Data-driven gait analysis with Smart Floor

Development of a Neural Network for fall-risk prediction

August 2025

Abstract

Introduction

Each year, 33% of people aged 65 and older in the Netherlands experience a fall, often with serious consequences. To prevent fall incidents, early and reliable identification of older adults at risk of falling is essential. This report describes the development of a new fall-risk prediction model based on Machine Learning (Neural Network, NN). The aim is to create a more accurate model compared to the current model used by Smart Floor. In developing the NN, the potential added value of previously unused input variables is also investigated.

Method

In this exploratory cohort study, between February 2023 and May 2025, a total of 4852 gait sessions were collected from 461 adults aged 65 and older by (geriatric) physiotherapists. Gait parameters were measured with the Smart Floor, and a POMA test was administered. Based on these data, a NN was designed, trained, and tested.

Results

The NN using gait speed, stride length, stride frequency and Gait Stability Ratio (GSR) as input variables identified individuals with an increased or high fall risk more accurately compared to the current model (sensitivity 0.756 and 0.707 vs 0.663 and 0.593, respectively). Furthermore, the NN misclassified fewer individuals as having a low fall risk compared to the current model (specificity for low fall risk 0.932 vs 0.829).

Conclusion

Based on the insights from this study, the newly developed NN using gait speed, stride length, stride frequency and GSR as input variables has been selected for implementation. This model aligns best with the goal of the Smart Floor to identify individuals at risk of falling.

Table of Contents

1. Introduction

On January 1st, 2025, the Netherlands had more than 3.7 million residents aged 65 and older (1). Among this group, falls are a frequent and serious problem. Each year, 33% of adults aged 65+ in the Netherlands experience a fall. This has major consequences for their health, independence, and healthcare costs (2,3). To prevent fall incidents, it is essential to identify older adults at increased risk of falling early and reliable, in order to apply interventions.

Since 2023, fall prevention for older adults has been a responsibility of Dutch municipalities. This was established in the Integrated Care Agreement (IZA) and the Healthy and Active Living Agreement (GALA) (4,5). Municipalities may opt for fall prevention through a so-called chain approach, in which detecting fall risk in older adults is the first step. The Smart Floor is an innovative system that uses a sensor-embedded floor and a wearable sensor to objectively measure various gait parameters. Based on these parameters, a fall risk profile (SF-FRP) is calculated. This profile can be used to offer older adults the appropriate next steps within the fall prevention chain approach. In August 2023, the first Dutch municipalities started to use one or more Smart Floors in this context. By August 1, 2025, more than 150 municipalities in the Netherlands are making use of the Smart Floor.

Until now, a multiple regression model based on gait speed, stride length, and stride frequency has been used to calculate SF-FRP scores. The validity and reliability of SF-FRP has been compared with the Performance-Oriented Mobility Assessment (POMA), a widely used test for assessing fall risk in older adults (6–8). Every year, Smart Floor conducts research in collaboration with various universities of applied science and healthcare institutions. The availability of an increasing amount of data created opportunities for developing a new prediction model, aiming for more accurate fall risk predictions.

This report describes the development and testing of a new prediction model based on Machine Learning, specifically a Neural Network (NN). A NN is an algorithm inspired by the functioning of the human brain. It consists of different interconnected layers and can recognize complex patterns and relationships in data. Whereas a linear regression model assumes a linear relationship between input variables and the outcome, a NN can also detect non-linear relationships based on training data. This enables more accurate prediction of outcomes from multiple, potentially subtly interrelated variables (9).

In developing the NN, the potential added value of previously unused input variables will also be examined. One measure used to assess the stability of gait in older adults is the Gait Stability Ratio (GSR). This ratio is calculated by dividing cadence (steps per second) by gait speed (m/s). Several studies have found a significant positive association between GSR and fall incidents, with higher

GSR values being linked to an increased likelihood of falls up to 78.2% (10,11). Therefore, in this study, GSR will be investigated as a potential input variable for the NN.

Another input variable to be explored is stride time variability (STV). This value reflects the variation in time between successive strides. In a one-year prospective study, STV was found to correlate significantly with factors such as strength, balance, gait speed, functional status, mental health, and lastly it was predictive of fall incidents (12). Other research found significantly higher STV values among older adults who had already experienced falls (13). For this reason, STV will also be investigated as a potential input variable in this study.

