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Predicting falls in community-dwelling older adults: a systematic review of prognostic models

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ABSTRACT

Objective To systematically review and critically appraise prognostic models for falls in community-dwelling older adults.

Eligibility criteria Prospective cohort studies with any follow-up period. Studies had to develop or validate multifactorial prognostic models for falls in community-dwelling older adults (60+ years). Models had to be applicable for screening in a general population setting.

Information source MEDLINE, EMBASE, CINAHL, The Cochrane Library, PsycINFO and Web of Science for studies published in English, Danish, Norwegian or Swedish until January 2020. Sources also included trial registries, clinical guidelines, reference lists of included papers, along with contacting clinical experts to locate published studies.

Data extraction and risk of bias Two authors performed all review stages independently. Data extraction followed the Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modelling Studies checklist. Risk of bias assessments on participants, predictors, outcomes and analysis methods followed Prediction study Risk Of Bias Assessment Tool.

Results After screening 11 789 studies, 30 were eligible for inclusion (n=86 369 participants). Median age of participants ranged from 67.5 to 83.0 years. Falls incidences varied from 5.9% to 59%. Included studies reported 69 developed and three validated prediction models. Most frequent falls predictors were prior falls, age, sex, measures of gait, balance and strength, along with vision and disability. The area under the curve was available for 40 (55.6%) models, ranging from 0.49 to 0.87. Validated models' The area under the curve ranged from 0.62 to 0.69. All models had a high risk of bias, mostly due to limitations in statistical methods, outcome assessments and restrictive eligibility criteria.

Conclusions An abundance of prognostic models on falls risk have been developed, but with a wide range in discriminatory performance. All models exhibited a high risk of bias rendering them unreliable for prediction in clinical practice. Future prognostic prediction models should comply with recent recommendations such as Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis.

PROSPERO registration number CRD42019124021.

Strengths and limitations of this study

- This systematic review is the first to summarise all prediction models on falls in community-dwelling older adults of the general population.
- The extensive search strategy supports identifying all available prospective cohort studies predicting falls in community-dwelling older adults (60+ years).
- Guidelines on prediction modelling reviews were strictly followed for search strings, data extraction (Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modelling Studies), risk of bias assessment (Prediction study Risk Of Bias Assessment Tool), along with development (Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA)-Protocol) and transparent reporting of the review (PRISMA).
- All review stages were performed independently and in duplicate.
- The exclusion of non-English language studies constitutes a risk of selection bias.

BACKGROUND

The propensity to fall is a serious and common health issue among older adults with one-third of community-dwelling adults ≥65 years and half of those ≥80 years falling annually.[1] Consequences of falls are considerable with loss of independence, increased morbidity and mortality.[2–4] Furthermore, the healthcare costs of falls increase substantially with age.[5] Therefore, as the prevalence of older fallers is predicted to increase with changes in demography, preventing falls is of utmost importance.[6]

Falls interventions have proven effective when aimed at older adults with a high risk of falling.[7] However, identifying these high-risk individuals is not straight-forward since falling is multifactorial. Prognostic models combine risk factors to estimate the individual's risk of a future outcome.[8] Thus, a prognostic model may be a valuable tool to discriminate between older adults at high versus low risk of falling. To prevent the consequences of falls, healthcare professionals could perform screening in the general population using prognostic models.[9] However, no systematic

review has addressed prognostic models on falls for community-dwelling older adults.

This systematic review aims to provide an updated overview of available models to be used by healthcare professionals and for researchers to improve on. The primary objective was to describe the discriminatory performance of prognostic models for falls in prospective cohort studies on community-dwelling older adults. Secondary objectives were to describe the study and model characteristics of these models.

METHODS

A protocol was preregistered before commencing the review process[10] and is available in data supplements (online supplemental appendix 1). The review and its protocol followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses statement (PRISMA)[11] and PRISMA-Protocols,[12] respectively. A completed PRISMA Checklist is available in data supplements (online supplemental appendix 2). During the review process, we found the protocol unclear in terms of eligibility criteria for the study designs, participants, models, outcomes and settings, for which reason we have further described these. Rationales for the changes are given in the protocol. Box 1 provides an introduction to commonly used prediction modelling terms.

Eligibility criteria

Participants and setting

All participants had to be community dwelling, 60 years of age or older, and be recruited from a general population setting. For that reason, we excluded models intended for hospitals, general practitioners and nursing homes. Studies restricted to participants with prespecified diseases, conditions or symptoms such as Parkinson's disease or stroke were excluded to raise external validity. However, we included studies that excluded certain types of community-dwelling older adults, such as those with known neurological, spinal or cognitive disorders.

Index (model)

Studies had to present a final multifactorial prognostic model defined by the inclusion of two prognostic factors or more. This definition was chosen as causes of falls are multifactorial and coexisting.[1] Thus, prognostic factor studies investigating the association between predictors and prospective falls were excluded. Both development studies and validation studies with and without model updating were included.

Outcome

We included studies defining falls as 'an unexpected event in which the participants come to rest on the ground, floor or lower level'.[13] However, studies without an outcome definition were also included since this would not rule out the definition mentioned above. We excluded studies using fall definitions excluding certain

Box 1 Commonly used prediction modelling terms with examples related to falls

Prognostic factor

A prognostic factor, also called a predictor, is any measure that, among people with a given health condition, is associated with a subsequent clinical outcome such as falls.[57]

Prognostic prediction model

A prognostic prediction model is a statistical combination of multiple predictors from which risks of a longitudinal outcome, for example, falls, can be calculated for individuals.[8]

Development and validation studies

A prediction model development study aims to develop a prediction model by combining essential predictors from a data set into a model and testing its predictive performance within the same development data set.[54] A model validation study aims to assess the predictive performance of a developed prediction model using new data not used in the development of the model.[54]

Model performance, overfitting and internal validation

A model's predictive performance is termed model performance. This term encompasses several measures with the two most important being discrimination and calibration.[17] Estimates of model performance derived directly from a data set used for developing the model is termed the apparent performance.[54] Since the model is fitted explicitly to the development data set, predictions on new data, that is, new older adults with different characteristics, may yield poorer model performance estimates, that is, poor generalisability. Hence, clinicians would typically find the apparent performance optimistic in terms of predicting a fall in their population which has not been used for developing the model. In consequence, fall preventive interventions could end up being provided to those not needing it and not offered to those actually in need hereof. The optimism in apparent performance is due to the model fitting too well to its data, a term known as overfitting. In such situations, predictions would be biased when the model is used on older adults with different characteristics, that is, frequency distributions of predictors.[17] Estimating the amount of optimism in the development study's model can be done using internal validation techniques such as bootstrap validation. However, since the population of older adults is heterogeneous, generalising a model's performance to the entire population would be more clinically relevant. Here, internal validation procedures fail, and the model should instead be tested in a validation study.

Model discrimination

Model discrimination is a performance measure referring to the models' ability to correctly predict if an individual will experience a fall or not. Therefore, as an example, it can be used by healthcare professionals to assess how confident a model assigns individuals to a high-risk group and guides the clinician when allocating fall preventive interventions.[58] A perfectly discriminating model assigns a higher risk of falling to all older adults experiencing a fall. Likewise, a lower risk is appointed to those not suffering a fall. Usually, discrimination is reported as a concordance index (c-index) or an area under the curve, but other measures are also available. Here, a value of 1 equals perfect discrimination, and 0.5 indicates that the model discriminates no better than chance. If a model shows poor discriminative performance, it could predict low-risk older adults to fall and high-risk older adults to not fall.

Model calibration

Model calibration is a performance measure used to examine whether a model over- or underestimates the predicted risks in a sample. More

Continued

Box 1 Continued

specifically, it is the agreement between predictions made by the model and the frequency of the outcome to be predicted.[54] Healthcare professionals can use this information to assess how confident the model predicts the specific risk of having a fall for the individual. In brief, it is crucial when counselling older adults on their fall risk that the risk estimate is as accurate as possible.[58] If the model predicts a person to have a 10% risk of falling within 1 year, the observed frequency of people falling with such a predicted risk should be 10 out of 100 for the model to have good calibration. However, should the frequency be only 5 of 100 people, the model overestimates the risk. Calibration is typically assessed graphically using calibration plots. In development studies, models are usually calibrated well to the data from which they are developed and therefore yield limited information.[4] Thus, it is more relevant how well the model is calibrated when introduced to a new sample of older adults used to validate the model. This information would enable healthcare professionals to evaluate whether the model over- or underestimates the risk of falling when used in their population of community-dwelling older adults. If the model is not correctly calibrated, it could predict low-risk older adults to have a higher risk and vice versa, or systematically overestimate or underestimate all predictions.

types of falls presumed to be due to a specific cause, for example, external forces or acute medical events. This approach was chosen since postfall classification methods may introduce recall bias.[14] Finally, we did not include studies predicting only injurious falls in older adults since risk factors for these are different from those experiencing non-injurious falls.[15] No restrictions were made on method or timing of outcome assessment other than it had to be prospectively recorded.

Study designs

We only included prospective cohort studies since this study design allows optimal control when measuring predictors and outcomes. Thus, it is the recommended study design for prognostic modelling studies.[16] We excluded randomised controlled trials since these can have different limitations incorporated within their design. Typically, strict eligibility criteria are used that generate a highly selected sample of participants. This narrows predictors' distribution and hence reduces the discriminatory performance in the prognostic models.[17] Also, strict criteria may compromise generalisability to the target population.[18] Lastly, interventions in the study may also influence the discriminatory performance of the models.[18] Retrospective cohort studies were also excluded due to issues of missing data and restrictions on which predictors to apply since data are already collected.[18]

Timing

No restrictions on follow-up or predictive horizon were made since we found it clinically relevant to include models both able to predict falls within short and long periods ahead in time.

Language and publication year

Due to the composition of the study group, we only included published studies reported in English, Danish, Norwegian or Swedish languages. No restrictions on publication year were made.

Information sources

We searched electronic databases, trial registries and clinical guidelines. Furthermore, we consulted with additional clinical experts. Lastly, we screened conference abstracts along with reference lists of both the included studies and systematic reviews found during the search. Databases included Pubmed.gov (PubMed interface), EMBASE (Embase.com), CINAHL (EBSCOhost interface), The Cochrane Library (Wiley interface), PsycINFO (APA PsycNET interface), and Web of Science (Web of Science Core Collection). All databases were searched from inception dates to the 3 January 2020. Trial registries included PROSPERO, ClinicalTrials.gov, WHO International Clinical Trials Registry Platform and Open Grey. Guidelines included Guidelines International Network, the National Institute for Health and Care Excellence, Centre for Reviews and Dissemination and to Health Technology Assessments and Scottish Intercollegiate Guidelines Network. Conference abstracts and studies in trial registries were used to obtain full-text papers through contact with authors. Letters to the editor were excluded.

Search

We used a validated search string for prediction models.[19] With the help of a research librarian in health science, we added the following terms to the search string: independent living, aged and accidental falls. Details on the search string are available online supplemental appendix 3. No search filters were applied. We included 'Aged' as a search term in the search string. Since this would restrict the number of search hits and thus the sensitivity of the search string, we pretested the search string without 'Aged' in all databases before commencing the review. From this, the first 3000 hits were screened independently and in duplicate, and we did not find studies not identified by the final search string. Thus, we believe this had a limited influence on the sensitivity of the search string.

Study selection

Duplicates were removed using EndNote (EndNote X9, Clarivate Analytics, Philadelphia, USA). Two reviewers independently screened titles and abstracts (GVG and JRi) and full-text papers (GVG and KT) according to the inclusion criteria. We contacted authors for clarification when information on this review's eligibility criteria was missing. Disagreement among reviewers was resolved by consensus for one study by including a third reviewer (MGJ). For screening of titles and abstracts along with full-text reading, we used Covidence (Covidence systematic review software, Veritas Health Innovation, Melbourne, Australia. Available at www.covidence.org). Exclusion of studies after full-text reading was performed using a

prioritised list of reasons (online supplemental appendix 4). Reviewers were not blinded to author names, institutions or journal titles.

Data collection process

We developed a standardised data collection form using Research Electronic Data Capture (REDCap),[20] a research electronic data capture software, following the Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modelling Studies checklist.[18] Data extraction was performed in duplicate and independently by two reviewers (GVG and JRi). Independence between reviewers was ensured using a double data entry module in REDCap, thereby denying access to each other's responses. Disagreements among the reviewers were discussed, and the third reviewer (MGJ) was not consulted during data collection since consensus was reached in all studies. We contacted all study authors for retrieval of information on data items not reported. None of the included studies were published more than once.

Data items

We extracted data on the following items: country, publication year, authors, inclusion criteria, exclusion criteria, age, outcome definition, number of falls and fallers, candidate predictors, missing data, choice of statistical analysis, C-statistic and area under the curve (AUC), internal and external validation procedures, final model presentation and sources of funding. If available, 51 data items were extracted from each paper as detailed in online supplemental appendix 5.

Risk of bias and reporting transparency

To follow current recommendations,[21] the Prediction study Risk Of Bias Assessment Tool[22] was used for the risk of bias assessment in individual studies. The tool comprises 20 signalling questions in four domains: participants, predictors, outcomes, and analysis. The tool also includes an evaluation of each model's applicability for the intended population, predictors and outcome of the review. Reporting transparency was assessed using the Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis, TRIPOD) adherence assessment form.[23] The bias, applicability and reporting assessments were performed in duplicate and independently by two reviewers (GVG and JRi). Independence between reviewers was ensured using a double data entry module in REDCap, thereby denying access to each other's responses. Disagreements among the reviewers were discussed, and consensus was reached for all studies. Thus, a third reviewer was not consulted for a final decision. The reviewers were not blinded to study authors, institutions or journal titles. The results of the risk of bias assessments of all included studies were incorporated into the qualitative synthesis. We sought to investigate outcome reporting bias by comparing the study papers to their pertaining protocols to examine whether outcomes were prespecified and not differing from the published paper.

Summary measures and planned method of analysis

The principal summary measure of this systematic review was the discriminatory performance measured either in a C-index or AUC. In the prespecified protocol, we decided not to perform meta-analyses due to the presumed heterogeneity of the prognostic models. This assumption was confirmed after the review was complete. Furthermore, we summarised the study and model characteristics using ranges and percentage proportions when appropriate. When data were available, we summarised continuous measures using medians and IQRs.

Patient public involvement

We did not involve patients or the public in the research.

RESULTS

Study selection

The search yielded 19 612 publications with 11 789 remaining after removal of duplicates. Screening titles and abstracts led to the exclusion of 11 611 publications leaving 178 for full-text reading. Of these, 148 were excluded due to: wrong outcome (n=45), wrong study design (n=45), not being a prediction model (n=25), no full-text paper published (n=14), wrong population (n=8), not multifactorial (n=8) or wrong setting (n=3). Thirty studies met the eligibility criteria and were included.[24–53] Figure 1 displays the PRISMA flow diagram

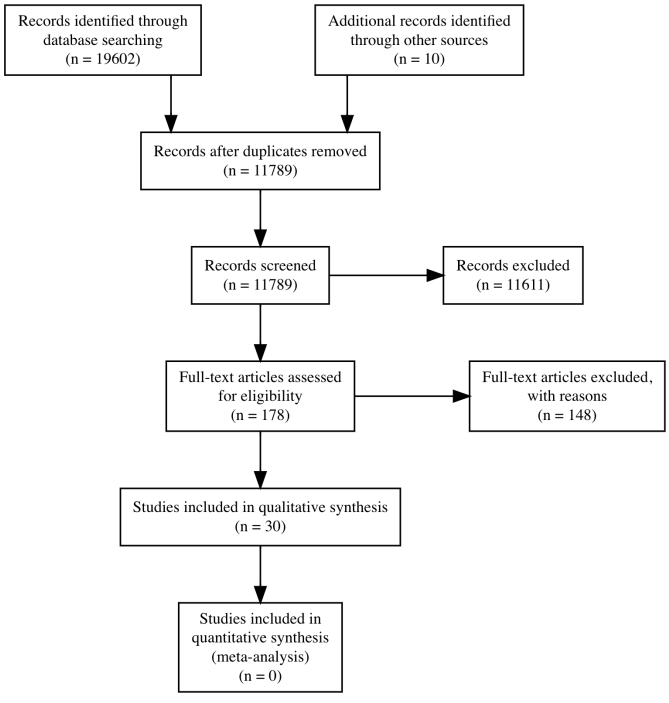

Figure 1 PRISMA diagram of the study selection process. PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses.

for the study selection. Details on excluded papers can be found as online supplemental appendices 6–8.

Characteristics of included studies

A summary of included studies along with models' performance can be found in online supplemental table 1 (online supplemental appendix 9). All studies were published in English from 1994 to 2019. Seventy-two prognostic models were reported, of which 69 models were developed, and three were validated.

Participants

Studies were conducted in Australia, Belgium, Canada, France, Germany, Israel, Italy, Japan, the Netherlands, Malaysia, Spain, the UK and the USA. Sample sizes ranged from 65 to 23 417 participants with median ages from 67.5 to 83 years. Studies used primarily a probability sampling method (n=16), followed by convenience sampling (n=8) and consecutive sampling (n=2). Four studies did not report their sampling methods.

Index/model

The median (IQR) number of predictors in the final models were five (3–9) and ranged from two to 96 predictors. Figure 2 shows the number of studies including a specific predictor. The most frequently applied predictors were prior falls, age, sex, measures of gait, balance and strength, along with vision and disability. Predictors were measured in homes (n=19), research centres (n=19), or both (n=12). Locations for measuring predictors were not reported for 22 models.

Outcomes and timing

The percentage of fallers ranged from 5.9% to 59%, and the number of recurrent fallers (≥2 falls) ranged from 6.3%–54.1%. Models primarily predicted any falls (n=34), that is, single and recurrent falls, and recurrent falls only (n=34). Two models predicted first-time falls[31 45] and two predicted time to a fall.[34 46] Participants were followed for a median (IQR) time of 12 (9.75–12) months. Individual study data items extracted are available in online supplemental appendix 10.

Model performance

Discriminatory measures were reported for 40 (55.6%) models. AUCs were 0.49–0.87 and 0.62–0.69 for developed (n=37) and validated (n=3) models, respectively. Corresponding CIs were reported for 27 (37.5%) models. Calibration measures were available for seven (9.7%) models. For validated models (n=1), calibration was imperfect due to over- and underestimated predicted risks of falling for high-risk and low-risk participants, respectively.[39] Regarding developed models (n=6), calibration was found acceptable, but studies did not assess model calibration in new participants.[41 44 47 49]

Risk of bias, reporting transparency and applicability within studies

Risk of bias

Table 1 summarises ratings on risk of bias, applicability and reporting transparency for the individual studies. All

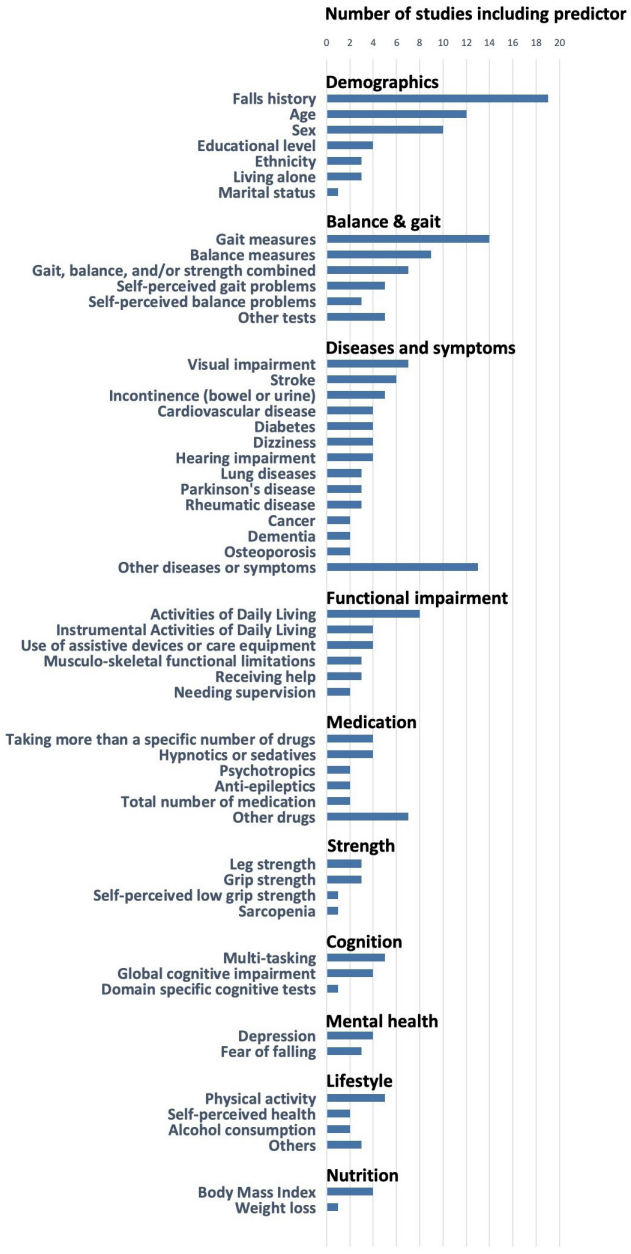

Figure 2 Number of studies using a specific predictor.

studies had a high risk of bias mainly due to methods of analysis and outcome assessment along with restrictive eligibility criteria. Regarding analysis methods, missing data were excluded in 13 out of 30 studies, and no internal validation methods were applied. As to the outcome, only four studies recorded falls daily with monthly notifications.[25 27 32 35] Also, the majority of studies did not report the outcome definition used or whether outcomes assessors were blinded. Eligibility criteria were found restrictive for the majority of studies due to the exclusion of individuals with falls-risk-increasing conditions. These selective criteria limit the usability of models for the target population of community-dwellers. Overall, risk of bias and applicability assessments were complicated by studies only reporting, on average, 50% of all items recommended in reporting guidelines. Furthermore, this

Table 1 Reporting, risk of bias and applicability ratings of individual studies

	Reporting	Risk of bias				Applicability			Overall	
Study	TRIPOD, %	Participants	Predictors	Outcome	Analysis	Participants	Predictors	Outcome	ROB	Applicability
Yamashita *et al*[28]	34	–	+	–	–	–	+	?	–	–
Weiss *et al*[32]	36	+	+	–	–	–	+	+	–	–
Muhaidat *et al*[35]	36	+	+	?	–	+	+	?	–	?
Brauer *et al*[25]	37	–	+	?	–	–	–	+	–	–
Panzer *et al*[30]	37	–	+	–	–	–	+	?	–	?
Maki *et al*[24]	41	+	+	–	–	+	+	+	–	+
Boulgarides *et al*[52]	41	+	+	?	–	+	+	?	–	?
Viccaro *et al*[31]	41	+	+	–	–	?	+	+	–	?
Lindemann *et al*[51]	44	–	+	–	–	–	+	+	–	–
Singh *et al*[44]	44	–	+	?	–	–	+	+	–	–
Nandy *et al*[53]	45	+	+	–	–	?	+	?	–	?
Okochi *et al*[50]	45	+	+	–	–	?	+	+	–	?
Rodriguez-Molinero *et al*[41]	46	–	+	–	–	+	+	+	–	+
Gadkaree *et al*[37]	48	+	+	–	–	+	+	+	–	+
de Vries *et al*[34]	50	+	+	–	–	+	+	+	–	+
Hnizdo *et al*[33]	52	+	+	?	–	–	+	+	–	–
Lohman *et al*[42]	52	+	+	–	–	+	+	–	–	–
Gillain *et al*[45]	54	–	+	–	–	–	–	+	–	–
Delbaere *et al*[27]	55	+	+	–	–	+	+	–	–	–
Cawthon *et al*[38]	56	+	+	–	–	–	+	+	–	–
Kim *et al*[43]	56	–	+	–	–	–	+	?	–	–
Tromp *et al*[36]	57	+	+	–	–	+	+	+	–	+
Stel *et al*[48]	57	+	+	–	–	+	+	+	–	+
Lamb *et al*[26]	61	+	+	–	–	–	+	?	–	–
Yamashita *et al*[29]	61	+	+	–	–	+	+	–	–	–
Stalenhoef *et al*[47]	62	?	+	–	–	–	+	+	–	–
Palumbo *et al*[40]	68	+	+	–	–	?	+	?	–	?
Bongue *et al*[46]	70	–	+	?	–	–	+	+	–	–
Palumbo *et al*[39]	73	+	+	–	–	+	+	?	–	?
Pluijm *et al*[49]	76	+	+	–	–	+	+	+	–	+

Note: + and green colour indicates low risk of bias /low concern regarding applicability; – and red colour indicates high risk of bias/high concern regarding applicability; ? and blue colour indicates unclear risk of bias/unclear concern regarding applicability; Bright colours pertain to the PROBAST domains, and dark colours pertain to the overall PROBAST assessments; ROB indicates risk of bias; TRIPOD indicates the percentage proportion of reported items recommended in reporting guidelines.
ROB, risk of bias; TRIPOD, Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis.

was complicated by a low response rate with four out of 30 study authors responding when contacted for clarification on study characteristics and data extraction items. Finally, outcome reporting bias assessments were not possible due to studies not referring to a preregistered protocol for their prognostic modelling study.

Applicability

Seven (23%) studies, with a total of 21 models, had low applicability concerns for the review question. Regarding participants, 17 (56.7%) studies were rated as having high or unclear applicability concerns for the review question. This concern was primarily due to restrictive eligibility criteria impeding generalisation to the general population of community dwellers. Restrictions were made by excluding participants with specific diseases or conditions that could increase the risk of falling, such as disability or impaired mobility. Furthermore, studies rated as having unclear applicability concerns did not sufficiently report whether the participants were community-dwellers or whether the setting was the general population rather than, for example, primary or secondary care. Regarding predictors, 28 (93.3%) studies had no concerns. The remaining two studies used specific laboratory measures which may be challenging to apply in a general population setting.[25 45] Regarding applicability concerns for the outcome, 18 (60%) studies had no concerns since they reported using the falls definition of the review or similar.

DISCUSSION

The current systematic review found 72 prognostic models on falls risk with the area under the curve ranging from 0.49 to 0.87. All models had a high risk of bias mostly due to limitations in statistical methods and outcome assessments, combined with restrictive eligibility criteria. Thus, using the models in clinical practice would entail unreliable predictions. This review provides an extensive overview of prediction models for falls and information for future study methodology.

Strengths

The current review followed guidelines on prediction modelling reviews strictly for search strings,[19] data extraction,[18] risk of bias assessment,[22] along with development[12 18] and transparent reporting of the review.[11]

Limitations

Review level

We excluded potentially eligible studies without full text (n=14) or published in other languages (n=7) during screening of titles and abstracts. These studies are listed in the data supplement. Furthermore, we excluded randomised controlled trials and retrospective cohort studies. Consequently, we were only able to include 0.25% (30/11 789) of studies screened even though other models, based on other study designs, may had been available. As prespecified in the study protocol, this exclusion criterion was chosen due to limitations with generalisability and missing data when developing or validating prediction models using these designs. Thus, this systematic review only provides an overview of models based on a specific study design, but we consider this exclusion of the other studies to be justified.

Study level

Limitations were found in the studies with a high risk of bias, poor quality of reporting, and finally, a low response rate when contacting authors for retrieval of missing data extraction items.

Risk of bias

We found a high risk of bias within all studies. Hence, the predictive performance may be low, and predictions unreliable when models are used in clinical practice. The bias ratings were primarily based on eligibility criteria, methods of outcome assessments, and statistical analysis. Building prediction models on selected subgroups of the target population can yield biased performance estimates when used in clinical practice on a different population.[17] Thus, study eligibility criteria should be aligned with the research questions, that is, broad and with as few exclusion criteria as possible. In terms of outcome assessments, we found the definition of falls missing for one-third of studies along with varying falls recording methods. These findings are similar to results of a previous review on methodology in falls prevention trials, where only half of the studies provided a falls definition and recording methods varied highly.[14] The problem with not defining a fall is that the notion of falls is taken for granted. As seen in our review, the prevalence of falls differed markedly between studies, which could be due to different understandings of the fall's definition. Consequently, falls become harder to predict[17] while at the same time, comparing and combining studies in systematic reviews with meta-analyses becomes complicated. To address these issues, a common outcome data set on falls trials is available along with a falls definition and recommendations for falls recording methods.[13] Finally, statistical analysis methods raised concerns for risk of bias. Primarily, this was due to the handling of missing data with most of the studies applying a complete-case analysis method. Significant limitations can arise from the exclusion of participants due to missing data, for example, on a single predictor among many, since otherwise useful predictors on each participant are lost. Consequently, this can lead to low sample sizes and biased model performances. In such cases, imputation methods have proved useful when dealing with missing data.[17] Furthermore, for the majority of developed models, no internal validation procedures were applied. This shortcoming typically causes models' predictive performance to be optimistic.[54] Finally, the critical appraisal was compromised due to incomplete reporting. We believe that future studies and systematic reviews would benefit from adhering to reporting guidelines for prediction modelling studies.[16]

Implications for clinical practice

Only seven studies could address the review question appropriately, and all of these had a high risk of bias. Consequently, the evidence available to inform healthcare professionals is limited and, as mentioned, possibly biased. Thus, no model can currently be recommended for clinical practice.

Implications for research

We recognise that most studies (n=23/30) were conducted before the publishing of prediction modelling guidelines.[16 22] Thus, with the benefit of hindsight, studies would be expected to have different shortcomings within their methods and reporting. On the other hand, this also supports the reason for publishing guidelines in the first place. Despite this, the included studies provide valuable information on future candidate predictors. Thus, selecting predictors for prediction models on non-statistical grounds, that is, based on literature and clinical knowledge, is commonly used to avoid predictor selection bias.[55] Therefore, future development studies may include the most frequently applied predictors found in this review. Lastly, it is essential to test the generalisability of developed models by performing validation studies to determine which models provide stable predictions across different populations.[56]

CONCLUSIONS

There are several studies on falls prognostic models intended for a general population setting, but only a few are fully applicable to the heterogeneous population of community-dwelling older adults. Thus, the evidence available to address this is limited. From all included studies, we found an abundance of falls prognostic models available. However, the discriminatory performance of these varied and was only reported for half of the models. Each model had concerns regarding risk of bias mainly due to restrictive eligibility criteria along with methods of statistical analysis and outcome assessments. Consequently, this could give rise to unreliable predictions should the models be used in clinical practice. Future prognostic prediction models should comply with TRIPOD.

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Contributors GVG is the guarantor. GVG drafted the manuscript for the protocol and performed preliminary searches and search strategy. GVG, JRy, MGJ, TM, KT and SA developed selection criteria. JRi assisted GVG in screening titles, abstracts and reference lists of papers included after full text reading along with data extraction, assessing risk of bias, presence of meta-bias along with adherence to reporting guidelines. KT assisted GVG in full-text reading, and MGJ was arbitrator if agreement could not be reached between reviewers. GVG drafted the manuscript for the paper, while MGJ, JRy, SA, TM, JRi and KT assisted in the interpretation of results, read, provided feedback and approved the final manuscript of the paper. The corresponding author attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.

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Disclaimer The study did not involve participants for whom the study results can be disseminated. The authors intend to distribute the results of the study by engaging with local healthcare providers for the general population setting during 2020 and 2021, along with social media to reach a broader audience.

Competing interests None declared.

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Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement All data relevant to the study are included in the article or uploaded as online supplemental information. The study protocol is available online at https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=124021. All information extracted for the included studies in the review is available as a data supplement.

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Supplemental material

Table of contents

Appendix 1: protocol for systematic review

Administrative information

Title:

Systematic review of prognostic models for predicting falls in community-dwelling older adults

Registration:

This protocol was registered with the International Prospective Register of Systematic Reviews (PROSPERO) on (1st February 2019).

Registration number: CRD42019124021

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Contributions:
GS is the guarantor. GS drafted the manuscript for the protocol and performed preliminary searches and search strategy. GS, JR, MGJ and SA developed selection criteria. JRI will assist GS in screening titles, abstracts and reference lists of papers included after full-text reading along with data extraction, assessing risk of bias, presence of meta-bias along with adherence to reporting guidelines. KT will assist GS in full-text reading. MGJ will be arbitrator if agreement cannot be reached between reviewers. GS will draft the manuscript for the paper. MGJ, JRY, SA, TM, JRI and KT will assist in interpretation of results, read, provide feedback and approve the final manuscript of the paper.

Amendments:
In the event of protocol amendments, this section will describe the date, changes and rationale of each amendment. Changes will be incorporated into the protocol sections. All authors will be responsible for approving the amendments. Also, GS will be responsible for documentation and implementation of these.
Current version of the protocol: 3.

- 7th of August 2019
    - **Change #1:**
        - Setting:

- We further specified which setting the review is, and is not, intended for. We changed the wording "community setting" to "general population setting". Also, we specified that prediction models intended for a primary care would also be excluded.

  - Rationale:
    - Change in wording: To apply the same terminology of the CHARMS checklist.
    - Primary care exclusion: To increase transparency and homogeneity in settings.

- **Change #2:**
  - Risk of bias:
    - As a supplement to the risk of bias assessments, the newly published TRIPOD adherence tool will be used.
  - Rationale
    - To assess adherence to reporting guidelines for prediction modelling studies.

- 17th of June 2019
  - **Change #1**
    - Study design:
      - We further specified which study designs would not be included. Thus, randomised controlled trials and retrospective cohort studies will not be included.
    - Rationale:
      - To increase transparency.
  - **Change #2:**
    - Participants: Age
      - We further specified the inclusion criterium regarding age. Thus, studies with total age ranges extending below 60 years will be excluded. Exclusion will also be made if mean age subtracted by two standard deviations extends below 60 years of age unless inclusion criterium in studies specifically states a lower age limit of 60 years or above.

- Rationale:
  - To increase transparency.

- **Change #3:**
  - Participants: Community-dwelling
    - We further specified which studies would be included. Thus, we will include studies excluding certain types of community-dwelling individuals, e.g. with known neurological, spinal or cognitive disorders.
  - Rationale:
    - These samples may also contribute with relevant information about the target population.
- **Change #4:**
  - Index (Model):
    - We further specified which studies to include based on the model presented. Thus, we will also include studies with:
      - Two or more prognostic factors combined into a scale giving an individual score used to assess the predictive performance on future falls.
      - Two or more prognostic factors included in a test instrument from which a prediction model would be generated.
  - Rationale:
    - To increase transparency.
- **Change #5:**
  - Outcome (and rationale):
    - We further specified which studies to include based on the outcome. Thus, studies without an outcome definition will also be included since this will not rule out the outcome definition of this review. We will exclude studies using falls definitions excluding certain types of falls presumed to be due to a specific cause e.g. acute medical events or external forces. This post fall classification method may introduce assessor-bias.

Gade GV, *et al. BMJ Open* 2021; 11:e044170. doi: 10.1136/bmjopen-2020-044170

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Introduction:

Rationale of the review

Falling over in community-dwelling older adults is a frequent problem with an annual prevalence of 30 % in 65+ year olds and 50 % in 80+ year olds.[1] Total number of falls are expected to increase significantly in the future due to the ageing population.[2,3] For instance, in 2017, the global population of 65+ year olds was estimated to be 962 million and is estimated to increase towards 1.4 and 2.1 billion in 2030 and 2050 respectively.[2] This frequent and escalating problem of fall accidents is a major concern globally due to their associations with elevated morbidity, mortality, poorer physical functioning and early admission to long-term care facilities which leads to elevated financial costs to society[4–6].

