MACQUARIE University

AUSTRALIAN INSTITUTE OF HEALTH INNOVATION

A dashboard of predictive analytics and decision support to drive care quality and person-centred outcomes in aged care

NSW Fall Prevention & Healthy Ageing Network Annual Forum

27th May, 2022

Karla Seaman, PhD

Nasir Wabe, PhD

Australian Institute of Health Innovation, Macquarie University

NHMRC Partnership Grant 5 years

Objective:

- To co-develop and evaluate an innovative predictive analytics dashboard with embedded decision support for aged care managers, staff, and clients and their families which drives measurable improvements in client outcomes in both residential and community aged care settings.

Primary Outcomes:

- Fall-related hospitalisations
- Quality of life

Aim 1: Co-develop an aged care dashboard of predictive analytics and decision support with staff and clients

Aim 2: Identify and assess design and work process features supporting dashboard use

Aim 3: Implement and evaluate the impact of the dashboard on client care and outcomes

Methods

Aim 1:
- Integrate aged care data sources
- Develop & validate risk models
- Design dashboard prototype

Aim 2:
- Observational work studies
- Qualitative interviews with staff and clients
- Think aloud scenario and usability testing

Aim 3:
- Stepped-wedge cluster randomised controlled trial in 12 facilities & 12 home care outlets
- Process and economic evaluations

Project aims

Project Partners

deeble institute
Deeble Institute for Health Policy Research

NSW GOVERNMENT Health
Northern Sydney
Local Health District

SYDNEY NORTH
Health Network

Australian Government
Aged Care Quality and Safety Commission

Anglicare

Investigators

Chief Investigators

Prof Johanna Westbrook, MQ

Prof Andrew Georgiou, MQ

Prof Stephen Lord, UNSW

Prof Len Gray, UQ

Prof Ric Day, UNSW

Prof Julie Ratcliffe, Flinders

A/Prof Melissa Baysari, USYD

Prof Jeffrey Braithwaite, MQ

Associate Investigators

Ms Jo Root, Consumers Health Forum

Dr Magda Raban, MQ

Prof Jacqueline Close, UNSW

Dr Wu Yi Zheng, USYD

Prof Elizabeth Beattie, Q Uni

Dr Deborah Debono, UTS

Mr David Roffe, IT consultant

Centre for Health Systems and Safety Research (CHSSR)

MACQUARIE University

AGED CARE EVALUATION AND RESEARCH TEAM (ACER)

@ACER_MQ


Professor Johanna Westbrook

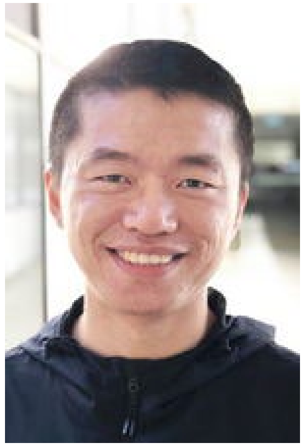

Dr Amy Nguyen


Dr Magda Raban


Dr Rachel Urwin


Dr Karla Seaman

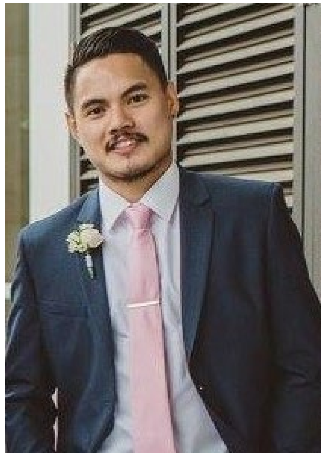

Dr Nasir Wabe


Dr Guogui Huang


Dr Sandun Malpriya Silva


Ms Laura Dodds


Ms Isabelle Meulenbroeks


Mr Cris Mercado

Open access Protocol

BMJ Open

Co-designing a dashboard of predictive analytics and decision support to drive care quality and client outcomes in aged care: a mixed-method study protocol

Kristiana Ludlow,[1,2] Johanna Westbrook,[1] Mikaela Jorgensen,[1] Kimberly E Lind,[3] Melissa T Baysari,[4] Leonard C Gray,[5] Richard O Day,[6] Julie Ratcliffe,[7] Stephen R Lord,[8,9] Andrew Georgiou,[1] Jeffrey Braithwaite,[10,11] Magdalena Z Raban,[1] Jacqueline Close,[8] Elizabeth Beattie,[12] Wu Yi Zheng,[13] Deborah Debono,[14] Amy Nguyen,[1,6] Joyce Siette,[1] Karla Seaman,[1] Melissa Miao,[15] Jo Root,[16] David Roffe,[17] Libby O'Toole,[18] Marcela Carrasco,[19] Alex Thompson,[20] Javed Shaikh,[20] Jeffrey Wong,[20] Cynthia Stanton,[21] Rebecca Haddock [22]

Need more info on this study?

Email me: karla.seaman@mq.edu.au

Background


Photo by De an Sun on Unsplash

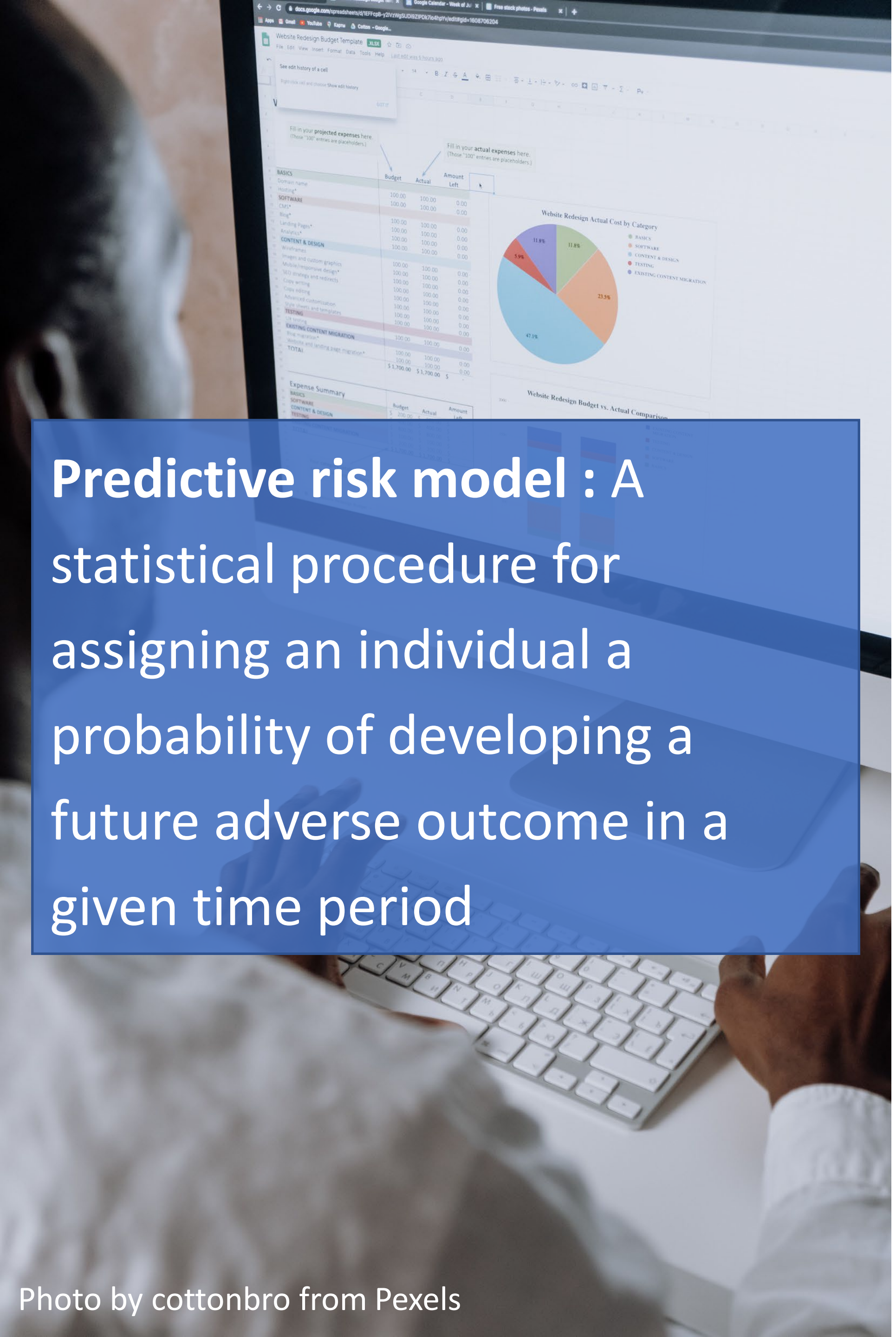
Falls in older adults

- ***1 in 4 people aged $\geq$ 65*** years experience a fall each year
- Results in serious physical harm or death, have enduring detrimental effects on mental health, and reduce the quality of life
- The largest contributor to injury-related hospitalisations ***(42%)***
- Cause significant economic burden ***(AUD$3.9 B nationally)***
- ***6 out of 7*** people who suffer fall-related injuries live in residential aged care homes, or receive aged care services from home-based or community providers