Normal ageing is accompanied by the decline of various physiological systems such as the musculoskeletal system, cardiovascular system, vision, and vestibular system. All these changes increase the risk of falls (14). In addition, age-related conditions such as arthritis, diabetes, a history of cerebrovascular disease, and impaired vision are significant predictors of functional limitations, which are strongly associated with an increased risk of falls (15). In another study, fall incidents were found to be significantly more frequent among women than among men (16). For the reasons mentioned above, the impact of including age and gender on the validity of the NN will be examined.

The hypothesis is that a Neural Network, trained on the newly expanded dataset, will be able to predict fall risk more accurately than has so far been possible with the multiple regression model.

2. Method

2.1 Design

This report describes an exploratory cohort study. To ensure optimal methodological quality, the STROBE (Strengthening The Reporting of Observational Studies in Epidemiology) guidelines and the quality standards of the Physical Therapy Journal (PTJ) were followed (17).

Participants were not required to perform behaviors or tasks that would temporarily alter their usual lifestyle (18,19). Because of that, the study does not fall under the Medical Research Involving Human Subjects Act (WMO). Ethical review by an independent medical ethics committee was therefore not required.

2.2 Participants

Participants were included and assessed by five research partners: De Posten, Archipel/Fysiotherapie Zuiderpark, Vitalis, Medifit Oss, and De Fysioclub. Recruitment was carried out by the (geriatric) physiotherapists employed at these organizations.

Participants over 65 years of age with a Functional Ambulation Categories (FAC) score of ≥3 were included. Participants recruited by de Posten, Archipel/Fysiotherapie Zuiderpark and Vitalis were institutionalized residents. Participants from Medifit Oss and De Fysioclub were community-dwelling older adults. Participants were excluded when they had a markedly asymmetrical gait pattern (e.g., post-stroke hemiparesis, lower-limb amputation, …).

All participants, and where applicable their legal representatives, received written information regarding the study. Written informed consent was obtained from each participant or their legal representative. Depending on the research partner, participants consented either to a single measurement or to repeated monthly data collections. Measurements were conducted by physiotherapists, as described below. Participants also provided written consent for the use of their data in future research.

2.3 Data Collection

2.3.1 Procedure

Data collection took place across the participating organizations during different time periods (Table 1). All physiotherapists involved received both oral and written instruction on the functioning and application of the Smart Floor. To reduce inter-rater variability, the number of physiotherapists per site was limited to a maximum of two.

For each participant, demographic and relevant medical data were recorded. At each assessment, both a Smart Floor measurement and a POMA were performed. Ideally on the same day, with a maximum interval of two days between them. All data were stored in the Smart Floor Vitality environment. Some participants underwent multiple measurements at intervals of at least one month, with a maximum of six assessments. These assessments were always conducted at the same location and under the same protocol.

Data from previously conducted studies were also incorporated into the present analysis (20).

Table 1: Overview of data collection periods per research partner

Organization	**Period**
Fysio Van der Knaap & Postmus*	02-2023 – 07-2023
Vitalis	04-2024 – 07-2024
Archipel/Fysiotherapie Zuiderpark	04-2024 – 10-2024
De Posten	06-2024 – 08-2024
De Fysioclub	09-2024 – 02-2025
Medifit Oss	11-2024 – 05-2025

**Previously conducted research*

2.3.2 Smart Floor

The Smart Floor is composed of a floor with integrated sensor foil and an ankle-worn gait sensor equipped with motion sensors (8). The sensor foil is either embedded in a mobile floor or installed beneath an existing floor (fixed), both of which function identically. The gait sensor interacts with passive RFID-tags embedded in the floor's sensor foil during walking. The resulting sensor data are transmitted to the Smart Floors platform, which processes and interprets them to extract gait parameters such as gait speed, stride length and stride frequency. Smart Floor holds an international patent for performing movement analyses using this method (International Publication Number WO 2018/088894 A1).

During each measurement, participants walked across the Smart Floor at their self-selected comfortable walking speed. Depending on the length of the mobile floor (6m or 10m), participants walked back and forth either twice (6m) or once (10m). When turning, participants remained on the floor. When a fixed floor was used, participants walked across the floor without turning. If a participant used a walking aid in daily life, it was also used during both the Smart Floor measurement and the POMA.

In everyday measurements, one of the four "single walks" (in the 6m floor protocol) is selected as the most representative for calculating the Smart Floor Fall Risk Profile (SF-FRP). In the present study, however, all single walks were retained, each constituting a footstep session. Consequently, a correctly executed 6m protocol yielded four footstep sessions, while a 10m protocol yielded two.