Fall prevention is therefore highly relevant to society, next of kin and to the individual. Unfortunately, more than 400 risk factors for falling have been identified thereby making it a complex area/problem.[7] In addition, the risk factors spread across different domains including socio-demographics, the environment, medical conditions and medications, physical performance, psychology and cognition[8]. In consequence, secondary multifactorial fall risk prevention has been recommended[3,9]. On the other hand, if individuals at high risk of falling could be identified before their first fall, primary preventive interventions could be instituted, which would be even more beneficial. Therefore, individual assessments of fall risk using multifactorial prognostic prediction models are imperative. Few reviews on the ability of prognostic prediction model studies to discriminate fallers from non-fallers in community-dwelling older adults exist[10–12]. However, in these reviews, methodologies were varied with no review protocols being reported[10–12], outcome definitions not following the current consensus definition[10–13], and search strategies being restricted[10,12] or based on search filters for diagnostic studies[11,12]. Also, risk-of-bias assessments were done using tools designed for diagnostic studies[11,12] and reporting of data extraction items and -methods were inconsistent[10,12].

Nonetheless, in recent years, prognostic research methods have evolved. Thus, new guidelines have been published to encourage researchers to transparently report prediction modelling studies[14], systematic reviews[15] and their respective protocols[16]. Also, within the field of prediction modelling reviews, literature search strategies[17] along with guidance papers on data extraction items[18] and risk

of bias tools[19] have been developed. However, no reviews on fall prediction studies have applied the abovementioned guidelines as yet.

The scope of this review is to provide a systematic update on current model performance, and other characteristics, on developmental and validation studies within the field of fall accidents on multifactorial prognostic prediction models in community-dwelling older adults.

Objective:

The aim of this systematic review is to describe model performance along with other model characteristics (predictors along with methods of model development, -evaluation and -presentation) of existing multifactorial prognostic prediction models on falls in 60+ year old non-institutionalised, community-dwelling older adults.

Methods:

This protocol follows the guidelines of the Preferred Reporting Items for Systematic reviews and Meta-analyses Protocols (PRISMA-P)[16]. The protocol is registered in the PROSPERO database.

Eligibility Criteria

The following criteria outlined below will be used to select studies for the review.

Study designs:

We will only include prospective cohort studies since this is the preferred design for prognostic prediction modelling studies[14]. We will include both developmental and validation studies with and without model updating. Randomised controlled trials will not be included since these tend to have narrow predictor distributions resulting in poor discriminatory performance. This may also be influenced by treatment effects in the design[18]. Furthermore, generalisation to the target population may be compromised due to strict eligibility criteria[20]. Retrospective cohort studies will be excluded since the predictive performance may be substantially limited by missing data, and only predictors available in the data set collected can be applied[18].

Participants:

Only studies with all participants aged 60 years or older will be included. This cut-off was chosen in order to encompass studies using different age cut-offs for being an older adult. Thus, studies with total age ranges extending below 60 years will be excluded. Also, mean age subtracted by 2 standard deviations must not extend below 60 years unless inclusion criteria specifically stated a lower age limit of 60 years or above.

Participants should be community-dwelling and not institutionalised, i.e. living independently and not in nursing homes or short term-care where the risk of falling is substantially different from

the general population[21]. Studies restricted to participants with pre-specified diseases, conditions or symptoms such as Parkinsonism or stroke will be excluded so that generalisation to the overall community population is not compromised. We will include studies excluding certain types of community-dwelling individuals, e.g. with known neurological, spinal or cognitive disorders since these samples may contribute with relevant information about the target population of the review.

Index (Model):

Multifactorial prognostic prediction models, i.e. including 2 prognostic factors or more due the multifactorial aetiology of falls[3,22]. Thus, explanatory studies investigating the association between a predictor and prospective falls were excluded. To broaden the search, we will include the following studies with:

- Two or more prognostic factors measuring on the same domain will be included.
- Two or more prognostic factors combined into a scale giving an individual score used to assess the predictive performance on future falls.
- Two or more prognostic factors included in a test instrument from which a prediction model would be generated.

Comparator:

None.

Outcome:

Primary outcome in the included prospective cohort studies will be falls defined by "an unexpected event in which the participants come to rest on the ground, floor, or lower level".[13] Both single and recurrent falls, i.e. >1 fall, will be included. Studies without an outcome definition were also included since this would not rule out the abovementioned definition. We excluded studies using falls definitions excluding certain types of falls presumed to be due to a specific cause e.g. acute medical events or external forces. This post fall classification method may introduce bias in the outcome assessment due to the subjective judgements involved[23].

Timing:

No restrictions on follow-up on falls will be made.

Setting:

The models should be used to screen for risk of prospective falls in a general population setting, and we will exclude models intended for primary care, hospitals and nursing homes.

Language:

Only studies reported in an English, Danish, Norwegian or Swedish language will be included. This was chosen due to resource limitations. However, a list of possibly relevant studies in other languages found during the literature search will be included in an appendix.

Publication year:

No restrictions on publication year will be made.

Information sources

Studies will be collected from the following databases: Pubmed.gov (PubMed interface, inception date to date of search), EMBASE (Embase.com, inception date to date of search), CINAHL (EBSCOhost interface, inception date to date of search), The Cochrane Library (Wiley interface, inception date to date of search), PsycINFO (APA PsycNET interface, inception date to date of search) and Web of Science (Web of Science Core Collection, inception date to date of search). Both controlled terms (i.e. MeSH or EMTREE terms) and simple phrase terms will be used to search the databases when appropriate. Also, hand searches from the reference lists of the included studies will be performed. Conference abstracts found during the literature search will only be used for obtaining their respective full-text articles. If not found elsewhere, we will try to contact the respective authors for this. If the full-text articles are not obtainable, the study will be excluded. However, a list of these possibly relevant studies found during the literature search will be included in an appendix. Primary literature within prior systematic reviews on fall prediction models found during the literature search will be screened. Finally, two experts in the field of falls research will be consulted to enquire for knowledge on additional studies fulfilling the eligibility criteria of this systematic review.

Grey literature

PROSPERO will be searched for completed reviews with this focus. Also, Clinicaltrials.gov, WHO International Clinical Trials Registry Platform, Open Grey, GIN, NICE, CRD/HTA, SIGN will be searched for relevant studies using key-terms from the main search (falling AND elderly OR Older adults). If not found elsewhere, we will try to contact authors of these relevant studies for retrieving of the full-text.

Search strategy

The search strategy follows current Cochrane recommendations for systematic reviews on prediction models[17,24]. Also, to accommodate the search strategy to our eligibility criteria, the search string was further developed by GS in collaboration with a Health Sciences Librarian at the Medical Library of Aalborg University Hospital, Denmark. The search strategies of the selected databases are included in Appendix 1. The final search strategy will be approved by a second reviewer (KT).

Study records:

Data management:

Duplicates will be removed using EndNote (EndNote X9, Clarivate Analytics, Philadelphia, USA). The results of the literature search will be uploaded to Covidence (Covidence systematic review software, Veritas Health Innovation, Melbourne, Australia. Available at www.covidence.org) to ease the collaboration between reviewers on titles and abstracts screening along with full-text reading. Risk of bias assessments and extraction of data will be performed using a standardised form in REDCap using a double data-entry module[25]. If several articles report results from the same trial, the "primary publication" will be prioritized; i.e. typically defined as the first full-text publication reporting on the primary outcome.

Selection process:

Screening titles and abstracts:

Two reviewers (GS and JRI) will independently screen titles and abstracts from the inclusion criteria. The screening process of titles and abstracts will undergo pilot testing. Reviewers (GS and JRI) will meet and discuss the inclusion of the first 50 articles found by the search strategy during screening of titles and abstracts. If agreement cannot be reached, a third author (MGJ) will be consulted for arbitration. If needed afterwards, refinement of inclusion criteria will be performed.

Full-text reading

Full-text reports will be obtained on eligible studies, and studies where uncertainty exists regarding eligibility based on titles and abstracts. GS and KT will independently screen the full-text reports for a final decision on eligibility. Disagreement among the reviewers will be discussed. If agreement cannot be reached, a third author (MGJ) will be consulted for arbitration. Reasons for excluding studies after full-text reading will be provided.

Data collection process:

Two reviewers (GS and JRI) will independently extract data from a pre-specified form (see Data items) in REDCap from each study found eligible for inclusion after full-text reading. If data reporting is incomplete, we will try to contact authors of the relevant studies to obtain data. A maximum of two attempts will be done to contact the authors by e-mail. If e-mails are not responded within 1 month from the first e-mail sent, the data field will be labelled as having no information. If the authors do not gain access to data, these will be extracted from figures and graphs if possible. If companion studies (multiple reports of the same study) with the same outcome of falls is found, data will be

extracted from the primary publication of the study. Disagreement among the reviewers will be discussed. If agreement cannot be reached, a third author (MGJ) will be consulted for arbitration. The total number of times arbitration by a third author was required will be given.

Data items:

Data extraction will comply with Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modelling Studies (CHARMS) guidelines.[18] The following data will be extracted if possible:

- General study information:
    - Authors.
    - Year of publication.
    - Study design.
    - Type of prediction modelling study:
        - Developmental without external validation.
        - Developmental with external validation.
        - External model validation without model updating.
        - External model validation with model updating.
        - Others
    - Country of origin.
    - Setting where candidate predictors were measured.
    - Number of study centres.
    - Inclusion criteria.
    - Exclusion criteria.
    - Sample size.
    - Methods for participant recruitment/sampling:
        - Consecutive sampling.
        - Convenience sampling.
        - Probability sampling.
        - Others
    - Dates of participant recruitment.
    - Duration of follow-up.
    - How many participants completed follow-up percentage-wise?
- Participants:

  - Gender.
  - Age.
  - Fall history.
- Outcome:
  - Outcome definition.
    - Was it pre-specified?
  - Type of fall recording/method of outcome measurement.
  - Was the same outcome definition and recording method used in all participants (Yes/No/Not Available)?
  - Was the outcome assessor blinded towards predictors (Yes/No/Not Available)?
  - Number of falls.
  - Number of fallers.
  - Number of non-fallers.
  - Number of frequent fallers.
  - Fall-rate per person per year.
  - Summary of follow-up period.
- Candidate predictors:
  - Number of candidate predictors studied.
  - Definitions of candidate predictors.
  - Methods for measuring candidate predictors.
  - Number of outcomes (falls) in relation to number of candidate predictors (events per variable (EPV)).
- Missing data:
  - Number of participants with missing data (both predictors and outcomes) in total.
  - Did participants with missing data differ from those without missing data (Yes/No/Not Available)?
  - Number of participants with missing data in total for each predictor
  - Method of handling missing data.
    - Single imputation
    - Multiple imputation
    - Participants with missing data were excluded from the analysis (complete case analysis)

        - Others (comment).
    - Were participants with missing data included in the model development, validation or updating (Yes/No/Not Available)?
- Model development (not relevant if the prediction modelling study does not include model development):
    - Type of model:
        - Linear regression
        - Logistic regression.
        - Survival analysis.
        - Others (comment).
    - Were assumptions for the model checked (Yes/No/Not available)?
    - Were assumptions for the model satisfied (Yes/No/Not available)?
    - Predictor selection methods for inclusion into the multivariable analysis:
        - All predictors were predetermined to be included in the analysis
        - Predictors were selected for inclusion based on univariate associations with the outcome
        - Others
    - Did any statistical transformation of candidate predictors occur (i.e. dichotomising a continuous or categorical variable) prior to inclusion in the multivariate modelling process (Yes/No/Not Available)?
        - If YES, what transformation procedure was applied?
    - Predictor selection methods during the multivariable modelling:
        - Full model approach (all predictors were predefined for the final model and no predictors were omitted).
        - Forward selection (candidate predictors were selected based on pre-specified criteria).
            - If forward selection was applied, which criteria/significance level were used?
                - P-value
                - Akaike's Information Criteria
                - R^2
                - Others

        - Backward elimination (all candidate predictors started in the model and were removed or kept based on a pre-specified criterion)
            - If backward elimination was applied, which criteria/ significance level were used?
                - P-value
                - Akaike's Information Criteria
                - R^2
                - Others
    - Were shrinkage techniques applied (Yes/No/Not available)?
        - If YES, which procedure was applied?
- Model performance:
    - Overall measures of model performance
        - R^2
        - Brier Score
    - Discrimination:
        - Area Under Curve/*c*-statistic
        - D-statistic
        - Others
    - Calibration:
        - Calibration plot
        - Calibration intercept and slope
        - Calibration table
        - Hosmer-Lemeshow test
        - Observed:Expected Ratio
        - Others.
    - Classification:
        - Sensitivity
        - Specificity
        - Positive Predictive Value
        - Negative Predictive Value
        - Net reclassification index
        - Others

        - Was the cut-point:
            - Predefined/made a priori?
            - Derived from the dataset?
- Model evaluation:
        - **External validation:** Were the model performance measures based on separate external data (Y/N/NA)?
            - If YES, how was the dataset different from the developmental dataset:
                - Temporal/differed in time
                - Different geographical location
                - Different setting
                - Different investigator
                - Others
        - **Internal validation:** Were the model performance measures based on the developmental dataset (Y/N/NA)?
            - Which approach was chosen to evaluate model performance?
                - Split-sample validation
                    - What was the percentage-wise allocation of participants?
                    - Was the split random to model development and validation(Y/N/NA)?
                - Cross-validation
                    - How many subsets were chosen?
                - Bootstrap validation
                - Jack-knife resampling
                - Others
                - None
- Model presentation:
    - What format did the study present their model in to permit calculations of individual risks?
        - Regression formula (comment)
        - Rounded scoring rules (comment)
        - Predefined risk groups (comment)

        - Were the risk-groups:
            - Predefined/made a priori?
            - Derived from the dataset?
    - Nomogram
    - Score chart
    - Others
    - None
- Sources of funding in the individual study.

Outcomes and prioritisation

Main outcomes:

The main outcome of this systematic review is to describe model performance. Secondary outcomes are to describe the following characteristics: Study setup, participants, final model predictors, outcomes together with model development, -evaluation and -presentation.

Risk of bias

The Prediction study Risk Of Bias Assessment Tool (PROBAST)[19] will be applied for risk of bias assessment. Two reviewers (GS and JRI both with no prior experience in risk of bias assessments) will independently assess for risk of bias. These will not be blinded to study titles or authors. If reporting is incomplete in order to make a complete assessment, we will try to contact authors of the concerned study. A maximum of two attempts will be done to contact the authors by e-mail. If e-mails are not responded within 1 month from the first e-mail sent, the data field will be labelled as "Unclear". Disagreement among the reviewers will be discussed. If agreement still is not reached, a third author (MGJ) will be consulted for arbitration. The total number of times arbitration by a third author was required will be given. Each domain rating will be reported instead of a summative score of all domains. Previously, one review on fall prediction models assessed reporting in included studies to be poor[12]. However, no standardised method of evaluating reporting in studies was reported. Thus, as a supplement to the risk of bias assessments, the newly published TRIPOD adherence tool[26] will be used to assess adherence to reporting guidelines for prediction modelling studies.

Data synthesis

Meta-analysis will not be considered due to this systematic review merely being descriptive. In the qualitative synthesis, information will be presented in text, figures, and tables of the included studies. Reporting of studies will be presented in tables by their publication year. Final model predictors will be presented in main categories in a figure.

Meta-bias

Presence of outcome reporting bias will be investigated by comparing the studies with their respective protocol if available. The following aspects will be considered:

- Was publication of the protocol done before recruitment of patients?
- Was the intended outcome in the protocol the same in the published study?

Confidence in cumulative estimate

Assessment of strength of evidence will be made using the PROBAST tool.

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Appendix 2: PRISMA checklist

See tables on the next page. Fields pertaining to meta-analyses have been labelled as not available (NA) since meta-analyses was not performed.

Section/topic	#	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	#2
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	#4
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	#6
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	#6
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	#6
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	#6-8
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	#8
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	#8 + Appendix 3
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	#8-9 + Appendix 4
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	#9
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	#9 + Appendix 5
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	#9-10
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	#10

Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	**NA**

Section/topic	#	Checklist item	Reported on page #
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	#10
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	**NA**
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	#10 + Fig 1 + Appendix 6-8
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	#10-12 + Fig 2 + Appendix 9-10
Risk of bias within studies	19	Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12).	#12 + Table 1
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot.	#12
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and measures of consistency.	**NA**
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15).	#12
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	**NA**
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., healthcare providers, users, and policy makers).	#12-13
Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review-level (e.g., incomplete retrieval of identified research, reporting bias).	#13
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research.	#13-15
FUNDING			

Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.	#10

Appendix 3: search strategy

Pubmed.gov

((((((home-dwell*[tw] OR "Independent Living"[Mesh] OR Independent*[tw] OR community-dwell*[tw] OR home-based*[tw] OR community-living*[tw]))

AND ("Aged"[Mesh] OR aged[tw] OR senior*[tw] OR elder*[tw] OR old[tw] OR older[tw])))) AND ("Accidental Falls"[Mesh] OR fall*[Text Word])))

AND ((((Validat*[tw] OR Predict*[ti] OR Rule*[tw]) OR (Predict*[tw] AND (Outcome*[tw] OR Risk*[tw] OR Model*[tw])) OR ((History[tw] OR Variable*[tw] OR Criteria [tw]OR Scor*[tw] OR Characteristic*[tw] OR Finding*[tw] OR Factor*[tw]) AND (Predict*[tw] OR Model*[tw] OR Decision*[tw] OR Identif*[tw] OR Prognos*[tw])) OR (Decision*[tw] AND (Model*[tw] OR Clinical*[tw] OR "Logistic Models"[MESH])) OR (Prognostic[tw] AND (History[tw] OR Variable*[tw] OR Criteria[tw] OR Scor*[tw] OR Characteristic*[tw] OR Finding*[tw] OR Factor*[tw] OR Model*[tw]))))) OR ((((((((((("ROC Curve"[Mesh]) OR stratificat*[tw]) OR discriminat*[tw]) OR c statistic*[tw]) OR Area under the curve*[tw]) OR AUC[tw]) OR Calibrat*[tw]) OR Indices[tw]) OR Algorithm*[tw]) OR Multivariable*[tw])) OR ((Predict*[tw] OR Predictive value of tests[mh] OR Scor*[tw] OR Observ*[tw] OR Observer variation[mh])))))

Embase:

('falling'/exp OR fall*:ti,ab,kw)

AND ('aged'/exp OR aged:ti,ab,kw OR senior*:ti,ab,kw OR elder*:ti,ab,kw OR old:ti,ab,kw OR older:ti,ab,kw)

AND (validat* OR rule* OR (predict* AND (outcome* OR risk* OR model*)) OR ((history OR variable* OR criteria OR scor* OR characteristic* OR finding* OR factor*)

AND (predict* OR model* OR decision* OR identif* OR prognos*)) OR (decision* AND (model* OR clinical* OR 'statistical model'/exp)) OR (prognostic AND (history OR variable* OR criteria OR scor* OR characteristic* OR finding* OR factor* OR model*)) OR 'receiver operating characteristic'/exp OR stratificat* OR discriminat* OR 'c statistic*' OR 'area under the curve*' OR auc OR calibrat* OR indices OR algorithm* OR multivariable* OR predict* OR 'predictive value'/exp OR scor* OR observ* OR 'observer variation'/exp) AND ('community living'/exp OR 'at home':ti,ab,kw OR (((community OR home OR independent*) NEAR/3 (dwell* OR based OR live OR living)):ti,ab,kw) OR 'home accident'/exp OR 'community dwelling person'/exp)

CINAHL:

((MH "Community Living") OR (MH "Assisted Living") OR ((community OR home OR independent*) N3 (dwell* OR based OR live OR living)) OR (MH "Accidents, Home") OR at home) AND ((MH "Accidental Falls") OR fall*)

AND ((MH "Aged") OR (MH "Aged, 80 and Over") OR (MH "Frail Elderly") OR aged OR senior* OR elder* OR old OR older)

AND (validat* OR rule* OR (predict* AND (outcome* OR risk* OR model*)) OR ((history OR variable* OR criteria OR scor* OR characteristic* OR finding* OR factor*) AND (predict* OR model* OR decision* OR identif* OR prognos*)) OR (decision* AND (model* OR clinical* OR (MH "Models, Statistical"))) OR (prognostic AND (history OR variable* OR criteria OR scor* OR characteristic* OR finding* OR factor* OR model*)) OR (MH "ROC Curve") OR stratificat* OR discriminat* OR 'c statistic*' OR 'area under the curve*' OR auc OR calibrat* OR indices OR algorithm* OR multivariable* OR predict* OR (MH "Predictive Value of Tests") OR scor* OR observ*)

Psycinfo
http://psycnet.apa.org.auh.aub.aau.dk/permalink/19512998-9a97-e90a-722c-bd157326fa55

((Any Field: (validat*) OR Any Field: (rule*) OR (Any Field: (predict*) AND (Any Field: (outcome*) OR Any Field: (risk*) OR Any Field: (model*))) OR ((Any Field: (history) OR Any Field: (variable*) OR Any Field: (criteria) OR Any Field: (scor*) OR Any Field: (characteristic*) OR Any Field: (finding*) OR Any Field: (factor*)) AND (Any Field: (predict*) OR Any Field: (model*) OR Any Field: (decision*) OR Any Field: (identif*) OR Any Field: (prognos*))) OR (Any Field: (decision*) AND (Any Field: (model*) OR Any Field: (clinical*))) OR (Any Field: (prognostic) AND (Any Field: (history) OR Any Field: (variable*) OR Any Field: (criteria) OR Any Field: (scor*) OR Any Field: (characteristic*) OR Any Field: (finding*) OR Any Field: (factor*) OR Any Field: (model*))) OR Any Field: (stratificat*) OR Any Field: (discriminat*) OR Any Field: ('c statistic*') OR Any Field: ('area under the curve*') OR Any Field: (ROC) OR Any Field: (auc) OR Any Field: (calibrat*) OR Any Field: (indices) OR Any Field: (algorithm*) OR Any Field: (multivariable*) OR Any Field: (predict*) OR Any Field: (scor*) OR Any Field: (observ*))))

AND ((((((Any Field: ('at home'))) OR ((((Any Field: (community))) OR ((Any Field: (home))) OR ((Any Field: (independent*)))) NEAR/3 (((Any Field: (dwell*))) OR ((Any Field: (based))) OR ((Any Field: (live))) OR ((Any Field: (living))))))) OR ((((IndexTermsFilt: ("Home Accidents"))))))

AND (((Any Field: (aged))) OR ((Any Field: (elder*))) OR ((Any Field: (old))) OR ((Any Field: (older))) OR ((Any Field: (senior*))))

AND (((IndexTermsFilt: ("Falls"))) OR ((Any Field: (fall*)))))

Cochrane Library:
ID Search

#1 MeSH descriptor: [Accidental Falls] explode all trees
#2 fall*:ti,ab,kw
#3 #1 OR #2
#4 MeSH descriptor: [Aged] explode all trees
#5 aged:ti,ab,kw
#6 senior*:ti,ab,kw
#7 elder*:ti,ab,kw
#8 old:ti,ab,kw
#9 older:ti,ab,kw
#10 #4 OR #5 OR #6 OR #7 OR #8 OR #9
#11 MeSH descriptor: [Independent Living] this term only
#12 "at home":ti,ab,kw
#13 MeSH descriptor: [Accidents, Home] explode all trees
#14 #3 or #13
#15 (((community OR home OR independent*) NEAR/3 (dwell* OR based OR live OR living)):ti,ab,kw)
#16 #11 OR #12 OR #13 OR #15
#17 #14 AND #16 AND #10
#18 MeSH descriptor: [Logistic Models] explode all trees
#19 MeSH descriptor: [ROC Curve] explode all trees
#20 MeSH descriptor: [Predictive Value of Tests] explode all trees
#21 MeSH descriptor: [Observer Variation] explode all trees
#22 ((((Validat* OR Predict*:ti OR Rule*) OR (Predict* AND (Outcome* OR Risk* OR Model*)) OR ((History OR Variable* OR Criteria OR Scor* OR Characteristic* OR Finding* OR Factor*) AND (Predict* OR Model* OR Decision* OR Identif* OR Prognos*)) OR (Decision* AND (Model* OR Clinical* OR #18)) OR (Prognostic AND (History OR Variable* OR Criteria OR Scor* OR Characteristic* OR Finding* OR Factor* OR Model*)))) OR ((((((((((#19) OR stratificat*) OR discriminat*) OR c statistic*) OR Area under the curve*) OR AUC) OR Calibrat*) OR Indices) OR Algorithm*) OR Multivariable*)) OR ((Predict* OR #20 OR Scor* OR Observ* OR #21))))
#23 #17 AND #22

Web of Science:
#1 ts=fall*
#2 ts=(aged OR senior* OR elder* OR old OR older)
#3 ts=((validat* OR rule* OR (predict* AND (outcome* OR risk* OR model*)) OR ((history OR variable* OR criteria OR scor* OR characteristic* OR finding* OR factor*) AND (predict* OR model* OR decision* OR identif* OR prognos*)) OR (decision* AND (model* OR clinical* OR "statistical model")) OR (prognostic AND (history OR variable* OR criteria OR scor* OR characteristic* OR finding* OR

factor* OR model*)) OR ("receiver operating characteristic" OR stratificat* OR discriminat* OR "c statistic" OR "area under the curve*" OR auc OR calibrat* OR indices OR algorithm* OR multivariable* OR predict* OR "predictive value" OR scor* OR observ* OR "observer variation")))
#4 ts=("community living" OR "at home" OR ((community OR home OR independent*) NEAR/3 (dwell* OR based OR live OR living)) OR "home accident" OR "community dwelling person")
#4 AND #3 AND #2 AND #1

PROSPERO:
https://www.crd.york.ac.uk/prospero

Clinicaltrials.gov:
https://clinicaltrials.gov/ct2/results?cond=falling+and+elderly+or+older+adults&term=&cntry=&state=&city=&dist=

WHO International Clinical Trials Registry Platform:
http://apps.who.int/trialsearch/

Open Grey:
http://www.opengrey.eu/search/request?q=Falling+AND+Elderly+OR+Older+adults

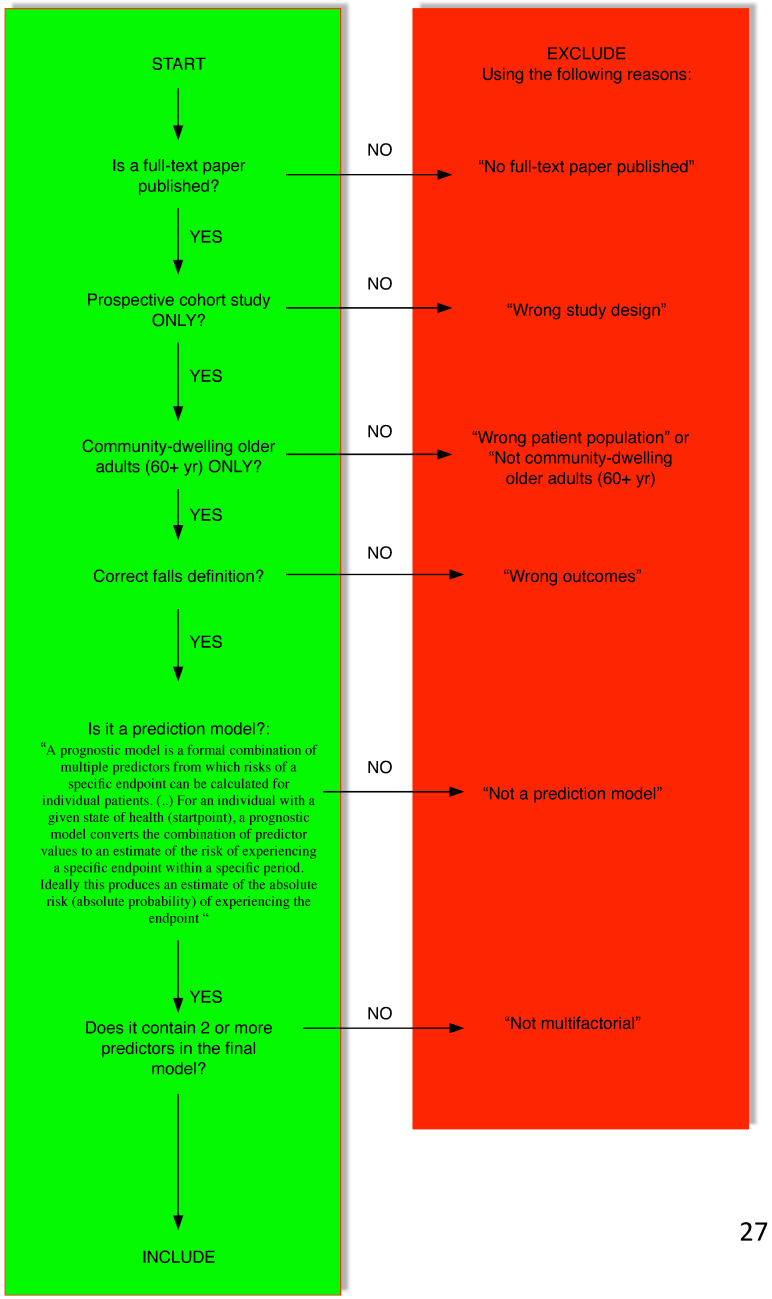
GIN:
https://www.g-i-n.net/library/international-guidelines-library/international-guidelines-library/@@guideline_search_results?basic-searchable-text=falling+and+elderly+or+older+adults&type=basic&action=Search&advanced-authors=&diseases=&meshterm=&search=

NICE:
https://www.nice.org.uk/Search?q=Falling+AND+Elderly+OR+Older+adults

CRD/HTA:
https://www.crd.york.ac.uk/CRDWeb/

SIGN:
https://www.sign.ac.uk/our-guidelines.html

Appendix 4: prioritised list for exclusion reasons



Appendix 5: data extraction items

- General study information:
  - Authors
  - Year of publication
  - Study design
  - Type of prediction modelling study:
    - Developmental without external validation
    - Developmental with external validation
    - External model validation without model updating
    - External model validation with model updating
    - Others
  - Country of origin
  - Setting where candidate predictors were measured
  - Number of study centres
  - Inclusion criteria
  - Exclusion criteria
  - Sample size
  - Methods for participant recruitment/sampling:
    - Consecutive sampling
    - Convenience sampling
    - Probability sampling
    - Others

    - Dates of participant recruitment
    - Duration of follow-up
    - How many participants completed follow-up percentage-wise?
- Participants:
    - Gender
    - Age
    - Fall history
- Outcome:
    - Outcome definition
        - Was it pre-specified?
    - Type of fall recording/method of outcome measurement
    - Was the same outcome definition and recording method used in all participants (Yes/No/Not Available)?
    - Was the outcome assessor blinded towards predictors (Yes/No/Not Available)?
    - Number of falls
    - Number of fallers
    - Number of non-fallers
    - Number of frequent fallers
    - Fall-rate per person per year
    - Summary of follow-up period
- Candidate predictors:
    - Number of candidate predictors studied
    - Definitions of candidate predictors
    - Methods for measuring candidate predictors

  - Number of outcomes (falls) in relation to number of candidate predictors (events per variable (EPV))
- Missing data:
  - Number of participants with missing data (both predictors and outcomes) in total
  - Did participants with missing data differ from those without missing data (Yes/No/Not Available)?
  - Number of participants with missing data in total for each predictor
  - Method of handling missing data
    - Single imputation
    - Multiple imputation
    - Participants with missing data were excluded from the analysis (complete case analysis)
    - Others (comment)
  - Were participants with missing data included in the model development, validation or updating (Yes/No/Not Available)?
- Model development (not relevant if the prediction modelling study does not include model development):
  - Type of model:
    - Linear regression
    - Logistic regression
    - Survival analysis
    - Others (comment)
  - Were assumptions for the model checked (Yes/No/Not available)?
  - Were assumptions for the model satisfied (Yes/No/Not available)?
  - Predictor selection methods for inclusion into the multivariable analysis:
    - All predictors were predetermined to be included in the analysis
    - Predictors were selected for inclusion based on univariate associations with the outcome
    - Others

- Did any statistical transformation of candidate predictors occur (i.e. dichotomising a continuous or categorical variable) prior to inclusion in the multivariate modelling process (Yes/No/Not Available)?
  - If YES, what transformation procedure was applied?
- Predictor selection methods during the multivariable modelling:
  - Full model approach (all predictors were predefined for the final model and no predictors were omitted)
  - Forward selection (candidate predictors were selected based on pre-specified criteria)
    - If forward selection was applied, which criteria/significance level were used?
      - P-value
      - Akaike's Information Criteria
      - R^2
      - Others
  - Backward elimination (all candidate predictors started in the model and were removed or kept based on a pre-specified criterion)
    - If backward elimination was applied, which criteria/ significance level were used?
      - P-value
      - Akaike's Information Criteria
      - R^2
      - Others
- Were shrinkage techniques applied (Yes/No/Not available)?
  - If YES, which procedure was applied?

- Model performance:
  - Overall measures of model performance
    - R^2

        - Brier Score
    - Discrimination:
        - Area Under Curve/*c*-statistic
        - D-statistic
        - Others
    - Calibration:
        - Calibration plot
        - Calibration intercept and slope
        - Calibration table
        - Hosmer-Lemeshow test
        - Observed:Expected Ratio
        - Others
    - Classification:
        - Sensitivity
        - Specificity
        - Positive Predictive Value
        - Negative Predictive Value
        - Net reclassification index
        - Others
        - Was the cut-point:
            - Predefined/made a priori?
            - Derived from the dataset?
- Model evaluation:

- **External validation:** Were the model performance measures based on separate external data (Y/N/NA)?
  - If YES, how was the dataset different from the developmental dataset:
    - Temporal/differed in time
    - Different geographical location
    - Different setting
    - Different investigator
    - Others
- **Internal validation:** Were the model performance measures based on the developmental dataset (Y/N/NA)?
  - Which approach was chosen to evaluate model performance?
    - Split-sample validation
      - What was the percentage-wise allocation of participants?
      - Was the split random to model development and validation(Y/N/NA)?
    - Cross-validation
      - How many subsets were chosen?
    - Bootstrap validation
    - Jack-knife resampling
    - Others
    - None

- Model presentation:
  - What format did the study present their model in to permit calculations of individual risks?
    - Regression formula (comment)
    - Rounded scoring rules (comment)
    - Predefined risk groups (comment)

- Were the risk-groups:
  - Predefined/made a priori?
  - Derived from the dataset?
- Nomogram
- Score chart
- Others
- None

- Sources of funding in the individual study

We used the following definitions of developmental studies and validation studies:

- Developmental study: "Model development studies aim to derive a prediction model by selecting predictors and combining them into a multivariable model"[1].
- Validation study: A fully specified existing prognostic model including both predictors and their coefficients [2].
  - Studies with prespecified predictors, but without any coefficients were classified as developmental studies.

1 Collins GS, Reitsma JB, Altman DG, *et al.* Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD Statement. *BMC Med* 2015;**13**:1. doi:10.1186/s12916-014-0241-z

2 Altman DG, Vergouwe Y, Royston P, *et al.* Prognosis and prognostic research: Validating a prognostic model. *BMJ* 2009;**338**:1432–5. doi:10.1136/bmj.b605

Appendix 6: studies excluded during screening of titles and abstracts:

See separate PDF file: "Appendix 6".

Appendix 7: possibly relevant studies in other languages excluded during screening of titles and abstract:

Title	Author	Year	Language:	Reference:
Fall Prediction Model for Community-dwelling Elders based on Gender	Eun Suk, Yun	2012	Korean	J Korean Acad Nurs. 2012;42(6):810-818. doi:10.4040/jkan.2012.42.6.810
Fall risk and fracture. Aging and fall/fracture	Kozaki, K.	2013	Japanese	Clin Calcium. 2013;23(5):653-660
Fall risk assessment in regular exercising elderly women	Kikuchi, R.; Kozaki, K.; Kawashima, Y.; Iwata, A.; Hasegawa, H.; Igata, A.; Toba, K.	2008	Japanese	Nihon Ronen Igakkai Zasshi. 2008;45(5):526-531. doi:10.3143/geriatrics.45.526
Risk profiles and preventive measures of falls in elderly persons	Tromp, E	2002	Dutch	Tijdschr Gerontol Geriatr. 2002;33(1):21-25.
Fall-related factors in a cohort of elderly community residents	Rodriguez Perracini, M.; Ramos, L. R.	2002	Spanish	Rev Saude Publica. 2002;36(6):709-716. doi:10.1590/s0034-89102002000700008
Identifying the elderly at risk for falling and accompanying protocols	Galinsky, D.; Fried, V.; Biderman, A.; Cwikel, J.; Ben Moshe, Y.	2000	Hebrew	Harefuah. 2000;138(3):189-271.
Impact of fall risk and fear of falling on mobility of independently living senior citizens transitioning to frailty: Screening results concerning fallprevention in the community	Anders, J.; Dapp, U.; Laub, S.; Von Renteln-Kruse, W.	2007	German	Z Gerontol Geriatr. 2007;40(4):255-267. doi:10.1007/s00391-007-0473-z

Appendix 8: studies excluded during full-text screening.

