

REVIEW ARTICLE

Development and validation of a prediction model for self-reported mobility decline in community-dwelling older adults

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Abstract

Objectives: The aim of this study is to develop and validate two models to predict 2-year risk of self-reported mobility decline among community-dwelling older adults.

Study Design and Setting: We used data from a prospective cohort study of people aged 65 years and over in England. Mobility status was assessed using the EQ-5D-5L mobility question. The models were based on the outcome: Model 1, any mobility decline at 2 years; Model 2, new onset of persistent mobility problems over 2 years. Least absolute shrinkage and selection operator logistic regression was used to select predictors. Model performance was assessed using C-statistics, calibration plot, Brier scores, and decision curve analyses. Models were internally validated using bootstrapping.

Results: Over 18% of participants who could walk reported mobility decline at year 2 (Model 1), and 7.1% with no mobility problems at baseline, reported new onset of mobility problems after 2 years (Model 2). Thirteen and 6 out of 31 variables were selected as predictors in Models 1 and 2, respectively. Models 1 and 2 had a C-statistic of 0.740 and 0.765 (optimism < 0.013), and Brier score = 0.136 and 0.069, respectively.

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Ethical considerations: Written informed consent was provided by all participants, and approval for the study was given by the London–Brent Research Ethics Committee (16/LO/0348) on March 10, 2016.

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Conclusion: Two prediction models for mobility decline were developed and internally validated. They are based on self-reported variables and could serve as simple assessments in primary care after external validation. © 2022 The Author(s). Published by Elsevier Inc. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Keywords: Prognostic; Impaired mobility; General population; Aging; Prediction model; Elderly; Model performance

1. Introduction

In later life, declining mobility is an early predictor of dependence [1], poor quality of life, increased health care use, and death [2–5]. Generally, mobility limitations increase with age and affect more women than men. Prospective studies identify socioeconomic status, lifestyle habits, physiological and psychological factors, health conditions, social networks and participation, environmental, and organizational/policy factors [6,7] as risk factors for mobility decline.

These factors may be measured using self-reported or objective measures. Objective measures are recommended in the evaluation of an individual's functional status, but are time-consuming and, therefore, difficult to implement in routine primary care. Self-reported measures have low response burden, can capture both current and historical information, and can assess psychological and social factors.

Prediction models estimate absolute risk of a particular outcome for individual people [8,9].

Models to predict mobility decline over a short time period (≤ 5 years) are scarce [10–12]. Most studies used small sample sizes, were developed using data collected many decades ago, and have methodological limitations, such as the absence of key model performance measures, selection of predictor variables based on univariable analyses, and absence of multivariable analyses [7].

An accurate and user-friendly model to predict mobility decline in older adults could identify higher risk people in the community setting, enabling better targeting of rehabilitation and other interventions in clinical practice. We wanted to examine whether easy to collect self-reported measures of health and mobility could be used for this purpose.

The aim of this study is to develop and internally validate two risk prediction models for predicting the 2-year risk of mobility decline, using a cohort of older adults aged 65–100 years recruited in a community-based study in England.

2. Materials and methods

We followed the TRIPOD (Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis) guidelines to report the development and validation of the prediction models [13,14].

2.1. Study design

We used data from the Oxford Pain, Activity and Lifestyle (OPAL) study which is a prospective cohort study

of older people living in England. Full details of the cohort protocol and baseline characteristics are provided elsewhere [15]. Briefly, eligible individuals were identified from electronic record searches of 35 general practice lists across England and randomly selected from two age bands (65–74 and 75 years and over). Exclusion criteria were living in residential care or nursing home, terminal illness with life expectancy < 6 months, severe health/social concerns sufficient to preclude approach, or unable to provide informed consent.

2.2. Cohort study population

Between October 2016 and March 2018, a sample of up to 400 patients from each participating practice were invited to take part in the cohort study (a total of 12,839 individuals) and 5,409 (42.1%) agreed to participate. After completion of the baseline questionnaire, follow-up data were collected by post annually for 2 years.

At 2-year follow up, 23.2% ($n = 1,256/5,409$) of the original cohort were lost to follow-up. Of these, 3.4% ($n = 181/5,409$) had died, 13.9% ($n = 753/5,409$) were due to withdrawal from the study by the participant (12.4%; $n = 669/5,409$) or general practitioner (1.6%; $n = 84/5,409$), and 6.0% ($n = 322/5,409$) were uncontactable (Appendix 1).