2.3.3 POMA

The Performance-Oriented Mobility Assessment (POMA) is a widely used and recommended tool for evaluating fall risk in older adults (3,6,7). Its validity has been extensively documented in prior research (20).

The POMA consists of two subscales: a balance subscale and a gait subscale, both designed to evaluate motor performance and identify potential fall risks. The balance subscale consists of nine tasks, including sitting, standing and response to balance perturbations. The gait subscale consists of seven items, including gait initiation, step length, and gait continuity. Each task or item is scored on a scale of 0-1 or 0-2, where 0 indicates severe impairment and 2 indicates no impairment.

The total POMA-score ranges from 0 to 28, with lower scores indicating greater fall risk. Risk categories are shown in Table 2 (7,21–23).

Table 2: Fall risk categories

POMA-score	Fall risk category
< 19	High
≥ 19 – < 25	Increased
≥ 25	Low

2.4 Data-analysis

2.4.1 Data cleaning

All data were checked, and demonstrably incorrect data were removed. If a participant performed the Smart Floor walking protocol incorrectly, this was visible in the footstep session. For example, if the participant stopped walking during the measurement, the time between two strides will be abnormally long. Figure 1 shows a footstep session where the time between stride 1 and 2 (Δt=4339ms) deviated substantially from the others (Δt=977ms, 1453ms, and 1210ms). This footstep session was therefore removed and not included in the analysis.

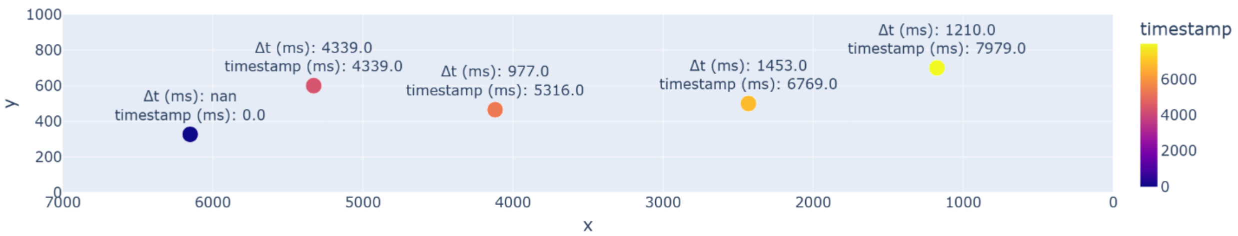

Figure 1: Example of footstep session with measurement error

In total, 67 footstep sessions were excluded, resulting in a cleaned dataset of 4852 footstep sessions.

2.4.2 Descriptive Statistics

Following the data cleaning, descriptive statistics were computed from demographic information and measurement results. Numerical variables were assessed for normality and screened for outliers using histograms, QQ plots, and Kolmogorov-Smirnov tests. For normally distributed continuous variables, mean values with standard deviations (SD) are reported. For non-normally distributed continuous variables, median values with interquartile ranges (IQR) are presented. Categorical variables are expressed as absolute counts and percentages across categories.

Each footstep session was linked to a corresponding POMA-score. The distribution of footstep sessions across fall risk categories is shown in Table 3.

Table 3: Number of footstep sessions per fall risk category

Fall-risk category	Footstep session (n)
Low	3239
Increased	1186
High	427

Correlations were assessed using Pearson correlation coefficient (r) for normally distributed data, and the Spearman correlation coefficient (R) for non-normally distributed data. All confidence intervals (CI) were set at 95%. Correlations coefficients were interpreted according to the following thresholds: 0.00-0.09 negligible, 0.10-0.39 weak, 0.40-0.69 moderate, 0.70-0.89 strong, and 0.90-1.00 very strong (24).

To test for group differences, ANOVA was used for normally distributed data, with Tukey HSD as post hoc test. For non-normally distributed data, the Kruskal-Wallis test was applied, with Mann-Whitney U test and Bonferroni correction for post hoc analyses. For all results, a p-value <0.05 was considered statistically significant (25).

2.4.3 Neural Network

Internal research indicated that, given the available dataset size, a Neural Network (NN) was suitable as the model for fall risk prediction (Figure 2) (9). Various input variables were tested using separate training and testing datasets. These variables were either directly measured or derived from directly measured gait parameters. The input variables with the strongest correlations with the POMA were selected for the final predictive model. In addition to gait parameters, demographic variables such as 'age' and 'gender' were evaluated as potential input variables.

