	27.6 ± 5.8 [26.6 28.6]	28.9 ± 5.6 [26.8 30.9]	27.7 ± 5.7 [26.3 29.1]	26.5 ± 6.1 [24.4 28.5]	0.244 (1.425) 0.021	1.000 [−2.07 4.71]	0.900 [−1.67 4.18]	0.289 [−1.16 6.30]
RCC, cm, mean (±SD)	35.1 ± 69.2 [339 362]	38.3 ± 38.4 [369 397]	34.3 ± 84.5 [322 364]	33.7 ± 47.4 [321 353]	**0.012** (4.596) 0.067	0.071 [−2.39 83.2]	1.000 [−22.7 51.8]	**0.017** [7.64 102.3]
Number of comorbidities, mean (±SD)	3.1 ± 1.7 [2.81 3.44]	2.9 ± 2 [1.71 4.01]	3 ± 1.6 [2.56 3.35]	3.5 ± 1.8 [2.94 4.14]	0.210 (1.580) 0.027	1.000 [−1.67 1.63]	0.150 [−1.64 0.17]	0.865 [−2.48 0.97]
Number of medications, mean (±SD)	3.4 ± 2.4 [3 3.89]	3.7 ± 2.1 [2.49 4.94]	3 ± 2.2 [2.48 3.55]	4.1 ± 2.8 [3.18 5.05]	0.078 (2.604) 0.044	1.000 [−1.77 3.36]	**0.050** [−2.72 0.00]	1.000 [−3.23 2.10]
MMSE score, mean (±SD)	27.5 ± 2.2 [27.1 27.8]	28.1 ± 1.9 [27.3 28.8]	27.6 ± 1.8 [27.2 28.1]	26.6 ± 2.6 [25.8 27.5]	0.068 (2.752) 0.061	1.000 [−1.25 1.18]	0.078 [−0.08 2.02]	0.277 [−0.40 2.27]
PASE score, mean (±SD)	97.9 ± 52.7 [88.8 107]	109.9 ± 31.3 [98.2 122]	106.6 ± 61 [91.5 122]	72.9 ± 42.3 [58.8 87]	**0.002** (6.312) 0.061	1.000 [−29.10 30.97]	**0.006** [7.81 59.60]	**0.036** [1.68 67.59]
FES-I score, mean (±SD)	22 ± 7.4 [20.7 23.36]	17.6 ± 3.3 [16.4 18.9]	23.3 ± 7.3 [21.4 25.1]	23.5 ± 8.7 [20.5 26.4]	**0.001** (7.519) 0.106	**0.002** [−10.50 −1.99]	1.000 [−4.28 3.21]	**0.002** [−11.53 −2.03]

* 95% Confidence intervals are presented in brackets []. SD = standard deviation. BMI = body mass index. RCC = right calf circumference. MMSE = Mini-Mental State Examination. PASE = Physical Activity Score for Elderly. FES-I = Falls Efficacy Scale-International. Statistically significant values are highlighted in bold. [a] One-way ANOVA, followed with post-hoc Tukey analysis to identify significant pairwise associations. [b] 95% CI (Confidence interval) (LL—lower limit, UL—upper limit).

Table 2. Gender, falls history and frailty criteria.

Gender and Falls History	Total Sample (n = 133)	Robust (n = 30)	Prefrail (n = 66)	Frail (n = 37)	*p* Value
Women, n (%)	86 (67.7)	20 (83.3)	41 (62.1)	25 (67.6)	0.16
History of falls in the last 12 months, n (%)	60 (47.6)	5 (20.8)	33 (50.8)	22 (59.5)	**0.01**
History of falls in the last 3 months, n (%)	28 (22.2)	3 (12.5)	13 (20.0)	12 (32.4)	0.155
Reported fear of falling, n (%)	73 (56.2)	9 (9.0)	43 (66.2)	21 (60.0)	**0.004**
	89 (70.1)	0	54 (81.8)	35 (94.6)	<0.001
Frailty criteria, n (%) Slow gait velocity	39 (30.7)	0	22 (33.3)	17 (45.9)	0.001
Low physical activity Low hand grip	26 (20.5)	0	4 (6.1)	22 (59.5)	<0.001
Weight loss Exhaustion	25 (19.7)	0	4 (6.1)	21 (56.8)	<0.001
	52 (40.9)	0	19 (28.8)	33 (89.2)	<0.001

Statistically significant differences are highlighted in bold.

Table 3. Results of the gait assessment stratified by frailty status.