2.3. Baseline candidate predictors

The list of candidate predictors and how they were defined are described in Table 1 and Appendix 2. We identified 31 candidate predictors based on a recent systematic literature [7] and expert opinion.

2.4. Outcomes

We used the mobility question from the EuroQol five-dimensional questionnaire (EQ-5D-5L) [16] to identify participants with mobility decline. Participants rated their mobility status as no problems, slight, moderate, severe problems, and unable to walk.

2.4.1. Model 1: 2-year risk of mobility decline.

All participants who were able to walk at baseline, regardless of their ability, were included ($n = 5,358/5,409$; 99%). Mobility decline was calculated by subtracting mobility score at 2 years from baseline scores and classifying participants using a binary outcome [no mobility decline (0) vs. mobility decline (1)].

What is new?

Key findings

- We have derived and internally validated two easy-to-use prediction models that quantify absolute risk of mobility decline in community-dwelling older people aged 65 years and over.
- Both models demonstrated moderate to good prediction to identify individuals at risk of mobility decline over a 2-year period.

What does this add to what is already known?

- These models are the first prediction models for self-reported mobility decline in a community-dwelling older adults in England.

What is the implication, what should change now?

- Our prediction models provide health care professionals with a small set of easy to collect variables that appear to discriminate well in the prediction of mobility decline in older adults living in the community.
- After appropriate external validation, these models may be useful in informing clinical decision-making about the need for rehabilitation to prevent mobility decline and maintain independence in older age.

2.4.2. Model 2: 2-year risk of new-onset persistent mobility problems.

People with no mobility problems at baseline were eligible ($n = 3,193/5,409$; 59%). *New onset of persistent mobility problems* over 2 years was defined as having any problems in mobility at both 1 and 2 years from baseline.

2.5. Sample size

The minimum sample size was based on Riley et al. [17]. The prevalence of mobility decline at 2 years (Model 1) was 18.6%. Based on a conservative Nagelkerke's R-squared of 0.15 [17] and a prespecified maximum number of predictor parameters of 50, the minimum sample size required to develop the model to minimize overfitting was estimated to be 4,585, with 853 events.

2.6. Statistical analysis

Nonlinearity between continuous predictors and the outcome was examined using fractional polynomials before multivariable modeling.

Missing data were imputed using multiple imputation by chained equation technique [18,19] (Appendix 3). Fifty imputed datasets were created. We included all candidate

predictors and the outcome variable in the imputation model. To impute for sample attrition (Table 1b/Appendix 1), we included ethnicity, smoking status, place of residence, and cognitive function.

To minimize the risk of overfitting we applied a penalized approach, the least absolute shrinkage and selection operator (LASSO) [20], and forced the inclusion of mobility status at baseline in Model 1. Logistic regression using the LASSO was applied on each imputed dataset separately. The tuning parameter λ value for the prediction model was chosen from a grid of 100 λ values through 10-fold repeated cross-validation [21]. The λ that had the average mean-squared error within one standard error from the minimum error was chosen. Predictors selected in 80% of the imputed datasets were retained. Average regression coefficient estimates over all imputed datasets of the variables retained were calculated to obtain the final model.

Model performance was assessed by calculating discrimination, calibration, decision curve analysis (DCA), and overall performance [9,22,23]. Discrimination, assessed by the C-statistic, is the ability of the prediction model to differentiate between those who report mobility decline and do not report decline. Calibration—how closely predicted risk corresponds with observed risk—was assessed visually using calibration plots. DCA determines the clinical validity of the prediction model by measuring the net benefit over a range of different threshold probabilities. As the risk threshold probability increases, the cost–benefit ratio increases accordingly [23]. Brier score quantifies how close predictions are to the observed data. Scores range from 0 to 1, with 0 representing perfect concordance between predicted and observed values. The model performance (C-statistic and Brier score) was evaluated on each multiple imputation (MI) dataset and median and range was reported [24]. DCA was assessed using the first MI dataset.

For internal validation 200 bootstrap samples were drawn with replacement from the first MI dataset, with the same size [25]. In each bootstrap sample, we repeated the entire modeling process, estimating the C-statistic in each bootstrap sample and then assessed the performance of each model in the first MI dataset. Optimism was estimated as the mean of the difference between the C-statistic of the bootstrap sample and that of the first MI sample. Optimism-corrected C-statistic was calculated as follows: C-statistic of the model developed in the first MI dataset – optimism.