The NN was trained using a train-test split approach, whereby the dataset was divided into two subsets. The training set was used to optimize the model, while the test set was used to evaluate performance and control for overfitting. For this study, an 80% training and 20% testing split was applied.

The validity of different variants of the newly developed NN was compared to the existing Smart Floor Fall Risk Profile (SF-FRP) model. Sensitivity and specificity were used as primary evaluation metrics. Sensitivity reflects the proportion of correctly identified positive cases (i.e., the percentage of individuals correctly classified into a fall risk category). Specificity reflects the proportion of correctly identified negative cases (i.e., individuals not belonging to a certain category were not incorrectly assigned to it). The sensitivity and specificity of the NN were benchmarked against the POMA-based fall risk categories defined in Table 2. For this purpose, the One-vs-All method was applied (26).

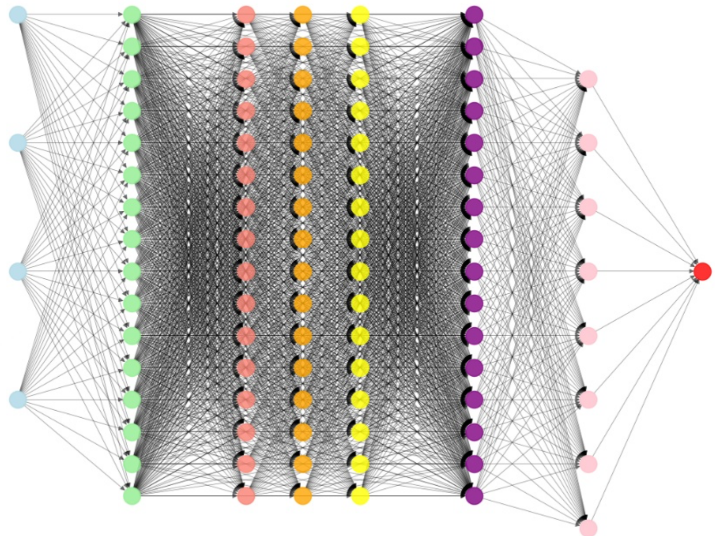

Figure 2: Example Neural Network

3. Results

3.1 Descriptive statistics

A total of 468 individuals participated in this study, accounting for 4919 footstep sessions. After data cleaning, 461 participants and 4852 footstep sessions were retained for analysis. Exclusions were due to measurement errors and incorrect execution of the walking protocol. Table 4 provides an overview of the number of participants included per research partner. Table 5 presents demographic characteristics.

Table 4: Overview of participant inclusion per research partner

Organization	**Included participants (n)**	**Measurements per participant**
Vitalis	44	1
De Posten	50	1
Archipel/Fysiotherapie Zuiderpark	28	1 - 16
Van der Knaap & Postmus	185	1 - 6
Medifit Oss	50	1 - 6
De Fysioclub	104	1
Total	*461*	

Table 5: Demographic characteristics

Gender	**Participants**	**Age (Years)**
	n (%)	Median [IQR]
Man	174 (37.7%)	79.5 [9.75]
Woman	287 (62.3%)	81.0 [12.00]
Total	*461*	*81.0 [11.00]*

3.2 Results gait parameters

The footstep sessions were categorized into fall risk groups according to their corresponding POMA-scores (Table 3) (23). Table 6 shows the mean or median values of gait parameters measured by the Smart Floor for all three fall risk categories.

Strong correlations with the POMA-score were observed for gait speed (r=0.74, 95% CI 0.72-0.75), stride length (r=0.73, CI 0.72-0.74), and GSR (r=-0.74, CI -0.75- -0.72). Stride frequency showed a weak correlation (r=0.38, CI 0.36-0.41). The correlation between STV and the POMA was also weak (R=-0.12, CI -0.15- -0.10). All correlations were statistically significant ($p<0.05$), as seen in Table 6.

Significant differences were found across all gait parameters between the three fall risk categories ($p<0.05$). Post hoc analyses confirmed significant pairwise differences between all groups ($p<0.001$).