See separate PDF file: "Appendix 8".

Appendix 9: supplementary table 1 with characteristics of included studies

Supplementary Table 1 Characteristics of included studies

First author, year, country, study type	Study characteristics (sample size, age distribution, % female, % of sample with prior falls)	Outcomes (n; %) and length of follow-up	Statistical model and validation technique	Final models and their presentation (model no. (outcome): predictors with/without weights)	Model performance
Maki et al. [1], 1994, Canada Development study study	n = 100 Age, mean (SD): 83 (6) years Female: 83% Prior falls: 46.8%	Any falls (59; 59%) Recurrent falls (23; 23%) Follow-up: 12 months	Logistic regression Cross-validation (n-1)	**Model** 1 (any falls): Spontaneous mediolateral sway (root-mean-square) with eyes blindfolded; induced sway in anterior-posterior direction with eyes open (mean COP location / length of base-of-support) **Model** 2 (recurrent falls): Induced sway in mediolateral direction with eyes blindfolded (mean coherence of the input-output model); induced sway in mediolateral direction with eyes blindfolded (Relative COP overshoot in the predicted transient response)	**Model** 1: AUC (SE): 0.76 (0.05) Calibration: no information SN: 78% (43/55) SP: 50% (18/36) **Model** 2: AUC (SE): 0.87 (0.05) Calibration: no information SN: 53% (9/17) SP: 89% (31/35)
Brauer et al. [2], 2000, Australia Developmental study	n = 100 Age, mean (SD): 71 (5) years Female: 100% Prior falls: 35%	Any falls (35; 35%) Follow-up: 6 months	Logistic regression Cross-validation (no information on subsets)	**Model** 1 (any falls): Gluteus medius onset time; Movement time in a high preparation step task; Step time in a high preparation step task; Maximum COP excursion when moving to the right LOS; COP maximum mediolateral velocity; Total distance moved in quiet stance **Model** 2 (any falls): Movement time in a high preparation step task; step time in a high preparation step task; total time in a high preparation step task; movement time in a neutral preparation step task; step time in a neutral preparation step task; total time in a neutral preparation step task **Model** 3 (any falls): Gluteus medius in a neutral preparation step task; tensor fascia latae in a neutral preparation step task; hip adductors in a neutral preparation step task; gastrocnemius onset times in a neutral preparation step task; gluteus medius in a high preparation step task; tensor fascia latae in a high preparation step task; hip adductors in a high	**Model** 1: AUC: no information Calibration: no information SN: 51% SP: 91% Total predictive ability: 77% **Model** 2: AUC: no information Calibration: no information SN: 34% SP: 89% Total predictive ability: 70% **Model** 3: AUC: no information Calibration: no information SN: 23% SP: 88% Total predictive ability: 65%

				preparation step task; gastrocnemius onset times in a high preparation step task **Model** 4 (any falls): COP maximum mediolateral velocity with eyes open; COP maximum mediolateral velocity with eyes closed; COP position in quiet stance with eyes open; COP position in quiet stance with eyes closed; COP total distance moved in quiet stance with eyes open; COP total distance moved in quiet stance with eyes closed **Model** 5 (any falls): COP maximum excursion when moving to the right LOS; COP maximum excursion when moving to the left LOS; COP maximum excursion when moving to the anterior LOS; COP maximum excursion when moving to the posterior LOS **Model** 6 (any falls): Left Functional Reach; Right Functional Reach; Right Lateral Reach; Left Lateral Reach; Step-Up number; Berg Balance Scale score **Model** 7 (any falls): Left Functional Reach; Right Functional Reach; Right Lateral Reach; Left Lateral Reach; Step-Up number; Berg Balance Scale score; Gluteus medius onset time; Movement time in a high preparation step task; Step time in a high preparation step task; Maximum COP excursion when moving to the right LOS; COP maximum mediolateral velocity; Total distance moved in quiet stance	**Model** 4: AUC: no information Calibration: no information SN: 29% SP: 88% Total predictive ability: 67% **Model** 5: AUC: no information Calibration: no information SN: 6% SP: 97% Total predictive ability: 65% **Model** 6: AUC: no information Calibration: no information SN: 12% SP: 95% Total predictive ability: 66% **Model** 7: AUC: no information Calibration: no information SN: 59% SP: 86% Total predictive ability: 77%
Tromp et al. [3], 2001, The Netherlands, Development study	n = 1,374 Age, mean (SD): 75.2 (6.5) years Age, range: 64.8-88.6 years Of the 1,285 with complete follow-up, female: 51%	Any falls (428; 31.1%) Recurrent falls (147; 10.7%) Follow-up: 12 months	Logistic regression No information on model validation	**Model** 1 (any falls): Regression table with regression coefficients: constant: no information; previous falls: 0.90; urinary incontinence: 0.46; visual impairment: 0.44; use of benzodiazepines: 0.44 Score chart - previous falls: 5; urinary incontinence: 2; visual impairment: 2; use of benzodiazepines: 2	**Model** 1: AUC: 0.65 Calibration: no information

	Prior falls: 31%			**Model** 2 (recurrent falls): Regression table with regression coefficients: constant: no information; previous falls: 0.99; urinary incontinence: 0.53; visual impairment: 0.82; use of benzodiazepines: 0.54 Score chart: previous falls: 5; urinary incontinence: 3; visual impairment: 4; use of benzodiazepines: 3	**Model** 2: AUC: 0.71 Calibration: no information Cut-off: 7 points SN: 54% SP: 79% PPV (CI): 24.9% (22.5-27.3%) NPV (CI): 93% (91.6-94.4%)
Stalenhoef et al. [4], 2002, The Netherlands, Development study	n = 302 Of the 287 with complete follow-up, age, mean (SD): - Female: 78.5 (5.2) years - Male: 77.2 (4.9) years Of the 287 with complete follow-up, female: 60% Prior falls: 66%	Recurrent falls (46; 15.2%) Follow-up: 9 months	Logistic regression No information on model validation	**Model** 1 (recurrent falls): Regression table including regression coefficients with SE: constant: -2.28; female gender: -0.39 (0.4); age >= 80 years: 0.04 (0.39); falls >= 2 in previous year: 1.14 (0.39); depression - SCL90 >= 22: 0.78 (0.37); hand dynamometry (men <= 22 kg or women: <= 12 kg: 1.14 (0.38); postural sway abnormal: 1.36 (0.58) Rounded scoring rule - men: age >= 80 years: was not included due to low impact; falls >= 2 in previous year: 6; depression - SCL90 >= 22 4; hand dynamometry (Men <= 22 kg or Women: <= 12 kg): 6; postural sway abnormal: 7 Rounded scoring rule – women: age >= 80 years: Was not included due to low impact; falls >= 2 in previous year: 4; depression - SCL90 >= 22: 2; hand dynamometry (men <= 22 kg or women: <= 12 kg): 4; postural sway abnormal: 5	**Model** 1: AUC: 0.79 Calibration: "The comparison of the percentages predicted probability with the percentage of observed recurrent fallers showed a general agreement. The predicted values of the model, calculated according to the Hosmer Lemeshow goodness of fit, showed good fit." Cut-off: 0.30 SN: 59% SP: 87% PPV: 52% NPV: 90%
Stel et al. [5], 2003, The Netherlands, Development study	n = 1,365 Age, mean (SD): 75.3 (6.4) years Age, range: 64.8-88.6 years Female: 51% Prior falls: 31%	Recurrent falls (337; 24.7%) Follow-up: - Primary length of follow-up: 3 years - Secondary length of follow-up: 1 year.	Tree-structured survival analysis No information on model validation	**Model** 1 (recurrent falls): Classification tree with a follow-up of 3 years: fall history, function limitations, dizziness, performance test score, grip strength, alcohol consumption, pain, educational level, and physical activity **Model** 2 (recurrent falls): Classification tree with a follow-up of 1 year: fall history, function limitations, and grip strength	**Model** 1: AUC: no information Calibration: no information **Model** 2: AUC: no information Calibration: no information
Boulgarides et al. [6], 2003, USA,	n = 106 Age, mean (SD):	Recurrent falls (20; 18.9%)	Logistic regression	**Model** 1 (recurrent falls): Regression table with coefficients and SE:	**Model** 1: AUC: no information Calibration: no information

Development study	74.02 (5.64) years Age range: 65-90 years Of 99 participants included in analysis: female: 61% Prior falls: 50.5%	Follow-up: 12 months	No information on model validation	constant: no information; postural sway while standing on a firm surface with eyes closed: 1.786 (1.332); age: 0.072 (0.048); sex: 0.822 (0.540)	% Correct prediction: 80.8%, though only predicted 2/20 of multiple fallers SN: 10% SP: 98.7%
Nandy et al. [7], 2004, UK, Development study	n = 510 Of the 345 with complete follow-up, age, mean (SD): 74.4 (6.4) years Of the 345 with complete follow-up, female: 55% Prior falls: 25%	Any falls (no information) Follow-up: 6 months	Only SN, SP, PPV, NPV, and Youden's index were calculated No information on model validation	**Model** 1 (any falls): Three or more of the following risk factors: history of falling in the previous year, taking four or more prescribed medications, history of stroke or Parkinson's disease, and reported problems with balance and loss of proximal muscle strength	**Model** 1: AUC: no information Calibration: no information SN: 0.42 (0.32-0.54) SP: 0.92 (0.88-0.94) PPV: 0.57 (0.43-0.69) NPV: 0.86 (0.83-0.89) Youden's Index: 0.339 (0.185-0.493)
Pluijm et al. [8], 2006, The Netherlands, Development study	n = 1,365 Age, mean (SD): 75.3 (6.4) years Age, range: 64.8-88.6 years Female: 51.1% Prior falls: 14.2%	Recurrent falls (457; 33.5%) Follow-up: - Primary: 3 years - Secondary: 1 year	Logistic regression No information on model validation	**Model** 1 (recurrent falls within 3 years): Regression table with regression coefficients: constant: - 2.19; two or more previous falls: 0.71; dizziness: 0.77; functional limitations: 0.53; weak grip strength: 0.55; low body weight: 0.37; fear of falling: 0.34; the presence of dogs/cats in the household: 0.40; a high education level: 0.21; drinking of 18 or more alcoholic consumptions per week: 0.11; interaction term (high education × 18 or more alcohol consumptions per week): 0.86; interaction term (two or more previous falls × fear of falling): 0.83 Score chart: two or more previous falls: 4; dizziness: 4; functional limitations: 3; weak grip strength: 3; low body weight: 2; fear of falling: 2; the presence of dogs/cats in the household: 2; a high education level: 1; drinking 18 or more alcoholic consumptions per week: 1; interaction term (high education × 18 or more alcohol consumptions per week): 4; interaction term (two or more previous falls × fear of falling): 4 **Model** 2 (recurrent falling within 1 year): Regression table with regression coefficients: constant: - 3.13; two or more previous falls: 0.64; dizziness: 0.52; functional limitations: 0.39; weak grip strength: 0.65; low body weight: 0.32;	**Model** 1: AUC (CI): 0.71 (0.67-0.74) Calibration: The Hosmer-Lemeshow goodness-of-fit test for the multiple logistic regression was not significant (p=0.56), indicating that the model fits the data well Cut-off: 5 points SN: 59% SP: 71.4% PPV: 38.6% NPV: 85.1% **Model** 2: AUC: (CI): 0.72 (0.67- 0.77) Calibration: The Hosmer-Lemeshow goodness-of-fit test for the multiple logistic regression

				fear of falling: 0.09; the presence of dogs/cats in the household: 0.81; a high educational level: 0.08; drinking of 18 or more alcoholic consumptions per week: - 0.15; interaction term (high education × 18 or more alcohol consumptions per week): 0.87; interaction term (two or more previous falls × fear of falling): 1.15	was not significant (p=0.94), indicating that the model fits the data well
Okochi et al. [9], 2006, Japan, Development study	n = 1,734 Age, mean (SD): 75.8 (6.8) years Female: no information Prior falls: 16%	Any falls (208; 12.0%) Follow-up: 6 months	Logistic regression Split-sample validation (random split, 50%/50%)	**Model** 1 (any falls): Scoring system from 0-13 based on the odds ratio at an integer level from logistic regression: history of falls - probable score 0/5; do you feel your walking speed has declined recently - probable score 0/2; do you use cane when you walk - probable score 0/2; is your back bended: probable score 0/2; do you take more than five kinds of prescription medicines - probable score 0/2	**Model** 1: AUC (95% CI): 0.74 (0.69-0.79) Calibration: no information Cut-off: 6 SN: 68% SP: 70% PPV: 27.9% Negative predictive power: 93%
Lindemann et al. [10], 2008, Germany, Development study	n = 65 Age, mean (SD): 67.7 (6.0) years Female: 57% Prior falls: 45%	Any falls (30; 46.2%) Follow-up: 12 months	The cut-off values for differentiating between persons, who fell and persons who did not, were defined for each parameter as the point on the Receiver Operating Characteristic curve with the minimal Euclidian distance to the point (0/1) No information on model validation	**Model** 1 (any falls): Adjusted mean valid step length (cut-off: 64% of body height), and at least one fall in previous year **Model** 2: (any falls): Adjusted max. valid step length (cut-off: 66% of body height), and at least one fall in previous year	**Model** 1: AUC and calibration: author response: "The information in the paper is the only we can provide. New calculations are not possible" SN (CI): 93% (86.7-100) SP (CI): 54% (40.5-67.1) PPV (CI): 70% (57.8-82.2) NPV (CI): 88% (78.7-96.3) +LR: 2.0 -LR: 0.1 **Model** 2: AUC: no information Calibration: no information SN (CI): 90% (82-98) SP (CI): 58% (44.5-70.9) PPV (CI): 71% (58.9-83.2) NPV (CI): 83% (73.4-93.3) +LR: 2.1 -LR: 0.2
Lamb et al. [11], 2008, USA, Development study	n = 1,002 Age, mean (SD): 78 (8.1) years	Any falls (346; 34.5%) Follow-up: 12 months	Tree-based classification Cross-validation (20 subsets)	**Model** 1 (any falls): Decision tree with self-report algorithm: how many falls have you had in the last year?; how often do you have problems balancing while	**Model** 1: AUC: no information Calibration: no information Fall probability threshold:

	Of the 885 included, female: 100% Of 830 included, prior falls: 34%			walking?; how much difficulty do you have with activities of daily living? **Model** 2 (any falls): Decision tree with self-report and performance item algorithm: how many falls have you had in the last year?; how often do you have problems balancing while walking?; knee extensor strength test; 4-metre usual gait speed; Body Mass Index	>= 0.34; SN: 0.59; SP: 0.64; +LR: 1.64; -LR: 0.64; Diagnostic Odds Ratio: 2.56 Fall probability threshold: >= 0.44; SN: 0.46; SP: 0.77; +LR: 2.00; -LR: 0.70; Diagnostic Odds Ratio: 2.85 Fall probability threshold: >= 0.55; SN: 0.32; SP: 0.87; +LR: 2.46; -LR: 0.78; Diagnostic Odds Ratio: 3.15 Fall probability threshold: >= 0.62; SN: 0.09; SP: 0.96; +LR: 2.25; -LR: 0.95; Diagnostic Odds Ratio: 2.37 **Model** 2: AUC: no information Calibration: no information Fall probability threshold: >= 0.25; SN: 0.78; SP: 0.46; +LR: 1.44; -LR: 0.48; Diagnostic Odds Ratio: 3.02 Fall probability threshold: >= 0.33; SN: 0.73; SP: 0.56; +LR: 1.66; -LR: 0.48; Diagnostic Odds Ratio: 3.44 Fall probability threshold: >= 0.42; SN: 0.54; SP: 0.74 +LR: 2.08; -LR: 0.62; Diagnostic Odds Ratio: 3.34 Fall probability threshold: >= 0.46; SN: 0.47; SP: 0.80; +LR: 2.35; -LR: 0.66; Diagnostic Odds Ratio: 3.54 Fall probability threshold: >= 0.56; SN: 0.33; SP: 0.90

					+LR: 3.30; -LR: 0.74; Diagnostic Odds Ratio: 4.43 Fall probability threshold: >= 0.69; SN: 0.16; SP: 0.97 +LR: 5.33; -LR: 0.87; Diagnostic Odds Ratio: 6.15
Delbaere et al. [12], 2010, Australia, Development study	n = 500 Age, mean (SD): 77.9 (4.1) years Female: 54% Prior falls: 29.6%	Recurrent falls (94; 18.8%) Follow-up: 12 months	Classification and Regression Tree (CRT) No information on model validation	**Model** 1 (recurrent falls): Risk groups: - Low risk: Physiological fall risk (Physiological Profile Assessment) <0.60. Subgroups were made from the Disability score >0. If Disability score >0, further subdivision was made using Incidental and Planned Exercise Questionnaire < 4hrs/week - High risk group: Physiological fall risk (Physiological Profile Assessment) >=0.60. Subgroups were made from Trail-Making-Test time <50. If Trail-Making-Test > 50, further subdivision was made using poor coordinated stability (error score >= 15). If score >= 15, further subdivision was done using Incidental and Planned Exercise Questionnaire > 0	**Model** 1: AUC and calibration: "We didn't calculate an AUC or related measure for our tree and our sample was not big enough to run a calibration analysis as well. No other classification measures were calculated " (author response)
Yamashita et al. [13], 2011, USA, Development study	n = 23,417 Age, mean (SD): 76.1 (8.94) years Female: 79% Prior falls: 3%	Any falls (approx. 1,400 (5.9%) Follow-up: between one day and 18 months due to the study using an open cohort design	Logistic regression No information on model validation	**Model** 1 (any falls): Regression table with coefficients: constant: no information; fall history: 0.997; female: 0.133; age: 0.013; blacks: -0.334; others: -0.363; married: -0.137; Alzheimer's disease: 0.055; cancer: -0.307; cataracts: -0.21; dementia: -0.135; depression: 0.334; diabetes: -0.034; emphysema: -0.171; glaucoma: 0.118; incontinence: 0.189; Parkinson's disease: 0.261; stroke: 0.103; vertigo: 0.085; total number of medications: 0.029; activities of daily living score: -0.07; instrumental activities of daily living score: 0.01; gait-shuffling: 0.027; gait-unsteady: 0.178; grasp-tremors: 0.426; grasp-weakness: -0.451; joint pain: 0.129; recent weight loss: 0.332; medication administration: 0.119; need for supervision: -0.265	**Model** 1: AUC: 0.61 Calibration: no information
Panzer et al. [14], 2011, USA, Development study	n = 74 Non-fallers: - Age, range: 65-87 years - Age, mean (SD): 75.1 (6.5) years	Recurrent falls (40; 54.1%) Follow-up: 12 months	Only sensitivity and specificity were calculated	**Model** 1 (recurrent falls): Multiple falls, gait velocity, turn time, turn number of steps, down 3 stairs, and step in tub **Model** 2 (recurrent falls):	**Model** 1: AUC: no information Calibration: no information Extracted from figure 2: SN: 52%; SP: 55%

	Fallers: - Age, range: 70-94 years - Age, mean (SD): 80.1 (6.2) years Female: no information Prior falls: 63.5%		No information on model validation	Multiple falls, gait velocity, turn time, turn number of steps, and down 3 stairs **Model** 3 (recurrent falls): Multiple falls, gait velocity, turn time, and turn number of steps **Model** 4 (recurrent falls): Multiple falls, quiet standing, maximal leaning, sway area, and medial-lateral excursion **Model** 5 (recurrent falls): Multiple falls, quiet standing, maximal leaning	**Model** 2: AUC: no information Calibration: no information Extracted from figure 2: SN: 55%; SP: 55% **Model** 3: AUC: no information Calibration: no information Extracted from figure 2: SN: 55%; SP: 52% **Model** 4: AUC: no information Calibration: no information Extracted from figure 2: SN: 78%; SP: 55% **Model** 5: AUC: no information Calibration: no information Extracted from figure 2: SN: 68%; SP: 55%
Bongue et al. [15], 2011, France, Development study	n = 1,759 Age, mean (SD): 70.7 (4.6) years Female: 51% Prior falls: 26%	Any falls (563; 32%) Follow-up: 12 months	Cox regression No information on model validation	**Model** 1 (time to any falls): Regression table (coefficient): baseline hazard: no information; women 0.506; living alone: in couple: 0, family: 0.438, alone: 0.315; self-reported osteoarthritis: 0.22; history of falls - 1 year: 0 falls: 0, 1 fall: 0.616, 2 falls: 0.907, 3 or more falls: 1.42; psychoactive drug use: 0.217; balance impairment: 0.270 Scoring rule (points): women (2); living alone (1); self-reported osteoarthritis (1); history of falls - 1 year: 1 fall (2), 2 falls (4), 3 or more falls (6); psychoactive drug use (1); balance impairment (1) Cut-off: 7 Low risk: Score: 0-3; frequencies: 55.3; OR: 1 Moderate risk: Score: 4-6; frequencies: 34.9; OR 2.4 (2.2-3.4) High risk: Score: 7-12; frequencies: 9.8; OR: 7.8 (5.5-11.1)	**Model** 1: AUC (CI): 0.70 (0.67-0.73) Calibration: no information Youden index = 3, for this: SN: 70.2% SP: 60.3% PPV: 45.5% NPV: 81.1% Evolution of PPV and NPV cut-off = 7, for this: SN: 19.2% SP: 96.5% PPV: 72% NPV: 72.7%
Viccaro et al. [16], 2011, USA,	n = 492	First time falls (83; 19.5%)	Logistic regression	**Model** 1 (first time fall):	**Model** 1: AUC: 0.60

Development study	Age, mean (SD): 74 (5.7) years Of the 457 with complete follow-up (except n = 18 who died during follow-up): female: 43.5% Prior falls: 29.7%	Any falls (155; 36.5%) Recurrent falls (58; 13.9%) Follow-up: 12 months	No information on model validation	Timed Up & Go test, 4 m gait speed test, age, and fall history **Model** 2 (any fall): Timed Up & Go test, 4 m gait speed test, age, and fall history **Model** 3 (recurrent falls): Timed Up & Go test, 4 m gait speed test, age, and fall history	Calibration: no information **Model** 2: AUC: 0.729 Calibration: no information **Model** 3: AUC: 0.786 Calibration: no information
Yamashita et al. [17], 2012, USA, Development study	n = 9,661 Age, mean (SD): 74.2 (7.16) years Of the 9,592 included in the analyses: female: 57.8% Prior falls: 31%	Any falls (3,299; 34%) Follow-up: 24 months	Logistic Tree with Unbiased Selection (LOTUS)/ Logistic Regression Tree Method Cross-validation (10 subsets)	**Model** 1 (any falls): Fall history, age, difficulty with knees, activities of daily living, cognitive impairment, self-rated health, instrumental activities of daily living, prescription drugs, and stroke	**Model** 1: AUC: 0.71 Calibration: no information
Weiss et al. [18], 2013, Israel, Development study	n = 71 Age, mean (SD): 78.36 (4.71) years Female: 65% Prior falls: 45%	Recurrent falls (12; 16.9%) Follow-up: 6 months	Logistic regression No information on model validation	**Model** 1 (recurrent falls): Four Square Step Test, total activity duration (Accelerometer), anterior-posterior acceleration range (Accelerometer), anterior-posterior width (Accelerometer), and age	**Model** 1: AUC: no information Calibration: no information SN: 75% SP: 100% "94.7% of the subjects were successfully identified as future fallers and non-fallers"
Hnizdo et al. [19], 2013, USA, Validation	n = 113 Age, mean: 79.8 years Female: 34.6% Prior falls: 49.5%	Any falls (33; 29.2%) Follow-up: participants were followed until discharged from home health services	Validation study	**Model** 1 (any falls): Age, fall history, elimination problems, high risk medications, use of patient care equipment, limited mobility, and altered cognition	**Model** 1: AUC (95% CI): 0.66 (0.55-0.78) Calibration: no information Cut-off: 14 points SN: 72.5% SP: 52.2% PPV: 39.6% NPV: 81.4%
de Vries et al. [20], 2013, The Netherlands, Development study	n = 1,509 Age, median (range): 75.6 (64.8-88.8) years Female: 51.8% Prior falls: 32.2%	Recurrent falls, ≥ 2 falls (174; 11.5%) Recurrent falls, ≥ 3 falls (91; 6%) Any falls	Cox regression Logistic regression No information on model validation	**Model** 1 (time to second fall): Low mastery, depression, urinary incontinence, hearing impairment, low physical activity, low visual acuity, body mass index ≤23, low peak flow, Mini-Mental State Examination ≤ 24 **Model** 2 (any falls): Low mastery, depression, urinary incontinence, hearing impairment, low physical activity, low	**Model** 1: AUC:0.58 (0.53-0.62) Calibration: no information **Model** 2: AUC: 0.51 (0.346-0.56) Calibration: no information **Model** 3:

		(468; 31.0%) Follow-up: 12 months		visual acuity, body mass index ≤23, low peak flow, Mini-Mental State Examination ≤ 24 **Model** 3 (recurrent falls, ≥ 2 falls): Low mastery, depression, urinary incontinence, hearing impairment, low physical activity, low visual acuity, body mass index ≤23, low peak flow, Mini-Mental State Examination ≤ 24 **Model** 4 (recurrent falls, ≥ 3 falls): Low mastery, depression, urinary incontinence, hearing impairment, low physical activity, low visual acuity, body mass index ≤23, low peak flow, Mini-Mental State Examination ≤ 24	AUC: 0.50 (0.42-0.57) Calibration: no information **Model** 4: AUC: 0.49 (0.39-0.59) Calibration: no information
Muhaidat et al. [21], 2014, United Kingdom, Development study	n = 66 Non-fallers: Age, mean (SD): 75 (11.5) years Fallers: Age, mean (SD): 82 (12) years Female: 66% Prior falls: 45%	Any fall (13; 19.7%) Follow-up: 6 months	Random Forrest Classification Training set 67% of the sample Test set: 33% of the sample	**Model** 1 (any falls): Table of predictors with corresponding Mean Decrease in Accuracy, and Mean Decrease in Gini: time required to complete triple task, time required avoiding a moving obstacle and cup, time required for TUG and cup, time required for single-task avoiding a moving obstacle, absolute difference in time between single-task TUG and dual-task TUG	**Model** 1: AUC: no information Calibration: no information Out-of-bag error rate: 27.4% Correct classification: 72.6%
Gadkaree et al. [22], 2015, USA, Development study	n = 7,609 Age groups, % (CI): - 65-69: 27.9% (27.0-29.0) - 70-74: 25.0% (24.1-25.8) - 75-79: 19.1% (18.2-19.9) - 80-84: 14.7% (14.0-15.4) - 85-89: 9.1% (8.5-9.8) - 90+: 4.3% (3.8-4.7) Female: 56.6% Prior falls: 30.5%	Any falls (2,028; 26.7%) Recurrent falls (957; 12.6%) Follow-up: 12 months	Logistic regression Split-sample validation (random split; 66.6%/33.3%) Cross-validation (no information on subsets)	**Model** 1 (any falls): Age, gender, and race **Model** 2 (recurrent falls): Age, gender, and race **Model** 3 (any falls): y = -1.44 + ((Age 70-74 years)* -0.33) + ((Age 75-59 years)*0.07) + ((Age 80-84 years)*0.17) + ((Age 85-89 years)*0.37) + ((Age 90+ years)*0.26) + Female*0.12 + (Black ethnicity * -0.27) + (Other ethnicity * -0.52) + (Hispanic ethnicity * 0.07) + Self-reported balance problems*0.69 + Fall history*1.15 **Model** 4 (recurrent falls)	**Model** 1: AUC (95% CI): 0.57 (0.54-0.60) Calibration: no information **Model** 2: AUC (95% CI): 0.59 (0.56-0.61) Calibration: no information **Model** 3: AUC (95% CI): 0.69 (0.67-0.71) Calibration: no information Performance in validation set: AUC (95% CI): 0.70 (0.67-0.73) **Model** 4: AUC (95% CI): 0.77 (0.74-0.79)

				y = 2.67 + ((Age 70-74 years)* -0.66) + ((Age 75-59 years)*-0.08) + ((Age 80-84 years)*0.11) + ((Age 85-89 years)*0.49) + ((Age 90+ years)*0.47) + Female*-0.22 + (Black ethnicity * -0.27) + (Other ethnicity * -0.99) + (Hispanic ethnicity * 0.02) + Self-reported balance problems*1.11 + Fall history*1.46 **Model** 5 (any falls): Age, gender, race, self-reported balance problems, history of falls, heart attack, heart disease, stroke, hypertension, diabetes, osteoporosis, vision impairment, and hearing impairment **Model** 6 (recurrent falls): Age, gender, race, self-reported balance problems, history of falls, heart attack, heart disease, stroke, hypertension, diabetes, osteoporosis, vision impairment, and hearing impairment **Model** 7 (any falls): Age, gender, race, self-reported balance problems, history of falls, heart attack, heart disease, stroke, hypertension, diabetes, osteoporosis, vision impairment, hearing impairment, and Short Physical Performance Battery **Model** 8 (recurrent falls): Age, gender, race, self-reported balance problems, history of falls, heart attack, heart disease, stroke, hypertension, diabetes, osteoporosis, vision impairment, hearing impairment, and Short Physical Performance Battery	Calibration: no information Performance in validation set: AUC (95% CI): 0.76 (0.73-0.80) **Model** 5: AUC (95% CI): 0.71 (0.69-0.73) Calibration: no information **Model** 6: AUC (95% CI): 0.78 (0.76-0.81) Calibration: no information **Model** 7: AUC (95% CI): 0.72 (0.70-0.73) Calibration: no information **Model** 8: AUC (95% CI): 0.79 (0.76-0.81) Calibration: no information
Cawthon et al. [23], 2015, USA, Development study	n = 5,994 Age, mean: 74 years (based on other studies on the same cohort)	Recurrent falls (694; 11.6%) Follow-up: 12 months	Logistic regression No information on model validation	**Model** 1 (recurrent falls): Age and Baumgartner Sarcopenia Definition **Model** 2 (recurrent falls): Age and Newman Sarcopenia Definition	**Model** 1: Change in AUC compared to age alone (AUC: 0.577): 0.000 (-0.002; 0.003) Calibration: "We did not generate calibration plots for these

	Female: 0% Prior falls: 21% (based on other studies on the same cohort)			**Model** 3 (recurrent falls): Age and IWG Sarcopenia Definition **Model** 4 (recurrent falls): Age and EWGSOP Sarcopenia Definition **Model** 5 (recurrent falls): Age and FNIH Definition#1 **Model** 6 (recurrent falls): Age and FNIH Definition#2	analyses, just the discrimination and the C statistic information" (author response) NRI events: 0.12 (0.08, 0.16) NRI non-events: -0.12 (-0.14, -0.11) **Model** 2: Change in AUC compared to age alone (AUC: 0.577): 0.001 (-0.002; 0.003) Calibration: no information NRI events: 0.07 (0.04, 0.11) NRI non-events: -0.08 (-0.09, -0.06) **Model** 3: Change in AUC compared to age alone (AUC: 0.577): 0.010 (0.002; 0.018) Calibration: no information NRI events: -0.33 (-0.38, -0.28) NRI non-events: 0.34 (0.32, 0.35) **Model** 4: Change in AUC compared to age alone (AUC: 0.577): 0.009 (0.002; 0.015) Calibration: no information NRI events: -0.33 (-0.38, -0.28) NRI non-events: 0.35 (0.34, 0.36) **Model** 5: Change in AUC compared to age alone (AUC: 0.577): 0.004 (-0.001; 0.008) Calibration: no information NRI events: -0.11 (-0.14, -0.08) NRI non-events: 0.07 (0.06, 0.08) **Model** 6:

					Change in AUC compared to age alone (AUC: 0.577): 0.001 (-0.001; 0.003) Calibration: no information NRI events: -0.05(-0.06, -0.03) NRI non-events: 0.03(0.02, 0.03)
Palumbo et al. [24], 2016, Italy, Germany, Ireland, and England, Validation	ActiFE: n = 1,416 ELSA: n = 3,303 InCHIANTI: n = 892 TILDA: n = 2,101 Age, mean (SD): ActiFE: 75.7 (6.76) years ELSA: 74.56 (7.31) years InCHIANTI: 73.78 (6.62) years TILDA: 72.79 (5.22) years Female: ActiFE: 56.8% ELSA: 56.7% InCHIANTI: 56.2% TILDA: 53.5% Prior falls: ActiFE: 36.1% ELSA: 22.7% InCHIANTI: 20.8% TILDA: 22.8%	Any falls ActiFE (466; 32.9%) ELSA (730; 22.1% 1 years adjusted) InCHIANTI (203; 22.8%) TILDA (569; 27.1% 2 years adjusted) Follow-up: ActiFE: 12 months ELSA: 2 years InCHIANTI: 1 year TILDA: 2 years	Validation study	**Model** 1 (any falls): Age, cognitive impairment, depression, diabetes, comorbidity, dizziness and vertigo, fear of falling, female sex, gait problems, hearing impairment, history of falls, history of stroke, instrumental disability, living alone, number of medications, pain, Parkinson's disease, physical activity limitation, physical disability, poor self-perceived health status, rheumatic disease, urinary incontinence, use of antiepileptics, use of antihypertensives, use of sedatives, vision impairment, and walking aid use	**Model** 1: ActiFE: AUC (95% CI): 0.562 (0.530 - 0.594) ELSA: AUC (95% CI): 0.699 (0.680 - 0.718) InCHIANTI: AUC (95% CI): 0.636 (0.594 - 0.681) TILDA: AUC (95% CI): 0.685 (0.660 - 0.709) Calibration: calibration plots were displayed for all four cohorts. For ActiFE and InCHIANTI, participants with low (high) risk scores, experienced more (respectively, less) falls than expected. For ELSA and TILDA, the model overestimated the risk consistently across strata
Rodriguez-Molinero et al. [25], 2017, Spain, Development study	n = 772 Of participants completing the first follow-up period, age, median (SD): 80.7 (0.1) years Of participants completing the first follow-up period, female: 62.5% Prior falls: 26.4%	Recurrent falls (43; 9.9%) Follow-up: 12 months	No regression analyses were performed. Sensitivity, specificity and area under the ROC curve (AUC) were calculated as well as the Odds Ratio (OR) and Relative Risk (RR) associated to positive responses	**Model** 1(recurrent falls): Score chart (range 1-6) on the questions: - Have you ever fallen in the last 6 months? - What is the probability that you fall in the next few months?	**Model** 1: AUC (95% CI): 0.74 (0.66-0.82) Calibration: after contacting study authors, a calibration plot was provided showing acceptable calibration. Calibration slopes were not considered. Cut-off: 3 points SN (95% CI): 70% (56%-84%) SP (95% CI): 72% (68%-76%)