To allow translation to clinical settings, we designed a simple scoring system based on procedures described by Sullivan et al. [26]. Penalized regression coefficients of the model were used to assign integer points to each level of each predictor. These score points were summed to derive a total risk score for each participant.

All analyses were carried out using STATA 16.1 and R 4.1.2. We used STATA for MI and R for model development, model performance, and internal validation [9].

Table 1. List of the potential predictors of mobility decline after 2 years of follow-up

Predictor factors
Demographic
Age (yr), continuous: range 65–100
Gender, binary: men (0) vs. women (1)
Living alone, binary: No (0) vs. Yes (1)
Education, categorical: Higher (1), Secondary (2), None or primary (3)
Adequacy of income, categorical: Quite comfortable (1), Able to manage without difficulty (2), To be careful with money (3)
Occupational physical demands, categorical: Very light (1), Light (2), Moderate (3), Strenuous (4), Very strenuous (5)
Social factors
Perceived receive enough support, binary: Yes (0) vs. No (1)
Miss other people around, categorical: No (1), Sometimes (2), Yes (3)
No of organizations/clubs/societies, continuous: range 0–10
Preclinical mobility factors
Usual walking pace, categorical: Fast/Fairly brisk (1), Normal (2), Stroll at any easy pace (3), Very slow (4)
Difficulties maintaining balance, binary: No (0) vs. Yes (1)
Confidence to walk, continuous: range 1 (more confident) to 10 (less confident)
Use of walking aid outside, categorical: No (1), Sometimes (2), Yes (3)
Use of walking aid inside, categorical: No (1), Sometimes (2), Yes (3)
Change in walking ability compared to last year, categorical: Better (1), Same (2), Worse (3)
Falls in the last 12 months, categorical: None (1), Once (2), More than one (3)
Fractures in the las 12 months, binary: No (0) vs. Yes (1)
Pain-related factors
BP and leg symptoms, categorical: No BP (1), BP without leg symptoms (2), BP with leg symptoms (3)
Pain distribution, categorical: No pain (1), One site (2), Multisite pain (3), Widespread (4)
Lower limb pain, binary: No (0) vs. Yes (1)
Pain/discomfort problems (EQ-5D-5L), continuous: range 1 (no pain) to 5 (extreme pain)
Other health-related factors
Hours/day moving around, categorical: 7 or more (1), 5–7 (2), 3–5 (3), Less than 3 (4)
BMI (kg/m ²), continuous: range 14–70
Number of health conditions, continuous: range 0–7
Fatigue, binary: No (0) vs. Yes (1)
Anxiety/depression (EQ-5D-5L), continuous: range 1 (no depressed) to 5 (extreme depressed)
Poor hearing, binary: No (0) vs. Yes (1)
Poor vision, binary: No (0) vs. Yes (1)
Problems in daily life due to lack of strength in hands, binary: No (0) vs. Yes (1)
Loss of weight, binary: No (0) vs. Yes (1)
Self-reported general health, continuous: range 0 (poor) to 100 (good)

Abbreviations: BMI, body mass index; BP, back pain; EQ-5D-5L, EuroQol five-dimensional questionnaire.

3. Results

3.1. Missing data among eligible individuals

Of the 5,358 eligible individuals who could walk at baseline (Model 1), 18.7% ($n = 1,001$) had one or more missing values for the candidate predictors. For most candidate predictors, the proportion of missing data was <5% (Table 2/Appendix 3).

An additional 916 (21.0% of 4,357) participants did not return questionnaires or did not complete the mobility question at year 2 (Fig. 1/Appendix 3).

3.2. Model 1: 2-year risk of mobility decline

3.2.1. Participants.

Of 5,358 participants who could walk at baseline, 174 had died by 2 years of follow-up. Thus, 5,184 participants were included (Fig. 1). The mean age of participants [standard deviation (SD)] was 74.7 years (6.6) and 51.8% ($n = 2,683/5,184$) were women. At baseline, most participants reported no mobility problems (60.7%; 3,146/5,184) and 5.4% (280/5,184) reported severe mobility problems.