Table 6: Gait parameters per fall risk category

	High risk (n=427)	**Increased risk (n=1186)**	**Low risk (n=3239)**	**Correlation coefficient vs. POMA (95% CI)**
Normally distributed parameters				
Gait speed (m/s)	0.47 (0.15)	0.71 (0.16)	1.00 (0.18)	0.74* (0.72-0.75)
Stride length (m)	0.65 (0.19)	0.89 (0.18)	1.16 (0.17)	0.73* (0.72-0.74)
Stride frequency (/s)	0.75 (0.16)	0.80 (0.12)	0.88 (0.09)	0.38* (0.36-0.41)
GSR	1.71 (0.58)	1.19 (0.30)	0.90 (0.14)	-0.74* (-0.75--0.72)
Non-normally distributed parameters				
STV (s)	0.16 [0.17]	0.14 [0.08]	0.13 [0.04]	-0.12* (-0.15--0.10)

High risk: POMA <19; Increased risk: POMA ≥19 – <25; Low risk: POMA≥25

GSR=Gait Stability Ratio; STV=Stride Time Variability

Normally distributed data: Pearson (r), non-normally distributed data: Spearman (R)

**p<0.001*

3.3 Neural Network

Based on the gait parameter results, two variants of the NN were developed and compared:

Variant 1: Gait speed, stride length, stride frequency, GSR

Variant 2: Gait speed, stride length, stride frequency

Due to its weak correlation with POMA, STV was excluded as an input variable.

To evaluate performance, the validity of both NN variants and the current predictive model were tested for validity. Table 7 provides an overview of sensitivity and specificity compared with the POMA-score, classified in fall risk categories.

Table 7: Validity of the different NN-variants with gait parameters and the current predictive model with respect to the POMA

	Sensitivity	**Specificity**
Variant 1: Gait speed, stride length, stride frequency, GSR		
• Low (n=3239)	0.662	0.932
• Increased (n=1186)	0.756	0.670
• High (n=427)	0.707	0.957
Variant 2: Gait speed, stride length, stride frequency		
• Low (n=3239)	0.690	0.921
• Increased (n=1186)	0.742	0.692
• High (n=427)	0.686	0.958
Current model: Gait speed, stride length, stride frequency (multiple logistic regression)		
• Low (n=3239)	0.785	0.829
• Increased (n=1186)	0.663	0.765
• High (n=427)	0.593	0.970

Variant 1 yielded the highest sensitivity for both the increased-risk group (0.756) and the high-risk group (0.707). The highest sensitivity for the low-risk group was achieved by the current model. Furthermore, Variant 1 demonstrated the highest specificity for the low-risk group (0.932). For the increased risk group, the current model showed the highest specificity (0.765). Specificity for the high-risk group was high across all models (>0.95).

3.3.1 Age and gender

Besides the addition of gait parameters, two models were investigated using age and gender as input variables respectively, and finally one model using both age and gender.

Variant 3: Gait speed, stride length, stride frequency, GSR, age

Variant 4: Gait speed, stride length, stride frequency, GSR, gender

Variant 5: Gait speed, stride length, stride frequency, GSR, age, gender

The validity of these models was assessed in the same way as Variant 1 and 2. The results were compared with Variant 1, which previously yielded the best results (Table 8).

Table 8: Validity of different NN-variants with gait parameters and demographic characteristics and Variant 1 with respect to the POMA

	Sensitivity	**Specificity**
Variant 3: Gait speed, stride length, stride frequency, GSR, age		
• Low (n=3239)	0.650	0.937
• Increased (n=1186)	0.761	0.659
• High (n=427)	0.698	0.956
Variant 4: Gait speed, stride length, stride frequency, GSR, gender		
• Low (n=3239)	0.666	0.927
• Increased (n=1186)	0.758	0.674
• High (n=427)	0.710	0.959
Variant 5: Gait speed, stride length, stride frequency, GSR, age, gender		
• Low (n=3239)	0.687	0.931
• Increased (n=1186)	0.758	0.693
• High (n=427)	0.710	0.957
Variant 1: Gait speed, stride length, stride frequency, GSR		
• Low (n=3239)	0.662	0.932
• Increased (n=1186)	0.756	0.670
• High (n=427)	0.707	0.957

The sensitivity and specificity values of Variant 3, 4 and 5 are comparable to those of Variant 1 across all risk categories.

4. Discussion

The aim of this study was to develop a novel fall risk prediction model (SF-FRP) using Machine Learning, specifically a Neural Network (NN). The primary objective of the model was to accurately identify older adults with increased or high fall risk. To achieve this, different variants incorporating gait parameters and demographic characteristics were evaluated and compared.

