Benchmarking predicting tools for falls in older adults

ITU/PAHO Webinar - Decade of healthy aging: role of digital technologies Session 1: Healthy Aging in the Digital Age

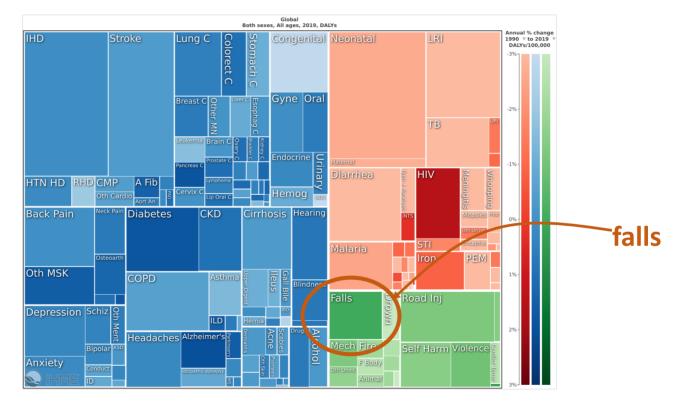
Pierpaolo Palumbo University of Bologna TG Falls – ITU/WHO FGAI4H

Overview

- Falls and fall prevention
- Fall prediction tools
- **ITU/WHO FGAI4H**
- Systematic review and IPD meta-analysis

Falls and fall prevention

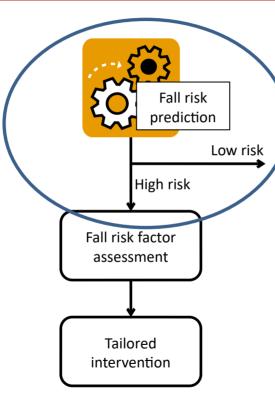
- About 30% older individuals fall at least once a year
- Falls occur as the consequence of multiple risk factors
- Falls may cause fear of falling, physical injuries, loss of independence, hospitalizations, death. About 10% falls require medical attention.
- Falls are preventable (RR ≈0.7-0.8)



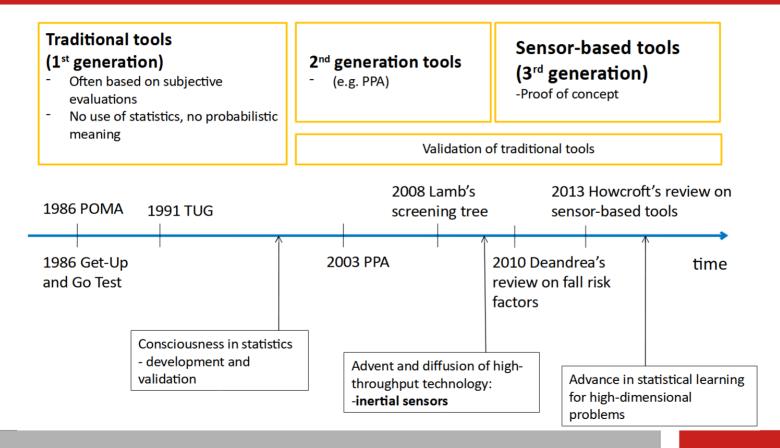
Institute for Health Metrics and Evaluation (IHME). GBD Compare Data Visualization. Seattle, WA: IHME, University of Washington, 2020. Available from http://vizhub.healthdata.org/gbd-compare.

Falls and fall prevention

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- Falls are preventable (RR ≈0.7-0.8)
- **Fall prediction tools** are recommended for identifying high risk individuals to target with preventive interventions

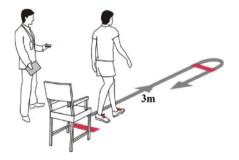


AGS/BGS Guidelines clinical practice guideline for prevention of falls in older persons 2011 M. Montero-Odasso, Global guidelines for falls in older adults. Age Ageing, 2022 M.E. Tinetti. NEJM 2003 D.A. Ganz et al. JAMA 2007