			No information on model validation		
Lohman et al. [26], 2017, USA, Development study	n = 7,609 Age groups, n (%): 65-69 years: 2,099 (28.4%) 70-74 years: 1,863 (25.2%) 75-79 years: 1,427 (19.3%) 80-84 years: 1,079 (14.6%) 85-89 years: 636 (8.6%) 90+ years: 288 (3.9%) Female: 56.4% Prior falls: no information	Any falls (3,903; 51.3%) Recurrent falls (2,181; 28.7%) Follow-up: 48 months	Logistic regression No information on model validation	**Model** 1 (any falls): STEADI algorithm: - Low risk, all present: no falls in past year, no worrying about falling, no unsafe/unsteady feeling while walking - Moderate risk, all present: yes, to one of the above-mentioned questions the low risk group, >4 chair stands in 30 sec., completion of all balance stages in 4 stage balance test. If NO to one of tests then both succeeding questions need to be answered as follows: no multiple falls in the past year, and no previous hip fracture since the age of 50 - High risk, all present: the same as in the moderate risk group except one of the succeeding questions are answered as follows: yes, to multiple falls in the past year or yes to previous hip fracture since the age of 50 **Model** 2 (any falls): Covariates: age, race, gender, education, living alone, smokings status, body mass index, vision impairment, hearing impairment, medical burden, functional Impairment, and frailty **Model** 3 (any falls): Model 1 and 2 combined	**Model** 1: AUC: 0.641 ("No CI was calculated" – author response) Calibration: no information SN: 65% SP: 65% PPV: 62% NPV 68% **Model** 2: AUC: 0.575 Calibration: no information **Model** 3: AUC: Calibration: no information
Kim et al. [27], 2017, USA, Development study + Validation study	Development: n = 5,593 (3,960 at follow-up) Validation: n = 4,424 (3,273 at follow-up) Age, median (IQR): Development: 77 (71, 83) Validation: 78 (71, 83) Female: Development: 58.4% Validation: 57.4% Prior falls: no information	Recurrent falls - Development: (834; 14.9%) - Validation: (514; 11.6%) Follow-up: No exact length of follow-up was reported. However, they reported that they wanted to predict the outcomes in the following year from baseline	Lasso regression model Bootstrap validation	**Model** 1 (recurrent falls - development): Age, sex, combined comorbidity index, 52 International Classification of Diseases 9-codes, 25 Current Procedural Terminology codes, and 16 Healthcare Common Procedure Coding System level II codes **Model** 2 (recurrent falls - validation): Age, sex, combined comorbidity index, 52 International Classification of Diseases 9-codes, 25 Current Procedural Terminology codes, and 16 Healthcare Common Procedure Coding System level II codes	**Model** 1: C-statistic: 0.62-0.66 Calibration: no information **Model** 2: C-statistic: consistent with C-statistic in Development study sample Calibration: no information

Palumbo et al. [28], 2018, Italy, Development study	n = 541 Age, mean (SD): 82.4 (6.5) years Of the 438 participants with a complete data set, female: 60.7% Prior falls: 27%	Recurrent falls (34; 6.3%) Any falls (87; 16.1%) Follow-up: 12 months	No regression analysis was performed. The predictive accuracy was quantified from TP, TN, FP and FN in terms of SN, SP, PPV, NPV, and accuracy No information on model validation	**Model** 1 (any fall): A table with classification measures for the model with 3 different cut-off values for the TUG-test. Predictors were two or more falls in the past 12 months, presents with acute fall, difficulty with walking or balance, single fall in the past 12 months, and Timed up and go test (cut-off: >12 s, >13.5s, and >15s) **Model** 2 (any fall): A table with classification measures for the model with 2 different cut-off values for the SPPB. Predictors were two or more falls in the past 12 months, presents with acute fall, difficulty with walking or balance, single fall in the past 12 months, and Short Physical Performance Battery (cut-off: < 9, and < 11 point) **Model** 3 (any falls): A table with classification measures for the model with 2 different cut-off values for the 7m gait speed test. Predictors were two or more falls in the past 12 months, presents with acute fall, difficulty with walking or balance, single fall in the past 12 months, and 7m gait speed test (cut-off: <0.8 m/s, and < 1m/s) **Model** 4 (recurrent falls): A table with classification measures for the model with 3 different cut-off values for the TUG-test. Predictors were two or more falls in the past 12 months, presents with acute fall, difficulty with walking or balance, single fall in the past 12 months, and Timed up and go test (cut-off: >12 s, >13.5s, and >15s) **Model** 5 (recurrent falls): A table with classification measures for the model with 2 different cut-off values for the SPPB. Predictors were two or more falls in the past 12 months, presents with acute fall, difficulty with walking or balance, single fall in the past 12 months, and Short Physical Performance Battery (cut-off: < 9, and < 11 point)	**Model** 1: AUC: no information Calibration: no information TUG > 12s: SN: 36.5% (22.3%-54.5%) SP: 82.5% (76.9%-87.1%) PPV: 25.5% (16.8%-37.6%) NPV: 88.8% (83%-93.6%) Accuracy: 76% (70.2%-81.4%) TUG > 13.5s: SN: 35.8% (23.2%-52.7%) SP: 84% (79.3%-88.4%) PPV: 26.9% (17.3%-38.8%) NPV: 88.8% (83.9%-93.7%) Accuracy: 77.2% (72.4%-82.3%) TUG > 15s: SN: 35.1% (22.7%-52.6%) SP: 84.1% (79.3%-88.4%) PPV: 26.7% (17.5%-38.7%) NPV: 88.7% (83.2%-93.1%) Accuracy: 77.2% (71.7%-82.4%) **Model** 2: AUC: no information Calibration: no information SPPB < 9: SN: 37.2% (24.1%-54.1%) SP: 83.4% (78.7%-87.7%) PPV: 27% (17.8%-37.6%) NPV: 89% (83.3%-94%) Accuracy: 76.9% (71%-81.8%) SPPB < 11: SN: 43.3% (28.4%-62.7%) SP: 79% (72.7%-84.5%) PPV: 25.4% (16.4%-35.8%) NPV: 89.4% (83.9%-94.3%) Accuracy: 74% (67.8%-79.9%) **Model** 3: AUC: no information Calibration: no information

				Model 6 (recurrent falls): A table with classification measures for the model with 2 different cut-off values for the 7m gait speed test. Predictors were two or more falls in the past 12 months, presents with acute fall, difficulty with walking or balance, single fall in the past 12 months, and 7m gait speed test (cut-off: <0.8 m/s, and < 1m/s)	Gait speed < 0.8 m/s: SN: 35.1% (22.6%-52.5%) SP: 84.3% (78.8%-88.6%) PPV: 26.9% (17.7%-39.1%) NPV: 88.8% (82.9%-93.4%) Accuracy: 77.4% (71%-82.5%) Gait speed < 1 m/s: SN: 35.8% (22.4%-54.4%) SP: 82.4% (76.9%-87.3%) PPV: 25.1% (15.9%-36.5%) NPV: 88.6% (83%-93.3%) Accuracy: 75.8% (69.8%-81.5%) **Model** 4: AUC: no information Calibration: no information TUG > 12 s: SN: 56.2% (32.2%-92.8%) SP: 82.1% (76.9%-86.6%) PPV: 16.8% (8.9%-27.8%) NPV: 96.7% (92.9%-99.7%) Accuracy: 80.5% (75%-85.3%) TUG > 13.5s SN 56.2% (27.6%-89.8%) SP: 83.6% (79.4%-87.6%) PPV: 18.1% (9.7%-29.2%) NPV: 96.7% (92.3%-99.6%) Accuracy: 81.9% (76.9%-86.4%) TUG > 15 s SN: 56.2% (30.3%-92.6%) SP: 83.8% (79.2%-87.7%) PPV: 18.3% (10%-28.6%) NPV: 96.7% (93.1%-99.7%) Accuracy: 82.1% (76.9%-86.8%) **Model** 5: AUC: no information Calibration: no information SPPB < 9: SN: 56.2% (32.1%-93.2%)

					SP: 82.9% (78.1%-87%) PPV: 17.5% (9.3%-28.4%) NPV: 96.7% (93%-99.7%) Accuracy: 81.3% (76%-85.6%) SPPB < 11: SN: 59% (32.3%-97.4%) SP: 78.1% (72.4%-83.3%) PPV: 14.8% (8.1%-24.3%) NPV: 96.7% (92.7%-99.9%) Accuracy: 76.9% (71%-82.6%) **Model** 6: AUC: no information Calibration: no information Gait speed < 0.8 m/s: SN: 56.2% (30.6%-91.7%) SP: 84% (79.3%-88.2%) PPV: 18.4% (9.9%-29.9%) NPV: 96.7% (93.1%-99.7%) Accuracy: 82.3% (77.2%-87.2%) Gait speed < 1 m/s: SN: 56.2% (30.8%-92%) SP: 82.1% (77.2%-86.5%) PPV: 16.8% (8.9%-27.4%) NPV: 96.7% (92.9%-99.6%) Accuracy: 80.5% (74.9%-85.3%)
Singh et al. [29], 2019, Malaysia, Development study	n = 325 Age, mean (SD): 67.55 (5.5) years Of the n = 305 analysed, female: 56.1% Prior falls: 16.7%	Any falls (81; 24.9%) Follow-up: 6 months	Logistic regression No information on model validation	**Model** 1 (any falls): constant: -5.03, age: -0.003, gender: 0.19, medication: -0.24, primary education: -0.27, secondary education: -0.85, history of falls: 0.67, Walk While Talking Test: 0.68, gait speed: 0.25, instrumental activities of daily living: -0.01, Timed up and go test: 0.14, and Physiological Profile Assessment: 1.16 **Model** 2 (any falls): constant: -5.06, age: 0.05, gender: 0.46, medication: -0.14, primary education: 0.07, secondary education: 0.85, history of falls: 0.12, Walk While Talking Test: 0.23, gait speed: -	**Model** 1: Cox-Snell R^2: 0.21 Nagelkerke R^2: 0.31 AUC: no information Calibration: "Hosmer-Lemeshow test result confirmed that the model was a good fit for the data $\chi 2(df = 8, N = 305) = 10.80, P = .21$" Accuracy: 76.6% **Model** 2: Cox-Snell R^2: 0.07 Nagelkerke R^2: 0.95 AUC: no information Calibration: "Hosmer-Lemeshow test results confirmed that the

				0.07, instrumental activities of daily living: -0.03, and Timed up and go test: 0.16	model was a good fit for the data $\chi 2$ (df = 8, N =305) = 4.77, P = 0.78" Accuracy: 74.1%
Gillain et al. [30], 2019, Belgium, Development study	n = 105 Age, mean (SD): 71.3 (5.4) years Age, range: 65-89 years Of the 96 analysed, female: 50% Prior falls: 0%	First time falls (35; 33.3%) Follow-up: 24 months	Classification tree Split-sample validation (no information on allocation) Cross-validation (10 subsets)	**Model** 1 (first time falls): Classification tree: symmetry dual task walking condition cost, fast walking condition stride length, stiffness, comfortable walking condition mean minimum toe clearance, dual task walking condition coefficient of variation of minimum toe clearance cost, fast walking condition variance of minimum toe clearance values, fast walking condition mean minimum toe clearance value, dual task walking condition delta1 minimum toe clearance, and gender	**Model** 1: AUC: 0.84 Calibration: no information SN: 80% SP: 87% PPV: 78% NPV: 88%

Note: AUC = Area Under the Curve; Any falls = both single a CI = confidence interval; COP = centre of pressure; FN = False negative; FP = False positive; kg = kilograms; LOS = limits of stability; +LR = positive likelihood ratio; -LR = negative likelihood ratio; PPV = positive predictive value; N = no; NPV = negative predictive value; n = number; SD = standard deviation; SE = standard error; SN = sensitivity; SP = specificity; TN = True negative; TP = True positive; Y = yes; % = percentage proportion

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Appendix 10: extracted data

See separate PDF file: “Appendix 10”.

APPENDIX 6: REFERENCES EXCLUDED DURING SCREENING OF TITLES AND ABSTRACTS:

PMID	Authors	Published Year	Journal	Volume	Issue	Pages	DOI
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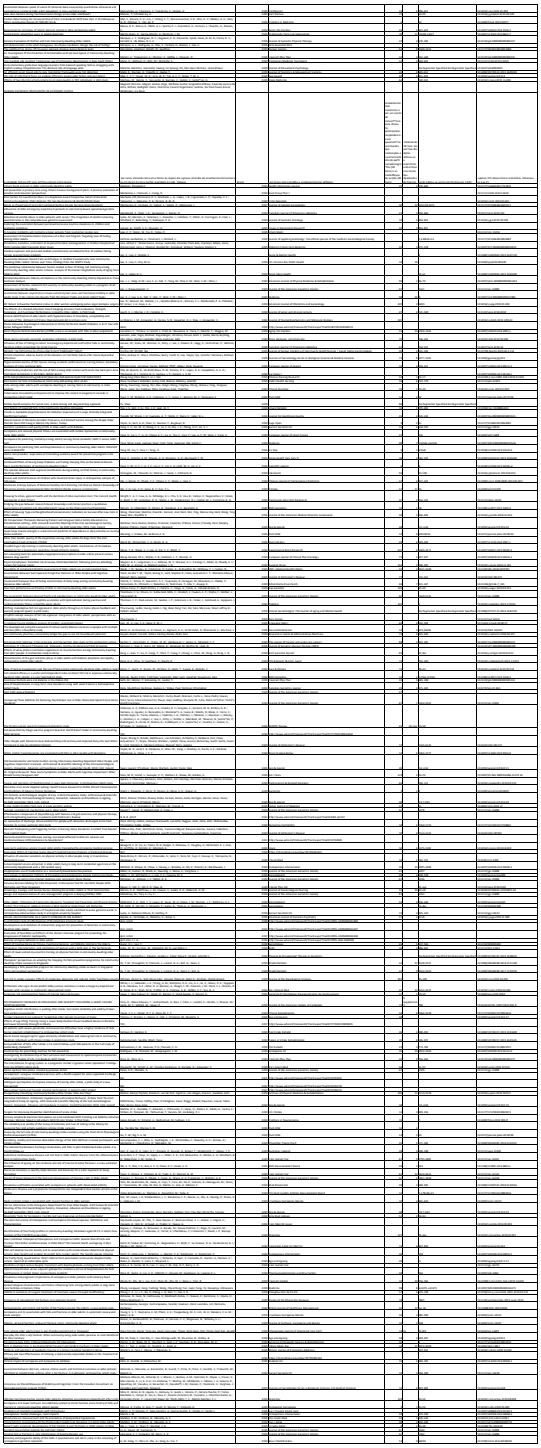