Gait parameters

First, the extent to which different gait parameters correlate with the POMA-score was investigated. A strong correlation was found for gait speed, stride length and GSR. In addition, a significant weak correlation was found between stride frequency and the POMA-score. These strong correlations were also found in previous Smart Floor research and are confirmed here (8). The gait parameters gait speed, stride length and stride frequency are part of the multiple regression model that has been used so far to calculate the SF-FRP score. The strong correlation of the GSR with the POMA-score is consistent with existing literature, where a higher GSR is associated with an increased risk of falling (10,11). Therefore, GSR was tested as a possible additional input variable for the Neural Network.

The goal of the SF-FRP is to correctly identify older adults with an increased or high fall risk. The NN with gait speed, stride length, stride frequency and GSR as input variables (Variant 1) performs best in this regard, with a sensitivity of 0.756 and 0.707 for elevated and high fall risk individuals, respectively. This means that the model correctly predicts the largest number of individuals, who according to the POMA have an elevated or high fall risk. The sensitivity for low fall risk of Variant 1 (0.662) is lower than in the current model (0.785) and Variant 2 (0.690). This indicated that the model including GSR is stricter in the assessment of SF-FRP for individuals with a low fall risk compared to the current model and the model without GSR.

The specificity for low fall risk of Variant 1 (0.932) is higher than in the current model (0.829) and Variant 2 (0.921). This means in Variant 1, 93% of the individuals who according to the POMA do not have a low fall risk, are also not classified as low fall risk by the model.

The main goal of the model is to correctly identify individuals at risk of falling, and therefore this has been an important factor in the choice of Variant 1 as the final model.

Although in existing literature stride time variability (STV) seems to predict fall incidents (12), in this study it showed only a weak correlation with the POMA-score. A possible explanation is the relatively small number of consecutive strides in the footstep sessions. Whereas in the abovementioned study, participants performed a couple hundred strides, a Smart Floor footstepsession usually consists of 4 to 6 strides. Therefore, STV was not included as an input variable for the NN.

Personal characteristics

In various studies, age is associated with fall risk (14,15). Here, an increase in age is said to be accompanied by an increase in fall risk. A variant of the NN with 'age' as an extra input variable was tested and compared to Variant 1. Sensitivity and specificity were comparable between both variants. This may be due to other input variables that were included in the model. A higher age is often associated with a lower gait speed, shorter stride length, and higher stride frequency (27,28). Since these gait parameters are measured and already serve as input variables of the model, the addition of age may be redundant.

Research has found differences in fall incidents between genders, with more fall incidents occurring among women (16). Therefore, in this study the influence of the input variable 'gender' was evaluated. Comparing this NN variant with Variant 1 also showed similar validity.

Finally, a variant of the model with both 'age' and 'gender' was evaluated and compared. This variant also showed similar sensitivity and specificity values as Variant 1.

Implementing personal characteristics in the prediction model is a challenge. Users would need to enter characteristics such as gender and age for every individual measured. For many, this would require a change in the current workflow. This, in combination with the comparable validity of the variants with and without personal characteristics, led to the decision to choose the model without personal characteristics.

Strengths and limitations

A strength of the current study is the high number of validated measurements. With more than 4800 data points, Machine Learning could be applied to develop the new model. Because the measurements were performed by (geriatric) physiotherapists, the likelihood of assessor bias was reduced. The dataset is heterogenous due to the inclusion of both community-dwelling participants and nursing home residents.

At present, there is no golden standard for estimating an individual's fall risk (6). The POMA is a widely used instrument and contains elements for both balance and gait (7). In future research it may be interesting to compare different fall risk tests with each other and with the SF-FRP score, with the aim of further developing the model.

Several studies have indicated that the time of day can affect postural control and gait pattern (29,30). For a small number of participants (n=2), the POMA could not be administered directly after the Smart Floor measurement. The period between the POMA and the Smart Floor measurement was a maximum of two days. The geriatric physiotherapist knew these participants. It was verified that both the POMA-score and the Smart Floor outcome corresponded with the subjective fall risk assessment of the geriatric physiotherapist.

Currently, the Smart Floor is implemented in more than 150 Dutch municipalities. Therefore, the implementation of the newly developed NN has immediate practical value. Results indicate the new model performs better than the current algorithm, particularly in correctly identifying individuals with an elevated or high fall risk. In practice, this increased accuracy will contribute to more effective fall prevention. Transitioning to the new prediction model will not only enhance the reliability of the Smart Floor, but also strengthen its added value for healthcare and welfare professionals.

Conclusion

Based on the insights mentioned above, implementation of the newly developed fall risk prediction model (SF-FRP), with gait speed, stride length, stride frequency, and Gait Stability Ratio as input variables, has been chosen. This model is expected to best align with the objective of the Smart Floor, identifying individuals at risk of falling.