Traditional tools

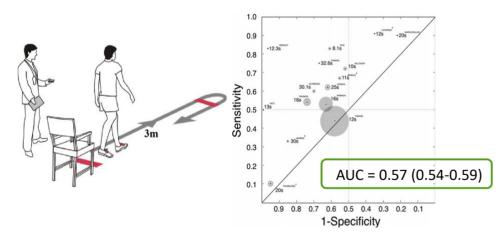
Timed Up and Go test (TUG)



D. Podsiadlo, S. Richardson. J Am Geriatr Soc., 1991

Traditional tools

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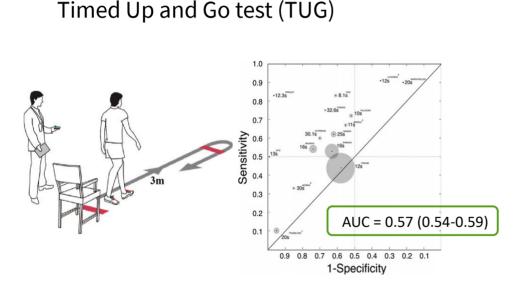


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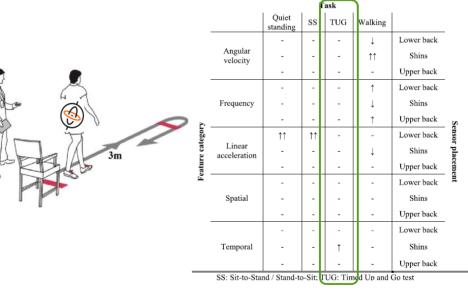




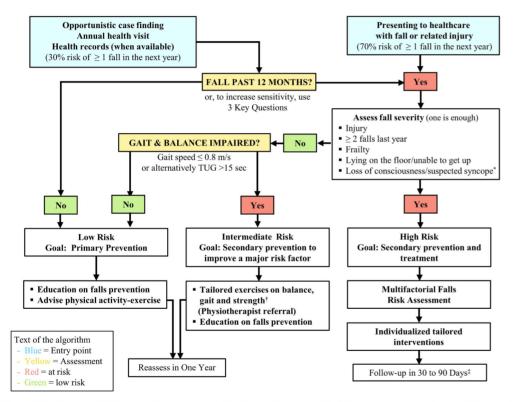
D. Podsiadlo, S. Richardson. J Am Geriatr Soc., 1991 D. Schoene et al., J. Am. Geriatr. Soc., 2013 E. Barry et al., BMC Geriatr., 2014

Instrumented TUG

ASSOCIATION TREND AND STRENGTH FOR ALL POSSIBLE TRIADS OF FEATURE CATEGORY, TASK AND SENSOR PLACEMENT

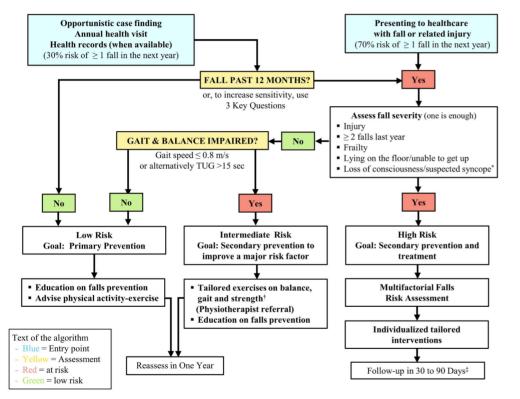


L. Montesinos, R. Castaldo, L. Pecchia. IEEE Trans Neural Syst Rehabil Eng., 2018



M. Montero-Odasso, Global guidelines for falls in older adults. Age Ageing, 2022

Nates: 2 Koy Quantione (2KQ) any positive answer to a) Use fallen in the next year? h) Easle unstandy when standing or walking? or a)



Nater: 2 Kay Quantiane (2KQ) any positive answer to a) Use fallon in the post year? (h) Easts unstandy when standing or walking? or a)