Fig. 2 shows the change in mobility status at year 2 (overall and stratified by mobility status). Among those with follow-up data at 2 years (79.4%; $n = 4,115/5,184$), 18.6% ($n = 765/4,115$) reported mobility decline (Fig. 2). Participants who reported slight mobility problems (lower panel, plot A) at baseline had the biggest decline over the 2 years of follow-up (35.6%). There were 427 (10.3%) individuals who improved their mobility at 2 years.

The absolute change was calculated as the mobility score at year 2 minus the score at baseline (negative values indicate worse change in mobility status and positive values indicate improvement in mobility status). The upper panel represents participants who could walk at baseline and the lower panel represents participants who stratify by mobility status at baseline.

3.2.2. Selection of predictor variables and model fitting.

In addition to mobility status at baseline, 13 variables were identified as predictors of mobility decline at 2 years in $\geq 80\%$ of the MI datasets (Table 2, Model 1).

Older participants and those who perceived their income to be inadequate were more likely to report mobility decline at 2 years (Table 2, Model 1). Participants who reported a slow usual walking pace had difficulty maintaining their balance, had low confidence to walk long distances, rated their walking as worse compared to last year and reported sometimes using a walking aid outside, and were more likely to report a decline in mobility after 2 years. Lower limb pain and the presence of severe general pain or discomfort were also predictors of mobility decline. Other health-related factors associated with decline in mobility at 2 years were having a higher body mass index, greater number of health conditions, problems in daily life due to physical tiredness, and poor general health (Table 2).

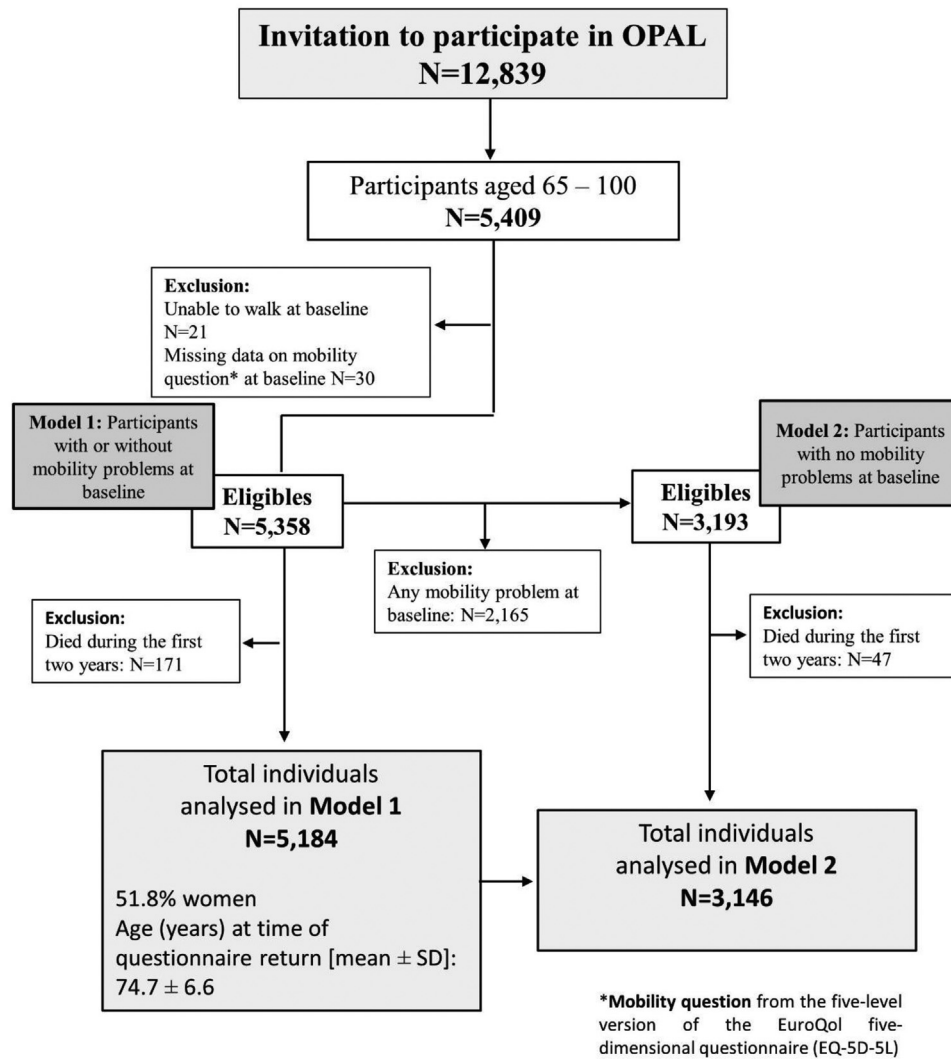


Fig. 1. Flowchart of the OPAL cohort study. OPAL, Oxford Pain, Activity and Lifestyle.