Acknowledgments

We would like to sincerely thank all our research partners for their efforts in collecting the data over the past years. We greatly appreciated the pleasant collaboration in setting up and conducting the projects at the various locations.

In addition, we would like to thank Pipple for reviewing the statistics and data-analyses, as well as for their valuable advice regarding the reporting process.

With your help, we are one step closer to a vital future!

Team Smart Floor

Literature

1. cbs visualisatie bevolking leeftijd ouderen - Google Zoeken [Internet]. [cited 2023 Jul 17]. Available from: https://www.google.com/search?q=cbs+visualisatie+bevolking+leeftijd+ouderen&rlz=1C1GCEA_enNL1055NL1056&oq=cbs+visualisatie+bevolking+leeftijd+ouderen&gs_lcrp=EgZjaHJvbWUyBggAEEUYOTIGCAEQRRhA0gEINzgyMmowajeoAgCwAgA&sourceid=chrome&ie=UTF-8

2. Infographic Valongevallen 65-plussers | VeiligheidNL [Internet]. [cited 2025 Jul 9]. Available from: https://www.veiligheid.nl/kennisaanbod/infographic/infographic-valongevallen-65-plussers

3. Montero-Odasso M, Van Der Velde N, Martin FC, Petrovic M, Tan MP, Ryg J, et al. World guidelines for falls prevention and management for older adults: a global initiative. Age Ageing [Internet]. 2022 Sep 1 [cited 2025 Aug 21];51(9). Available from: https://pubmed.ncbi.nlm.nih.gov/36178003/

4. GALA - Gezond en Actief Leven Akkoord | Rapport | Rijksoverheid.nl [Internet]. [cited 2025 Jul 9]. Available from: https://www.rijksoverheid.nl/documenten/rapporten/2023/01/31/gala-gezond-en-actief-leven-akkoord

5. Integraal Zorgakkoord: “Samen werken aan gezonde zorg” | Rapport | Rijksoverheid.nl [Internet]. [cited 2025 Jul 9]. Available from: https://www.rijksoverheid.nl/documenten/rapporten/2022/09/16/integraal-zorgakkoord-samen-werken-aan-gezonde-zorg

6. Preventie van valincidenten bij ouderen. Federatie Medisch Specialisten. 2017;

7. Tinetti ME. Performance-Oriented Assessment of Mobility Problems in Elderly Patients. J Am Geriatr Soc. 1986;34(2):119–26.

8. Drost K, Lefeber F, Dierkx R. Smart Floor - Een innovatief meetinstrument voor valrisico bij ouderen. Nederlands Tijdschrift voor Geriatriefysiotherapie. 2020 Dec;19–28.

9. Lecun Y, Bengio Y, Hinton G. Deep learning. Nature [Internet]. 2015 May 27 [cited 2025 Jul 9];521(7553):436–44. Available from: https://pubmed.ncbi.nlm.nih.gov/26017442/

10. Nascimento M de M, Gouveia ÉR, Gouveia BR, Marques A, Martins F, Przednowek K, et al. Associations of Gait Speed, Cadence, Gait Stability Ratio, and Body Balance with Falls in Older Adults. International Journal of Environmental Research and Public Health 2022, Vol 19, Page 13926 [Internet]. 2022 Oct 26 [cited 2025 Jul 30];19(21):13926. Available from: https://www.mdpi.com/1660-4601/19/21/13926/htm

11. Cromwell RL, Newton RA. Relationship between Balance and Gait Stability in Healthy Older Adults. J Aging Phys Act [Internet]. 2004 [cited 2025 Jul 30];12(1):90–100. Available from: https://pubmed.ncbi.nlm.nih.gov/15211023/

12. Hausdorff JM, Rios DA, Edelberg HK. Gait variability and fall risk in community-living older adults: A 1-year prospective study. Arch Phys Med Rehabil [Internet]. 2001 [cited 2025 Jul 30];82(8):1050–6. Available from: https://pubmed.ncbi.nlm.nih.gov/11494184/

13. Hausdorff JM, Edelberg HK, Mitchell SL, Goldberger AL, Wei JY. Increased gait unsteadiness in community-dwelling elderly failers. Arch Phys Med Rehabil [Internet]. 1997 [cited 2025 Jul 30];78(3):278–83. Available from: https://pubmed.ncbi.nlm.nih.gov/9084350/