Predicting and preventing falls

- Falls causing harm are ***often avoidable***
- ***Multifactorial interventions*** may reduce fall incidence
- Risk assessments are usually completed ***intermittently***
- Risk is complex and subject to variation—***it does not remain static***
- ***Electronic health records*** provide comprehensive and real-time information, presenting an opportunity for dynamic fall risk assessments

Rationale



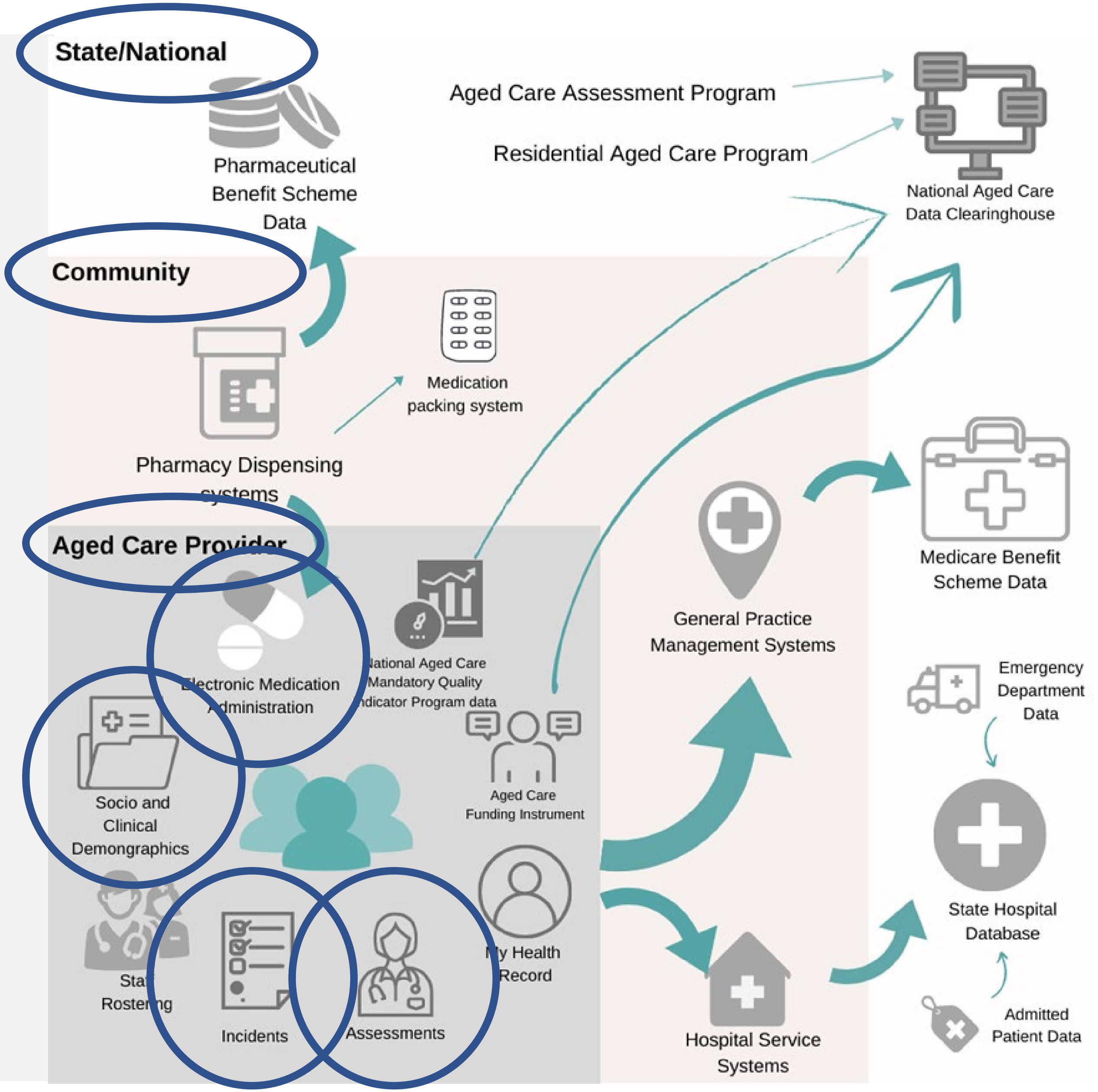
Predictive risk model : A statistical procedure for assigning an individual a probability of developing a future adverse outcome in a given time period

Photo by cottonbro from Pexels

- Aged care providers are ***replacing paper*** record systems with electronic systems
- The integration of consumer data into a ***single comprehensive electronic health record*** provides access to contemporary information about health care and risks
- Predictive models and algorithms which draw on data about risk factors can be used to ***perform real-time assessments of falls risk***
- Used to develop predictive models for fall risk identification and decision support in ***acute and primary care***

Aged Care Data Sources

- Key aged care data sources can be collected at ***state/national levels, community*** and ***aged care provider***
- ***Routinely collected aged care provider data*** refer to data collected electronically at an aged care provider level, within there information systems for day-to-day care purposes
- Assessments include the Peninsula Health Falls Risk Assessment Tool (PH-FRAT) and quality of life tool



Benefits of Aged Care Provider Data

- Readily accessible
- Timeliness
- More granular information

	Pharmaceutical Benefit Scheme	Electronic Medication Record
Drug Name	X	X
Strength	X	X
Dose		X
Duration of use		X
Date and time medication were taken		X
Off label / Private use / unsubsidised medications		X
Doses administered, including ‘PRNs’		X
Reason for the missed dose		X

Australasian Journal on Ageing

INNOVATION AND TRANSLATION | Full Access

Transforming routinely collected residential aged care provider data into timely information: Current and future directions

Karla L. Seaman, Mikaela L. Jorgensen, Magdalena Z. Raban, Kimberly E. Lind, J Simon Bell, Johanna I. Westbrook