3.2.3. Model performance.

Model 1 revealed a median C-statistic of 0.740 (range: 0.737–0.743) and the median Brier score was 0.136 (range: 0.135–0.137). The model showed good calibration: 95% confidence interval bars and some of the mean values (data points) intersect with the 45° line that indicates perfect agreement between the predicted and observed values of mobility decline at 2 years (Fig. 1/Appendix 4).

The DCA plot showed (Fig. 3A, Model 1) a clear net benefit gain of the prediction model over the entire range of selected thresholds (0–50%).

The optimism-corrected C-statistic estimate was 0.734 (optimism = 0.010). The model's performance on internal validation showed only a slight reduction in the C-statistic, indicating low overfitting.

The y-axis shows the net benefit of Model 1 (A) and Model 2 (B). The x-axis of DCA is the threshold of the predicted probability using Model 1 (A) and Model 2 (B) to

classify individuals with and without mobility decline. The DCA compares the net benefits of an intervention in three scenarios: intervention for all individuals regardless of prediction (black solid line), intervention for no individuals (black dotted line, horizontal line), and intervention for individuals based on the prediction models (black dashed line); Model 1: 2-year risk of mobility decline; Model 2: 2-year risk of new-onset persistent mobility problems. Models included predictors that selected at least 80% of the imputed datasets.

3.2.4. Point scoring system.

The point scoring system for Model 1 had a score range from 0 to 39 with predicted risks corresponding to each point score ranging from 0.9% (0 points) to 90.1% (39 points) (Tables 1 and 2/Appendix 5). The median C-statistic of this scoring system was 0.734 (range: 0.730–0.735),