- Not trained on data
- Need for validation
- Advocacy for multifactorial models
- Need to address the usabilityperformance trade-off
- Advantages of a continuous risk score
- EHRs and wearable inertial sensor data
- Need to estimate the clinical and organizational impact

M. Montero-Odasso, Global guidelines for falls in older adults. Age Ageing, 2022 TG Falls ITU/WHO AI4H, Age Ageing, accepted

To establish a standardized assessment framework for the evaluation of AI-based methods for health, diagnosis, triage or treatment decisions

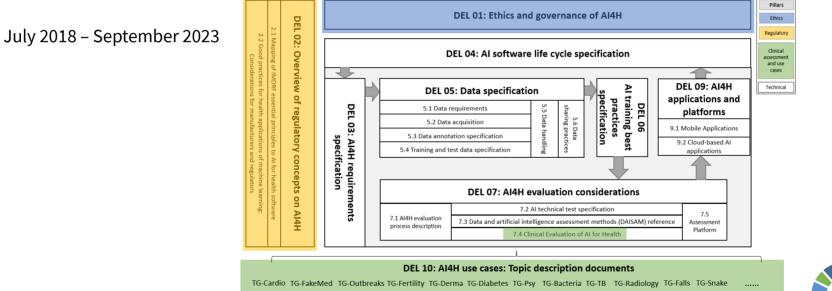
July 2018 – September 2023



https://www.itu.int/en/ITU-T/focusgroups/ai4h/ Wiegand T, et al. WHO and ITU establish benchmarking process for artificial intelligence in health. Lancet. 2019



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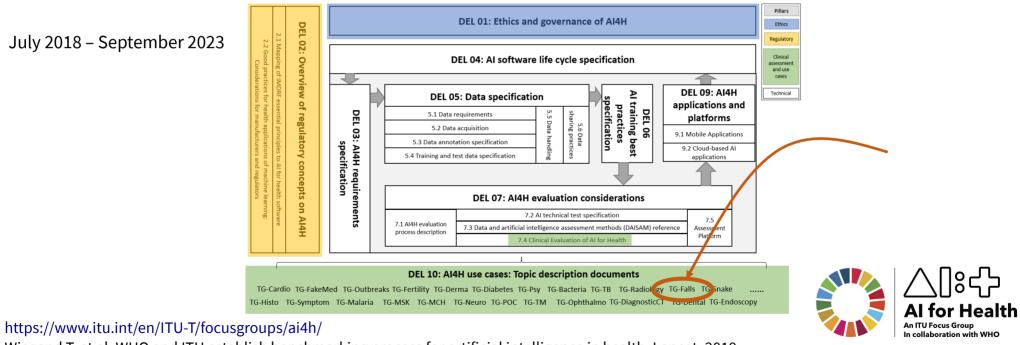


TG-Histo TG-Symptom TG-Malaria TG-MSK TG-MCH TG-Neuro TG-POC TG-TM TG-Ophthalmo TG-DiagnosticCT TG-Dental TG-Endoscopy