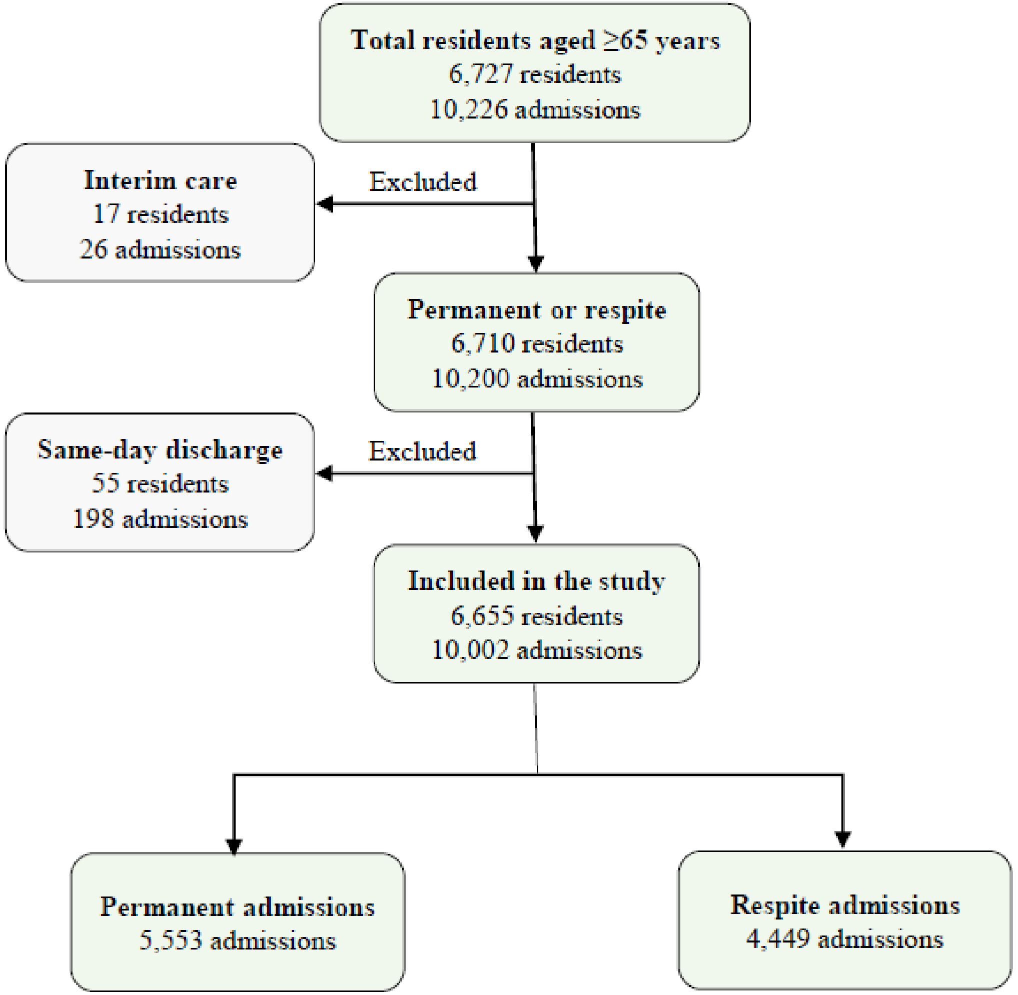
First published: 06 August 2021 | https://doi.org/10.1111/ajag.12985 |

- **Need more info on this study?**
  - Email me: karla.seaman@mq.edu.au

Epidemiology of falls in residential aged care

Cohort and baseline characteristics (examples)

- 6,163 residents: 57% permanent
- Female = 66.2%
- Median age = 86 years
- Pre-existing health conditions
  - ✓ Dementia = 48.2%
  - ✓ Depression = 38.0%
  - ✓ Cerebrovascular accident = 23.8%
  - ✓ Diabetes mellitus = 21.9%



Falls incident rate (IR)

6,163 residents = 3,508,842 person-day

25,040 fall incidents

IR= 7.1 falls /1000 person-day

What does this mean?

7 new incidents of falls for every 1,000 person days of care.

A median of 3 falls per resident

Falls incident rate (IR)…

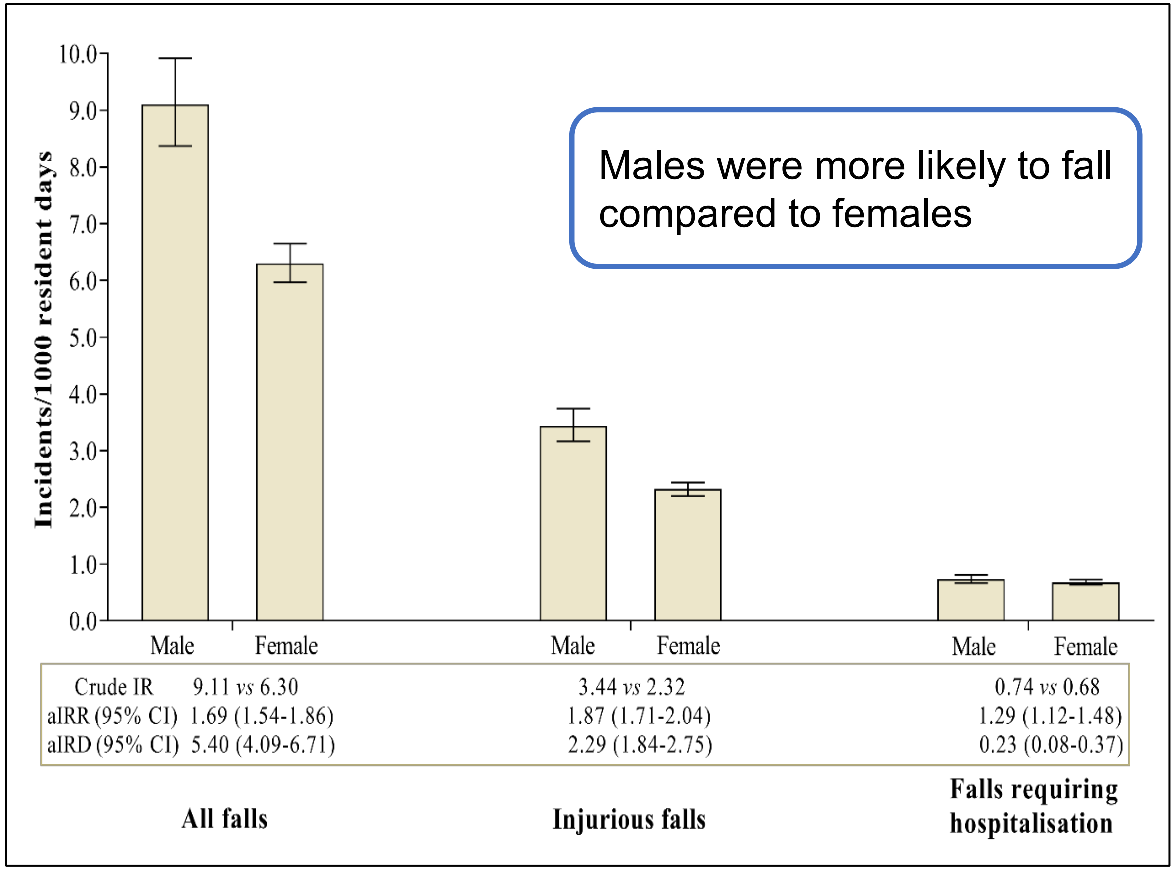
6,163 residents = 3,508,842 person-day

25,040 fall incidents → IR= 7.1 falls /1000 person-day

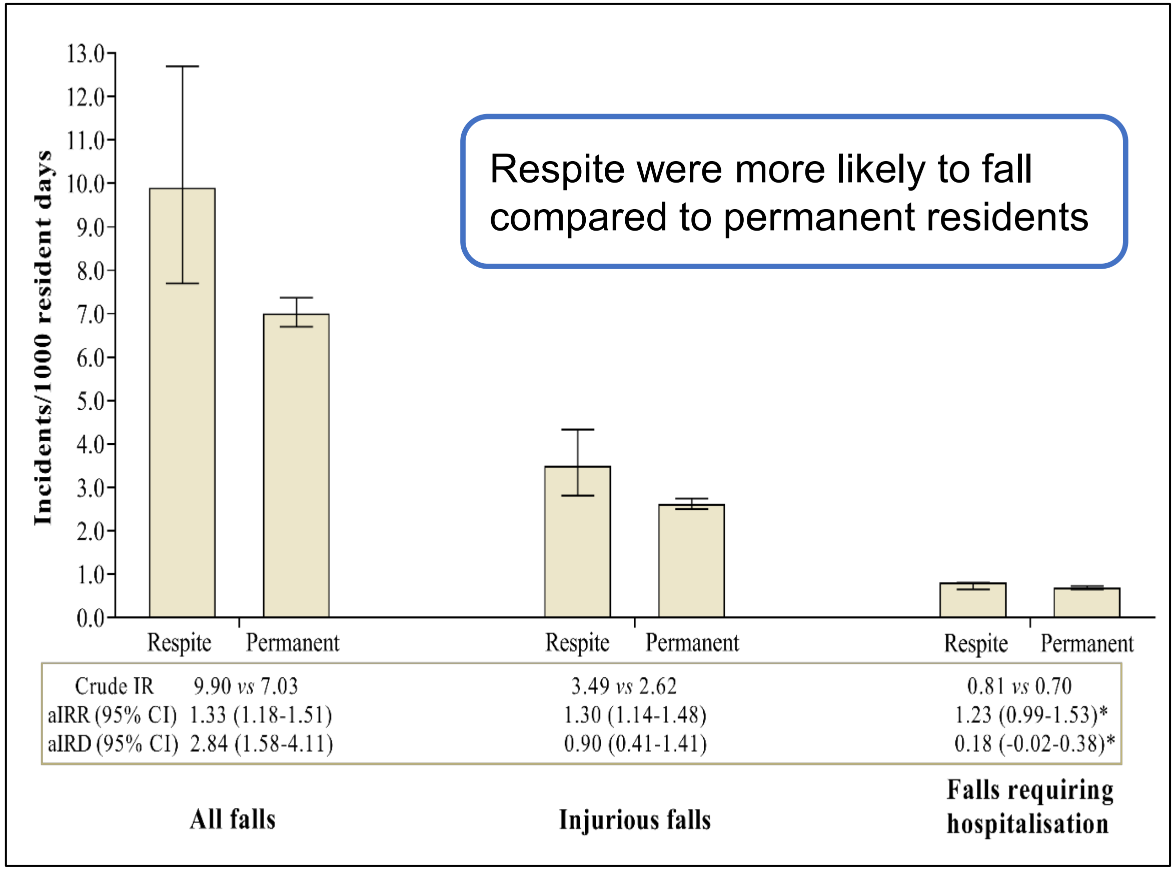
- 9,289 (37.1%) injurious falls → IR= 2.7 falls /1000 person-day
- 2,442 (9.8%) falls requiring hospitalisation → IR= 0.7 falls /1000 person-day