Variable *	Total Sample (n = 133)	Robust (n = 30)	Prefrail (n = 66)	Frail (n = 37)	*p* Value [a] (F)	Partial η^2	*p* Value [a] 95% CI [LL UL] [b]		
							R vs. P	P vs. F	R vs. F
TUG, s	12.34 ± 5.03	7.68 ± 1.86	12.71 ± 4.56	15.56 ± 4.87	**<0.001** (29.195)	0.238	**<0.001** [−7.23 −2.84]	**0.004** [2.84 7.23]	**<0.001** [−10.3 −5.41]
DGI, score	16.25 ± 4.04	18.90 ± 3.63	16.12 ± 3.52	14.32 ± 4.15	**<0.001** (12.547)	0.139	**0.003** [0.83 4.73]	0.053 [−0.02 3.61]	**<0.001** [2.4 6.75]
Gait speed, m/s	0.68 ± 0.22	0.98 ± 0.17	0.63 ± 0.13	0.52 ± 0.13	**<0.001** (96.334)	0.374	**<0.001** [0.275 0.42]	**<0.001** [0.045 0.18]	**<0.001** [0.38 0.54]
Stride time, s	1.31 ± 0.24	1.06 ± 0.16	1.35 ± 0.16	1.46 ± 0.25	**<0.001** (39.415)	0.274	**<0.001** [−0.38 −0.19]	**0.010** [−0.206 −0.023]	**<0.001** [−0.51 −0.29]
Swing time, s	0.49 ± 0.08	0.44 ± 0.06	0.51 ± 0.08	0.50 ± 0.09	**<0.001** (8.562)	0.104	**<0.001** [−0.109 −0.028]	0.92 [−0.033 0.043]	**0.003** [−0.108 −0.018]
Stance time, s	0.83 ± 0.19	0.63 ± 0.11	0.84 ± 0.13	0.96 ± 0.21	**<0.001** (41.763)	0.281	**<0.001** [−0.29 −0.14]	**0.001** [−0.19 −0.05]	**<0.001** [−0.42 −0.25]
Swing phase,%	37.58 ± 4.97	41.29 ± 3.35	37.59 ± 4.40	34.53 ± 5.05	**<0.001** (19.685)	0.189	**0.001** [1.41 5.99]	**0.003** [0.93 5.2]	**<0.001** [4.21 9.32]
Stance phase,%	62.42 ± 4.97	58.71 ± 3.35	62.40 ± 4.40	65.47 ± 5.05	**<0.001** (19.685)	0.189	**0.001** **0.90** [−5.99 −1.41]	**0.003** 0.66 [−5.2 −0.93]	<0.001 **1.55** [−9.32 −4.21]
DS time, s	0.15 ± 0.08	0.08 ± 0.04	0.15 ± 0.07	0.20 ± 0.09	**<0.001** (27.098)	0.227	**<0.001** [−0.106 −0.033]	**<0.001** [−0.09 −0.023]	**<0.001** [−0.17 −0.085]
Cad., step/min	95.38 ± 17.29	117.17 ± 13.18	91.35 ± 11.92	84.89 ± 12.71	**<0.001** (62.697)	0.329	**<0.001** [19.32 32.3]	**0.033** [0.41 12.52]	**<0.001** [25.04 39.52]

* Physical performance tests scores and gait parameters (mean ± SD) derived from sensor data for different frailty status groups are presented. R = robust, P = prefrail, F = frail. TUG = timed up and go test, DGI = Dynamic Gait Score, DS = Double Support, Cad. = Cadence. Statistically significant values are highlighted in bold. [a] One-way ANOVA, followed with post-hoc Tukey analysis to identify significant pairwise associations. [b] 95% CI (Confidence interval) (LL—lower limit, UL—upper limit).

All the comparisons revealed statistically significant differences, except the DGI score and swing phase time between prefrail and frail subjects (effect size indicated by the partial eta squared is medium). Gait velocity best discriminated robust versus frail participants (partial $\eta^2 = 0.374$), whereas the second best discriminator was cadence (partial $\eta^2 = 0.329$). When comparing the means of stride time, stance phase and swing phase time on the left and right leg, we obtained identical results, so only the parameters from the right leg were used for this and further analyses.

The results of multinomial logistic regression are presented in Table 4. All the evaluated variables were able to discriminate between prefrail and robust and frail and robust levels with statistically significant differences. TUG time, stride, stance time in milliseconds, swing and stance phases normalized to a percentage of gait cycle, and double support time increased the odds of being prefrail versus robust and frail versus robust, whereas a higher DGI score, gait velocity, and cadence decreased the odds.

Table 4. The parameters for discriminating three frailty levels (robust, prefrail, and frail).

