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| **Abstract:** | The document presents the status report on the topic Standardized benchmarking of AI to prevent falls among the elderly. A database of 403 subjects who were evaluated for multiple fall risk factors and 12-months prospective falls is available for benchmarking. The database aims at contributing to standardize fall risk assessment and creating tools to easily implement it in the clinical practice. |

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# Introduction

Former documents:

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| [FGAI4H-C-014](https://extranet.itu.int/sites/itu-t/focusgroups/ai4h/docs/FGAI4H-C-014.docx) | Lausanne, 22-25 January 2019 | Status Report of: Reducing risk of falling among elderly |

This submission was provided in response to the ITU-T FG-AI4H's call for proposals on use cases and data [A‑102](https://extranet.itu.int/sites/itu-t/focusgroups/ai4h/docs/FGAI4H-A-102docx). The document was presented remotely. The project aims at contributing to standardize fall risk assessment and creating tools based on Artificial Intelligence to easily implement it in the clinical practice.

## Topic Description

### Relevance - How relevant is the health problem to be addressed?

Falls are one of the most common health problems in the elderly population, about a third of community-dwelling adults aged 65 years or older fall each year [1], and these events represent more than 50% of the hospitalizations due to lesions in this age group. Falls are also considered one of the main causes for loss of independence and institutionalization. In 10% of cases falls result in fractures, thus contributing to significant increases in morbidity and mortality. Direct health care costs associated with this phenomenon are high, reaching yearly costs of 25 billion euros in the European Union [2] and 31 billion dollars in the United States of America [3]. Falls have a multifactorial origin, however most of the fall risk factors are amendable by implementing falls prevention programs based on improving strength and balance and modifying behaviours. Even though, fall risk screenings and the implementation of such falls’ prevention programs are rarely part of the community-dwelling elder’s routine. The current state of the art assessment of fall risk factors is based mainly in applying clinical scales, such as the Morse Fall Scale [4], Berg Balance Scale [5], and Performance Oriented Assessment of Mobility Problems in Elderly Patients [6]. Despite being recommended by international health bodies, such as the National Institute for Health and Care excellence (NICE)[[1]](#footnote-1), multifactorial assessment of fall risk factors is still not widespread in the clinical practice. One of the reasons for this shortcoming is the difficulty in combining the multiple parameters evaluated in a meaningful scale that is able to differentiate those who are more likely to fall in a period of time following the assessment.

### Impact - What level of impact will a benchmark in the context of the proposed project have?

Raise awareness for multifactorial assessment of fall risk factors, contribute to standardize fall risk assessment and create tools to easily implement it in the clinical practice.

Artificial Intelligence (AI) techniques can be of great value in generating models that combine multiple sources of data and enable the implementation and standardization of a multifactorial assessment of the risk of falling. This would enable the creation of a meaningful scale that is able to differentiate those who are more likely to fall in one year after the assessment.

## Ethical Considerations

TBC

## Existing AI Solutions

TBC

### Existing work - Does the project start from scratch, or are there preliminary experiences?

There is previous work developed under the project [FallSensing](http://www.fallsensing.com) where Fraunhofer AICOS, Coimbra Health School and Sensing Future Technologies, have collected a dataset of 537 test subjects, to whom a multifactorial assessment of fall risk factors was applied following the [protocol](https://www.researchprotocols.org/2018/8/e10304/) described in [7].

After the assessment, 403 of the participants received monthly phone calls over a 12-month period to record the rate of falls in this period. The dataset is thus annotated with the rate of reported falls in the period of 12 months to record whether a fall occurred in this period. The dataset is thus annotated with the number and month of reported falls in the period of 12 months following the assessment. This annotation can be converted in a binary outcome, diving the dataset in fallers (subjects who fell at least once in the 12-month follow-up period), and non-fallers (remaining).

The screening includes questions about demographic and anthropometric data, health and lifestyle behaviours, a detailed explanation about procedures to accomplish 6 functional tests (grip strength, Timed Up and Go, 30 seconds sit to stand, step test, 4-Stage Balance test “modified,” and 10-meter walking speed), 3 questionnaires concerning environmental home hazards, and an activity and participation profile related to mobility and self-efficacy for exercise.