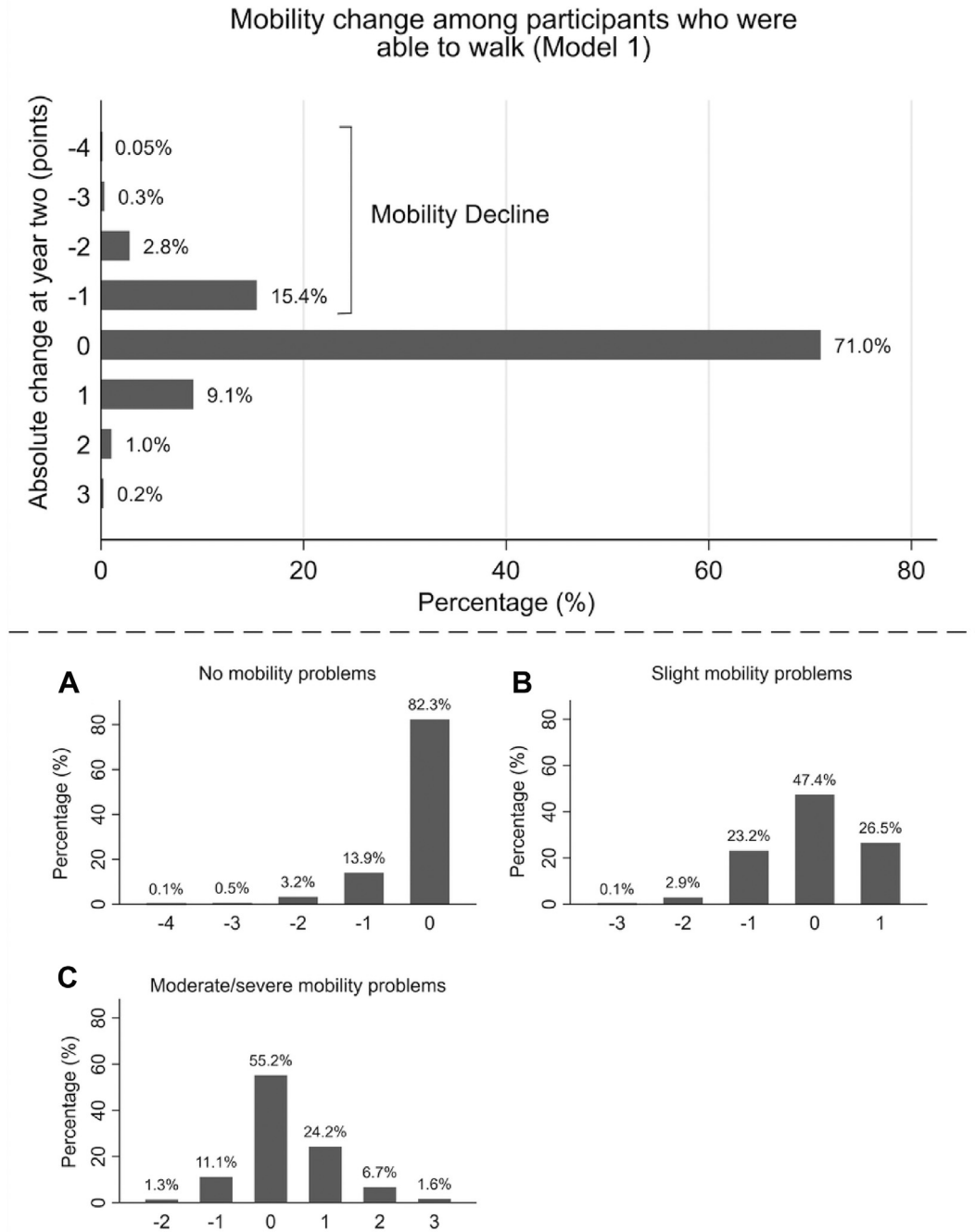


Fig. 2. Absolute change in mobility status between baseline and year 2 for all participants and stratified by mobility status at baseline. (A) no mobility problems; (B) slight mobility problems; and (C) moderate or severe mobility problems).

similar to the regression model indicating no noticeable loss in performance.

3.3. Model 2: 2-year risk of new-onset persistent mobility problems

3.3.1. Participants.

Participants with no mobility problems at baseline who were alive at 2 years of follow-up were included ($n = 3,146$) (Fig. 1). The mean age (standard deviation) was 73.3 (5.8) years, 51.0% (1,604/3,146) were women,

and 7.1% ($n = 201/2,832$) had new onset of persistent mobility problems.

3.3.2. Selection of predictor variables and model fitting.

In total, 28 variables (42 parameters) were included in this analysis. Six variables were selected as predictors of new-onset persistent mobility decline (Table 2, Model 2). These were slow usual walking pace, difficulty maintaining balance, low confidence to walk long distances and worse walking ability compared to last year, and two health-

Table 2. Predictors of mobility decline selected in $\geq 80\%$ of the imputed datasets

Predictor variables	Model 1		Model 2	
	LASSO regression (% times selected)	Average penalized coefficient	LASSO regression (% times selected)	Average penalized coefficient
Intercept		−6.757		−1.844
Age (65–100 yr)	100%	0.035	-	-
Adequacy of income				
Have to be careful with money	100%	0.239	-	-
BMI (15–70 kg/m ²)	100%	0.025	-	-
Usual walking pace				
Stroll at any easy pace	100%	0.494	-	-
Very slow/slow	100%	0.573	100%	0.611
Difficulties maintaining balance	96%	0.166	90%	0.329
Confidence to walk	100%	0.056	100%	0.106
Use of walking aid outside				
Sometimes	96%	0.158	-	-
Change in walking ability compared to last year (Better)				
About the same	80%	−0.087	-	-
Worse	96%	0.141	100%	0.465
Lower limb pain in the last 6 wk	100%	0.226	-	-
Current pain/discomfort severity	98%	0.070	-	-
Number of health conditions	100%	0.117	88%	0.046
Physical tiredness	98%	0.092	-	-
Self-reported general health	100%	−0.011	100%	−0.015
Predictors forced to be included in the final model				
Mobility problems at baseline (moderate/severe problems)				
I have slight problems	100%	1.963	-	-
I have no problems	100%	2.387	-	-

Abbreviations: BMI, body mass index; LASSO, least absolute shrinkage and selection operator.

Model 1: 2-year risk of mobility decline; Model 2: 2-year risk of new-onset persistent mobility problems.

related factors (greater number of health conditions and poor general health assessed by EuroQol Visual Analog Scale (EQ-VAS)).

3.3.3. Model performance.

The median C-statistic was 0.765 (range: 0.762–0.768). The median Brier score was 0.069 (range: 0.068–0.070). Model calibration was good, with close agreement between predicted and observed values of new onset of persistent mobility problems (Fig. 2/Appendix 4).