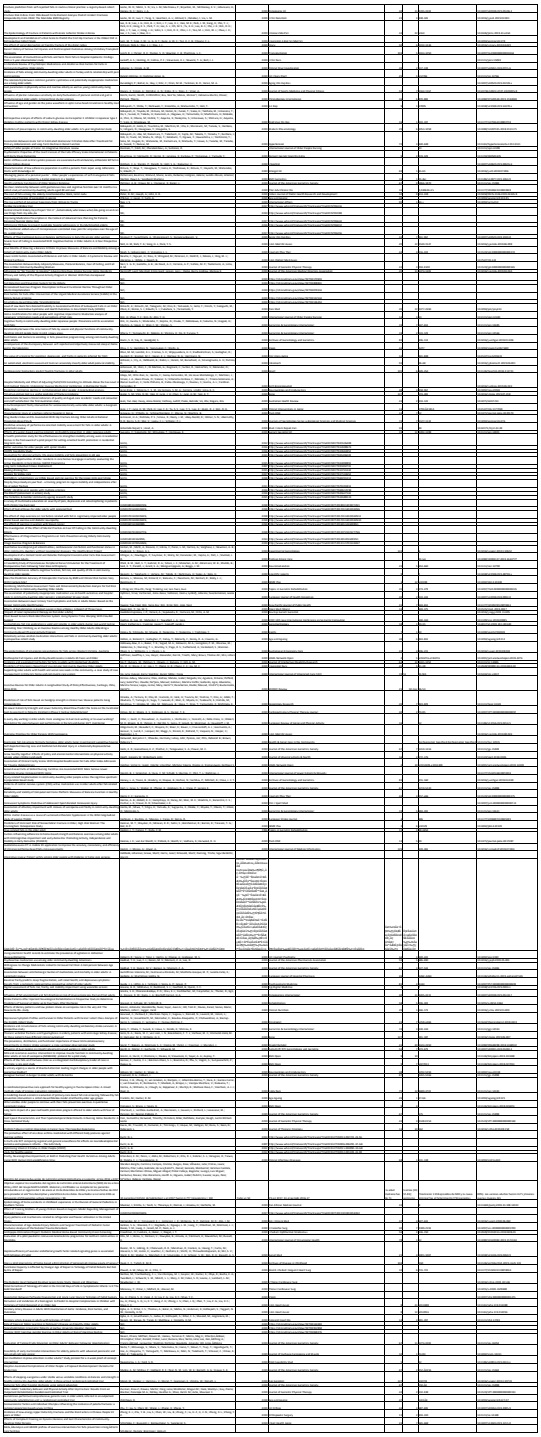

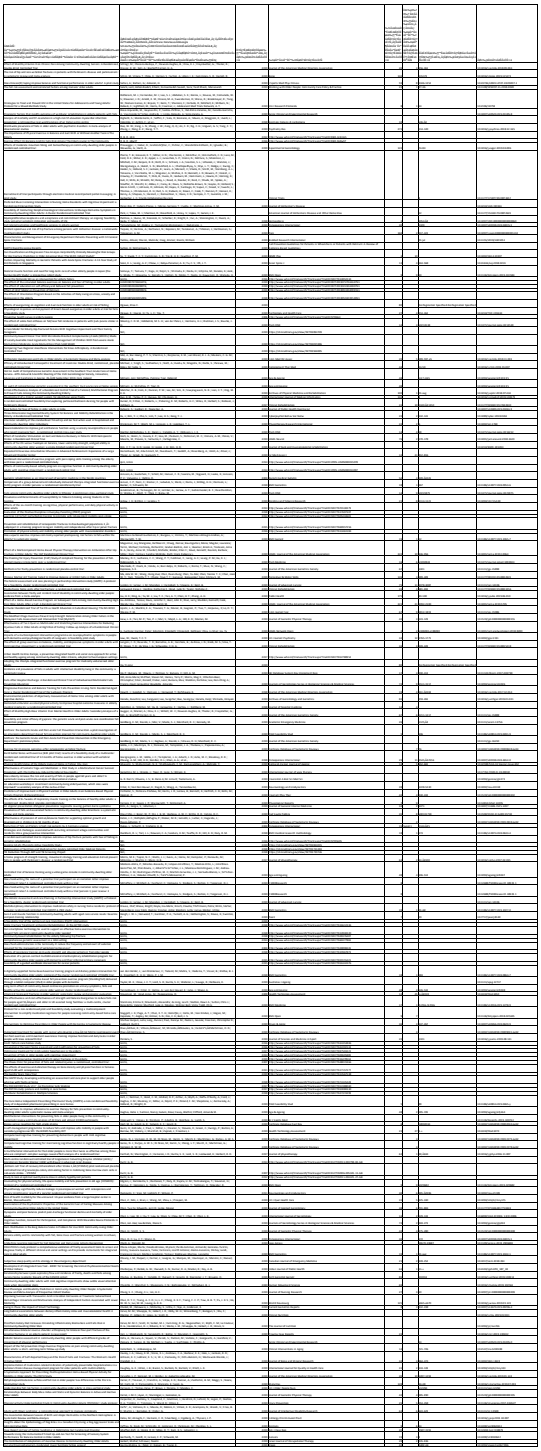

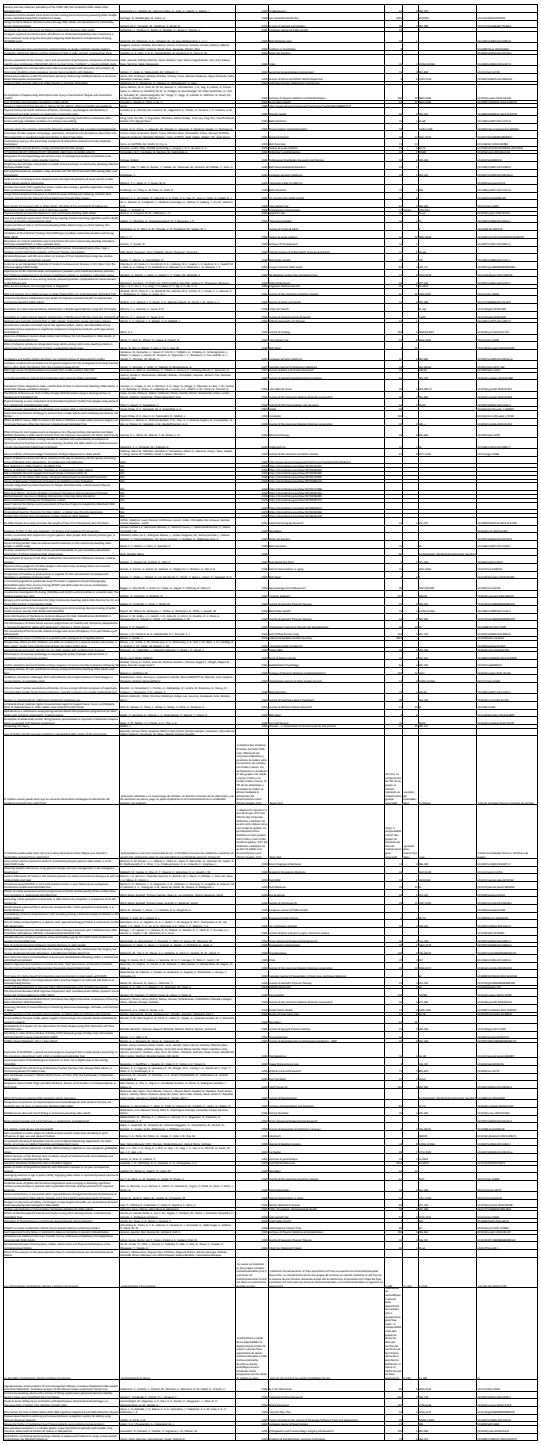

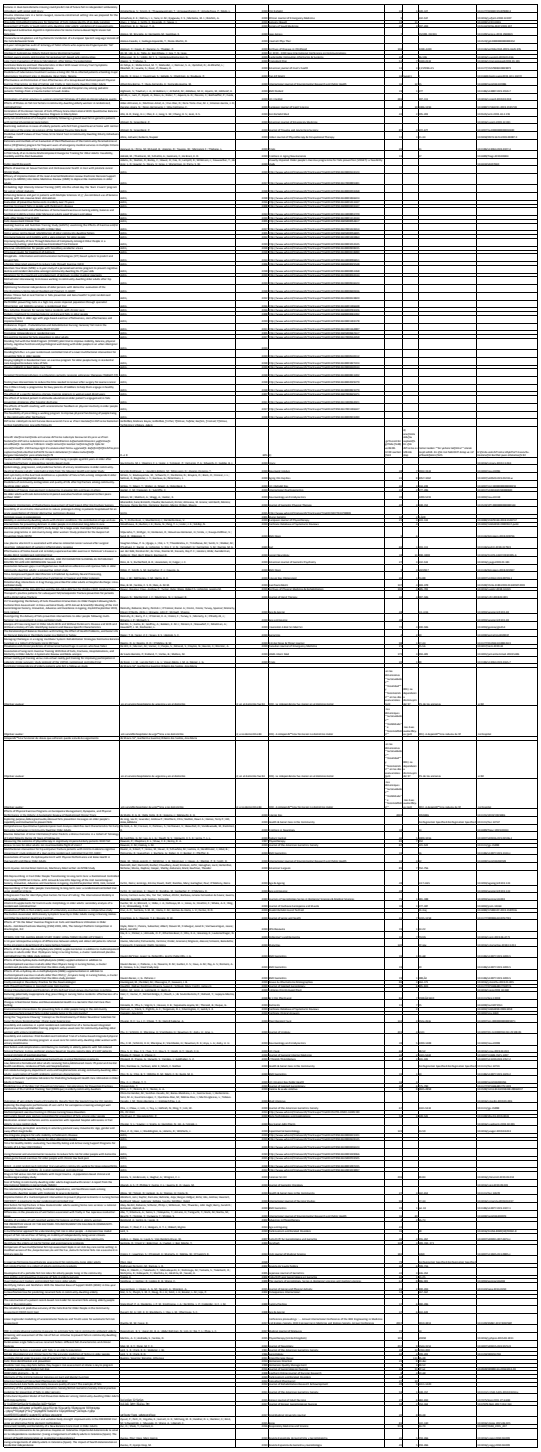

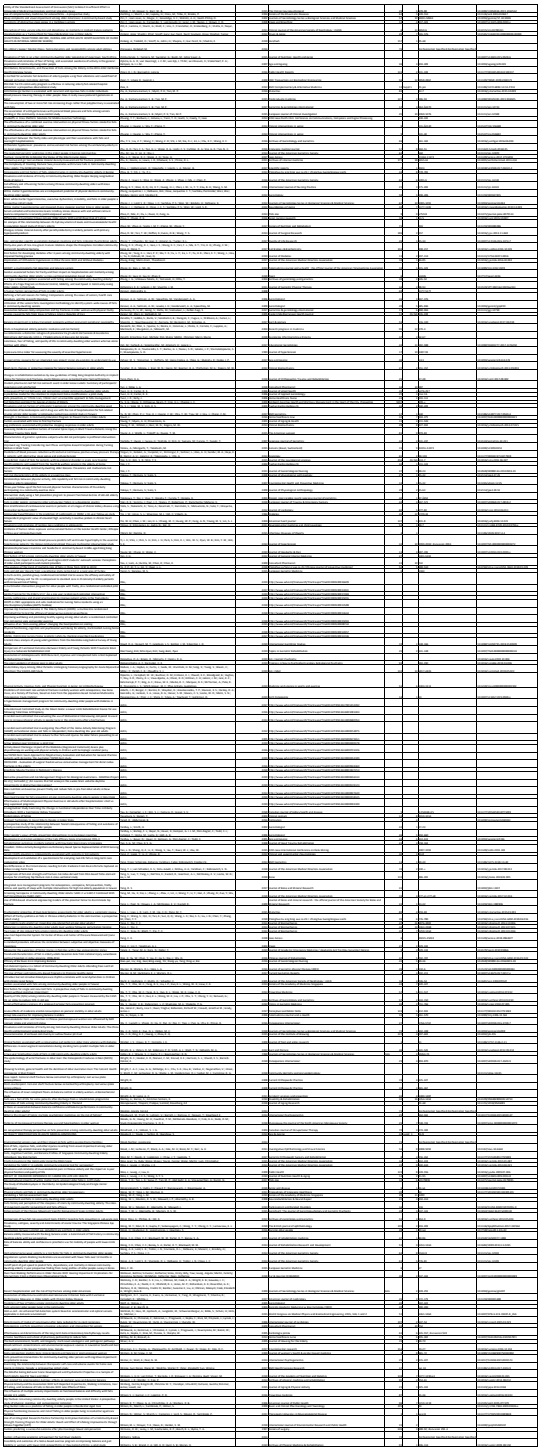

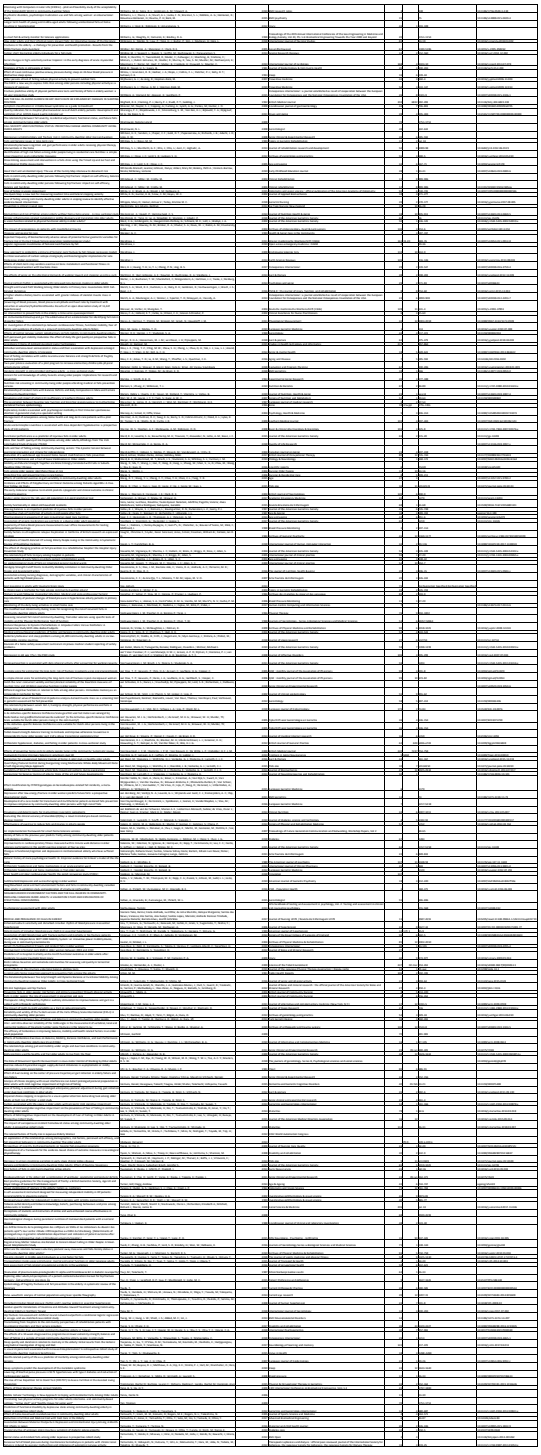

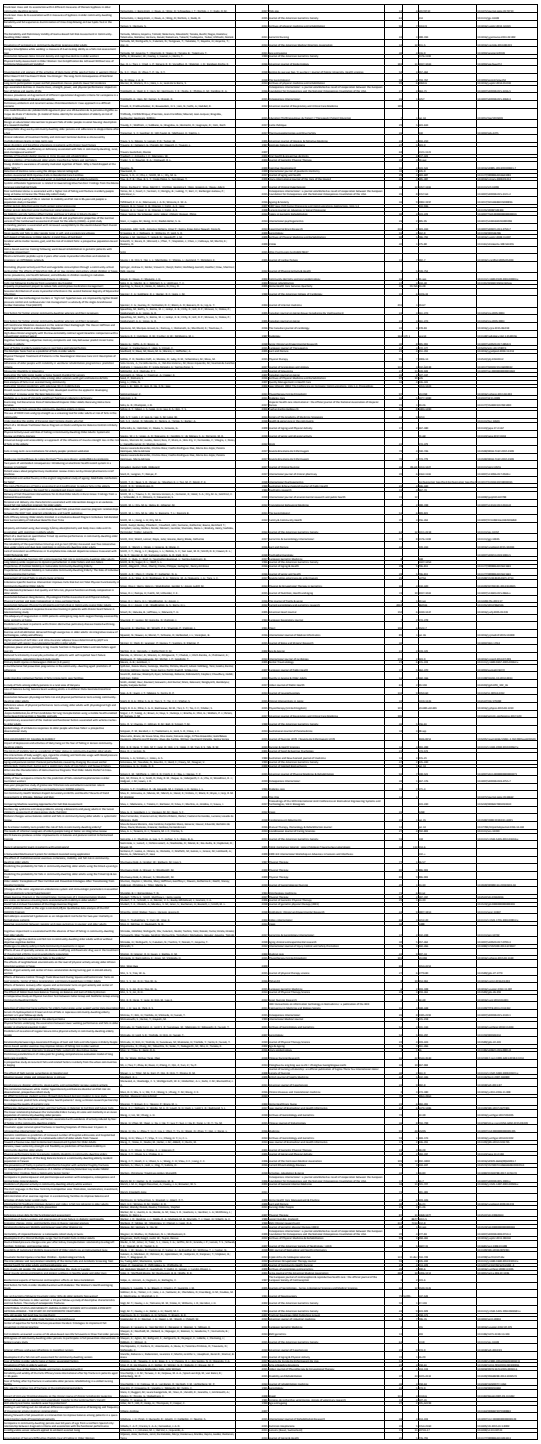

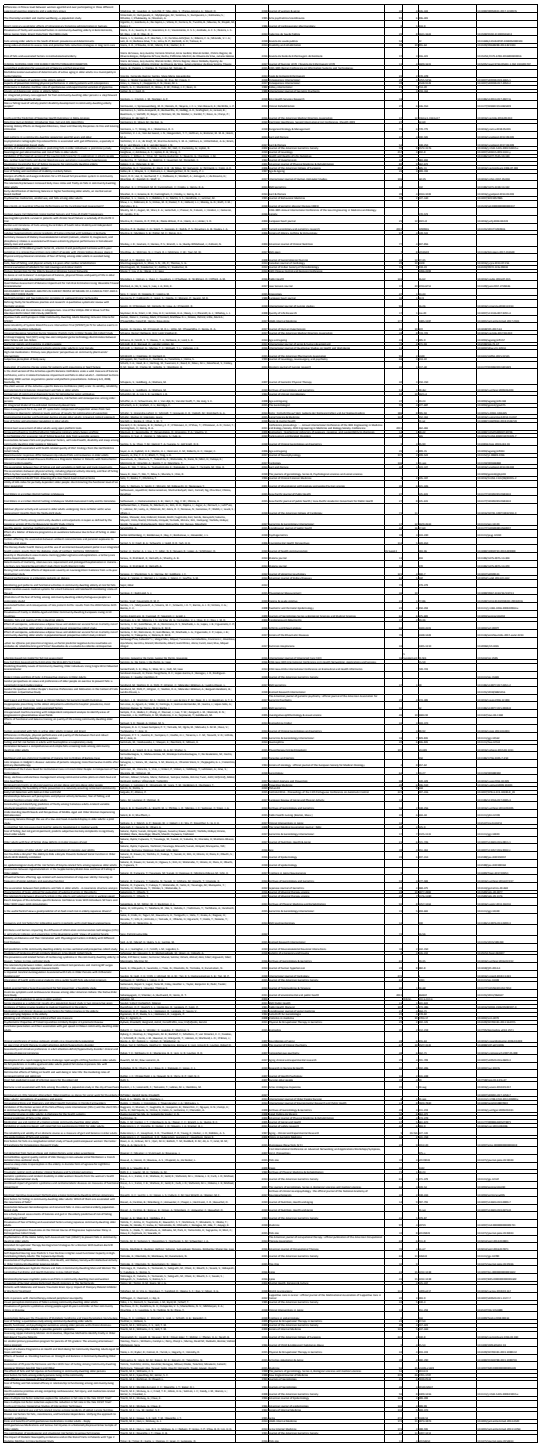

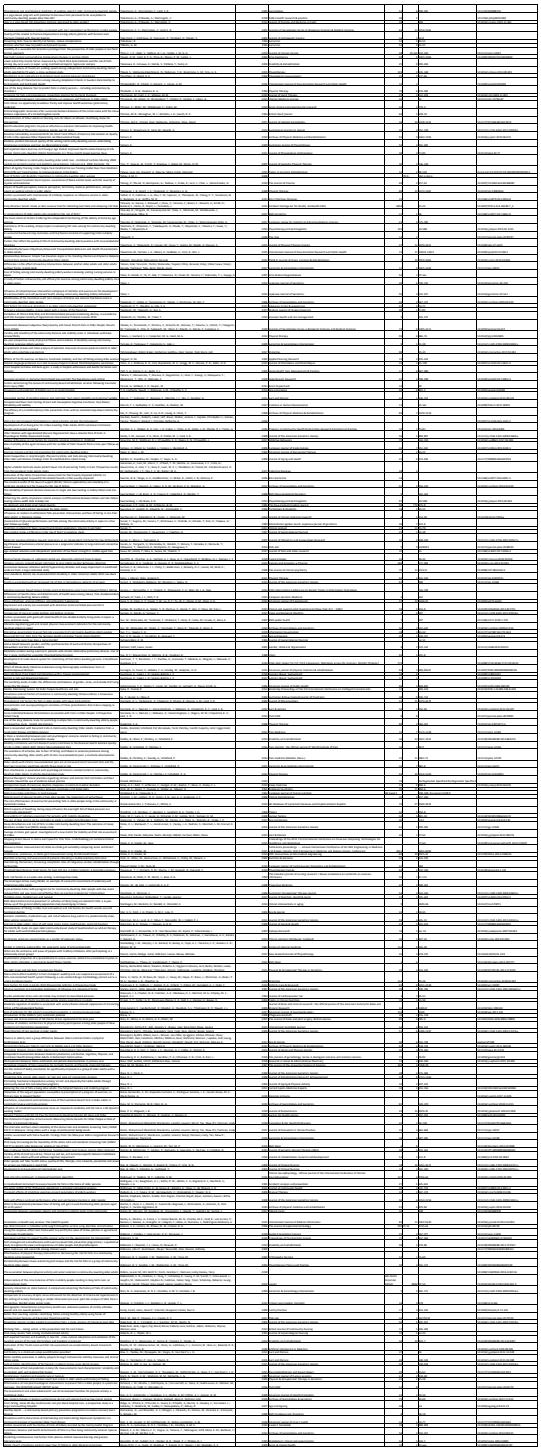

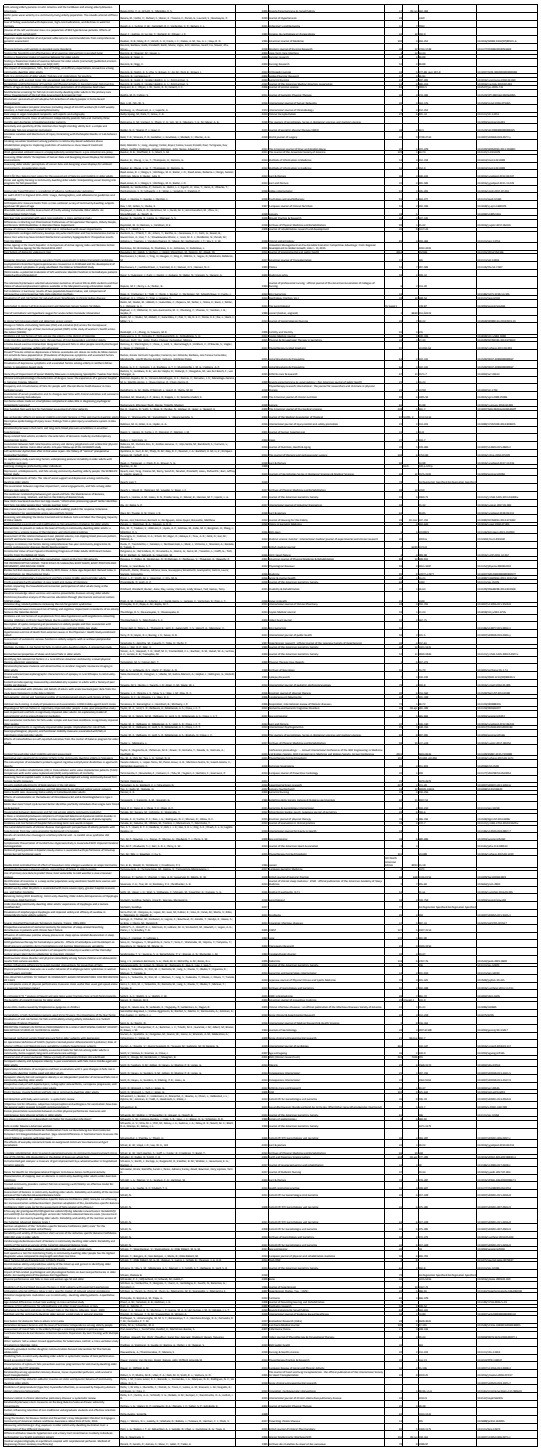

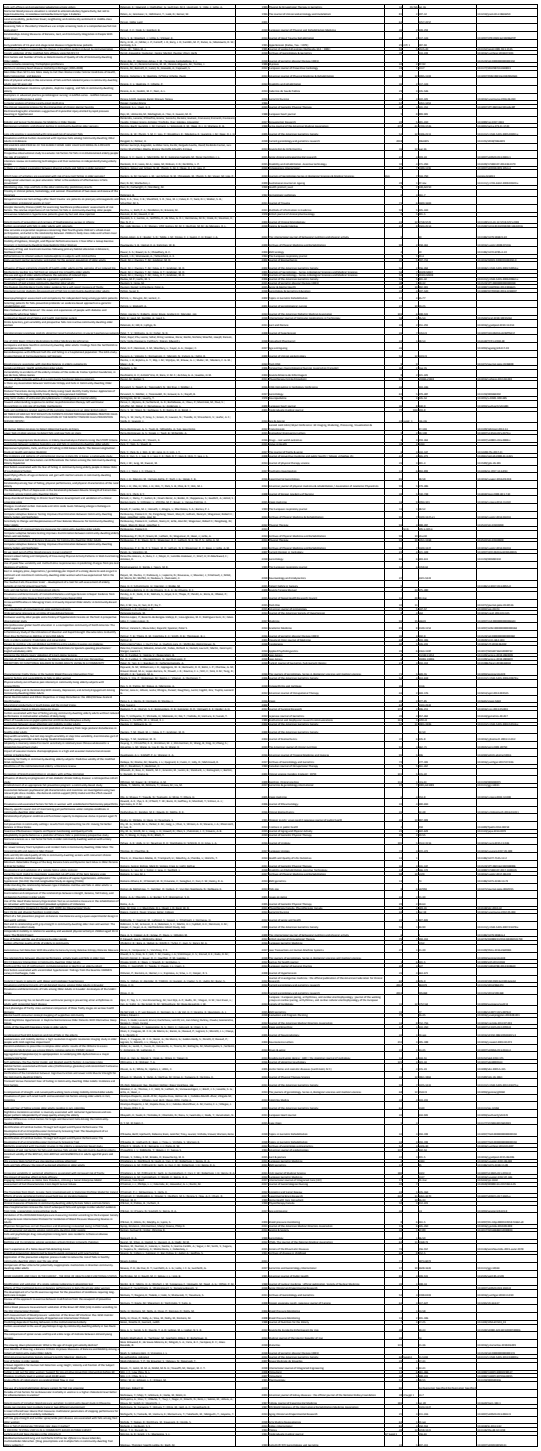

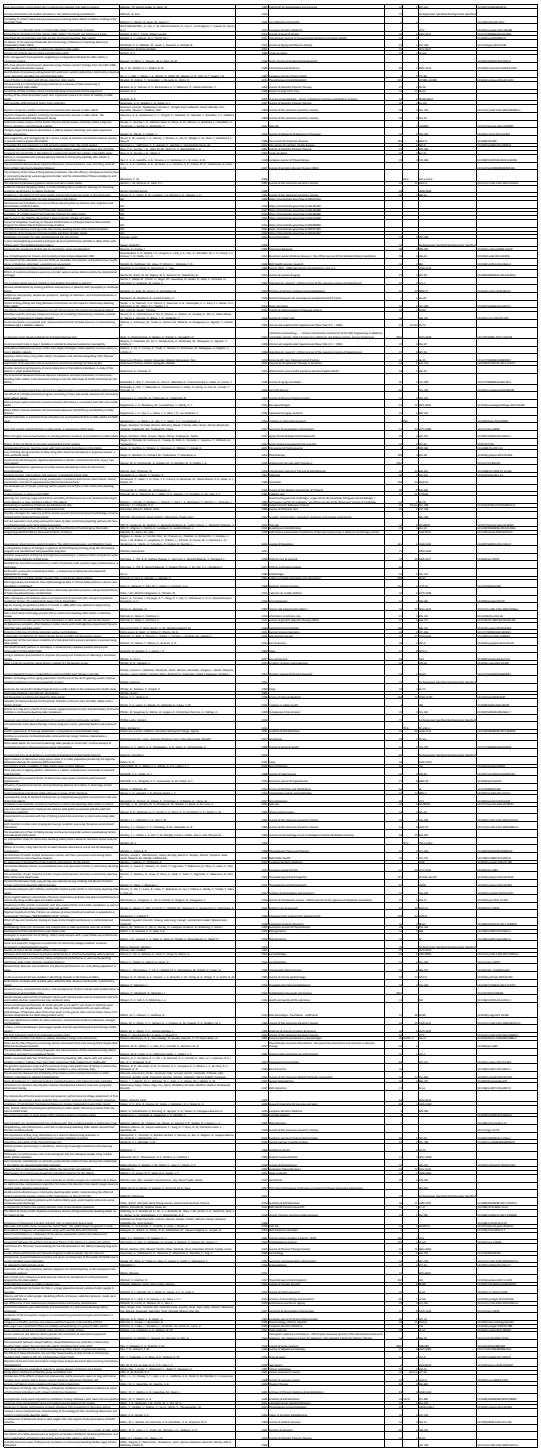

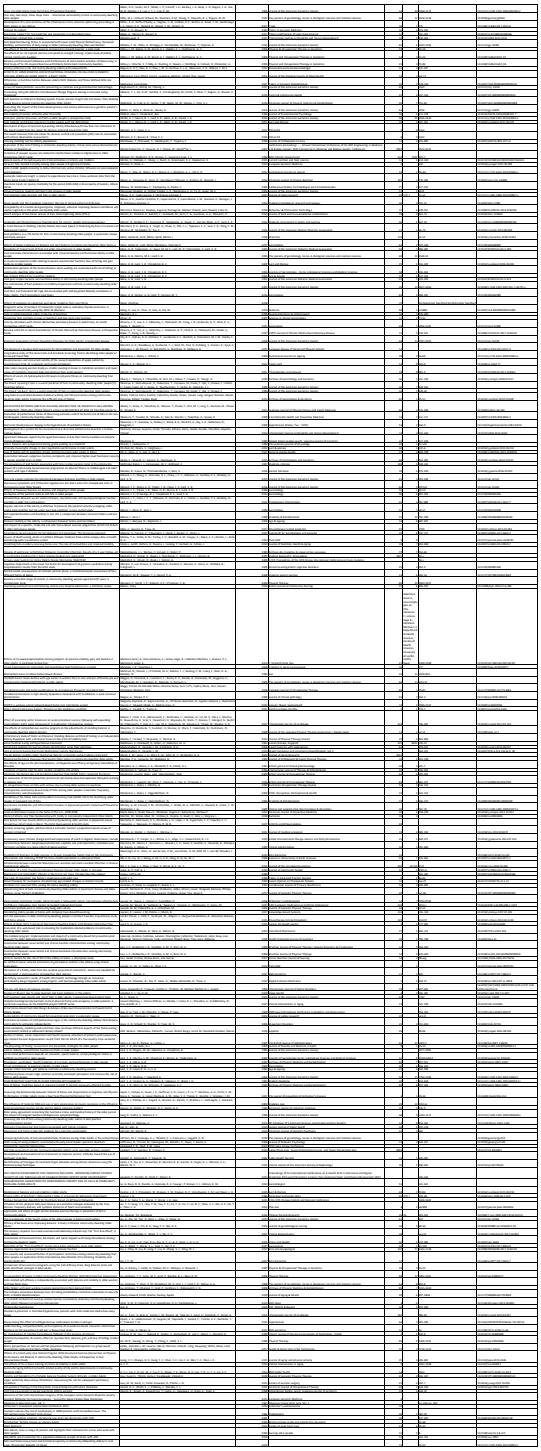

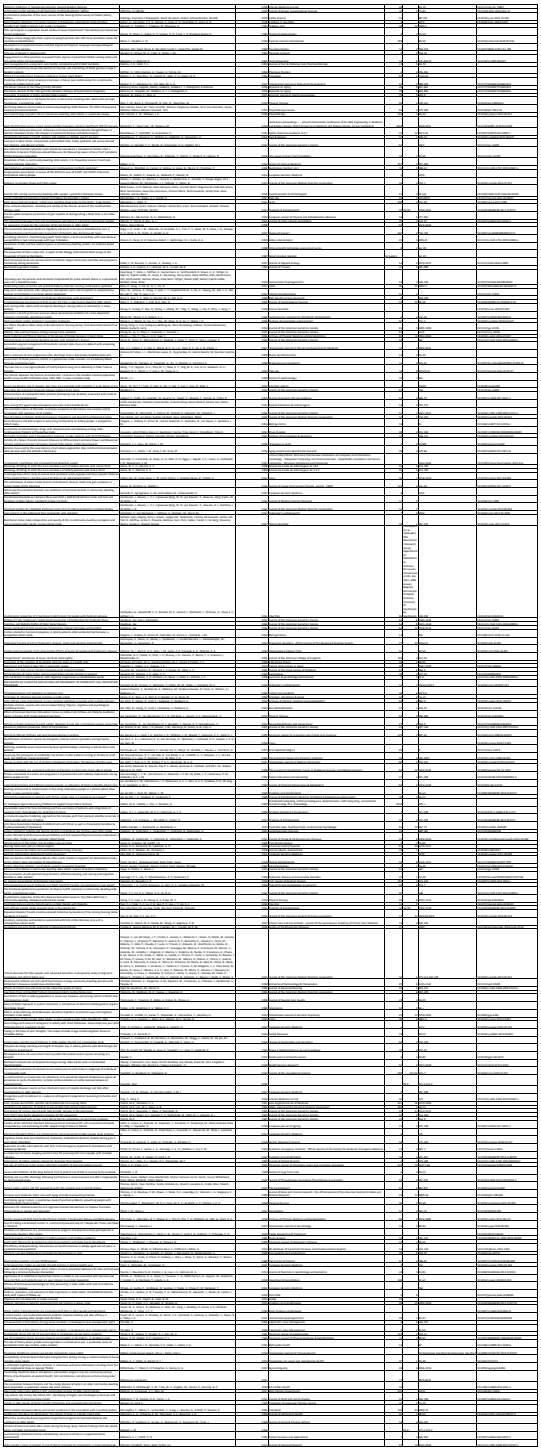

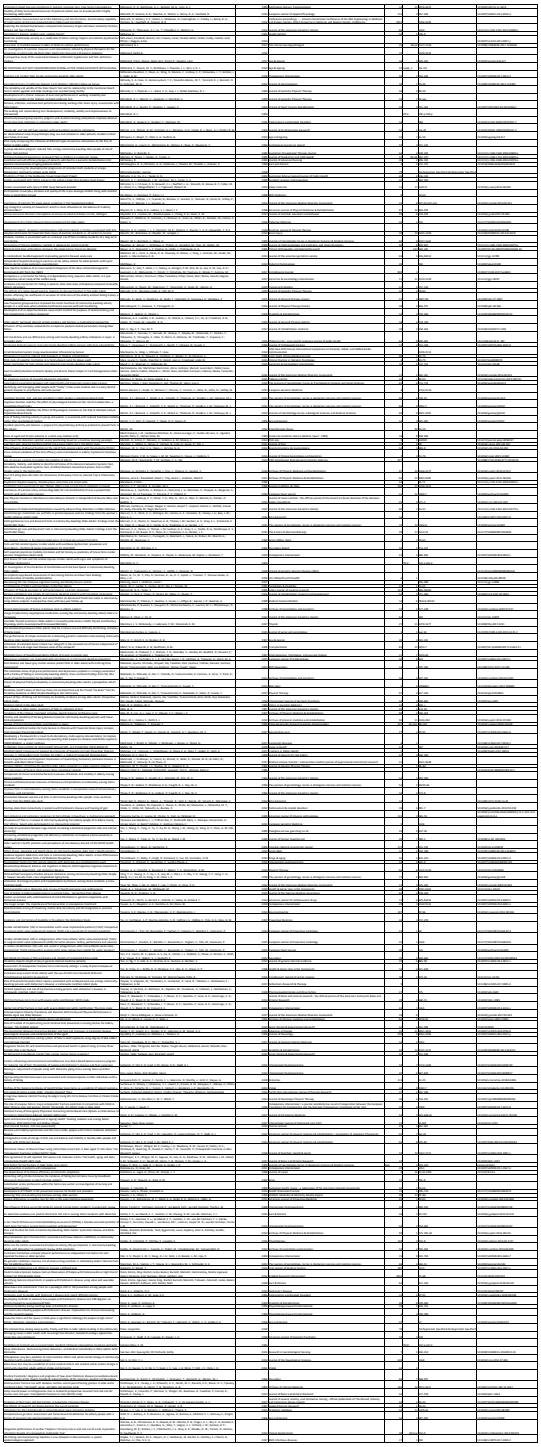

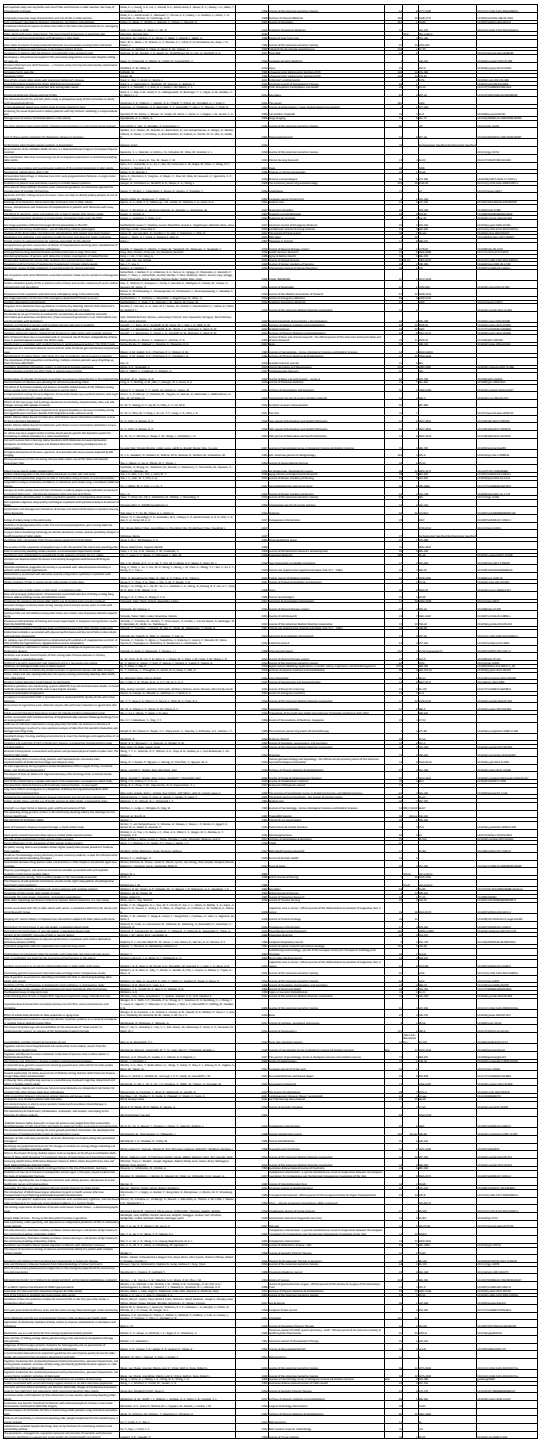

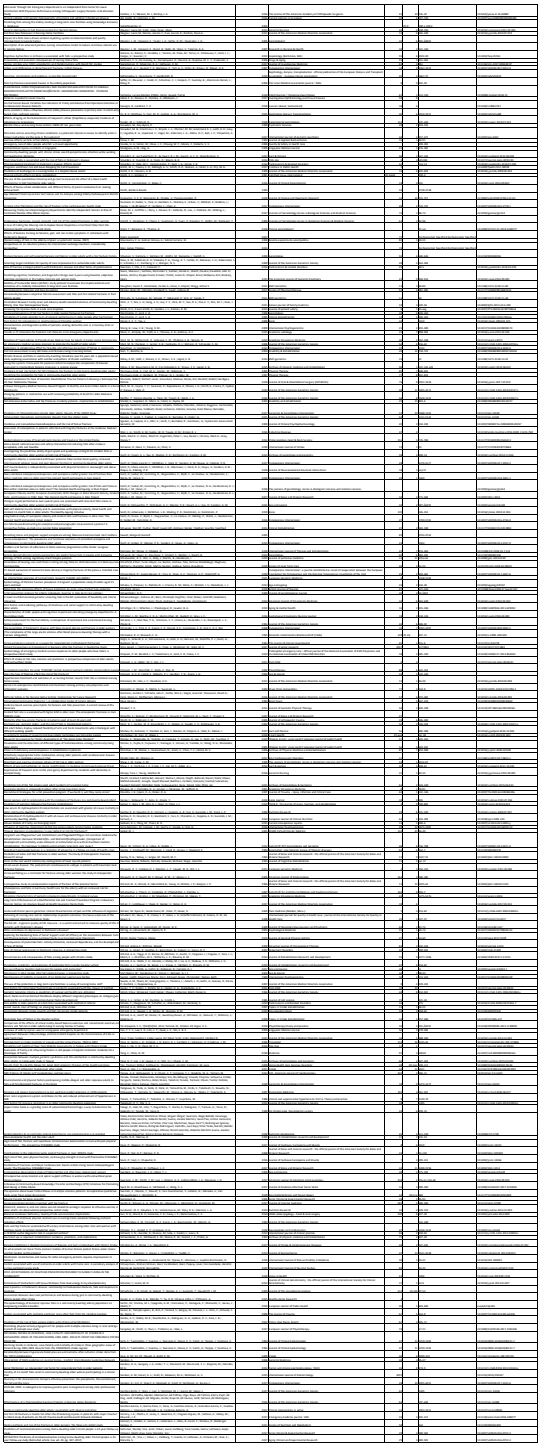

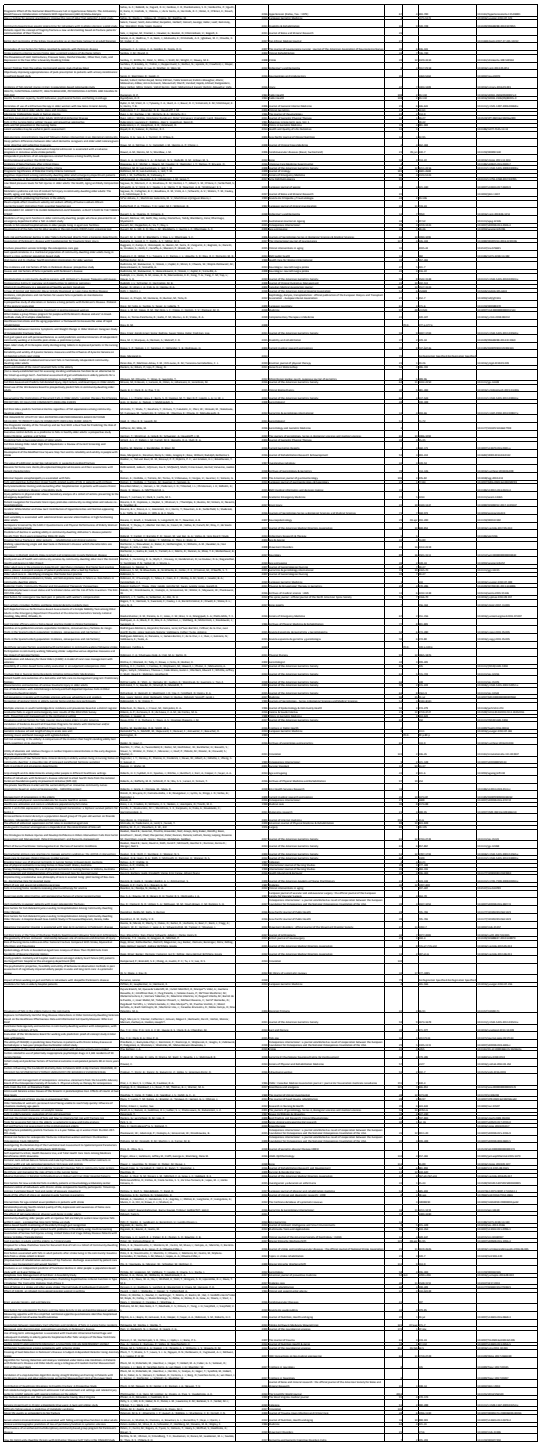