In addition to these state-of-the-art fall risk evaluation methods, some of the functional tests have been instrumented that has been integrated in some standard assessment tests, potentially adding value to the existing methods because it gives additional quantitative information and eliminates the bias introduced by observation [8]. However, since the use of sensors may not be widespread or feasible for most organizations, the inclusion of these data is still under evaluation.

## Existing work on benchmarking

TBC

### Feasibility - Is the project feasible, based on the current state of the art?

Preliminary data analysis shows promising results.

# AI4H Topic Group

TBC

# Method

## AI Inputs Data Structure

### Data Availability

 Is there sufficient data available? How much of it can be openly available? How much of it as part of the non-disclosed data set?

Regarding data availability, there are 403 data samples annotated. All of the data is currently an undisclosed data set. Only a small part of it can be made publicly available (1 ou 2%), however, since the data acquisition [protocol](https://www.researchprotocols.org/2018/8/e10304/) is published in an open access journal, it can be easily replicated by peers.

### Data Quality

Is the available data of high quality?

Data was acquired by health professionals trained to the effect in a prospective longitudinal study, following a convenience sampling method. All participants completed the whole assessment, unless they were not physically able to do so. The database is a *comma*-*separated values* file.

Shortcomings: Data was collected solely on the Portuguese population.

## AI Output Data Structure

1. **Annotation / Label Quality** - Are the annotations / labels of the data of high quality?

The health professionals called each participate every month for one year after the assessment in order to record the rate of falls. This procedure follows similar studies in the literature.

1. **Data Provenance** - Has the data been obtained in a professional and ethically correct way?

Ethical approval was obtained from the Research Ethics Committee of Polytechnic Institute of Coimbra (Nº6/2017). All participants gave written informed consent before data collection begins as per the Declaration of Helsinki.

## Test Data Labels

TBC

## Score and Metrics

TBC

## Undisclosed Test Data Set Collection

## Benchmarking Methodology and Architecture

### Benchmarking

Do the applicants have a clear proposal about what exactly should be evaluated / measured?

For the benchmarking task, participants should submit AI models to combine multiple fall risk factors assessed in community-dwelling adults aged over 50 years old and distinguish fallers from non-fallers, i.e. the subjects that suffered at least one fall in the year subsequent to the assessment from those who did not fall in that period. As possible metrics we are currently considering the Sensitivity, Specificity and area under the receiver operating characteristic curve (ROC AUC) applied to a binary classification problem (occurrence of at least one fall in subsequent year vs. non-occurrence of falls in that period). Other possible outcomes are the predicted time until the first fall (in months), or the probability of suffering a fall in a given period during the year after the assessment. The problem can also be formulated as multiclass classification, allowing to distinguish groups of first-time fallers after the assessment, recurrent fallers and non-fallers, for example.

### Organizers

Can the Focus Group work with the applicants, and do they have the time / resources to work with the Focus Group on the problem?

The topic driver is Inês Sousa, PhD in Biomedical Engineering, and Head of Intelligent Systems at Fraunhofer AICOS.

### Participants

Pierpaolo Palumbo, biomedical engineer, working on algorithms for health risk assessment, with a focus on fall risk in community-dwelling older adults and lower-limb amputees. He is a post-doctoral fellow at the Personal Health Systems Laboratory, headed by Prof. Lorenzo Chiari, at the University of Bologna.

### Next steps

The topic group would benefit from further expertise of the medical and AI communities and from additional data.

Disseminate the [Call for Topic Group Participation](https://www.itu.int/en/ITU-T/focusgroups/ai4h/Documents/tg/CfP-TG-Falls.pdf) among groups with similar research interest.

## Reporting Methodology

TBC

# Results

TBC

# Discussion

TBC

# Declaration of Conflict of Interest

TBC

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[8] Silva J, Sousa I. Instrumented timed up and go: Fall risk assessment based on inertial wearable sensors. 2016 Presented at: 2016 IEEE International Symposium on Medical Measurements and Applications (MeMeA); 15-18 May 2016; Benevento, Italy. [doi: 10.1109/MeMeA.2016.7533778]

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1. https://www.nice.org.uk/guidance/cg161/chapter/recommendations#multifactorial-assessment-or-multifactorial-falls-risk-assessment [↑](#footnote-ref-1)