Who was more likely to fall?

Males vs Females



- Respite vs Permanent



Key implications

1. The need for special focus on respite and men residents
    - e.g., adequate resourcing/staffing

2. High frequency of injurious falls confirms the need for increased funding for prevention strategies

3. Implications for the national indicator:
    - Our results indicate the importance to consider case-mix when reporting fall incidents

International Journal for Quality in Health Care

Article Contents

ACCEPTED MANUSCRIPT

Epidemiology of Falls in 25 Australian Residential Aged Care Facilities: A Retrospective Longitudinal Cohort Study Using Routinely Collected Data

Nasir Wabe, Karla L Seaman, Amy Nguyen, Joyce Siette, Magdalena Z Raban, Peter Hibbert, Jacqueline Close, Stephen R Lord, Johanna I Westbrook

International Journal for Quality in Health Care, mzac050, https://doi.org/10.1093/intqhc/mzac050

Published: 19 May 2022 **Article history** ▾

- **Need more info on this study?**
  - Email me: nasir.wabe@mq.edu.au

The use and predictive performance of Peninsula Health Falls Risk Assessment Tool (PH-FRAT) in residential aged care

Overview

- Developed in 1999 by Peninsula Health in Victoria
- Validated and easy-to-use tool
  - Fallers: Risk score >14
  - Non-fallers: Risk score ≤14

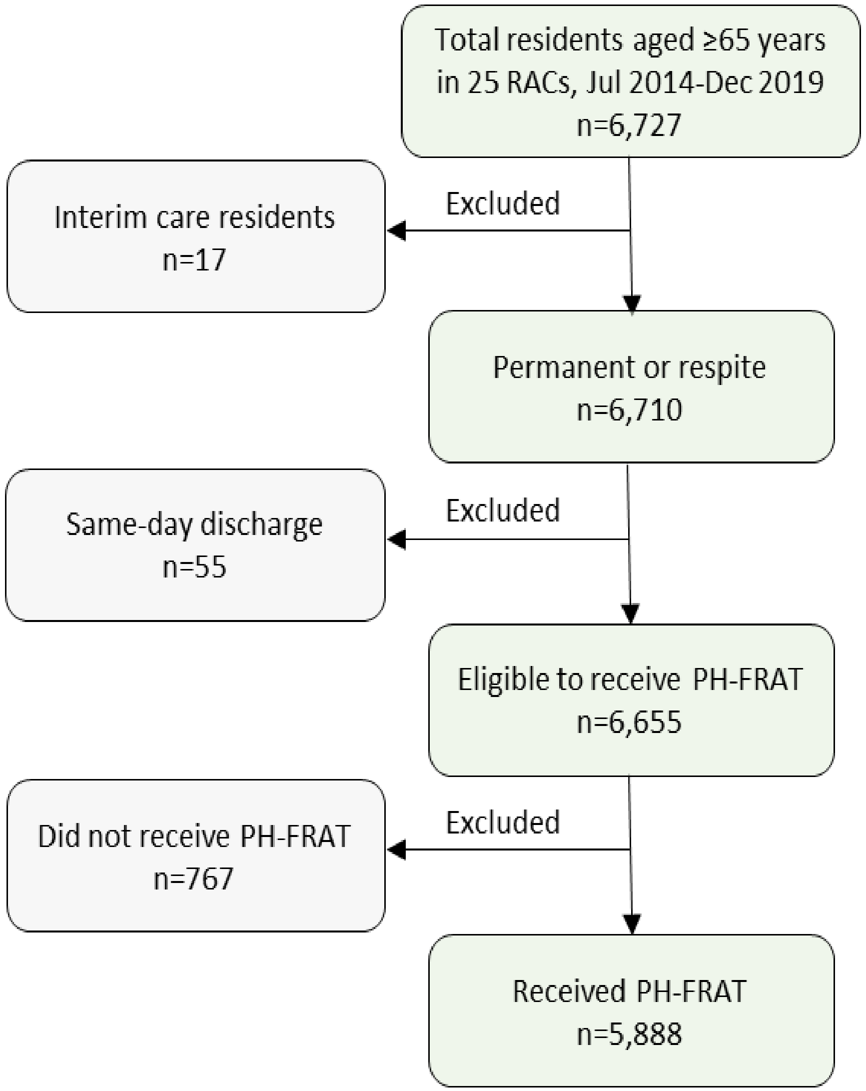
Objective:

- To determine the use and performance of PH-FRAT by comparing fall risk status (as predicted by PH-FRAT) against the occurrence of actual falls

RISK FACTOR	LEVEL	RISK SCORE
RECENT FALLS *(To score this, complete history of falls, overleaf)*	none in last 12 months..........	2
	one or more between 3 and 12 months ago..........	4
	one or more in last 3 months..........	6
	one or more in last 3 months whilst inpatient / resident....	8
MEDICATIONS *(Sedatives, Anti-Depressants Anti-Parkinson's, Diuretics Anti-hypertensives, hypnotics)*	not taking any of these..........	1
	taking one	2
	taking two	3
	taking more than two..........	4
PSYCHOLOGICAL *(Anxiety, Depression ↓Cooperation, ↓Insight or ↓Judgement **esp. re mobility**)*	does not appear to have any of these..........	1
	appears mildly affected by one or more..........	2
	appears moderately affected by one or more..........	3
	appears severely affected by one or more..........	4
COGNITIVE STATUS *(AMTS: Hodkinson Abbreviated Mental Test Score)*	AMTS 9 or 10 / 10 **OR** intact..........	1
	AMTS 7-8 mildly impaired..........	2
	AMTS 5-6 mod impaired..........	3
	AMTS 4 or less severely impaired	4
(Low Risk: 5-11 Medium: Risk: 12-15 High Risk: 16-20)	**RISK SCORE**	/20

Cohort and baseline characteristics (examples)