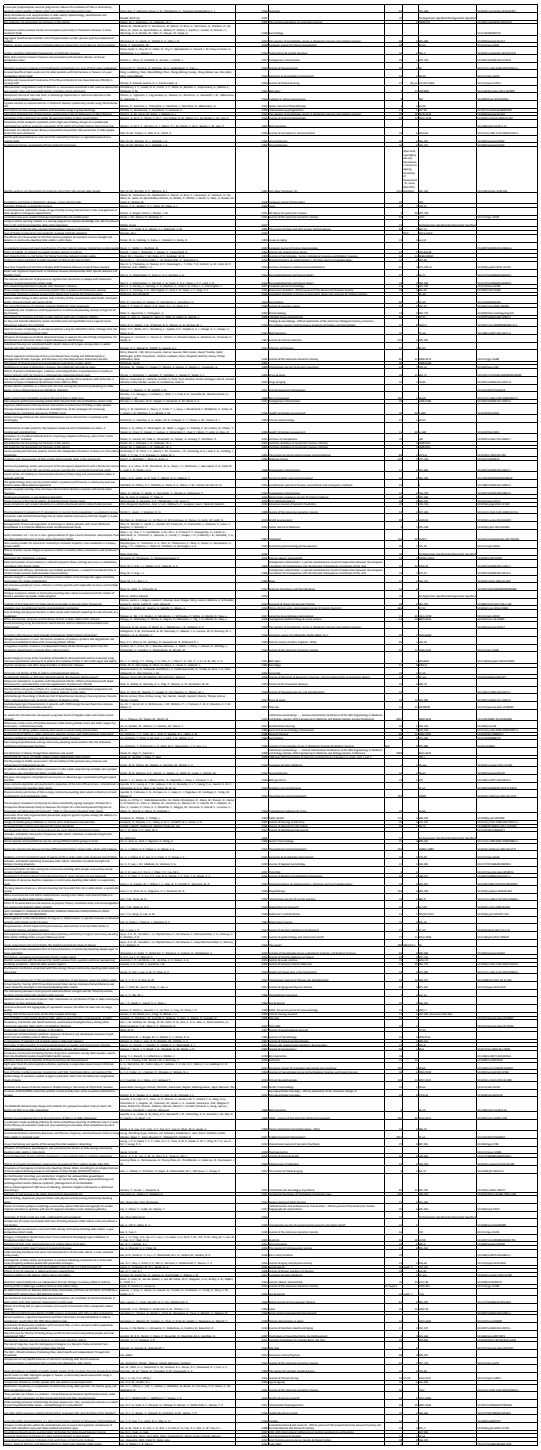

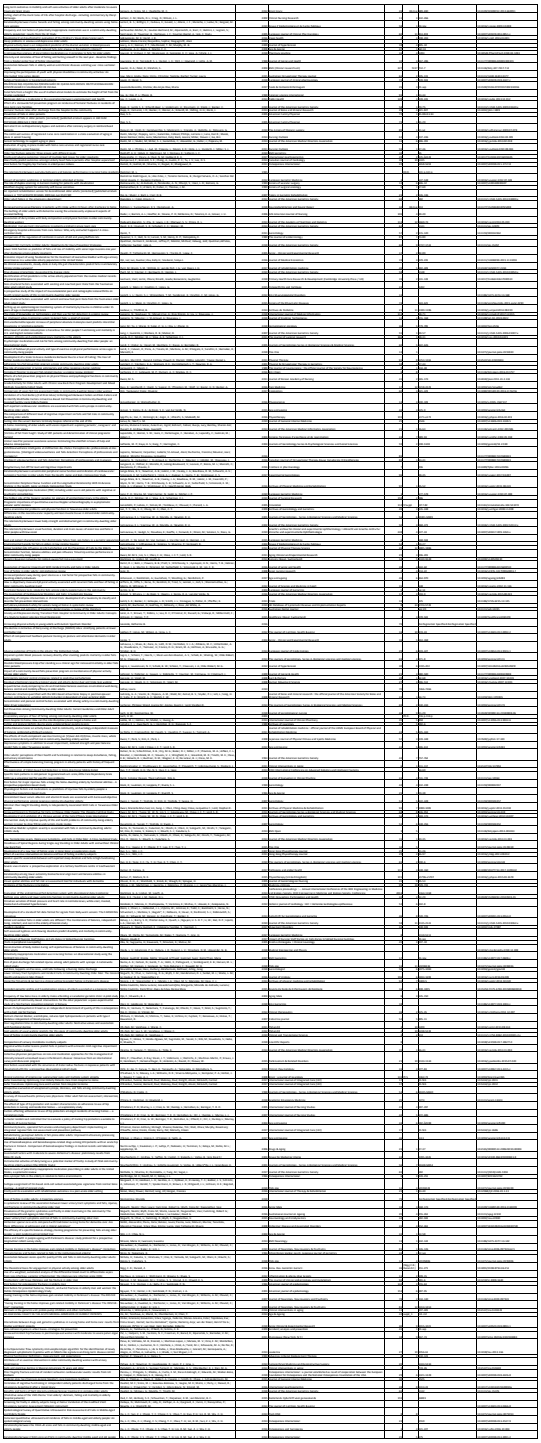

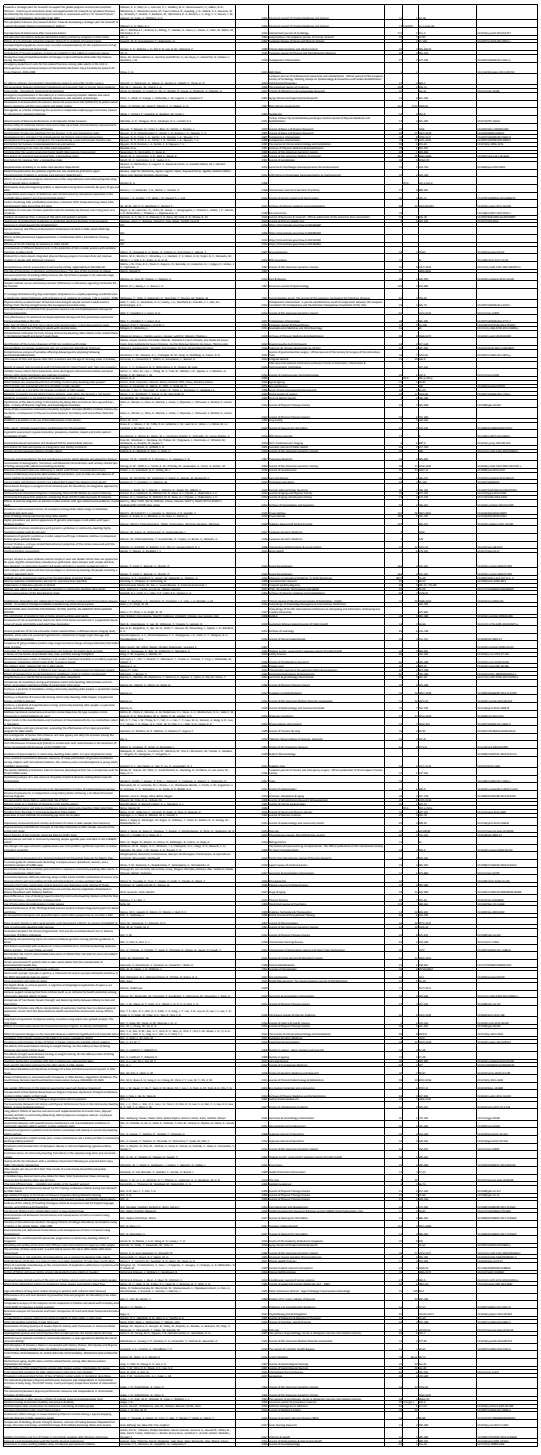

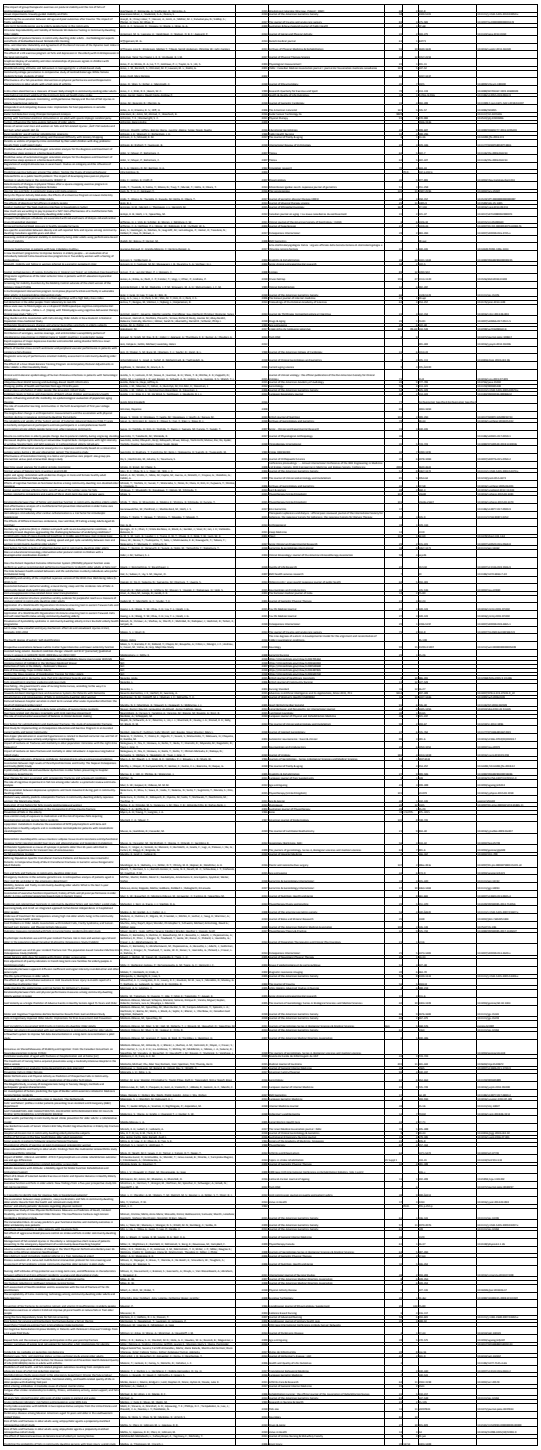

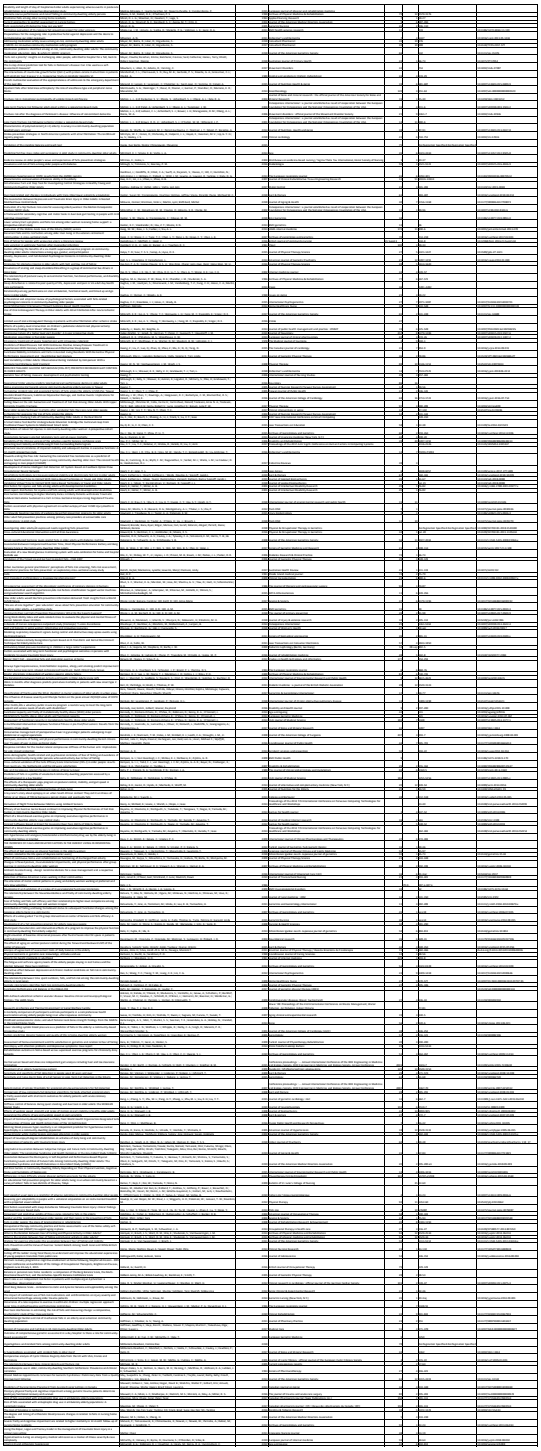

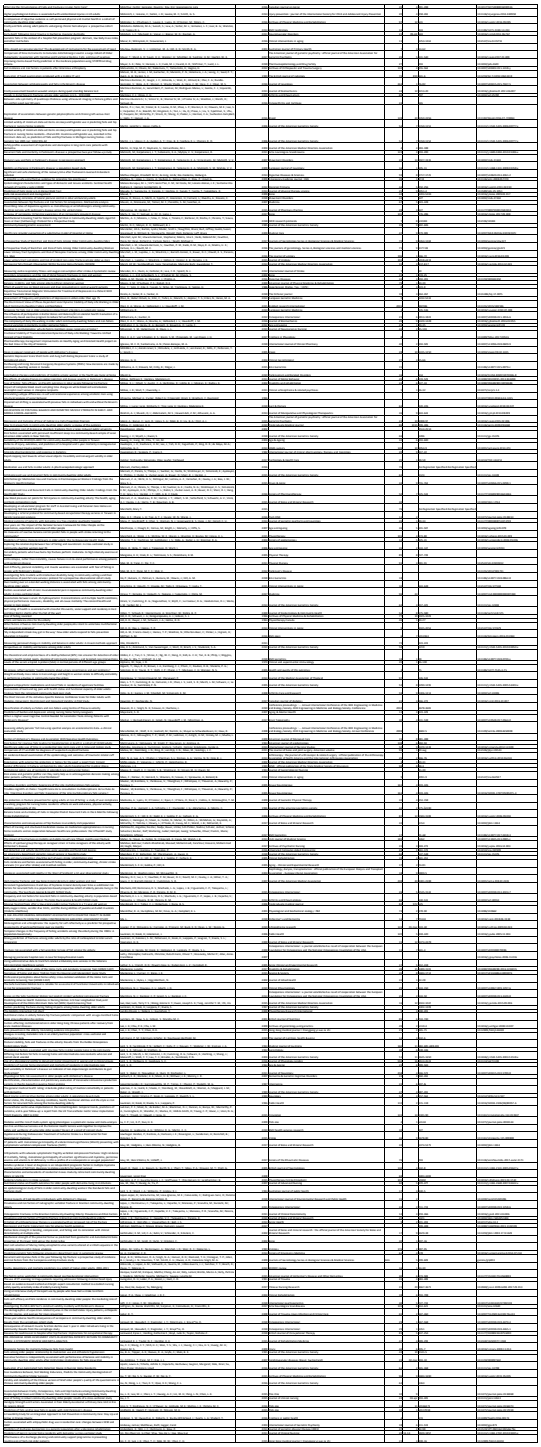

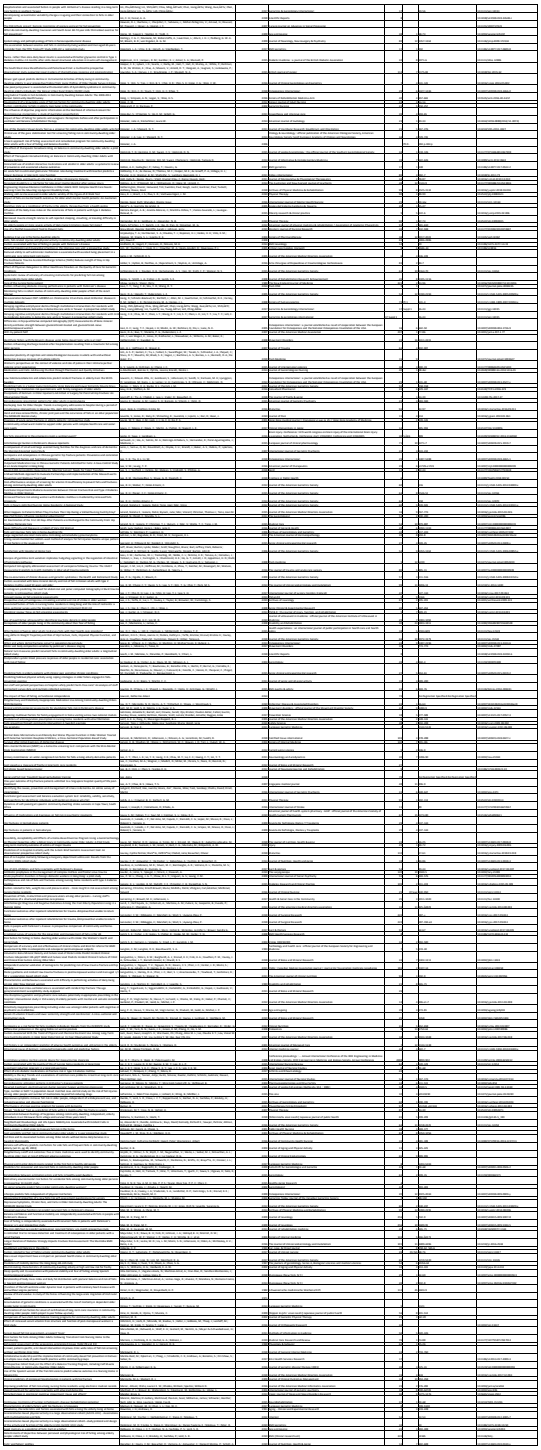

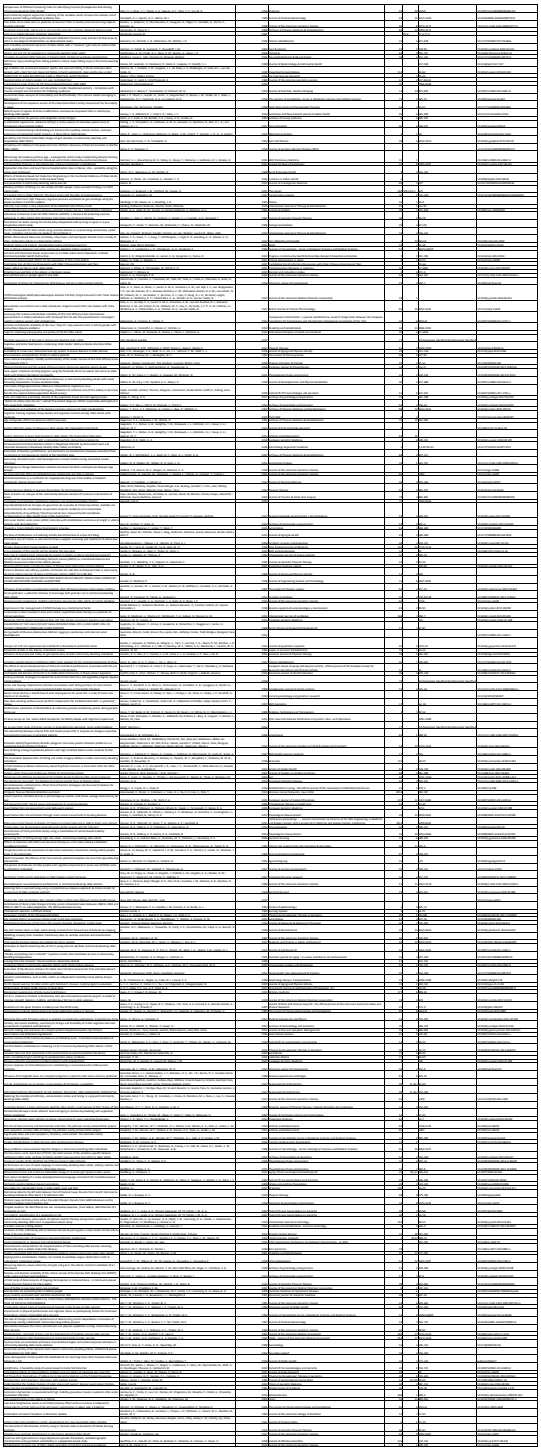

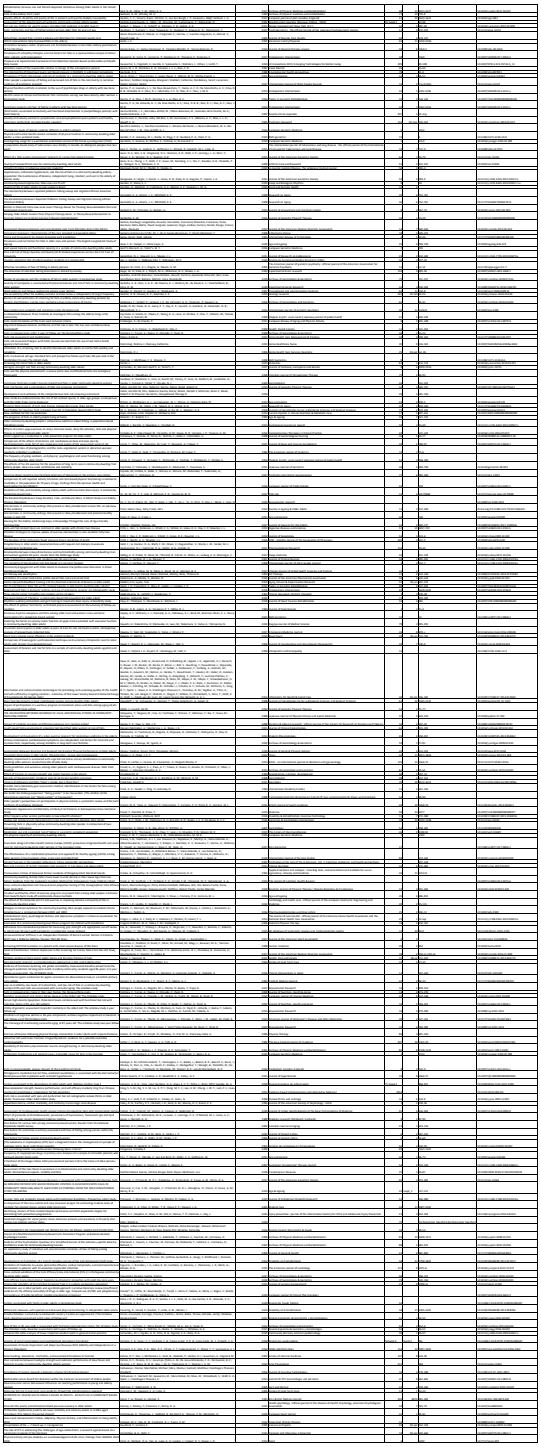

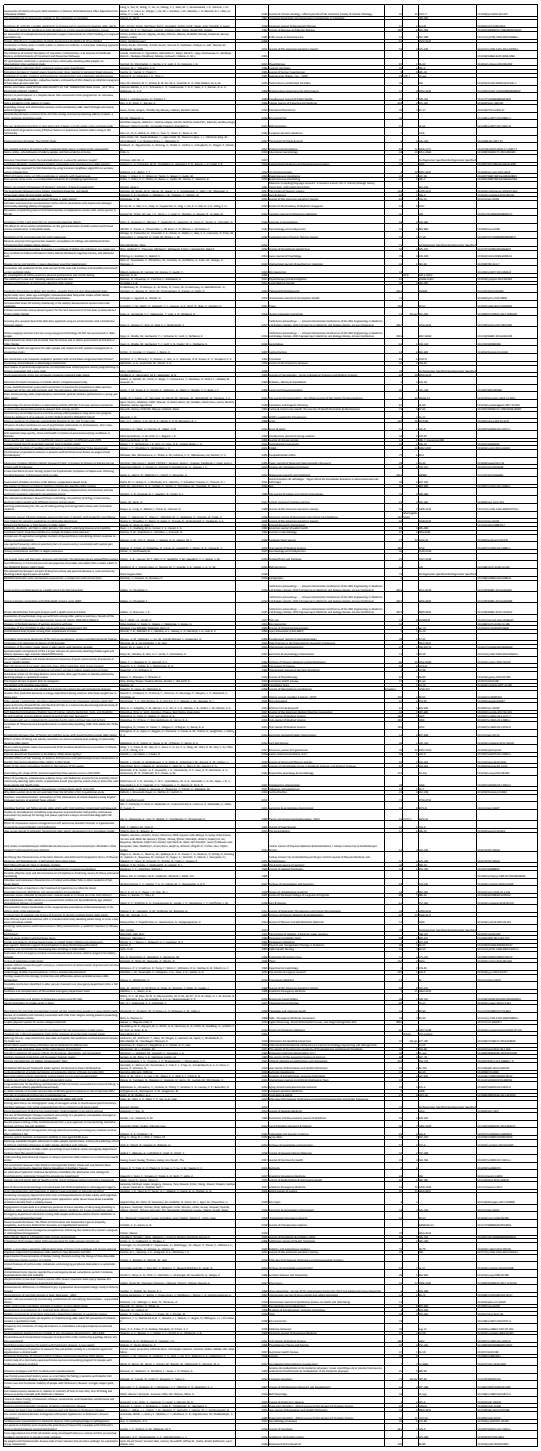

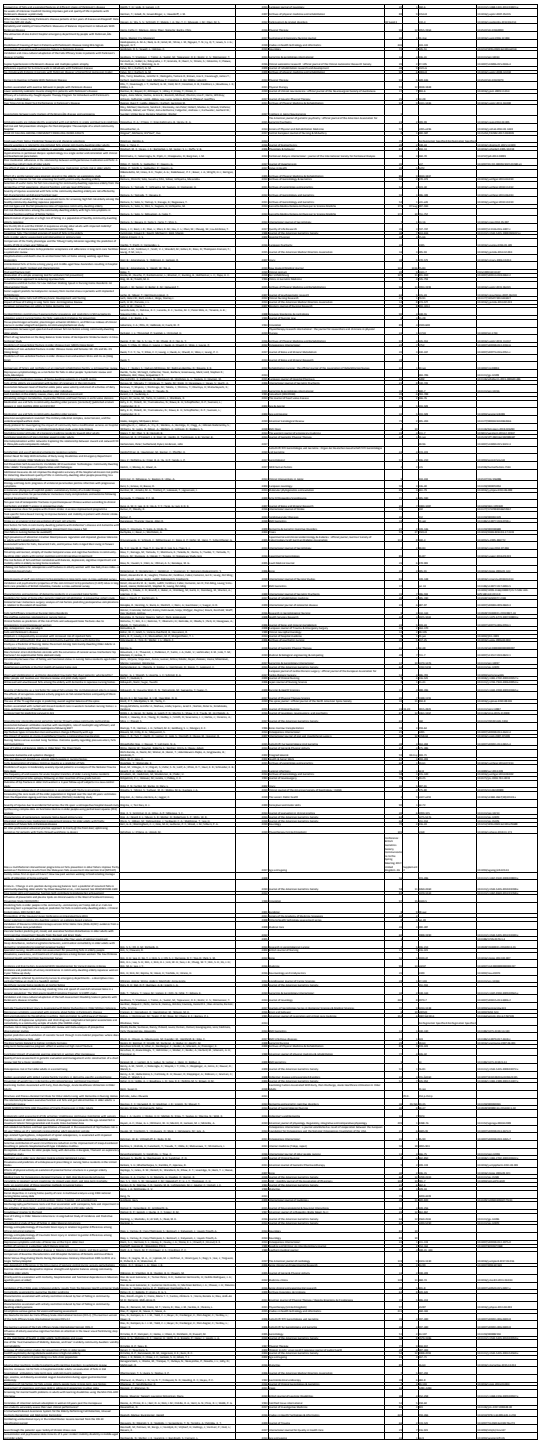

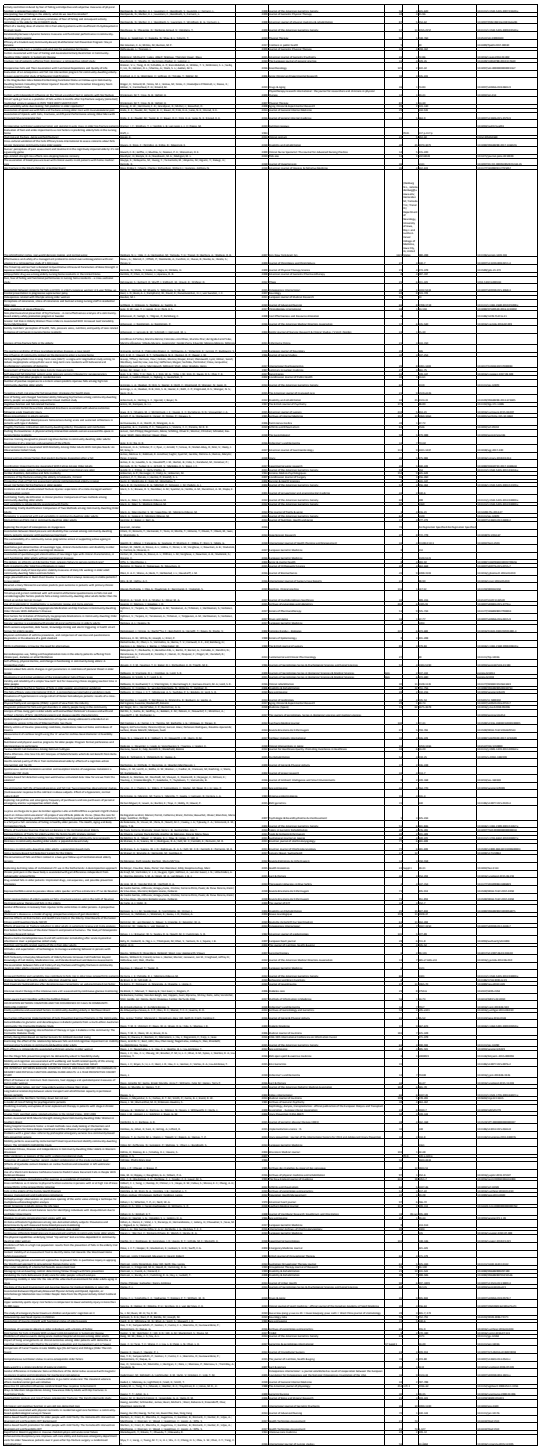

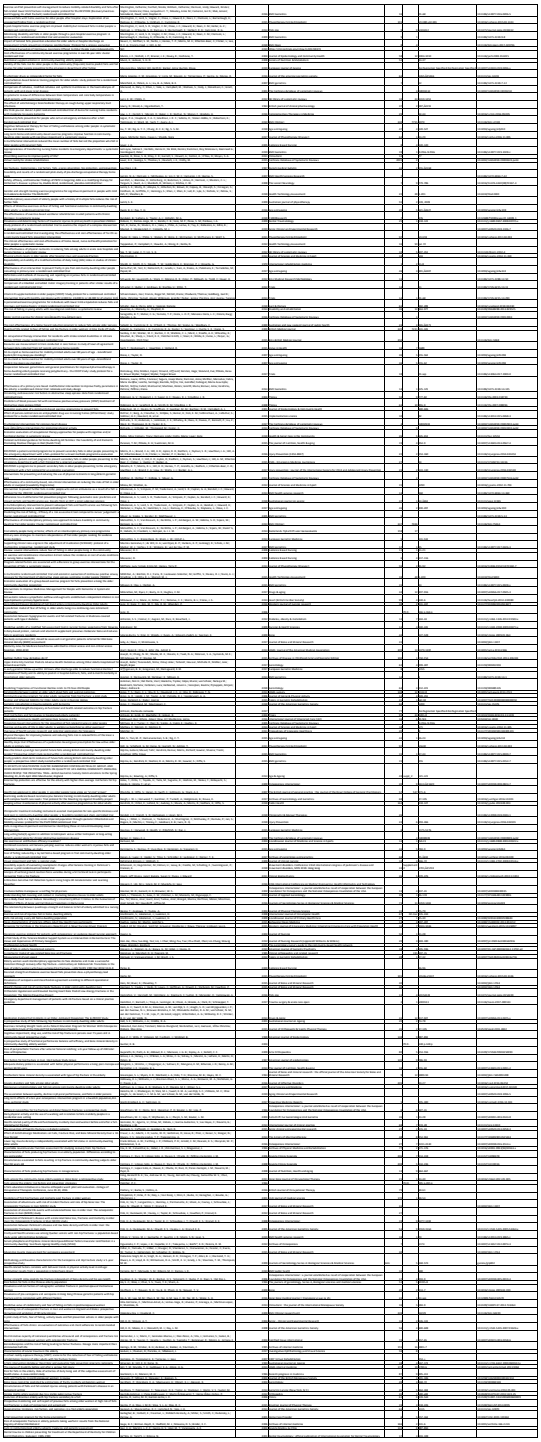

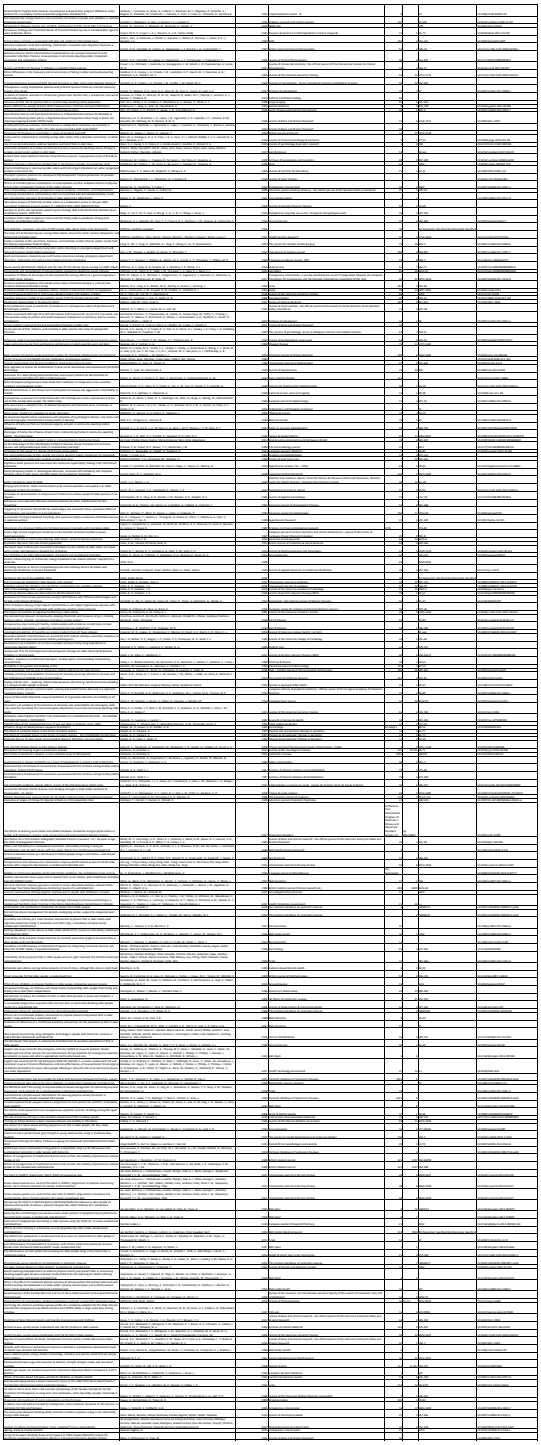

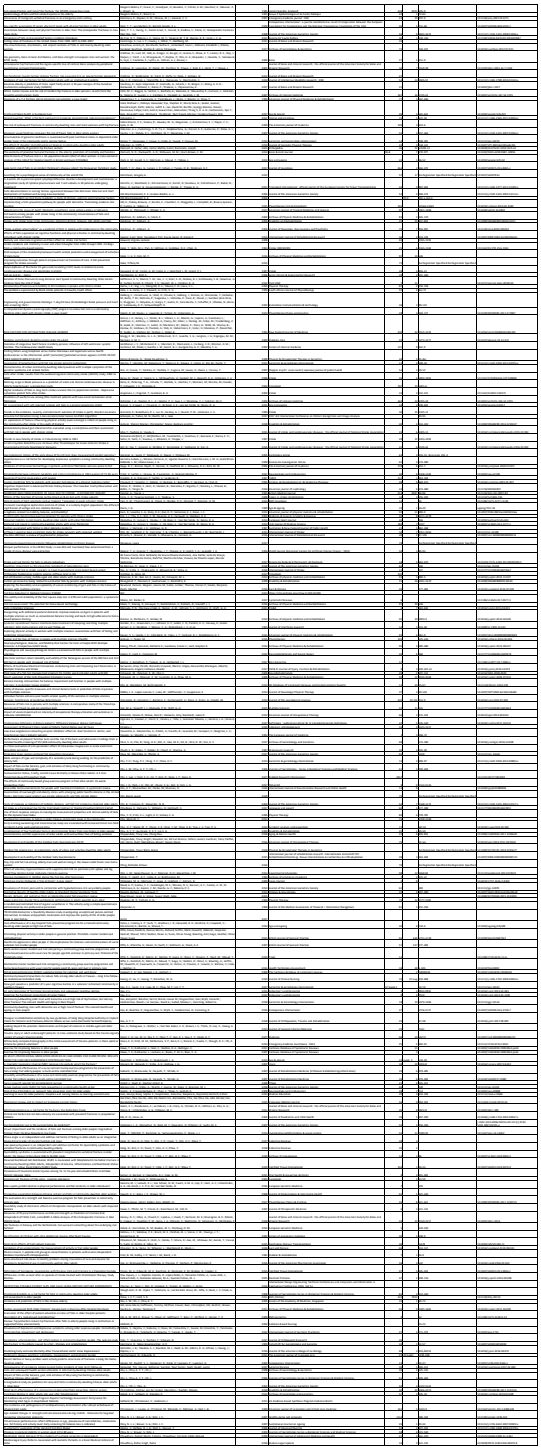

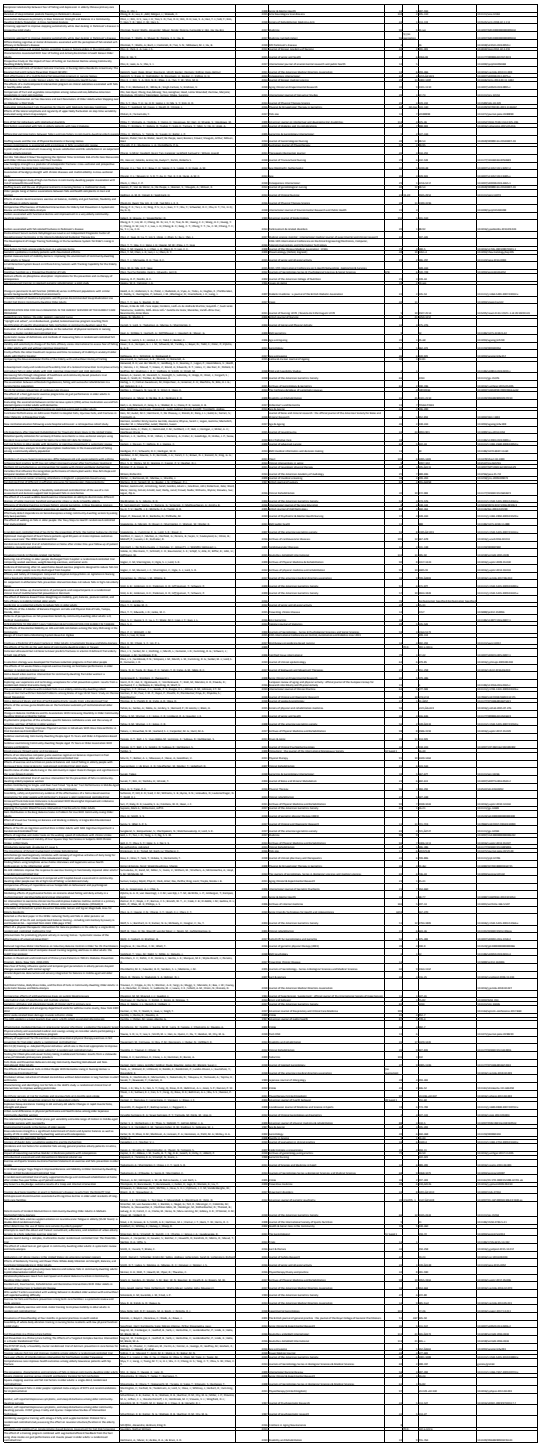

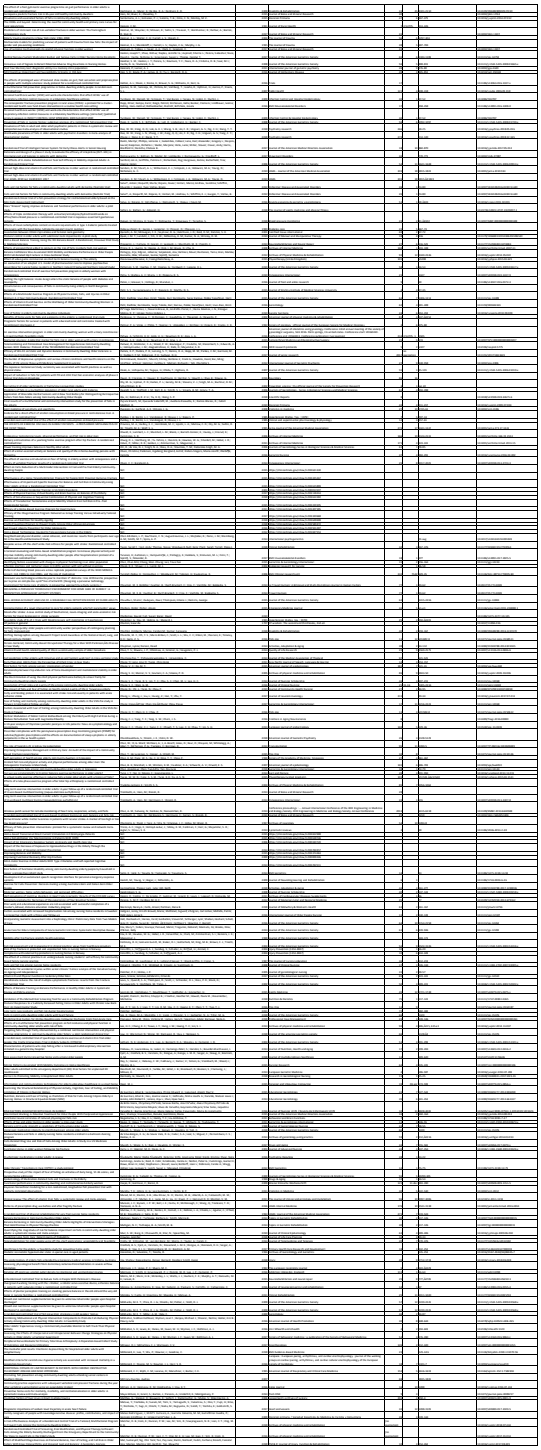

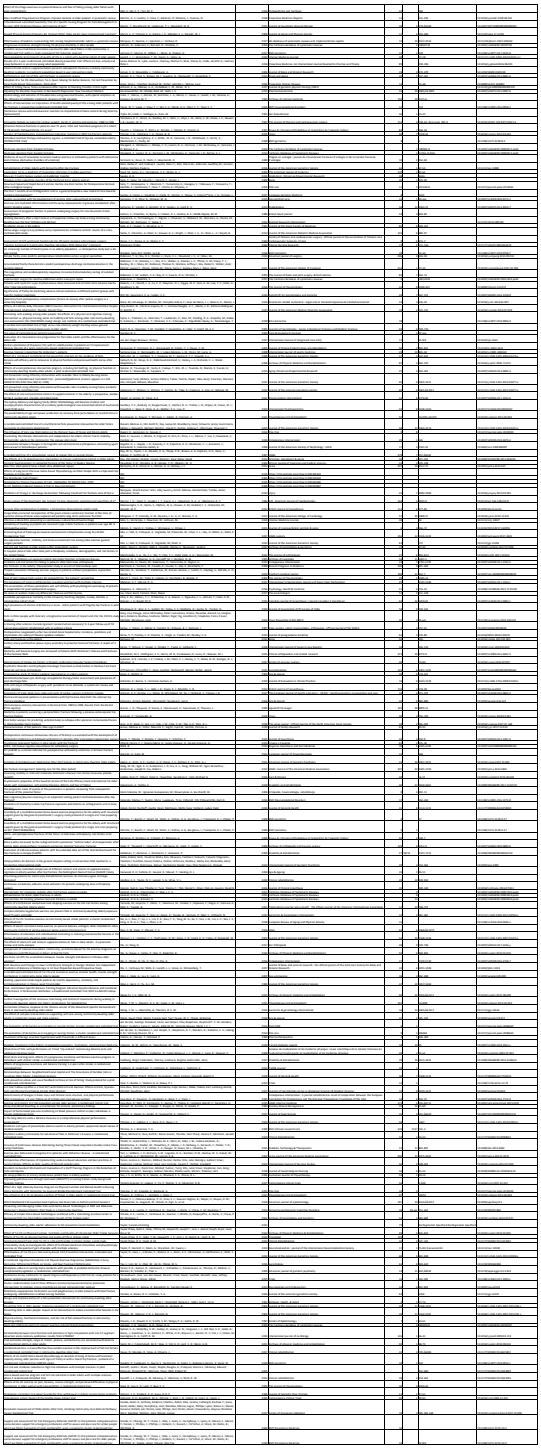