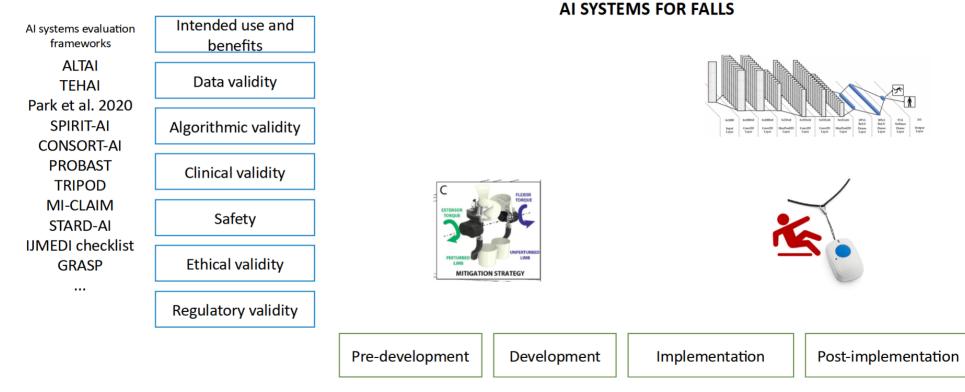


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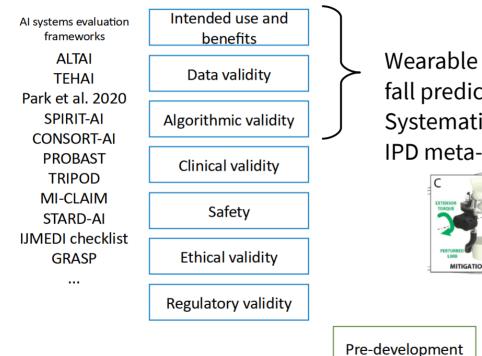
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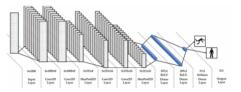
Images from: F. Buisseret et al., "Timed Up and Go and Six-Minute Walking Tests with Wearable Inertial Sensor: One Step Further for the Prediction of the Risk of Fall in Elderly Nursing Home People," Sensors (Basel)., vol. 20, no. 11, pp. 1–15, Jun. 2020 and V. Monaco et al., "An ecologically-controlled exoskeleton can improve balance recovery after slippage," Sci. Rep., vol. 7, p. 46721, May 2017.



ALSYSTEMS FOR FALLS

Wearable sensor-based fall prediction tools. Systematic review and **IPD** meta-analysis







Implementation

Post-implementation

Images from: F. Buisseret et al., "Timed Up and Go and Six-Minute Walking Tests with Wearable Inertial Sensor: One Step Further for the Prediction of the Risk of Fall in Elderly Nursing Home People," Sensors (Basel)., vol. 20, no. 11, pp. 1–15, Jun. 2020 and V. Monaco et al., "An ecologically-controlled exoskeleton can improve balance recovery after slippage," Sci. Rep., vol. 7, p. 46721, May 2017.

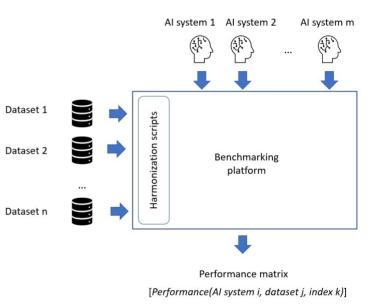
Development

Review title:

"Systematic review and individual participant data metaanalysis of publicly available datasets for wearable inertial sensor-based fall risk assessment"

Aim/question:

- Which datasets are available for training and validating models for wearable inertial sensor-based fall risk assessment? *
- What is the prognostic value for falls of features and models derived from wearable inertial sensors?



* Khan, S. M. *et al.* A global review of publicly available datasets for ophthalmological imaging: barriers to access, usability, and generalisability. *Lancet Digit. Heal.* **3**, e51–e66 (2021).

Inclusion criteria:

Peer-reviewed articles/conference proceedings in English including datasets with the following characteristics:

- Datasets including at least 20 individuals
- Datasets where the predicting features comprised of at least one inertial sensorbased feature
- Datasets from any community-dwelling population
- Datasets with individual-level (not aggregated) information about falls*
- Falls collected after the predicting features (prospective design) #

* occurrence of at least one fall in a given time period OR number of falls OR date of first fall occurrence

retrospective studies included only for sensitivity analyses

Registration: PROSPERO 2022 CRD42022367394 https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=367394 Review on datasets for wearable inertial sensorbased fall prediction

Analyses on the pooled dataset

PROSPERO International prospective register of systematic reviews

Features to extract [1]:

- Study population
 - Sampled population
 - Sample size
 - Geographic location
- Study design
 - Clinical features for fall prediction
 - Characteristics of inertial sensors (acc., acc. + gyro, etc.)
 - Protocol for inertial sensor assessment (sensor location, standardized task/free living)
- Outcome measures
 - Fall definition
 - Protocol for collecting fall information (fall diaries, phone calls, etc.)
- Dataset accessibility (open access, open access with barriers, regulated access, not accessible)

[1] Moons KGM et al. Critical appraisal and data extraction for systematic reviews of prediction modelling studies: the CHARMS checklist. PLoS Med. 2014 Oct ;11(10):e1001744.