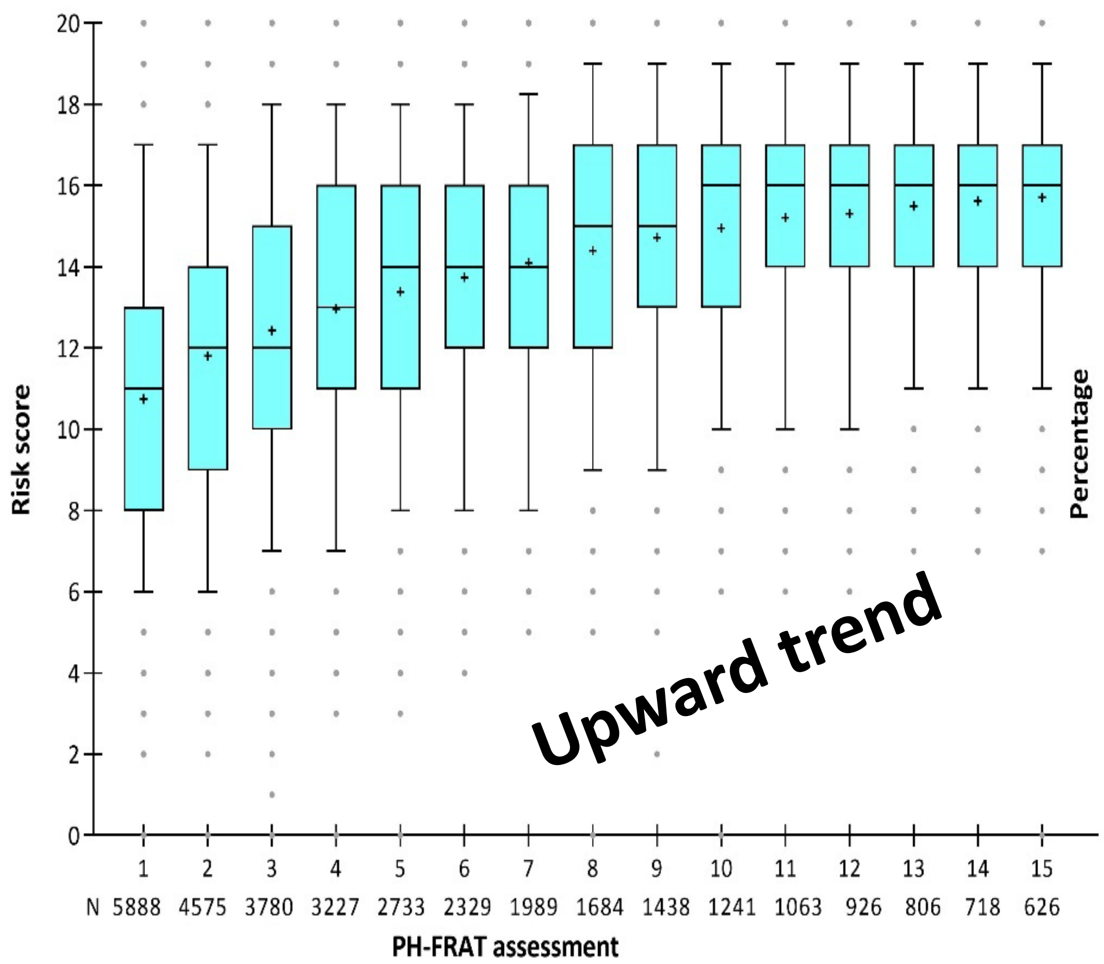
- Female = 66%
- Median age = 86 years
- Dementia =51.7%
- Depression, mood or BD = 42%
- Cerebrovascular accident = 25.4%
- Diabetes mellitus = 22.6%

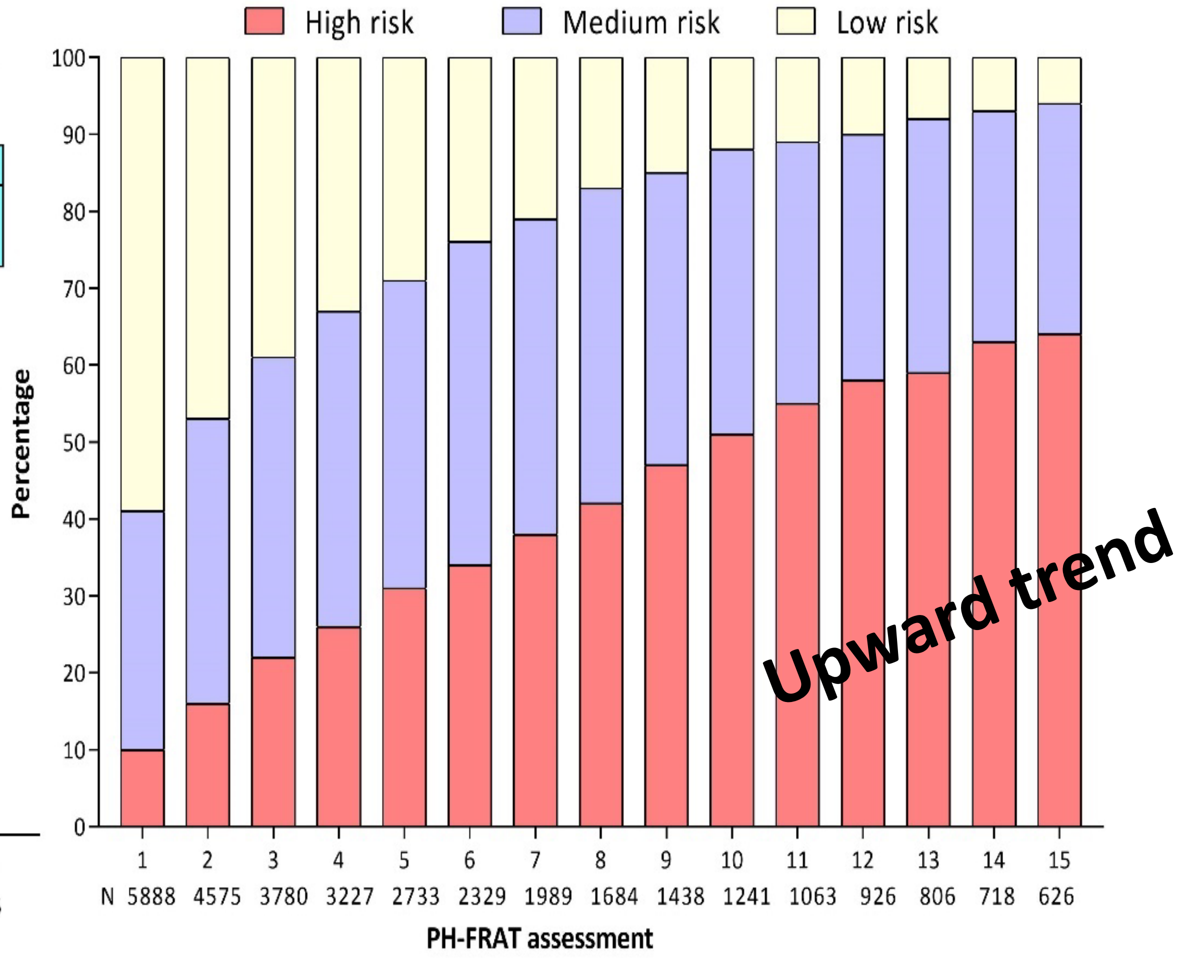


Utilisation of PH-FRAT

- **9 in 10 eligible residents received at least one PH-FRAT assessment**
  - Median no. PH-FRATs per resident = 4 (IQR 2-8)
  - Median time between assessments = 43.8 days (IQR 10.7-144.0)
  - Fall risk score = 14 (IQR 11-16)
  - Fall risk category = high (36.4%), med (35.0%) & low (28.2%)

Trends in PH-FRAT over time

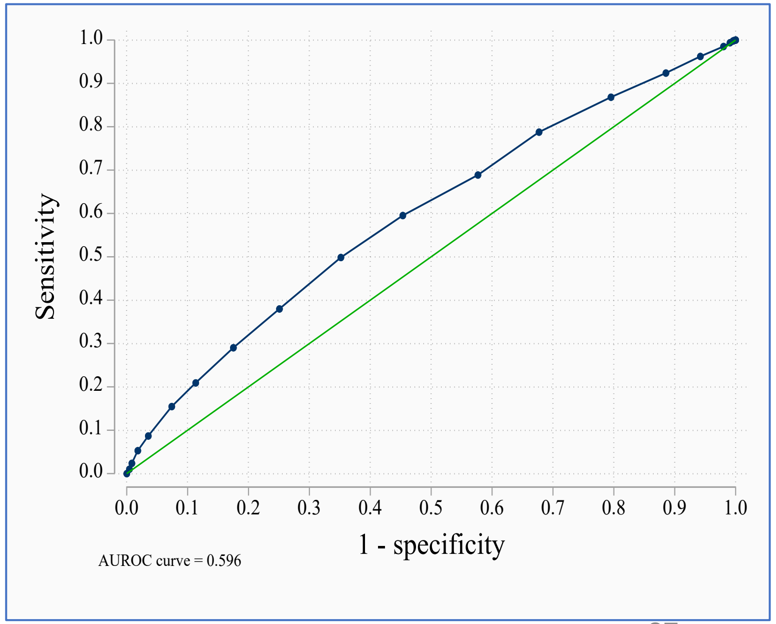




PH-FRAT performance

- The tool showed poor predictive performance:
  - AUC =0.57
  - Sensitivity =34%
  - Specfcity = 82%