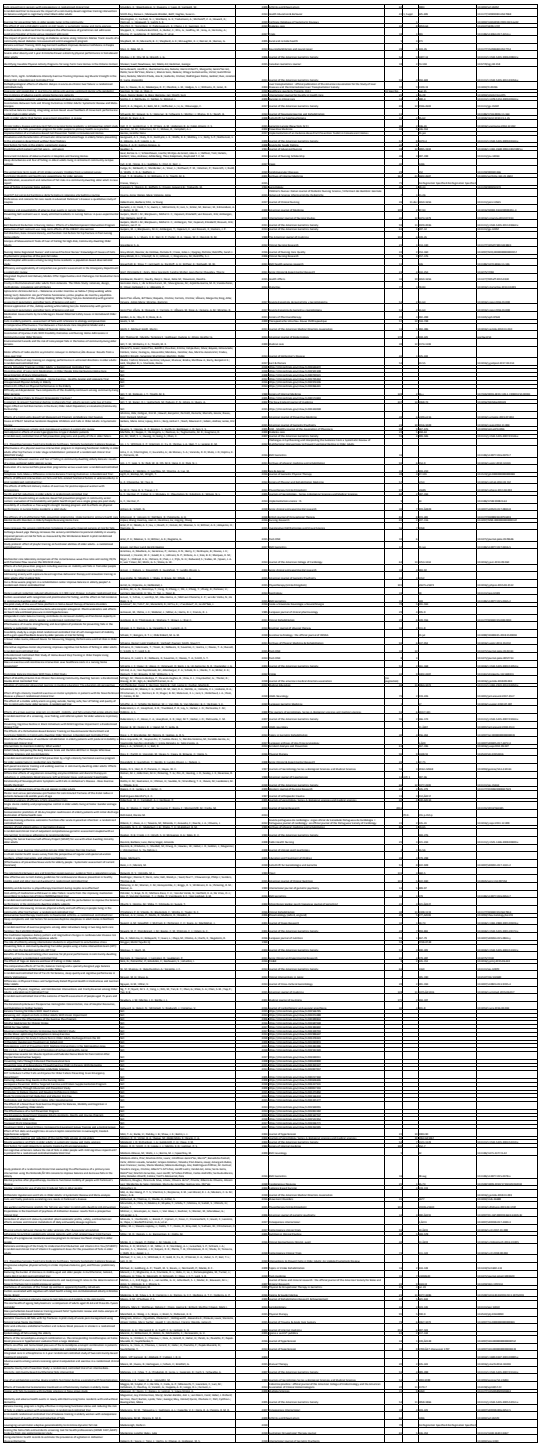

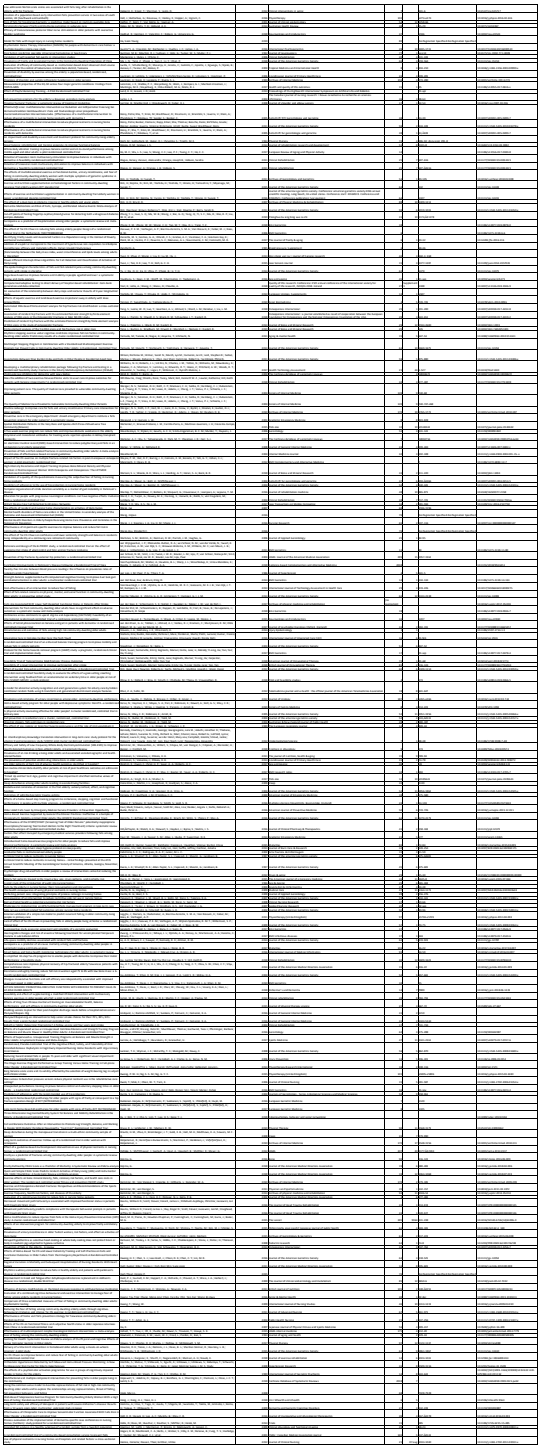

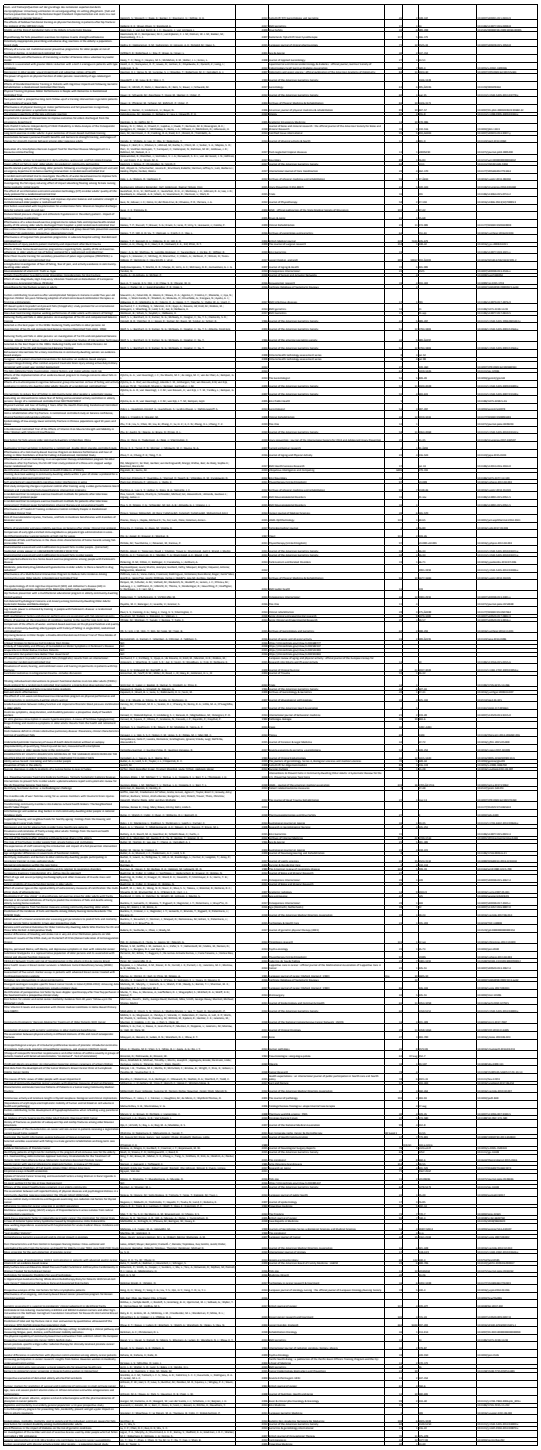

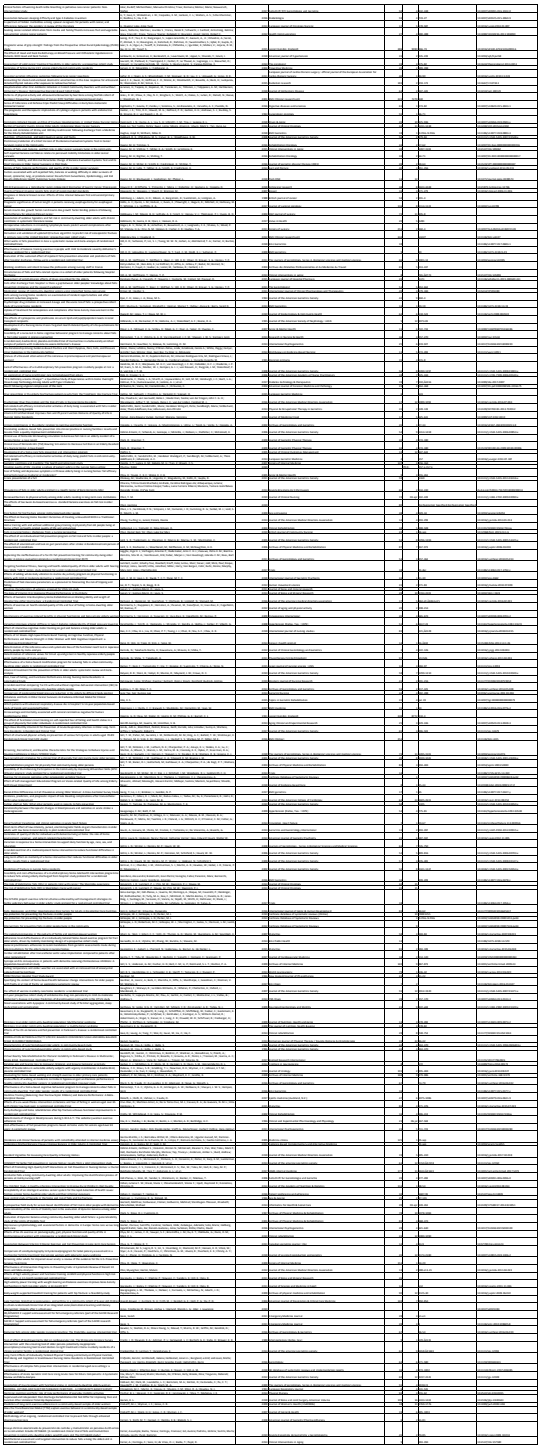

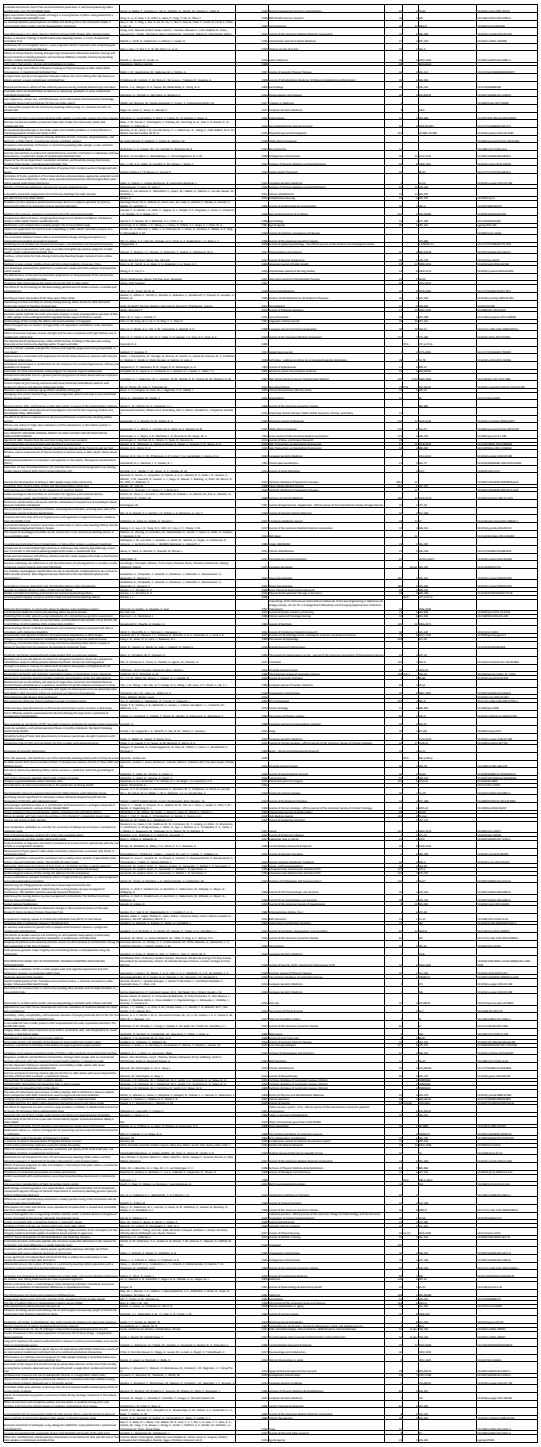

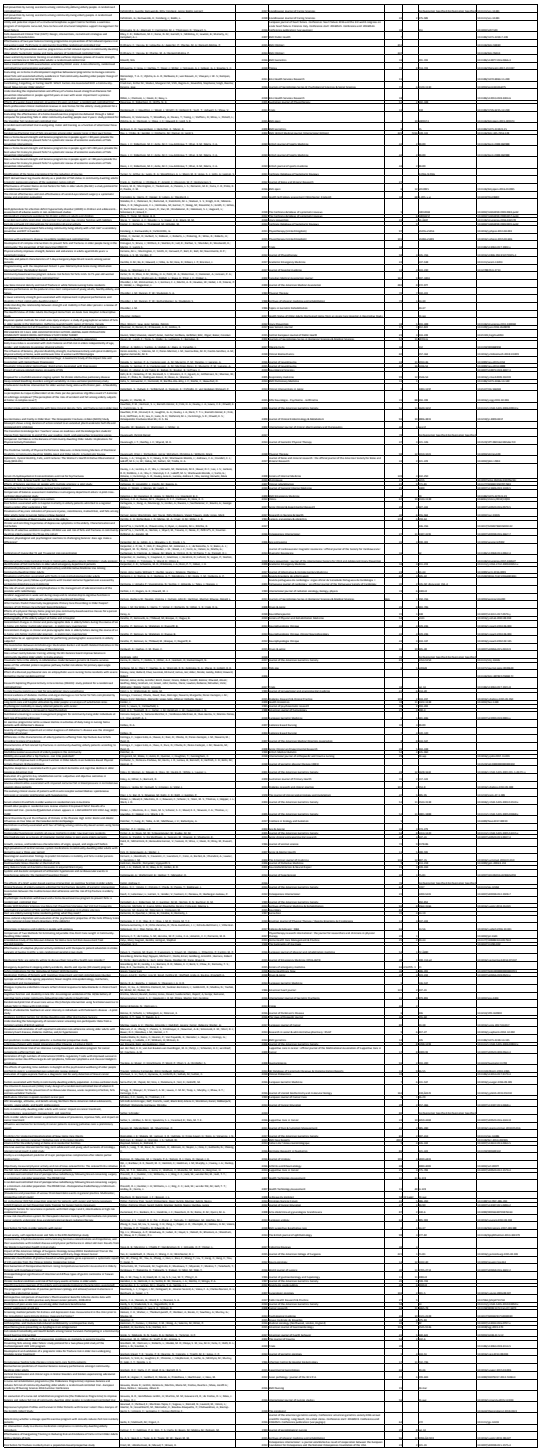

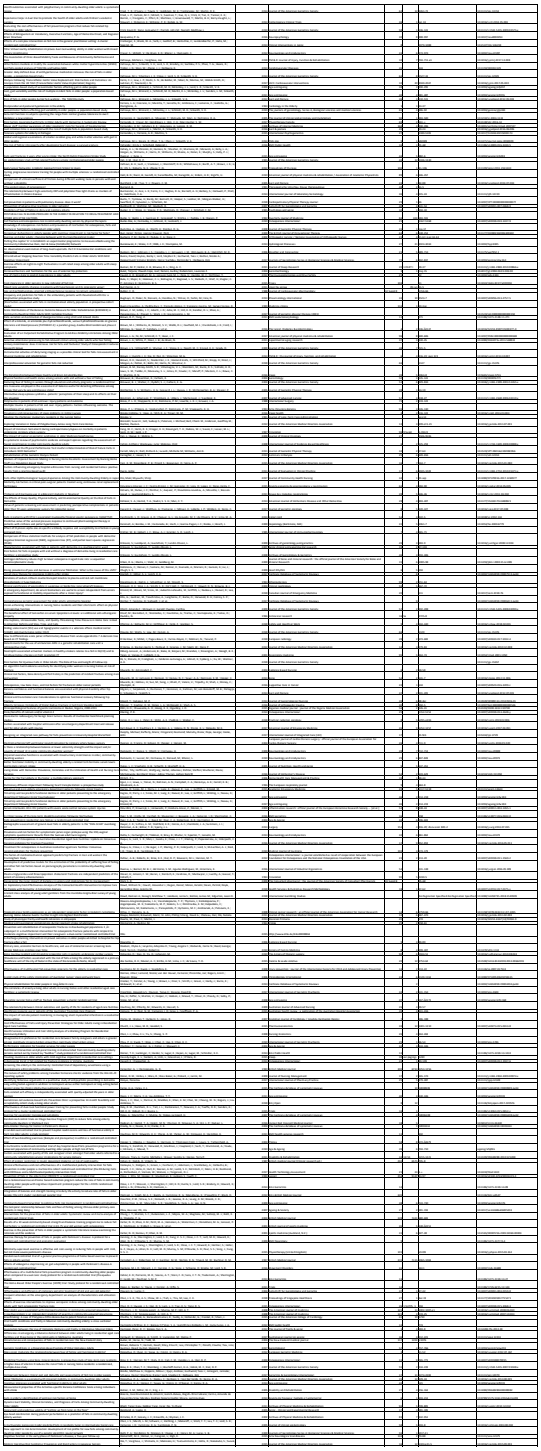

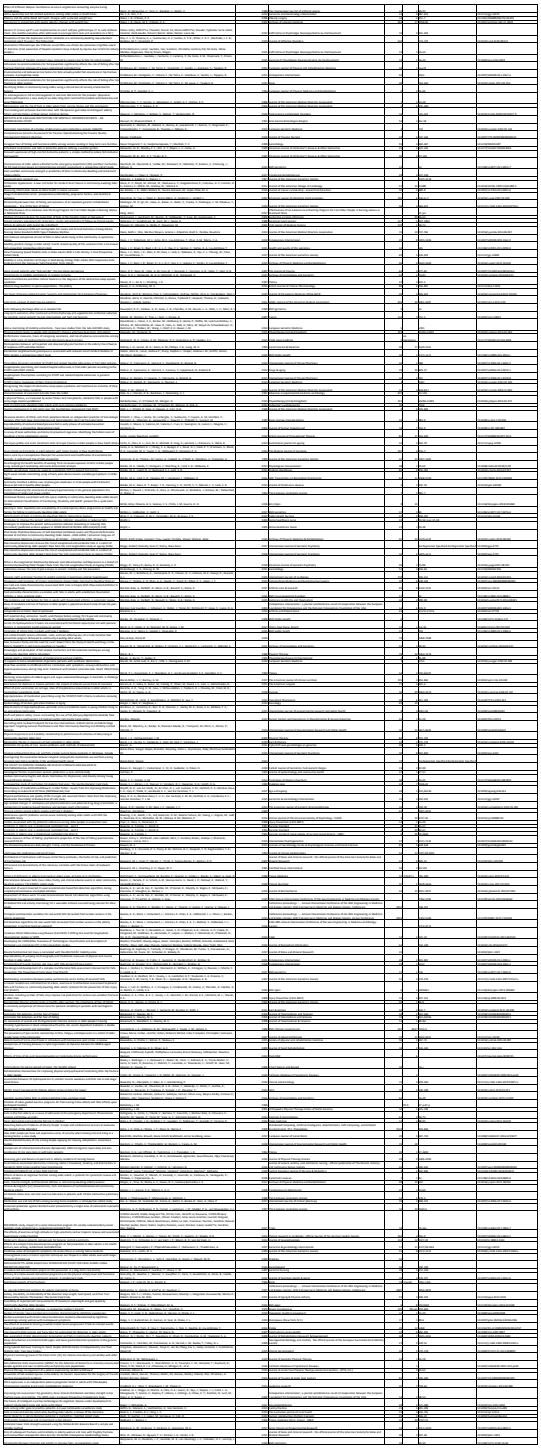

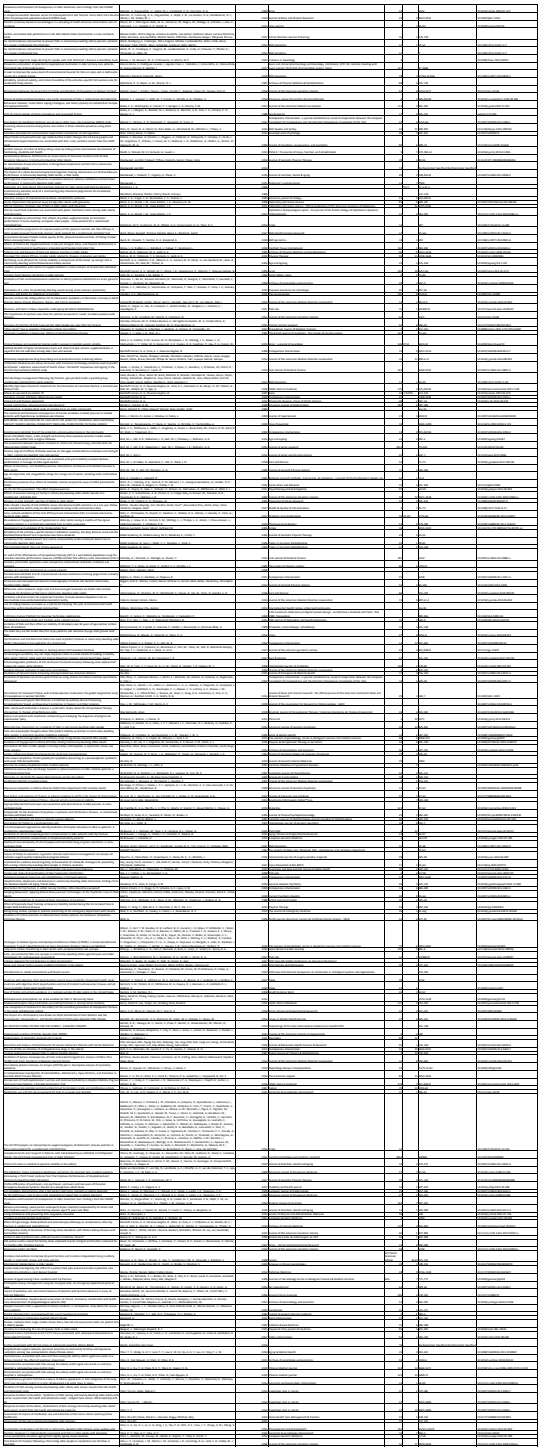

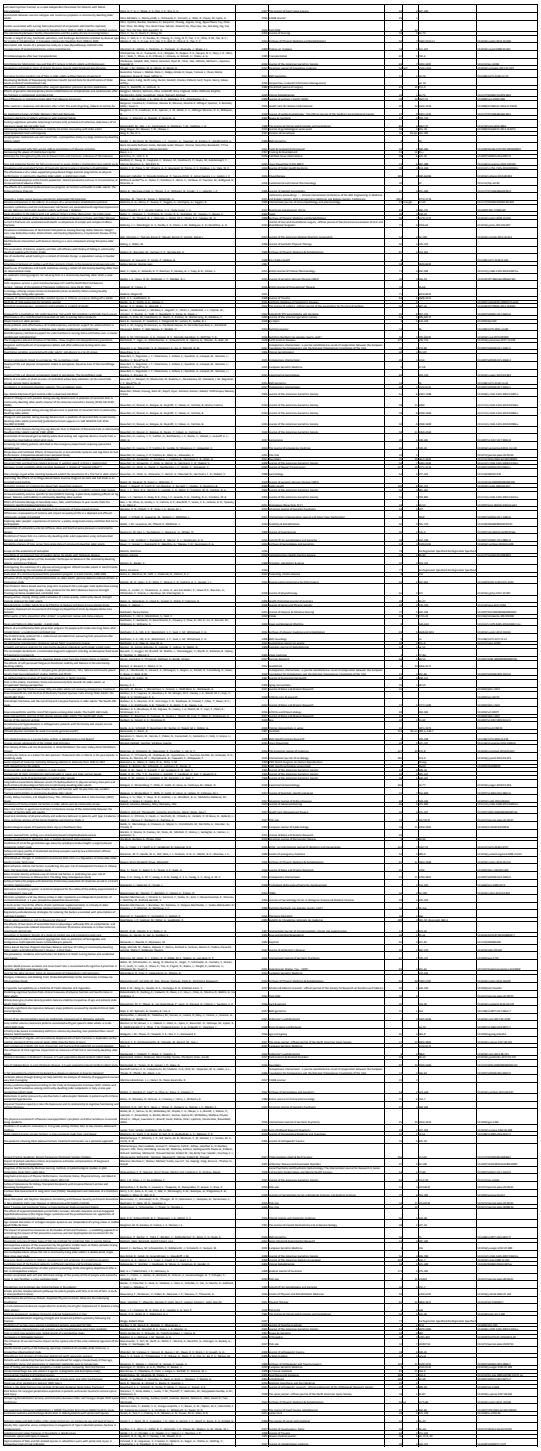

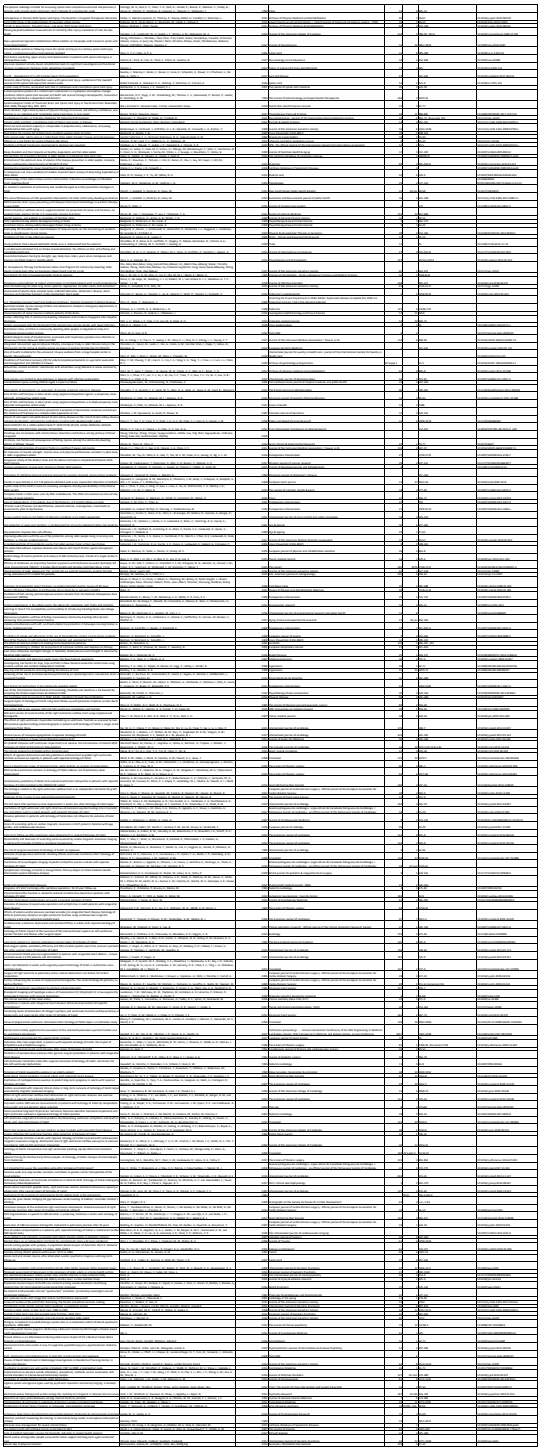

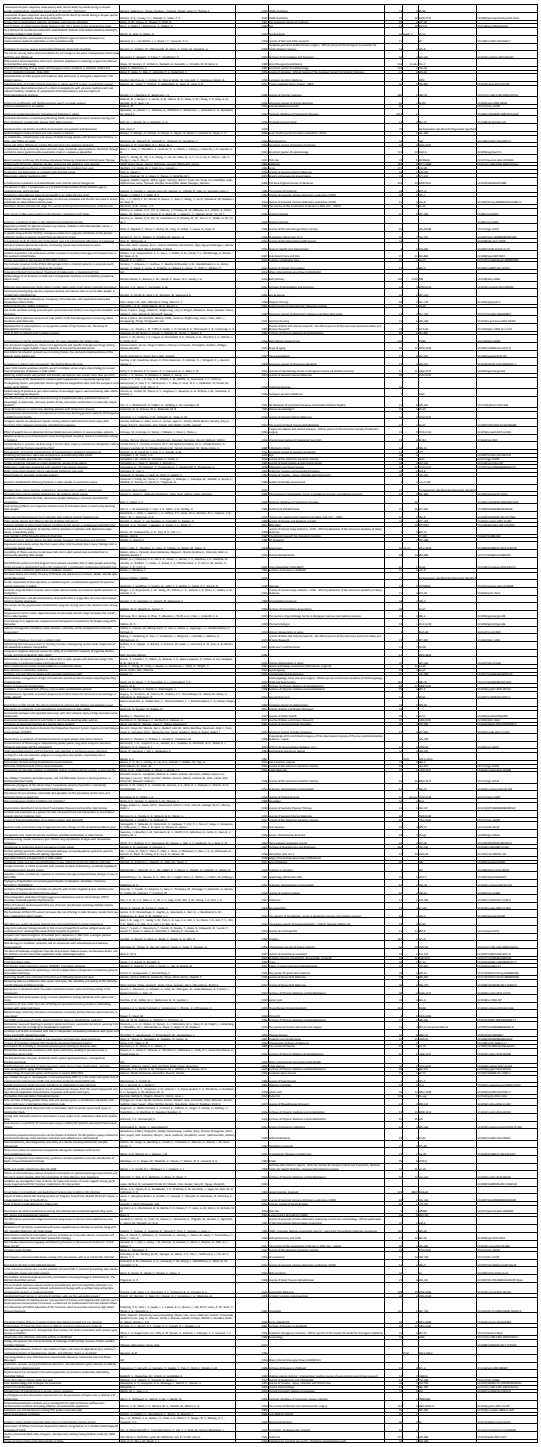

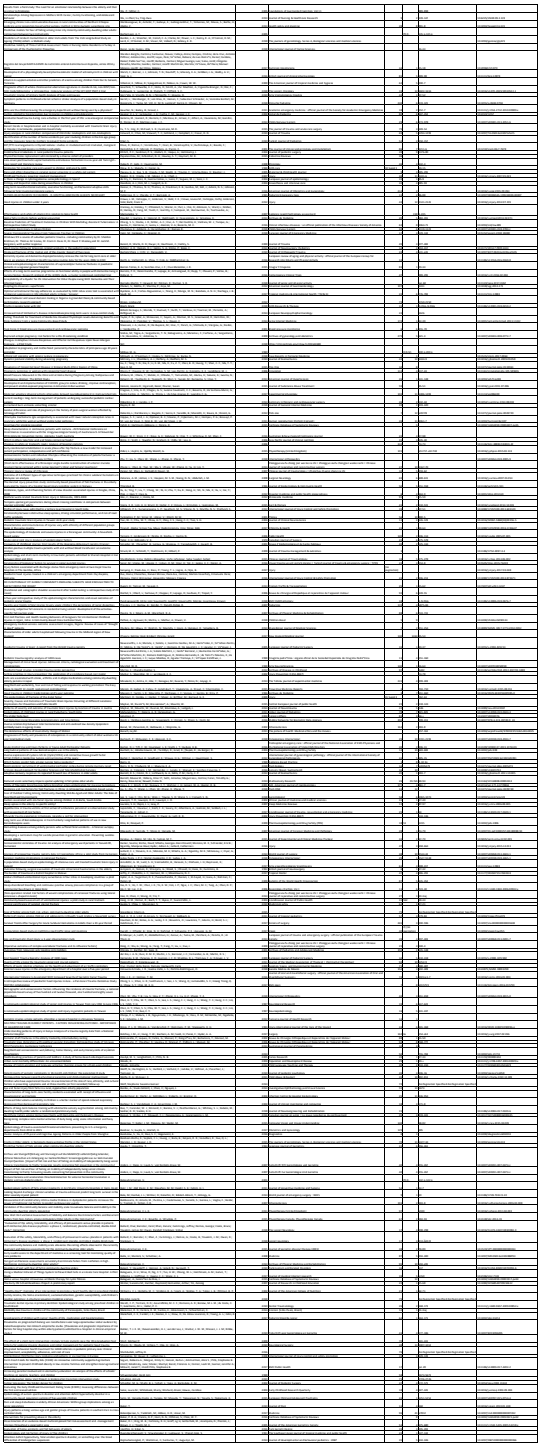

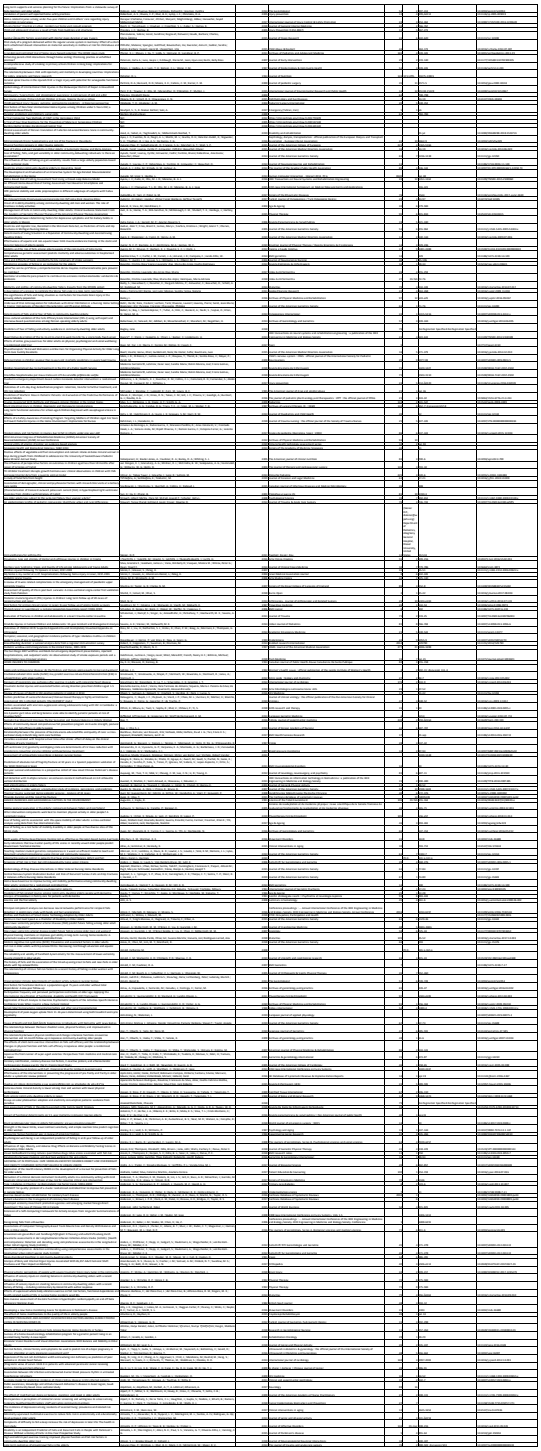

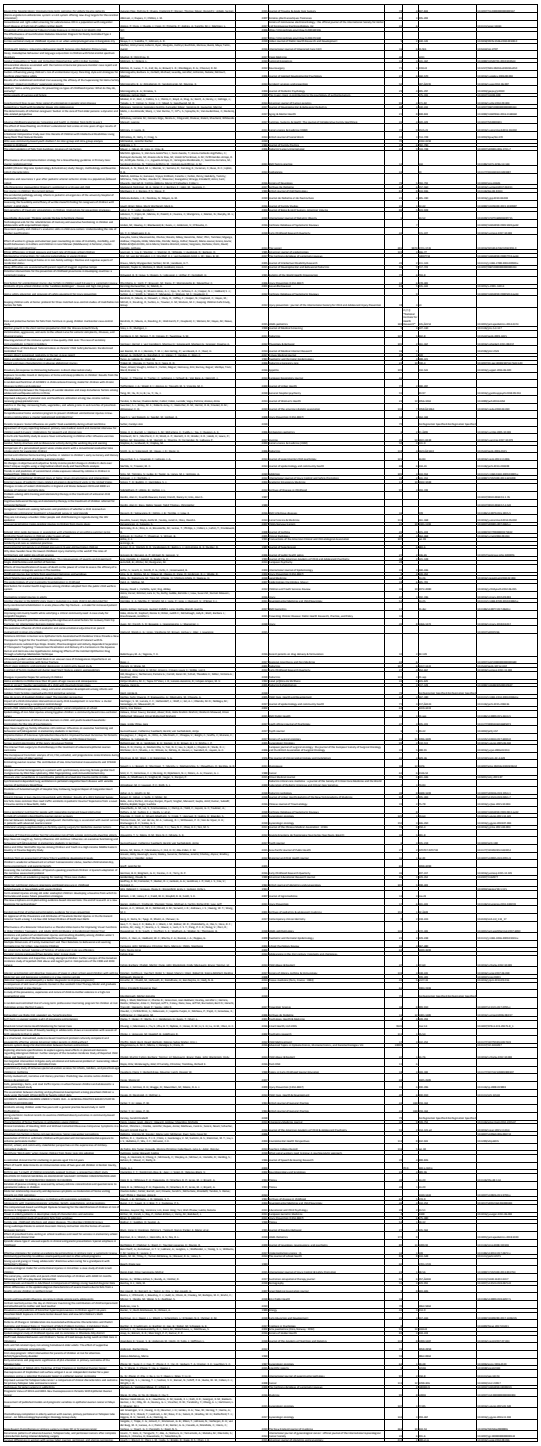

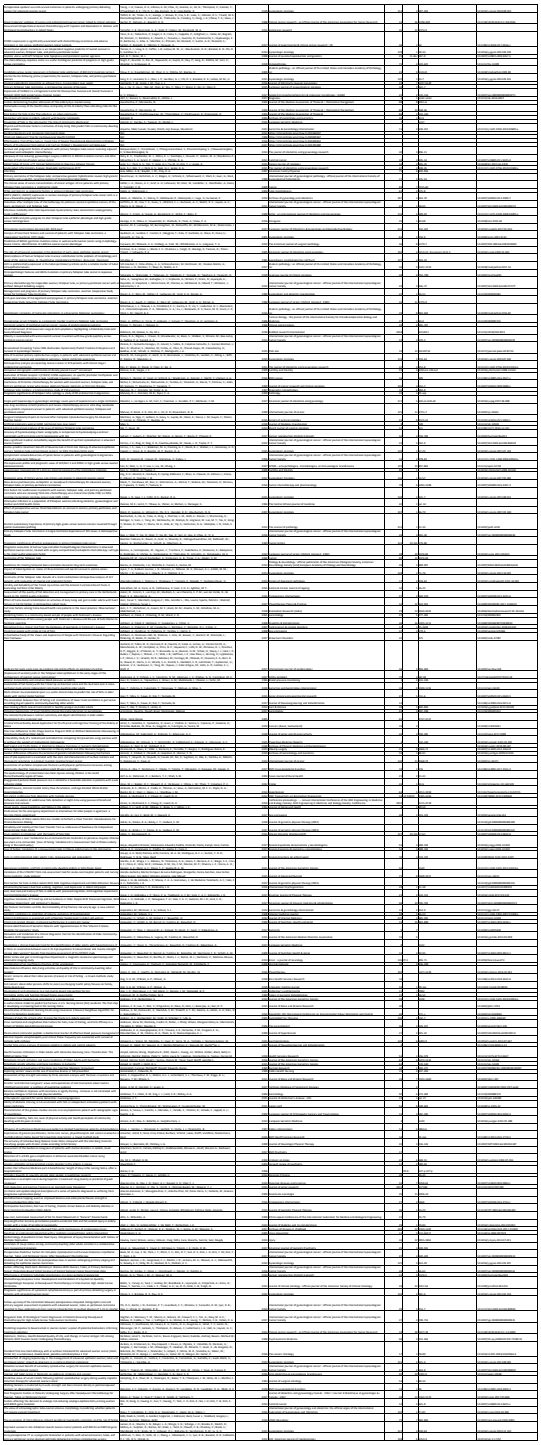

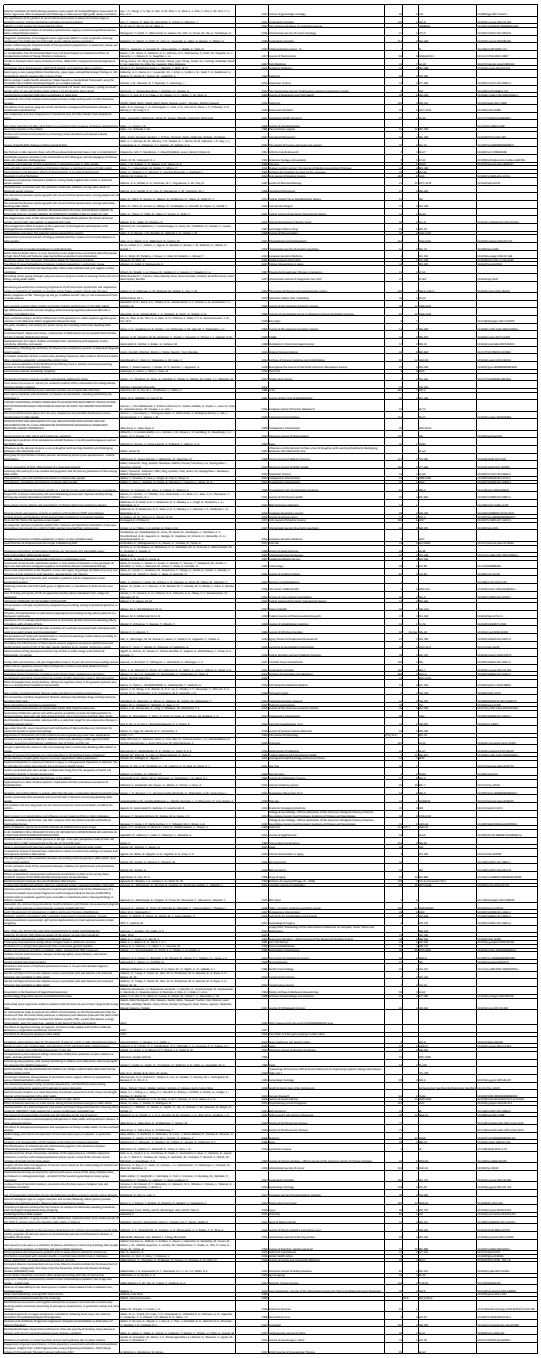

APPENDIX 8: REFERENCES EXCLUDED DURING FULL-TEXT READING:

Title	Authors	Published Year	Journal	Volume	Issue
Accuracy of clinical-functional tools to identify risk of falls among community-dwelling older adults	Sampaio, Raphaela Xavier; Santos Abreu, Amanda Maria; Almeida Nagata, Cristiane; Azevedo Garcia, Patrícia	2019	Fisioterapia em Movimento	32	1
Do voluntary step reactions in dual task conditions have an added value over single task for fall prediction? A prospective study	Melzer, Itshak; Kurz, Ilan; Shahar, Danit; Oddsson, Lars I. E.	2010	Aging Clinical & Experimental Research	22	05.jun
Use of the BESTest and the Mini-BESTest for Fall Risk Prediction in Community-Dwelling Older Adults Between 60 and 102 Years of Age	Magnani, P. E.; Genovez, M. B.; Porto, J. M.; Zanellato, N. F. G.; Alvarenga, I. C.; Freire, R. C., Jr.; de Abreu, D. C. C.	2019	J Geriatr Phys Ther		
Psychometric comparisons of the timed up and go, one-leg stand, functional reach, and Tinetti balance measures in community-dwelling older people	Lin, M.; Hwang, H.; Hu, M.; Wu, H. I.; Wang, Y.; Huang, F.	2004	Journal of the American Geriatrics Society	52	8
Comparison of 2 Frailty Indexes for Prediction of Falls, Disability, Fractures, and Death in Older Women	Ensrud, Kristine E.; Ewing, Susan K.; Taylor, Brent C.; Fink, Howard A.; Cawthon, Peggy M.; Stone, Katie L.; Hillier, Teresa A.; Cauley, Jane A.; Hoc	2008	Archives of Internal Medicine	168	4
A comparison of frailty indexes for the prediction of falls, disability, fractures, and mortality in older men	Ensrud, Kristine E; Ewing, Susan K; Cawthon, Peggy M; Fink, Howard A; Taylor, Brent C; Cauley, Jane A; Dam, Thuy-Tien; Marshall, Lynn M; Orwo	2009	Journal of the American Geriatrics Society	57	3
Predicting falls in community dwelling older adults using the Activities-specific Balance Confidence Scale	Cleary, Kimberly; Skornyakov, Elena	2017	Archives of Gerontology & Geriatrics	72	
Predicting falls in older adults using the four square step test	Cleary, K.; Skornyakov, E.	2017	Physiotherapy theory and practice	33	10
Fusion of Clinical, Self-Reported, and Multisensor Data for Predicting Falls	Silva, J. R.; Sousa, I.; Cardoso, J. S.	2019	IEEE J Biomed Health Inform		
Using Machine Learning on Home Health Care Assessments to Predict Fall Risk...The 17th World Congress of Medical and Health Informatics, 25-30 August 2019, Lyon, France	Yancy, Lo; Lynch, Selah F.; Urbanowicz, Ryan J.; Olson, Randal S.; Ritter, Ashley Z.; Whitehouse, Christina R.; O'Connor, Melissa; Keim, Susan K.	2019	Studies in Health Technology & Informatics	264	
Agreement and predictive power of six fall risk assessment methods in community-dwelling older adults	Menezes, M.; de Mello Meziat-Filho, N. A.; Araujo, C. S.; Lemos, T.; Ferreira, A. S.	2019	Arch Gerontol Geriatr	87	
The Clinical Potential of Frailty Indicators on Identifying Recurrent Fallers in the Community: The Mr. Os and Ms. OS Cohort Study in Hong Kong	Lam, F. M. H.; Leung, J. C. S.; Kwok, T. C. Y.	2019	J Am Med Dir Assoc	20	12
Development and validation of an algorithm to assess risk of first-time falling among home care clients	Kuspinar, Ayse; Hirdes, John P.; Berg, Katherine; McArthur, Caitlin; Morris, John N.	2019	BMC Geriatrics	19	1
A frailty profile for use in the community: Inclusion of psychological variables improves prediction of care needs and falls	Holland, C.; Garner, I.; O'Donnell, J.; Gwyther, H.	2019	Age and Ageing	48	
A model of falls risk in older adults	Genna, Gregory Joseph	2019	ProQuest (Dissertation)	80	
A decision model to predict the risk of the first fall onset	Deschamps, T.; Le Goff, C. G.; Berrut, G.; Cornu, C.; Mignardot, J. B.	2016	Experimental gerontology	81	
How steady is the STEADI? Inferential analysis of the CDC fall risk toolkit	Nithman, R. W.; Vincenzo, J. L.	2019	Arch Gerontol Geriatr	83	
The Aachen Falls Prevention Scale: Multi-Study Evaluation and Comparison	Rasche, P.; Nitsch, V.; Rentemeister, L.; Coburn, M.; Buecking, B.; Bliemel, C.; Bollheimer, L. C.; Pape, H. C.; Knobe, M.	2019	JMIR Aging	2	1
Accuracy of modified 30-s chair-stand test for predicting falls in older adults	Roongbenjawan, N.; Siriphorn, A.	2019	Ann Phys Rehabil Med		
When will my patient fall? Sensor-based in-home walking speed identifies future falls in older adults	Piau, A.; Mattek, N.; Crissey, R.; Beattie, Z.; Dodge, H.; Kaye, J.	2019	J Gerontol A Biol Sci Med Sci		
Reliability, validity, and clinical utility of a self-reported screening tool in the prediction of fall incidence in older adults	Lai, F. H. Y.; Yan, E. W. H.; Mackenzie, L.; Fong, K. N. K.; Kranz, G. S.; Ho, E. C. W.; Fan, S. H. U.; Lee, A. T. K.	2019	Disabil Rehabil		
Predicting incident falls: Relationship between postural sway and limits of stability in older adults	Johansson, J.; Jarocka, E.; Westling, G.; Nordstrom, A.; Nordstrom, P.	2019	Hum Mov Sci	66	
Automatic measurement of fall risk indicators in timed up and go test	Dubois, A.; Bihl, T.; Bresciani, J. P.	2019	Informatics for Health & Social Care	44	3
Prevalence, Severity, and Risk of Future Falls in Community-Dwelling Older Adults Living in a Rural Community: The Atahualpa Project	Del Brutto, O. H.; Mera, R. M.; Peinado, C. D.; Sedler, M. J.	2019	Journal of Community Health	44	3
Assessment of Balance and Risk for Falls in a Sample of Community-Dwelling Adults Aged 60 and Older	Chojar, Harshita; Kaur, Gurpreet	2019	Indian Journal of Physiotherapy & Occupational Therapy	13	2
Reliability and construct validity of the stepping-forward affordance perception test for fall risk assessment in community-dwelling older adults	Almeida, G.; Bravo, J.; Folgado, H.; Rosado, H.; Mendes, F.; Pereira, C.	2019	PLoS ONE	14	11
The predictive value of gait speed and maximum step length for falling in community-dwelling older persons	Bongers, K. T. J.; Schoon, Y.; Graauwmans, M. J.; Schers, H. J.; Melis, R. J.; Rikkert, Mgmo	2015	Age and Ageing	44	2
A Simple Algorithm to Predict Falls in Primary Care Patients Aged 65 to 74 Years: The International Mobility in Aging Study	Gomez, F.; Wu, Y. Y.; Auais, M.; Vafaei, A.; Zunzunegui, M. V.	2017	Journal of the American Medical Directors Association	18	9
Evaluation of falls risk in community-dwelling older adults using body-worn sensors	Greene, B. R.; Doheny, E. P.; Walsh, C.; Cunningham, C.; Crosby, L.; Kenny, R. A.	2012	Gerontology	58	5
Activities-specific balance confidence scale for predicting future falls in Indian older adults	Moiz, J. A.; Bansal, V.; Noohu, M. M.; Gaur, S. N.; Hussain, M. E.; Anwer, S.; Alghadir, A.	2017	Clinical Interventions in Aging	12	
Gait disturbances as specific predictive markers of the first fall onset in elderly people: A two-year prospective observational study	Mignardot, J. B.; Deschamps, T.; Barrey, E.; Auvinet, B.; Berrut, G.; Cornu, C.; Constans, T.; De Decker, L.	2014	Frontiers in Aging Neuroscience	6	FEB
Improved Prediction of Falls in Community-Dwelling Older Adults Through Phase-Dependent Entropy of Daily-Life Walking	Ihlen, E. A. F.; van Schooten, K. S.; Bruijn, S. M.; van Dieen, J. H.; Vereijken, B.; Helbostad, J. L.; Pijnappels, M.	2018	Frontiers in Aging Neuroscience	10	
The harmonic ratio of trunk acceleration predicts falling among older people: results of a 1-year prospective study	Doi, T.; Hirata, S.; Ono, R.; Tsutsumimoto, K.; Misu, S.; Ando, H.	2013	Journal of neuroengineering and rehabilitation	10	
History and Mobility Exam Index to Identify Community-Dwelling Elderly Persons at Risk of Falling	Covinsky, Kenneth E.; Kahana, Eva; Kahana, Boaz; Kercher, Kyle; Schumacher, John G.; Justice, Amy C.	2001	Journals of Gerontology Series A: Biological Sciences & Medical Sciences	56	4
Functional gait assessment: concurrent, discriminative, and predictive validity in community-dwelling older adults	Wrisley, D. M.; Kumar, N. A.	2010	Physical Therapy	90	5
Development of a simple scoring tool in the primary care setting for prediction of recurrent falls in men and women aged 65 years and over living in the community	Woo, J.; Leung, J.; Wong, S.; Kwok, T.; Lee, J.; Lynn, H.	2009	Journal of Clinical Nursing	18	7
Performance and impairment-based assessments among community dwelling elderly: sensitivity and specificity	Trueblood, P. R.; Hodson-Chennault, N.; McCubbin, A.; Youngclarke, D.	2001	Issues on Aging	24	1
Predictors for falls and fractures in the longitudinal aging study Amsterdam	Tromp, A. M.; Smit, J. H.; Deeg, D. J. H.; Bouter, L. M.; Lips, P.	1998	Journal of Bone and Mineral Research	13	12
Predictive validity of the functional independence and difficulty scale in community-dwelling Japanese older adults	Saito, T.; Matsui, N.; Watanabe, S.	2017	Journal of physical therapy science	29	5
Fall Risk Assessment Tools for Elderly Living in the Community: Can We Do Better?	Palumbo, P.; Palmerini, L.; Bandinelli, S.; Chiari, L.	2015	PloS one	10	12
Mobility, balance and frailty in community-dwelling older adults: at is the best 1-year predictor of falls?	Mulasso, A.; Roppolo, M.; Gobbens, R. J.; Rabaglietti, E.	2017	Geriatrics & Gerontology International	17	10
Validation of an accelerometer-based fall prediction model	Liu, Y.; Redmond, S. J.; Shany, T.; Woolgar, J.; Narayanan, M. R.; Lord, S. R.; Lovell, N. H.	2014	Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biolo	2014	
FRAT-up, a Web-based fall-risk assessment tool for elderly people living in the community	Cattelani, L.; Palumbo, P.; Palmerini, L.; Bandinelli, S.; Becker, C.; Chesani, F.; Chiari, L.	2015	Journal of medical Internet research	17	2
Depression and falls among community dwelling elderly people: a search for common risk factors	Biderman, A.; Cwikel, J.; Fried, A. V.; Galinsky, D.	2002	Journal of Epidemiology & Community Health	56	8
Local dynamic stability during gait for predicting falls in elderly people: A one-year prospective study	Bizovska, L.; Svoboda, Z.; Janura, M.; Bisi, M. C.; Vuillerme, N.	2018	Plos One	13	5
Frailty in older adults: evidence for a phenotype	Fried, L. P.; Tangen, C. M.; Walston, J.; Newman, A. B.; Hirsch, C.; Gottdiener, J.; Seeman, T.; Tracy, R.; Kop, W. J.; Burke, G.; McBurnie, M. A.	2001	Journals of Gerontology Series A: Biological Sciences & Medical Sciences	56	3
Twenty-one-item Fall Risk Index predicts falls in elderly community-dwelling Japanese	Wada, T.; Ishimoto, Y.; Hirosaki, M.; Konno, A.; Kasahara, Y.; Kimura, Y.; Nakatsuka, H.; Sakamoto, R.; Ishine, M.; Okumiya, K.; Fujisawa, M.; Ots	2009	Journal of the American Geriatrics Society	57	12
Screening older adults at risk of falling with the Tinetti balance scale	Raîche, M.; Hébert, R.; Prince, F.; Corriveau, H.	2000	Lancet	356	9234
Quantitative gait assessment as a predictor of prospective and retrospective falls in community-dwelling older women	Feltner, M. E.; MacRae, P. G.; McNitt-Gray, J. L.	1994	Archives of Physical Medicine & Rehabilitation	75	4
A modified fall risk assessment tool that is specific to physical function predicts falls in community-dwelling elderly people	Hirase, T.; Inokuchi, S.; Matsusaka, N.; Nakahara, K.; Okita, M.	2014	Journal of geriatric physical therapy (2001)	37	4
Frailty as a risk factor for predicting falls and fractures in community dwelling older women	Bartosch, P.; Malmgren, L.; Buchebner, D.; McGuigan, F.; Akesson, K.	2018	Osteoporosis International	29	1
A Quantitative Frailty Index Predicts Falls and Fractures in 75y Old Community Dwelling Women - A 10 Year Longitudinal Study	Akesson, K.; Bartosch, P.; Malmgren, L.; Buchebner, D.; Fiona, E.	2017	Journal of Bone and Mineral Research	32	
Cognitive dual-task Timed-Up-and-Go test as a predictor of falls in the community-dwelling elderly	Tong, Y.; Tian, X.; Wang, Y.; Han, J.; Waddington, G.; Adams, R.	2018	Journal of Science and Medicine in Sport	21	
Validation of a fall-risk screening test, the Elderly Fall Screening Test (EFST), for community-dwelling elderly	Cwikel, J. G.; Fried, A. V.; Biderman, A.; Galinsky, D.	1998	Disability & Rehabilitation	20	5
Predictive validity and cut-off scores in four diagnostic tests for falls—A study in frail older people at home	U. Olsson Möller, J. Kristensson, P. Midlöv, C. Ekdahl & U. Jakobsson	2012	Physical & Occupational Therapy In Geriatrics	30	
Two-Year Follow-Up of Fall Prediction Among Older Adults in an Independent-Living Community	Zur, O.; Berner, Y.; Ohel, Y.; Carmeli, E.	2018	Advances in experimental medicine and biology	1040	
Morse fall scale predicts falls in home-bound frail elderly population	Willard, J.; Thomas, C. M.	2011	Journal of the American Geriatrics Society	59	
Predictive performance of four frailty measures in an older Australian population	Widagdo, Imaina S.; Pratt, Nicole; Russell, Mary; Roughead, Elizabeth E.	2015	Age & Ageing	44	6
Daily-life gait quality as predictor of falls in older people: A 1-year prospective cohort study	Van Schooten, K. S.; Pijnappels, M.; Rispens, S. M.; Elders, P. J. M.; Lips, P.; Daffertshofer, A.; Beek, P. J.; Van Dieën, J. H.	2016	PLoS ONE	11	7
Thai falls risk assessment test (Thai-FRAT) developed for community-dwelling thai elderly	Thiamwong, L.; Thamarpirat, J.; Maneesriwongul, W.; Jitapunkul, S.	2008	Journal of the Medical Association of Thailand	91	12
60 THE PREDICTIVE VALUE OF THE EASYCARE-TOS INSTRUMENT ON FALLING IN COMMUNITY-DWELLING ELDERLY...British Geriatrics Society Communications to the Spring Meeting 23 – 25 A	Schoon, Y.; Poel, P. I. J.; Bongers, K. T. J.; Olde Rikkert, M. G. M.	2014	Age & Ageing	43	suppl_2
Risk factors for falling in older Mexican Americans	Reyes-Ortiz, C. A.; Al Snih, S.; Loera, J.; Ray, L. A.; Markides, K.	2004	Ethnicity & disease	14	3
Predictive Value of Frailty Indices for Adverse Outcomes in Older Adults	Perez-Zepeda, M. U.; Cesari, M.; Garcia-Pena, C.	2016	Revista de investigacion clinica; organo del Hospital de Enfermedades de la Nutricion	68	2
Application of a fall screening algorithm stratified fall risk but missed preventive opportunities in community-dwelling older adults: a prospective study	Muir, Susan W.; Berg, Katherine; Chesworth, Bert; Klar, Neil; Speechley, Mark	2010	Journal of Geriatric Physical Therapy	33	4
Modifiable risk factors identify people who transition from non-fallers to fallers in community-dwelling older adults: a prospective study	Muir, S. W.; Berg, K.; Chesworth, B. M.; Klar, N.; Speechley, M.	2010	Physiotherapy Canada	62	4
Strength measures are better than muscle mass measures in predicting health-related outcomes in older people: time to abandon the term sarcopenia?	Menant, J. C.; Weber, F.; Lo, J.; Sturnieks, D. L.; Close, J. C.; Sachdev, P. S.; Brodaty, H.; Lord, S. R.	2017	Osteoporosis International	28	1
Does the short physical performance battery (SPPB) predict falls in older community-dwelling people?	Lundin-Olsson, L.; Nordin, E.	2011	Physiotherapy (United Kingdom)	97	
Fall risk in an active elderly population - Can it be assessed?	Laessoe, U.; Hoeck, H. C.; Simonsen, O.; Sinkjaer, T.; Voigt, M.	2007	Journal of Negative Results in BioMedicine	6	
Validity of a new fall risk screen	Killough, J.	2005	Journal of Geriatric Physical Therapy	28	3
Validation and comparison of two frailty indexes: the MOBILIZE Boston Study	Kiely, D. K.; Cupples, L. A.; Lipsitz, L. A.	2009	Journal of the American Geriatrics Society	57	9
Predicting Value of Nine-Item Berg Balance Scale Among the Aged: A 3-Year Prospective Follow-Up Study	Hohtari-Kivimäki, U.; Salminen, M.; Vahlberg, T.; Kivelä, S. L.	2016	Experimental aging research	42	2
Falls in the elderly: A prospective study of risk factors and risk profiles	Graafmans, W. C.; Ooms, M. E.; Hofstee, H. M. W.; Bezemer, P. D.; Bouter, L. M.; Lips, P.	1996	American Journal of Epidemiology	143	11
Clinical history and biologic age predicted falls better than objective functional tests	Gerdhem, P.; Ringsberg, K. A.; Akesson, K.; Obrant, K. J.	2005	Journal of clinical epidemiology	58	3
Encore presentation predicting falls in a senior living community using balance and lower extremity muscle mass	Gaines, J.; Marx, K. A.; Burke, K. L.; Parrish, J. M.	2011	Journal of the American Geriatrics Society	59	
Kinect-based choice reaching and stepping reaction time tests for clinical and in-home assessment of fall risk in older people: a prospective study	Ejupi, A.; Gschwind, Y. J.; Brodie, M.; Zagler, W. L.; Lord, S. R.; Delbaere, K.	2016	European Review of Aging and Physical Activity	13	
The Physical Performance Test as a predictor of frequent fallers: a prospective community-based cohort study	Delbaere, K.; Van den Noortgate, N.; Bourgois, J.; Vanderstraeten, G.; Tine, W.; Cambier, D.	2006	Clinical Rehabilitation	20	1
Fear-related avoidance of activities, falls and physical frailty. A prospective community-based cohort study	Delbaere, K.; Crombez, G.; Vanderstraeten, G.; Willems, T.; Cambier, D.	2004	Age & Ageing	33	4
Reliability and validity of a steadiness score	Clark, D. O.; Callahan, C. M.; Counsell, S. R.	2005	Journal of the American Geriatrics Society	53	9
Comparison of Fallers and Nonfallers on Four Physical Performance Tests: A Prospective Cohort Study of Community-Dwelling Older Indigenous Taiwanese Women	Chen, J. C.; Liang, C. C.; Chang, Q. X.	2018	International Journal of Gerontology	12	1
Special feature: the Home Assessment Profile -- a reliable and valid assessment tool	Chandler, J. M.; Duncan, P. W.; Weiner, D. K.; Studenski, S. A.	2001	Topics in Geriatric Rehabilitation	16	3
Reactive stepping behaviour in response to forward loss of balance predicts future falls in community-dwelling older adults	Carty, C. P.; Cronin, N. J.; Nicholson, D.; Lichtwark, G. A.; Mills, P. M.; Kerr, G.; Cresswell, A. G.; Barrett, R. S.	2015	Age and ageing	44	1
Parkinsonian signs and incident falls in older persons without Parkinson's disease	Buracchio, Teresa; Arvanitakis, Zoe; Leurgans, Sue; Bennett, David A.	2010	Journal of the American Geriatrics Society	58	1
Use of the Berg Balance Test to predict falls in elderly persons	Bogle Thorbahn, L. D.; Newton, R. A.	1996	Physical therapy	76	6
Comparative performance of current definitions of sarcopenia against the prospective incidence of falls among community-dwelling seniors age 65 and older	Bischoff-Ferrari, H. A.; Orav, J. E.; Kanis, J. A.; Rizzoli, R.; Schlogl, M.; Staehelin, H. B.; Willett, W. C.; Dawson-Hughes, B.	2015	Osteoporosis International	26	12
Self-reported walking, balance testing and risk of fall	Bergland, A.; Jarnlo, G. B.; Wyller, T. B.	2006	Tidsskrift for den Norske Laegeforening	126	2
Correlates of recurrent falling in independent community-dwelling older adults	Berg, W. P.; Alessio, H. M.; Mills, E. M.; Tong, C.	1997	Journal of Motor Behavior	29	1
New approach to risk determination: development of risk profile for new falls among community-dwelling older people by use of a Genetic Algorithm Neural Network (GANN)	Bath, P. A.; Pendleton, N.; Morgan, K.; Clague, J. E.; Horan, M. A.; Lucas, S. B.	2000	The journals of gerontology. Series A, Biological sciences and medical sciences	55	1
Can FRAX predict falls in older women?	Atkinson, E.; Achenbach, S.; Crenshaw, J.; Kaufman, K.; Khosla, S.; Melton, L. J.	2015	Journal of Bone and Mineral Research	30	
The role of postural instability/gait difficulty and fear of falling in predicting falls in non-demented older adults	Allali, Gilles; Ayers, Emmeline I.; Holtzer, Roee; Verghese, Joe	2017	Archives of Gerontology & Geriatrics	69	
Multiple modes of assessment of gait are better than one to predict incident falls	Allali, G.; Ayers, E. I.; Verghese, J.	2015	Archives of gerontology and geriatrics	60	3
Clinical parameters associated with falls in an elderly population	Clark, R. D.; Lord, S. R.; Webster, I. W.	1993	Gerontology	39	2
Force Platform Balance Measures as Predictors of Indoor and Outdoor Falls in Community-Dwelling Women Aged 63-76 Years	Pajala, Satu; Era, Pertti; Koskenvuo, Markku; Kaprio, Jaakko; Törmäkangas, Timo; Rantanen, Taina	2008	Journals of Gerontology Series A: Biological Sciences & Medical Sciences	63	2
Changes in step-width during dual-task walking predicts falls	Nordin, E.; Moe-Nilssen, R.; Ramnemark, A.; Lundin-Olsson, L.	2010	Gait and Posture	32	1
Clinically meaningful cutpoints of leg power in predicting disability, falls, and hospitalizations in older adults	Ni, M.; Ward, R.; Bean, J.	2017	Archives of Physical Medicine and Rehabilitation	98	10
Use of the Berg Balance Scale for predicting multiple falls in community-dwelling elderly people: a prospective study	Muir, S. W.; Berg, K.; Chesworth, B.; Speechley, M.	2008	Physical Therapy	88	4
Comparison of the validity of four fall-related psychological measures in a community-based falls risk screening	Moore, D. S.; Ellis, R.; Kosma, M.; Fabre, J. M.; McCarter, K. S.; Wood, R. H.	2011	Research Quarterly for Exercise and Sport	82	3
Is it possible to predict falls in older adults using gait kinematics?	Marques, Nise Ribeiro; Spinoso, Deborah Hebling; Cardoso, Bruna Carvalho; Moreno, Vinicius Christianini; Kuroda, Marina Hiromi; Navega, Marcelo	2018	Clinical Biomechanics	59	
Risk factors for falling among community-based seniors using home care services	Fletcher, P. C.; Hirdes, J. P.	2002	Journals of Gerontology - Series A Biological Sciences and Medical Sciences	57	8
Falls and fear of falling: which comes first? A longitudinal prediction model suggests strategies for primary and secondary prevention	Friedman, S. M.; Munoz, B.; West, S. K.; Rubin, G. S.; Fried, L. P.	2002	Journal of the American Geriatrics Society	50	8
Development of a new fall risk assessment index for older adults	Yamada, M.; Arai, H.; Nagai, K.; Tanaka, B.; Uehara, T.; Aoyama, T.	2012	International Journal of Gerontology	6	3
Can the Ordered Multi-Stepping over Hoop test be useful for predicting fallers among older people? A preliminary 1 year cohort study	Tsutsumimoto, K.; Doi, T.; Misu, S.; Ono, R.; Hirata, S.	2013	Aging Clinical and Experimental Research	25	4
"Fall risk index" helps clinicians identify high-risk individuals	Toba, K.; Kikuchi, R.; Iwata, A.; Kozaki, K.	2009	Japan Medical Association Journal	52	4
Risk assessment for falls in the elderly population	Toba, K.	2008	Geriatrics & Gerontology International	8	
The comparative ability of eight functional mobility tests for predicting falls in community-dwelling older people	Tiedemann, A.; Shimada, H.; Sherrington, C.; Murray, S.; Lord, S.	2008	Age & Ageing	37	4
Fall prediction based on biomechanics equilibrium using Kinect	Tao, X.; Yun, Z.	2017	International Journal of Distributed Sensor Networks	13	4
Which neuromuscular or cognitive test is the optimal screening tool to predict falls in frail community-dwelling older people?	Shimada, H.; Suzukawa, M.; Tiedemann, A.; Kobayashi, K.; Yoshida, H.; Suzuki, T.	2009	Gerontology	55	5
Multifactorial screening for fall risk in community-dwelling older adults in the primary care office: Development and validation of the Fall Risk Assessment & Screening Tool (FRAST)	Renfro, Mindy Oxman	2012	ProQuest (Dissertation)	72	
Quantitative trunk sway and prediction of incident falls in older adults	Mahoney, Jeannette R.; Oh-Park, Mooyeon; Ayers, Emmeline; Verghese, Joe	2017	Gait & Posture	58	
Choice stepping reaction time: a composite measure of falls risk in older people	Lord, S. R.; Fitzpatrick, R. C.	2001	The journals of gerontology. Series A, Biological sciences and medical sciences	56	10
Visual risk factors for falls in older people	Lord, S. R.; Dayhew, J.	2001	Journal of the American Geriatrics Society	49	5
Risk factors for falling among community-dwelling seniors using home-care services: An extended hazards model with time-dependent covariates and multiple events	Leclerc, B. S.; Bégin, C.; Cadieux, É; Goulet, L.; Leduc, N.; Kergoat, M. J.; Lebel, P.	2008	Chronic Diseases in Canada	28	4
Conceptualizing a Dynamic Fall Risk Model Including Intrinsic Risks and Exposures	Klenk, J.; Becker, C.; Palumbo, P.; Schwickert, L.; Rapp, K.; Helbostad, J. L.; Todd, C.; Lord, S. R.; Kerse, N.	2017	J Am Med Dir Assoc	18	11
Postural stiffness, distractions, and prospective falls: The mobilize boston study	Kang, H. G.; Quach, L.; Li, W.; Lipsitz, L.	2010	Parkinsonism and Related Disorders	16	
Risk factors for falls in older adults in a South African Urban Community	Kalula, S. Z.; Ferreira, M.; Swingler, G. H.; Badri, M.	2016	BMC geriatrics	16	
Short Berg Balance Scale, BBS-9, as a predictor of fall risk among the aged: A prospective 12-month follow-up study	Hohtari-Kivimäki, U.; Salminen, M.; Vahlberg, T.; Kivelä, S. L.	2013	Aging Clinical and Experimental Research	25	6
Falls among healthy, community-dwelling, older women: A prospective study of frequency, circumstances, consequences and prediction accuracy	Hill, K.; Schwarz, J.; Flicker, L.; Carroll, S.	1999	Australian and New Zealand Journal of Public Health	23	1
Balance self-efficacy predicts risk factors for side falls and frequent falls in community-dwelling elderly	Gunter, K. B.; De Costa, J.; White, K. N.; Hooker, K.; Hayes, W. C.; Snow, C. M.	2003	Journal of Aging & Physical Activity	11	1
Fall Risk Assessment Through Automatic Combination of Clinical Fall Risk Factors and Body-Worn Sensor Data	Greene, B. R.; Redmond, S. J.; Caulfield, B.	2017	IEEE Journal of Biomedical and Health Informatics	21	3
Comparison of regression models for the analysis of fall risk factors in older veterans	Gill, D. P.; Zou, G. Y.; Jones, G. R.; Speechley, M.	2009	Annals of Epidemiology	19	8
A Multinomial Regression Model of Risk for Falls (RFF) Factors Among Filipino Elderly in a Community Setting	de Guzman, Allan B.; Garcia, Jan Michael G.; Garcia, Juan Paulo S. P.; Garcia, Monica B.; German, Ross T.; Gerong, Martha Sabrina C.; Grajo, Alm	2013	Educational Gerontology	39	9
Falls among older adults: Characteristics of fallers, predictors of falls, and the impact of falls on health care and long-term care utilization	Choi, In Hee	2009	ProQuest (Dissertation)	69	
Pilot study: Predictive measures of self-reported confidence levels and physical performance related to fall risk in community dwelling older adults	Bright, B.; Staley, J.; Tirey, L.; Vrchota, S.; Watson, K.	2016	Archives of Physical Medicine and Rehabilitation	97	10
The Standardization of Frailty Phenotype Criteria Improves Its Predictive Ability: The Toledo Study for Healthy Aging	Bouzon, C. A.; Carnicero, J. A.; Turin, J. G.; Garcia-Garcia, F. J.; Esteban, A.; Rodriguez-Manas, L.	2017	Journal of the American Medical Directors Association	18	5
Differential risk factor profiles for indoor and outdoor falls in older people living at home in Nottingham, UK	Bath, P. A.; Morgan, K.	1999	European Journal of Epidemiology	15	1
An 8-year prospective study of the relationship between cognitive performance and falling in very old adults	Anstey, K. J.; von Sanden, C.; Luszcz, M. A.	2006	Journal of the American Geriatrics Society	54	8
Discriminative and Predictive Ability of Physical Performance Measures in Identifying Fall Risk among Older Adults	Abu Samah, Z.; Singh, D. K. A.; Murukesu, R. R.; Shahar, S.; Nordin, N. A. M.; Omar, M. A.; Ai-Vyrn, C.	2018	Sains Malaysiana	47	11
Performance-Oriented Assessment of Mobility Problems in Elderly Patients	ME Tinetti	1986	Journal of the American Geriatrics Society	34	2
Predicting the probability of falls in community-dwelling elderly individuals using the trail-walking test	Yamada, M.; Ichihashi, N.	2010	Environmental Health and Preventive Medicine	15	6
The development and validation of a brief performance-based fall risk assessment tool for use in primary care	Tiedemann, A.; Lord, S. R.; Sherrington, C.	2010	Journals of Gerontology Series A: Biological Sciences & Medical Sciences	65A	8
Falls prediction in elderly people: A 1-year prospective study	Swanenburg, J.; de Bruin, E. D.; Uebelhart, D.; Mulder, T.	2010	Gait and Posture	31	3
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