Variable *	Prefrail vs. Robust			Frail vs. Robust		
	OR	95% CI	*p* Value	OR	95% CI	*p* Value
TUG time, s	2.36	1.68–3.31	**<0.001**	2.67	1.89–3.78	**<0.001**
Dynamic gait index, score	0.80	0.70–0.92	**0.001**	0.71	0.60–0.83	**<0.001**
Gait speed, cm/s	0.93	0.90–0.95	**<0.001**	0.92	0.89–0.95	**<0.001**
Stride time, ms	1.006	1.003–1.009	**<0.001**	1.006	1.003–1.009	**<0.001**
Swing phase time, ms	1.007	1.001–1.013	**0.028**	1.008	1.001–1.015	**0.024**
Stance phase time, ms	1.009	1.005–1.013	**<0.001**	1.008	1.004–1.012	**<0.001**
Swing phase,%	0.80	0.71–0.91	**0.001**	0.69	0.60–0.90	**<0.001**
Stance phase,%	1.24	1.10–1.41	**0.001**	1.44	1.25–1.67	**<0.001**
Double support time, ms	1.02	1.01–1.03	**<0.001**	1.01	1.01–1.02	**0.002**
Cadence, steps per min	0.87	0.83–0.92	**<0.001**	0.83	0.78–0.89	**<0.001**

* Multinomial logistic regression with the robust group as reference. Statistically significant values highlighted in bold. OR = odds ratio, CI = confidence interval. TUG = timed up and go test.

Table 5 shows the sensitivity and specificity of different gait parameters when used to identify the frail and prefrail populations and their cut-offs. All the variables had higher validity to separate prefrail or frail from robust (AUC = 0.735 − 0.969) than frail from prefrail or robust (AUC = 0.675 − 0.810).

Table 5. The most sensitive parameters for discriminating frail from prefrail or robust and prefrail or frail from robust.

Variables *	Frail vs. Prefrail or Robust				Prefrail or Frail vs. Robust			
	AUC	Cut-Off Value [a]	Sens. (%)	Spec. (%)	AUC	Cut-Off Value [a]	Sens. (%)	Spec. (%)
TUG test time, s	0.790	11.60	86.1	65.6	0.929	9.27	89.2	86.7
DGI, score	0.675	15.00	54.1	75.0	0.735	19.0	73.8	56.7
Ch. gait speed, m/s	0.801	0.59	83.8	68.8	0.969	0.74	91.3	90.0
S. gait speed, m/s	0.810	0.60	78.4	75.0	0.958	0.82	94.2	86.7
Stride time, s	0.740	1.27	91.9	51.0	0.915	1.19	90.3	86.7
Stance time, s	0.773	0.80	83.8	62.5	0.923	0.68	96.1	73.3
Swing time, s	0.569	0.48	59.5	57.3	0.759	0.48	58.3	86.7
Stance phase,%	0.749	63.15	75.7	68.8	0.788	63.27	53.4	96.7
Swing phase,%	0.749	36.85	75.7	68.8	0.790	36.73	53.4	96.7
DS time, s	0.778	0.16	70.3	76.0	0.858	0.14	62.1	96.7
Cad., step/min	0.724	99.54	94.6	44.8	0.930	101.22	84.4	90.0

* AUC = area under curve. TUG = timed up and go test. DGI = Dynamic Gait Score. Ch. gait speed measured by a chronometer. S. gait speed derived from sensor data. DS = Double Support. Cad = Cadence. Sens = Sensitivity. Spec = Specifity. [a] Cut-off value based on the Youden Index

Among gait parameters, other than gait speed, stride time (AUC = 0.915), stance phase time (AUC = 0.923), and cadence (AUC = 0.930) were the best discriminators to separate frail or prefrail from robust. Other gait parameters, such as stance phase, normalized in percent of gait cycle, and double support time had sufficient validity to separate prefrail or frail from robust, although both had poor

sensitivity (53.4% and 62.1%). Among the physical performance tests, TUG test time (AUC = 0.929) emerged as a sensitive parameter to discriminate between prefrail or frail and robust. The predictive validity of the dynamic gait index (AUC = 0.735) was inferior when compared to the other variables.