- By examining the ROC curve, we identified the cut-off point of 10 presents the optimal sensitivity and specificity.
  - >10 fallers and ≤10 non-fallers
  - AUC = 0.61,
  - Sensitivity=74.4%,
  - Specificity=45.6%



Key implications

The poor predictive performance raises concerns about resident safety

Poor predictive performance or incorrect risk profiling

↓

Poor clinical decisions

↓

Potentially high-risk residents may miss out on receiving fall prevention programs

Recommendations

Reducing risk score cut-point to define fall risk status:

- Cut-point of 10 showed better performance.
- The risk category should be re-defined, e.g., High risk (>10), medium (5-10), low (<5)

Model *recalibration:*

- Incorporating any new relevant variables to enhance prediction.

Dynamic fall risk prediction models:

- use of real-time data to enable up-to-date risk prediction.

BMC Geriatrics

Home About Articles Submission Guidelines Collections

Research | Open Access | Published: 01 April 2022

The use and predictive performance of the Peninsula Health Falls Risk Assessment Tool (PH-FRAT) in 25 residential aged care facilities: a retrospective cohort study using routinely collected data

Nasir Wabe, Joyce Siette, Karla L. Seaman, Amy D. Nguyen, Magdalena Z. Raban, Jacqueline C. T. Close, Stephen R. Lord & Johanna I. Westbrook

BMC Geriatrics **22**, Article number: 271 (2022) | Cite this article

- **Need more info on this study?**
  - Email me: nasir.wabe@mq.edu.au

Models for predicting falls in aged care: Systematic Review

Study Characteristics and Quality Appraisals

Publication	Country	Setting	Population aged group	Study Design	Critical Appraisal Skills Program Checklist
Volrathongchai, et al. 2005	United States	Residential Care	65-100 years	Retrospective	27.3%
Marier, et.al. 2016	United States	Residential Care	Not reported	Retrospective	72.7%
Kuspinar, et al. 2019	Canada	Home care	77±14 years with no previous fall in the last 90 days	Prospective	72.7%
Lo, et al. 2019	United States	Home care	65+ years	Retrospective	54.5%

Study Models

Publication	Data Source	Statistical Model	Derivation Cohort (% of total cohort)	Internal Validation Cohort (% of total cohort) External Validation Cohort	Falls Outcome Prediction	Risk Score/ Category	Number of models	Discrimination (Area under the curve), (95% CI)
Volrathongchai, et al. 2005	Minimum Data Set	Likelihood Basis Pursuit	9,980 (100%)	-	Fall within 3-months	No	1	-
Marier, et.al. 2016	Electronic Medical record and Minimum Data Set	Repeated events survival model	2,527 (49.3%)	2,602 (50.7%)	-	Yes	4	Akaike Information Criteria 1: 6733 2: 6749 3: 6614 4:6626
Kuspinar, et al. 2019	Resident Assessment Instrument-Home Care	Decision tree	88,690 (70%)	Internal: 38,013 (30%) External: 2,738 1,226 9,566	-	Yes	1	-
Lo, et al. 2019	Outcome and Assessment information Set and Electronic Medical record	Random Forest Algorithm	29,514 (50%)	29,514 (50%)	-	No	3	1: 0.67 2: 0.67 (0.66, 0.68) 3: 0.6 (0.59,0.62)

Synthesis: Risk Factor Predictors

We identified seven categories:

(1) Demographics (1 out of 9 models)

(2) Assessments conducted with the client or resident, for example, cognitive performance scale (4 out of 9 models)

(3) Fall history (5 out of 9 models)

(4) Medication (5 out of 9 models)

(5) Health conditions (6 out of 9 models)

(6) Physical abilities (6 out of 9 models)

(7) Environmental factors (4 out of 9 models)

Key findings

- Limited information on the predictive performance of the identified models
  - Limiting the utility for others
- Use of sub-optimal statistical methods to develop the prediction models
  - Falls is a recurrent events as they can occur multiple times
  - Should account for the potential recurrence and correlation of the outcome data (e.g., joint models, landmark models and machine learning based on deep learning approaches)
- The implementation and evaluation of these models within aged care service is critical to determine their true effectiveness and cost-effectiveness for health and wellbeing outcomes

BMC Geriatrics

Home About Articles Submission Guidelines Collections

Research | Open Access | Published: 16 March 2022

The use of predictive fall models for older adults receiving aged care, using routinely collected electronic health record data: a systematic review

Karla Seaman, Kristiana Ludlow, Nasir Wabe, Laura Dodds, Joyce Siette, Amy Nguyen, Mikaela Jorgensen, Stephen R. Lord, Jacqueline C. T. Close, Libby O'Toole, Caroline Lin, Annaliese Eymael & Johanna Westbrook

BMC Geriatrics **22**, Article number: 210 (2022) | Cite this article

- **Need more info on this study?**
  - Email me: karla.seaman@mq.edu.au

Development and internal validation of a dynamic falls risk prediction tool in Aged Care

Predicting falls risk – Traditional methods

- Traditional methods (e.g., logistic regression):
    - use data collected at a one-time point → **static prediction**
    - unable to reflect the changes in risk factors over time
- Most existing fall-related predictive tools utilise unsuitable methods
    - only 1 in 4 studies used an appropriate method(Seaman et al, 2021).
    - < one-third of 83 trials used appropriate methods (Donaldson, 2009)

Sub-optimal prediction method → Poorly performing tool → Potentially misleading or harmful tool

Predicting falls risk – modern methods

- **Methods for dynamic predictions:**

1. **Joint modelling**:
   - ✓ models longitudinal and survival processes jointly
   - ✓ efficient but computationally intensive
   - ✓ requires specialised software/programs
2. **Landmarking**:
   - ✓ apply Cox PH or extended Cox models (e.g., AG, frailty model) at any follow-up ‘**landmark**’ time to obtain dynamic predictions
   - ✓ require fewer modelling assumptions, and are more straightforward compared to joint models.
   - ✓ can be done using standard software

Why dynamic prediction models?

1. use longitudinal data to enable up-to-date risk predictions
2. incorporate both time-varying and time-fixed variables
3. account for the potential recurrence of the events
4. personalised prediction and improved decision-making

- They have been applied in other conditions (e.g., cancer), but have not been used for fall prediction.
- Opportunity
  - readily available electronic data presents an opportunity for applying dynamic fall risk models in aged care settings

Objective

1. To develop and internally validate a dynamic falls risk prediction tool using a landmark dynamic prediction method

2. To develop a point-based scoring system to determine the risk of falls

Model development and internal validation

MACQUARIE University SYDNEY·AUSTRALIA

Full sample
n=3,998

Training/derivative sample
- 70%, n=2,799
- For model development

Validation/hold-out sample
- 30%, n=1,199
- For internal validation

- Dynamic AUC and Sens/Spec

Full sample
n=3,998

- Point-based scoring system
- Risk groups

Results

Time invariant variables (examples)	n=3,998
Female	68%
Median age (year)	87
Dementia	57.8%
Falls history	52.8%
Parkinson's disease	7.5%
Stroke	26.1%
Osteoporosis/fracture	49.3%
Arthritis	57.3%