14. Segev-Jacubovski O, Herman T, Yogev-Seligmann G, Mirelman A, Giladi N, Hausdorff JM. The interplay between gait, falls and cognition: Can cognitive therapy reduce fall risk? Expert Rev Neurother [Internet]. 2011 Jul [cited 2025 Aug 13];11(7):1057–75. Available from: https://pubmed.ncbi.nlm.nih.gov/21721921/

15. Dunlop DD, Manheim LM, Sohn MW, Liu X, Chang RW. Incidence of functional limitation in older adults: The impact of gender, race, and chronic conditions. Arch Phys Med Rehabil [Internet]. 2002 [cited 2025 Aug 13];83(7):964–71. Available from: https://pubmed.ncbi.nlm.nih.gov/12098157/

16. Smith A de A, Silva AO, Rodrigues RAP, Moreira MASP, Nogueira J de A, Tura LFR. Assessment of risk of falls in elderly living at home. Rev Lat Am Enfermagem [Internet]. 2017 [cited 2025 Aug 13];25. Available from: https://pubmed.ncbi.nlm.nih.gov/28403333/

17. Physical Therapy Journal. https://academic.oup.com/ptj/pages/Author_Guidelines#Article%20Types%20and%20Manuscript%20Preparation. Author Guidelines.

18. Centrale Commissie Mensgebonden Onderzoek (CCMO). https://www.ccmo.nl/onderzoekers/wet-en-regelgeving-voor-medisch-wetenschappelijk-onderzoek/uw-onderzoek-wmo-plichtig-of-niet. Uw onderzoek: WMO-plichtig of niet?

19. https://wetten.overheid.nl/BWBR0009408/2022-07-01 [Internet]. 2022. Wet medisch-wetenschappelijk onderzoek met mensen.

20. Smart Floor. Smart Floor Valrisico-Test (SF-VRT) als meetinstrument voor periodieke valrisicovoorspelling van thuiswonende ouderen. 2023;

21. Kegelmeyer DA, Kloos AD, Thomas KM, Kostyk SK. Reliability and validity of the tinetti mobility test for individuals with Parkinson disease. Phys Ther. 2007 Oct;87(10):1369–78.

22. De Backer FMJ. UNCO-MOB 2.1. 2018.

23. Senden R, Savelberg HHCM, Grimm B, Heyligers IC, Meijer K. Accelerometry-based gait analysis, an additional objective approach to screen subjects at risk for falling. Gait Posture [Internet]. 2012 Jun [cited 2023 Jul 13];36(2):296–300. Available from: https://pubmed.ncbi.nlm.nih.gov/22512847/

24. Schober P, Boer C, Schwarte LA. Correlation Coefficients: Appropriate Use and Interpretation. Anesth Analg. 2018 May;126(5):1763–8.

25. Baarda Ben, Bakker Esther, Fischer Tom, Julsing Mark, Vianen R van. Basisboek methoden en technieken : kwantitatief praktijkgericht onderzoek op wetenschappelijke basis. 2021;403.

26. Rocha A, Goldenstein SK. Multiclass from binary: Expanding One-versus-all, one-versus-one and ECOC-based approaches. IEEE Trans Neural Netw Learn Syst [Internet]. 2014 Feb [cited 2025 Aug 21];25(2):289–302. Available from: https://pubmed.ncbi.nlm.nih.gov/24807029/

27. Cruz-Jimenez M. Normal Changes in Gait and Mobility Problems in the Elderly. Phys Med Rehabil Clin N Am [Internet]. 2017 Nov 1 [cited 2025 Aug 13];28(4):713–25. Available from: https://pubmed.ncbi.nlm.nih.gov/29031338/

28. Boyer KA, Johnson RT, Banks JJ, Jewell C, Hafer JF. Systematic review and meta-analysis of gait mechanics in young and older adults. Exp Gerontol [Internet]. 2017 Sep 1 [cited 2025 Aug 13];95:63–70. Available from: https://pubmed.ncbi.nlm.nih.gov/28499954/

29. Gribble PA, Tucker WS, White PA. Time-of-day influences on static and dynamic postural control. J Athl Train. 2007;42(1):35–41.

30. Jorgensen MG, Rathleff MS, Laessoe U, Caserotti P, Nielsen OBF, Aagaard P. Time-of-day influences postural balance in older adults. Gait Posture [Internet]. 2012 Apr [cited 2025 Aug 13];35(4):653–7. Available from: https://pubmed.ncbi.nlm.nih.gov/22390960/