4. Discussion

This study examined the associations between many gait parameters, derived from wearable sensors, and frailty levels and identified which parameters can differentiate between different levels of frailty. Gait speed was the most sensitive parameter for the identification of frailty. It should be noted that the Fried frailty criteria includes slow gait speed [2], which explains the high discriminative power of this variable. In the present study, the discriminative ability of gait speed can be used as a reference for comparison with other parameters analyzed. We found that the stride time was significantly longer in frail and prefrail compared to robust. This finding is in accordance with the results reported by Montero-Odasso et al. [16], which revealed the stride time is longest in frail (mean ± SD, 1.2 ± 0.1 sec.), followed by prefrail (1.1 ± 0.1) and non-frail (1.0 ± 0.1). We suggest that stride time is sensitive for discriminating prefrail or frail from robust and determined a value of stride time for identifying individuals with prefrailty or frailty of 1.19 s, with sufficient sensitivity and specificity. We also found that stride time had a good sensitivity to separate frail from prefrail or robust; however, the specificity and area under the ROC curve were quite modest, thus potentially limiting its clinical usefulness.

Other gait parameters that significantly differed between frailty levels were stance phase and swing phase. In comparisons of the average duration of the stance and swing phase time, the mean percentage of the gait cycle spent in the stance and swing phases was difficult to interpret due to the lack of sufficient data reported in the literature. We found a sufficiently sensitive and specific stance time estimate to separate prefrail or frail from robust, i.e., 0.68 s. The values for the sensitivity, specificity, and AUC of swing phase and stance phase percentage were quite modest.

We found that prefrail and frail subjects had increased double support time. Schwenk et al. [20] identified double support time as one of the most sensitive discriminators between these three frailty levels. However, in our study, double support time had modest validity to discriminate prefrail or frail from robust (AUC = 0.858), poor sensitivity (62.1%), and high specificity (96.7%).

This study revealed that cadence was reduced in frail and prefrail compared to robust; this result is consistent with the results of Montero-Odasso et al. [16], showing variations in mean ± SD cadence (steps/min) in frail (101 ± 21), prefrail (106 ± 9), and non-frail (118 ± 6). Our study showed that cadence is a sensitive and specific gait parameter that discriminates prefrail or frail from robust. The estimated cut-off was 101 steps per minute.

Our study has limitations. Even with a sufficient sample for the current study, we consider that it is too small to conduct more comprehensive studies: comparison of frail vs. prefrail having the robust group as reference in unbalanced groups; study specific effects and interactions between factors. The proposed gait parameters derived from our analysis must be validated in a larger sample to evaluate their true predictive potential. Other limitation is related to the gait assessment technique. During the 4-m walk test, additional sections for the acceleration and deceleration phases were not marked. During these phases, the walking speed was usually slower, which affected the measurement of the 4-m walking speed and led to errors. The gait speed was not measured by a dedicated device but calculated as the distance divided by time calculated as number of samples between the first gait event marker and last gait event marker divided by sampling rate. Adding a dedicated gait speed measuring device or increasing the walking distance would allow more consistent gait speed estimation; however, it might be limited by available space constraints during the testing in a clinical setting.

Traditional diagnosis of frailty is based on visual evaluation of functional tests, which could lead to a different and contradictive outcome. For example, if not one but several investigators analyze the same case there is a chance that the results will not match each other. Our study is one of the first to provide thresholds for sensor-derived gait indicators to determine frailty and prefrailty. The hypotheses of the study were confirmed. Instrumented gait analysis gives us unambiguous data

regarding the patient's condition. Gait indicators measured by a motion capture system enriches evaluation of frailty with quantitative results thus not leaving space for contradiction. The sensor technology we used is quite complex in terms of the sophisticated data processing require due to a larger number of sensors we used as compared to a study where a single wearable sensor was able to extract similar gait parameters [21]. However, the application of multiple sensors would enable to add more quantitative parameters to the analysis that may be sensitive to distinguish frailty levels. This information could be useful for clinicians, so it would be useful to conduct further studies with these parameters. Moreover, building a database of investigated individuals let us to create a clinical decision support system with embedded machine learning algorithms that would enable to separate robust, prefrailty and frailty cases. Further studies should also include longitudinal follow-up to determine which changes in gait parameters predict frailty over time.

5. Conclusions

The results of our study show that gait analysis using wearable sensors can discriminate between frailty levels. We were able to identify several gait indicators that distinguish frail or prefrail from robust with sufficient sensitivity and specificity. We found that frailty is associated not only with slow walking speed, but also with longer stride time, stance phase, double support time, and reduced cadence. If improved and adapted for everyday use, gait assessment technologies could contribute to frailty screening and monitoring.

Author Contributions: A.A., V.A., M.T., K.D., and J.G. were involved in the conception and design of the study. A.A. drafted the manuscript, with support from V.S. and D.V., M.T., A.M., K.D., V.A., and J.G. offered insights on manuscript revisions. A.M., L.P., and J.G. contributed to data interpretation. V.S., D.V., and L.P. contributed to data collection and acquisition. The corresponding author attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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