Time-dependent variables (examples)	n=3,998
Medication (ever received)	
Any FRIDs	80.0%
Opioids (N02A)	51.6%
Antidepressants (N06A)	38.1%
Antipsychotics (N05A)	25.4%
Hypnotics and sedatives (N05C)	23.7%
Diuretics (C03)	36.0%
Beta-blockers (C07)	26.2%
Severe psychological status	18.2%
Change in functional status incl dizziness/postural hypotension	46.0%
Mobility/transfer issues	81.5%
Risk-taking behaviours	68.6%
Difficulties with orientation to the environment	29.4%

Incidence of falls

	Training	Validation	Total
Total resident days	1,994,481	826,702	2,821,183
No. of falls	14,901	6,212	21,113
Crude IR (per 1000 resident days)	7.47	7.51	$\boxed{7.48}$
Experienced a fall, n (%)	75.4%	75.5%	75.5%
Experienced a recurrent fall, n (%)	59.6%	59.6%	59.6%

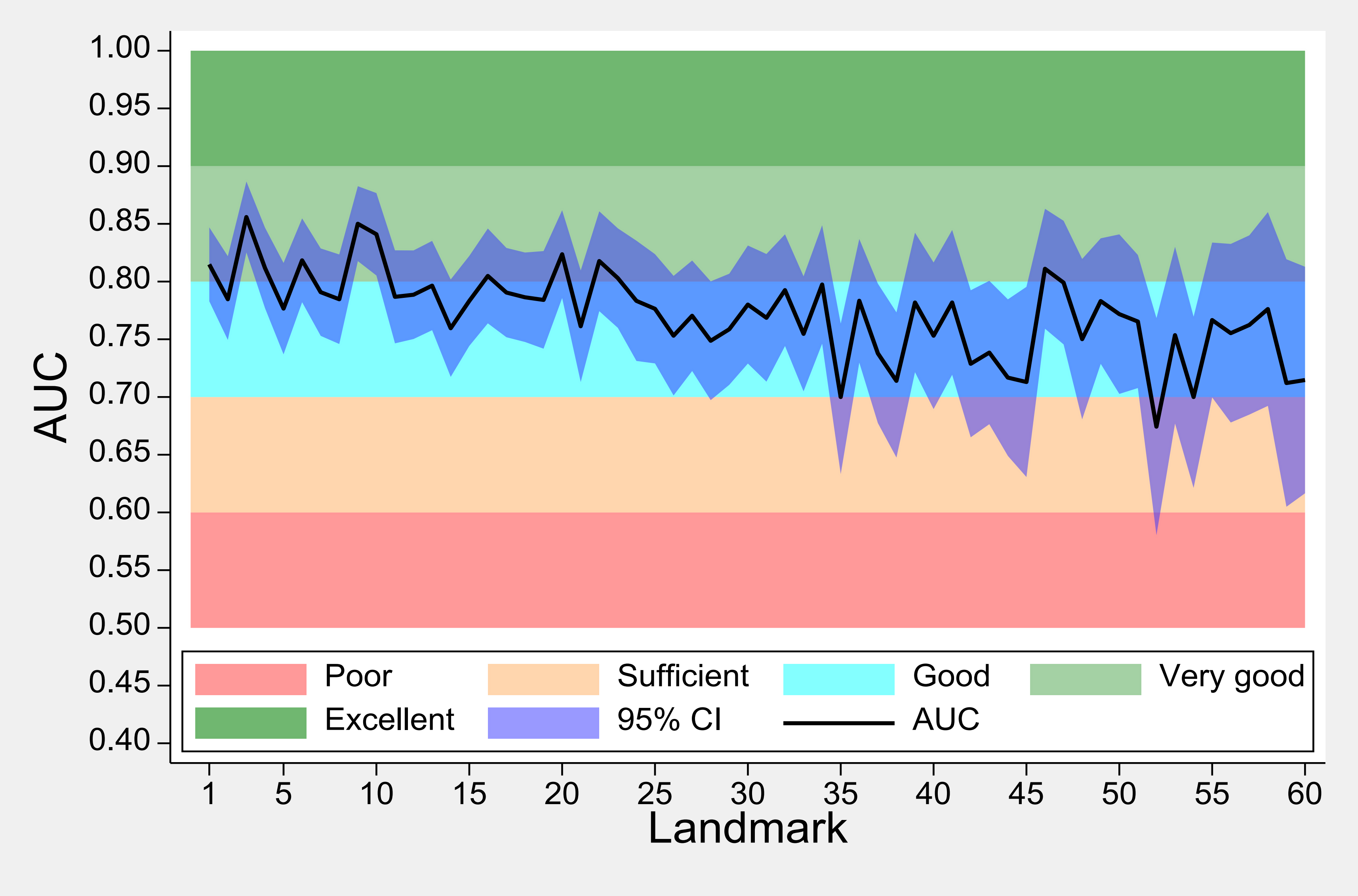
Predictors of falls: Multivariate analysis

Time invariant	HR (95% CI)	P
Male vs Female	1.22 (1.14-1.30)	<0.001
Dementia	1.13 (1.04-1.21)	0.002
Parkinson’s disease	1.28 (1.11-1.48)	0.001
Falls history	1.14 (1.07-1.21)	<0.001
Cognitive impairment	1.14 (1.01-1.30)	0.041
Incontinence	0.94 (0.88-1.01)	0.100
Time-dependent		
No. of falls prior to a LM		
0	Ref	
1	2.90 (2.72-3.09)	<0.001
2-4	5.02 (4.70-5.36)	<0.001
5-10	9.36 (8.66-10.12)	<0.001
>10	16.43 (14.61-18.49)	<0.001

Psychological status		
No	Ref	
Mild	1.07 (0.98-1.17)	0.140
Moderate	1.09 (0.98-1.20)	0.099
Severe	1.18 (1.04-1.34)	0.010
Mobility/transfer issue	1.24 (1.15-1.32)	<0.001
Change in functional status	1.15 (1.08-1.22)	<0.001
Risk-taking behaviours	1.10 (1.03-1.18)	0.006
Environment	1.05 (0.98-1.12)	0.192
Opioids (N02A)	1.11 (1.04-1.18)	0.002
Hypnotics and sedatives (N05C)	1.15 (1.05-1.27)	0.004
Antidepressants (N06A)	1.11 (1.04-1.18)	0.003
Antipsychotics (N05A)	1.17 (1.08-1.27)	<0.001
Beta blockers (C07)	1.07 (1.01-1.15)	0.034
Anxiolytics (N05B)	1.17 (0.94-1.45)	0.152
Vasodilators (C01D)	1.13 (0.99-1.28)	0.065