Fig. 3B (Model 2) displays the net benefit curves equation. The net benefit clinical decision-making is superior across the range of risk thresholds of roughly 8–40%.

The average optimism of the C-statistic estimate was 0.013.

3.3.4. Point scoring system.

The point scoring systems is given in Tables 3 and 4/Appendix 5. The final score ranged from 0 to 22 with predicted risks corresponding to each point score ranging from 4.5% (0 points) to 53.8% (22 points). The model showed

good predictive validity, with median C-statistic of 0.754 (range: 0.750–0.757).

4. Discussion

We developed and internally validated two prediction models for self-reported mobility decline in community-dwelling older adults aged 65 years and over, using self-reported measures of health and mobility measures that are easy to collect and could be used in clinical practice. Both models demonstrated moderate to good prediction capacity to identify individuals at 2-year risk of mobility decline. Model calibration showed good agreement between the observed and predicted mobility change. Both models also showed greater net benefit across a range of thresholds compared with not using any model.

Many of the variables identified as important predictors in both our models were associated with mobility decline in a recent systematic literature we conducted to inform this work [7], supporting the plausibility of this model.

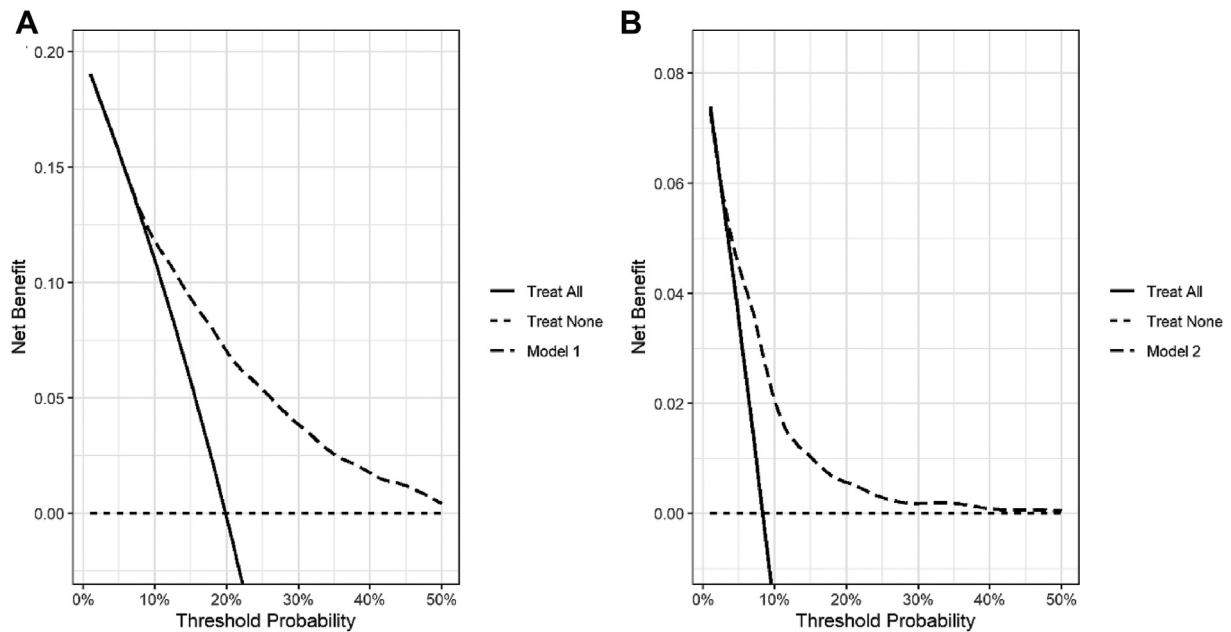


Fig. 3. Decision curve analysis for participants in the OPAL cohort study. Model 1 (A) and Model 2 (B). OPAL, Oxford Pain, Activity and Lifestyle.

We found evidence that older age, perceived inadequacy of income, preclinical mobility modifications (ie, use of walking aid, change in walking ability), lower limb pain, comorbidities [with diabetes and arthritis the most important individual conditions in our study (data not shown)], physical tiredness, and self-reported general health are predictors of mobility decline. The evidence for balance difficulties, general pain/discomfort severity, and body mass index was previously limited or unclear, but our findings confirm these as predictors of mobility decline [7].