[2] Wolff RF et al. PROBAST: A tool to assess the risk of bias and applicability of prediction model studies. Ann Intern Med. 2019 Jan 1;170(1):51–8.

Quality assessment:

- PROBAST (Prediction model Risk Of Bias ASsessment Tool) [2]
- Risk of bias, applicability
- Participants, predictors, outcome, analysis
- 11 + 9-signalling questions

Access request:

- Email
- Form: rationale, data management, authorship policy [1]

Meta-analysis:

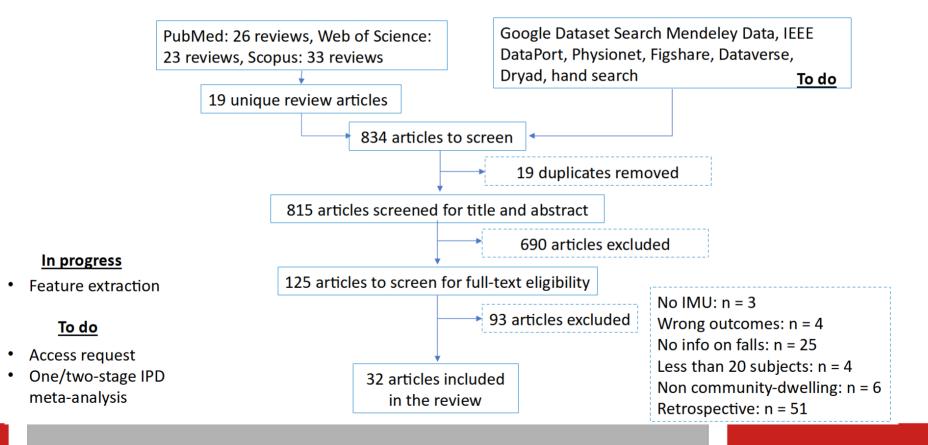
- Data storage facility: secure, large
- Three data sharing (DS) possibilities
 - DS1: sharing dataset, including raw sensor data, into a secure centralised repository. onestage IPD meta-analysis
 - DS2: To run the signal processing scripts prepared by the TG-Falls at their own premises and share data on digital biomarkers and falls at individual level
 - DS3: To run at their own premises the processing scripts prepared by the TG-Falls for calculating the digital biomarkers and their association with falls, and share the final association/performance measures (e.g., odds ratios, AUC).
- Univariate analysis: i) ORs, RaRs, and HRs, ii) Mixed-effect logistic regressions
- Multivariate model [2]

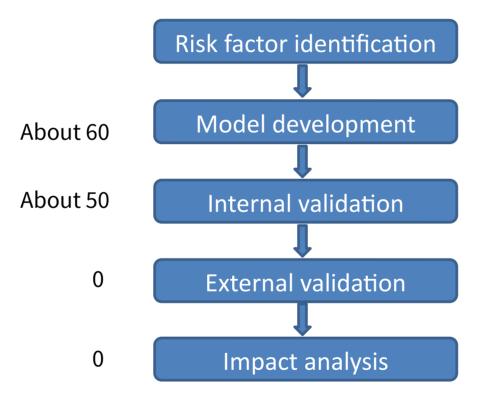
[1] https://www.icmje.org/recommendations/browse/roles-and-responsibilities/defining-the-role-of-authors-and-contributors.html

[2] Ahmed I, Debray TPA, Moons KGM, Riley RD. Developing and validating risk prediction models in an individual participant data meta-analysis. BMC Med Res Methodol. 2014;14(3).

One-stage metaanalysis

Two-stage metaanalysis





E. W. Steyerberg et al., "Prognosis Research Strategy (PROGRESS) 3: Prognostic Model Research," PLoS Med. 2013.

ITU

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Thank you!