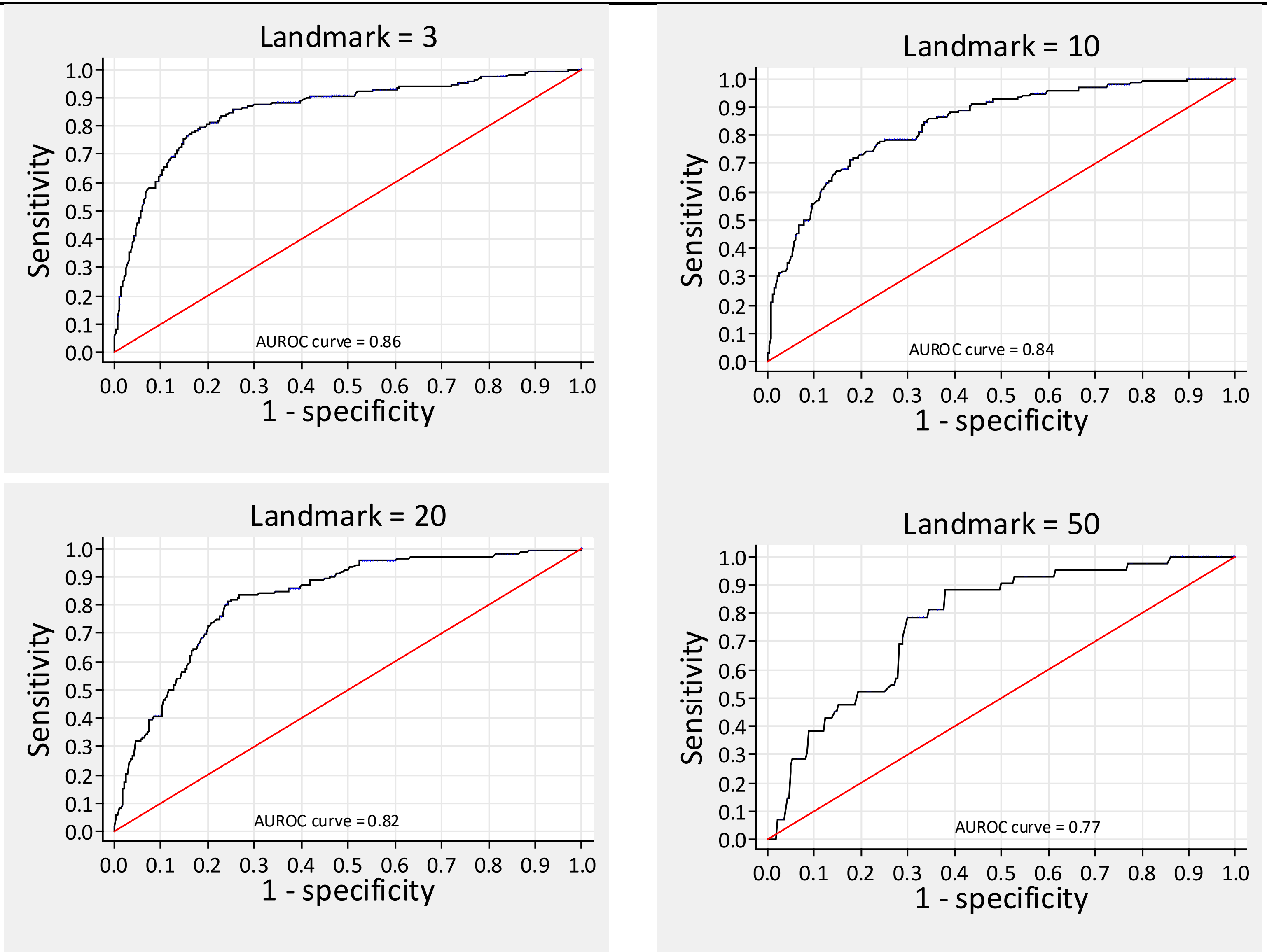
Interpretation (example): The use of opioids was associated with an 11% increased risk of falls compared to non-opioids users after adjusting for other variables

Model performance in the hold-out data: Dynamic AUC

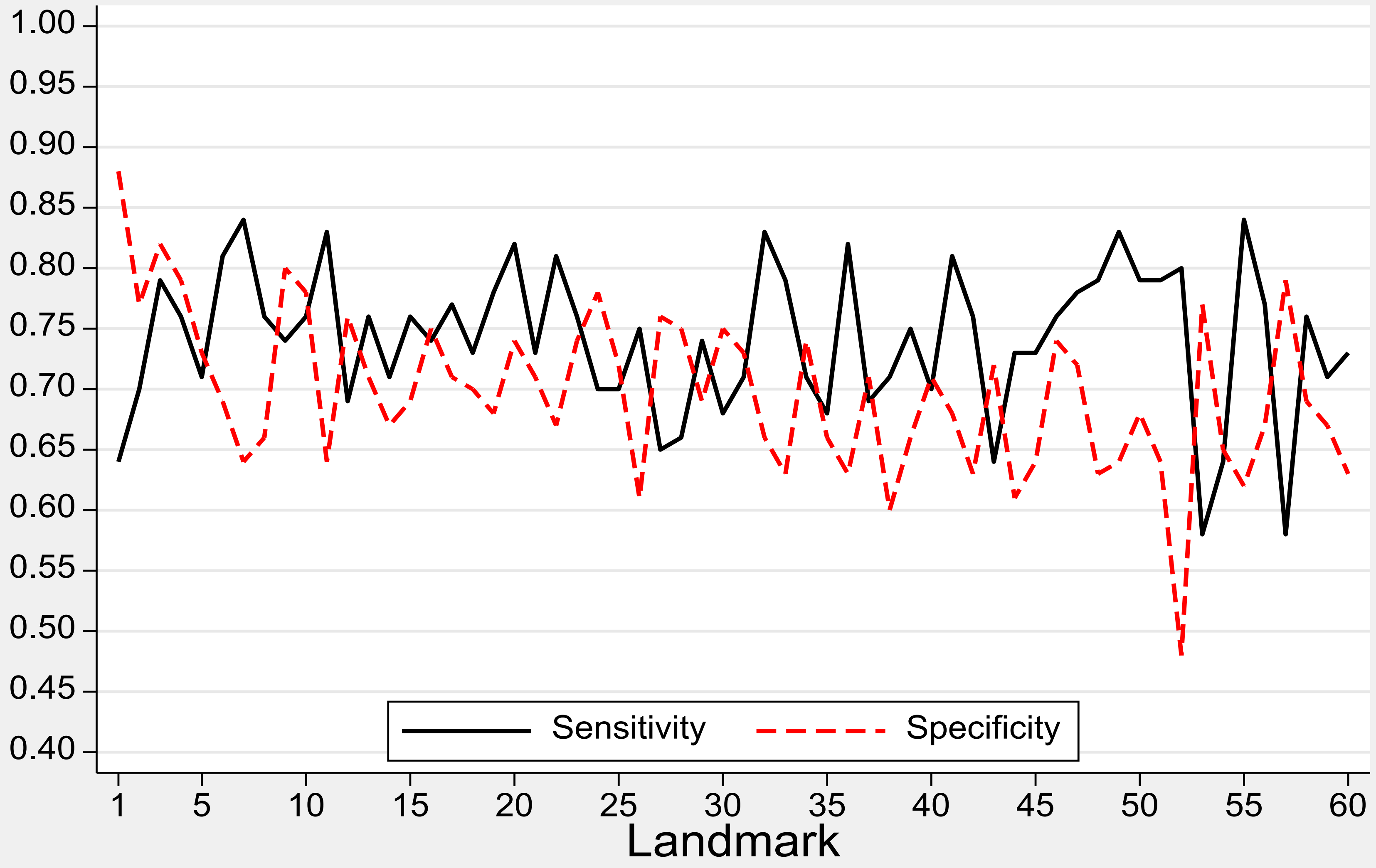


- Overall AUC
  = 0.78
- Range across the landmarks
  = 0.67-0.86
- >0.8 in 11 of 60 landmarks
- <0.7 in only 1 landmarks

Model performance: examples of ROC curves



Model performance: Dynamic sensitivity and specificity



Sensitivity

- Median = 0.75
- Range = 0.58-0.84
- >0.8 in 11 of 60 landmarks
- <0.6 in 2 of 60 landmarks

Specificity

- Median = 0.69
- Range = 0.48-0.88
- >0.8 in 3 of 60 landmarks
- <0.6 in 1 of 60 landmarks

Point-based risk-scoring system & risk groups

MACQUARIE University SYDNEY·AUSTRALIA

Risk factors	Point
Male	2
Dementia	1
Parkinson’s disease	3
Falls history	2
Cognitive impairment	2
No. of falls since admission	
1	11
2-4	18
5-10	26
>10	33
Psychological status	
Moderate	1
Severe	2
Mobility/transfer issue	3
Change in functional status	2
Risk-taking behaviours	1
Opioids (N02A)	2
Hypnotics and sedatives (N05C)	2
Antidepressants (N06A)	1
Antipsychotics (N05A)	2
Beta blocker (C07)	1
Vasodilators(C01D)	1

Max possible score=**60**

Very high risk
- >40

High risk
- 25-40

Medium risk
- 10-24

Low risk
- <10

Next steps

- The dashboard is being co-designed with aged care clients (residential and home care), family members, aged care staff and GPs
- Complete the prototype of the dashboard comprising i) integrated client data; b) incorporate the falls risk model; c) decision-support
- Implementation and evaluation of the dashboard

Thank you

Questions:

karla.seaman@mq.edu.au

nasir.wabe@mq.edu.au

Funding:

This project was funded by an Australian National Health and Medical Research Council (NHMRC) Partnership Project Grant in partnership with Anglicare (1170898). JW is supported by a NHMRC Elizabeth Blackburn Leadership Investigator Grant (1174021).