Self-reported predictors newly identified by this study include confidence to walk half a mile and self-reported speed of usual walking pace. Self-reported slow, or very slow, usual walking pace at baseline was one of the most important predictors of mobility decline in this study, and has previously been validated as a marker of measured walking speed [27].

Unlike some previous studies, we did not find widespread pain to predict mobility decline [28,29]. Discrepancies may be due to the following reasons: differences in the way predictors and outcome were measured; the different sets of predictors/confounders included in the model; and/or those studies that did not consider severity of pain as an independent variable in their models.

Studies developing prediction models for the onset of mobility problems over a short period of time (less than 5 years of follow-up) are scarce [10–12]. Only one of the three previous models was developed and internally validated for onset of mobility difficulty after 18 months of follow-up [11]. This study was based on high physically and cognitively functioning women, aged 70–80 years, in the United States. Both models included self-reported

preclinical mobility limitations; however, our model (Model 2) had better performance and is simpler to implement because it is based on self-reported variables only. In a different model, Papachristou et al. included age, slow walking speed, physically inactivity, and exhaustion as predictors. The C-statistic of their model was smaller (C-statistic = 0.68), and measures of calibration were not assessed. Reynolds and Silverstein constructed a prediction model for onset of walking among community-dwelling adults aged 70 years and older. They reported a C-statistic = 0.82, for their full model including 42 baseline and time-dependent predictors but did not report the statistic for their abbreviated clinical model. None of the previous studies have used rigorous internal validation.

Our prediction models provide health care professionals with a small set of easy to collect variables that discriminate well in the prediction of mobility decline in older men and women living in the community. The number and format of variables in the risk prediction model, mean that it could be used during a routine clinical consultation. Some of these variables are also modifiable and can effectively be targeted through rehabilitation. First, there are several variables that are markers of reduced walking ability and balance. These include slow walking pace, reduced confidence to walk longer distance, and difficulty maintaining balance. We, and others, have demonstrated that walking ability can be improved through a progressive tailored rehabilitation program that targets walking confidence, walking ability (distance and speed), muscle strength, and balance [30,31]. Second, lower limb pain, such as that arising from hip and knee osteoarthritis, is common in older adults and can be effectively managed

through rehabilitation incorporating pain self-management, coping strategies, and exercise, as well as surgery [32]. General bodily pain severity was also a predictor suggesting that pain management should be considered more broadly (not just for lower limb pain) as it is often not prioritized against a backdrop of other health conditions by older people themselves [33] or by health professionals [34].

4.1. Strengths and limitations

The OPAL cohort study represents a large, representative prospective cohort study with baseline characteristics similar to those in general English population of the same age [15]. This study reports the first prediction model for self-reported mobility decline in a community-dwelling older adults in England. A wide range of predictors were used. The reproducibility of the model was ensured by using MI and penalized regression methods, so that only significant predictors were selected, and anomalous predictors were rejected, reducing the risk of overfitting.

There are several potential limitations to this study. Self-reported mobility variables can be criticized because of subjectivity, but they provide important information about the difficulties people perceive in their everyday environment, can incorporate time-varying estimations such as frequency of balance problems, and are thus clinically highly relevant. Self-reported predictors may be particularly useful in clinical settings face to face or by telephone, or postal follow-up of cohort study participants when more-intense testing is impractical because of time, cost, space, or venue-related concerns. Although the main study mobility outcome was based on EQ-5D-self-report, this is known to have strong validity for measuring mobility performance in older adults [35,36].

We excluded 51 participants who could not walk at baseline, and it is theoretically possible that they could have recovered during follow up. Third, we did not externally validate the models although bootstrap validation takes model over-optimism into account and is considered better than data splitting [37]. Fourth, there were differences between characteristics of participants who remained in the study and those who withdrew, and this may have introduced attrition bias. Although MI was used to reduce the potential biases, this may not overcome all the bias associated with withdrawals. Finally, the small number of participants who died during the first 2 years were excluded from the main analyses.

5. Conclusion

We have derived and internally validated two easy-to-use prediction models that quantify absolute risk of mobility decline in community-dwelling older people. Our models are based on self-reported health and mobility questions that are easy to collect and can inform clinical decision-making regarding the need for rehabilitation

aimed at preventing mobility decline and maintaining independence in older age. The models displayed good discrimination.

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Supplementary data

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