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The Development of a Model to Predict Cognitive Decline Within 12 Months in Home Care Clients

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ABSTRACT

Aim: To develop and validate a model to predict cognitive decline within 12 months for home care clients without a diagnosis of dementia.

Design: We included all adults aged ≥18 years who had at least two interRAI Home Care assessments within 12 months, no diagnosis of dementia and a baseline Cognitive Performance Scale score ≤1. The sample was randomly split into a derivation cohort (75%) and a validation cohort (25%). Significant cognitive decline was defined as an increase (deterioration) in Cognitive Performance Scale scores from '0' or '1' at baseline to a score of ≥2 at the follow-up assessment.

Methods: Using the derivation cohort, a multivariable logistic regression model was used to predict cognitive decline within 12 months. Covariates included demographics, disease diagnoses, sensory and communication impairments, health conditions, physical and social functioning, service utilisation, informal caregiver status and eight interRAI-derived health index scales. The predicted probability of cognitive decline was calculated for each person in the validation cohort. The c-statistic was used to assess the model's discriminative ability. This study followed the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) reporting guidelines.

Results: A total of 6796 individuals (median age: 82; female: 60.4%) were split into a derivation cohort ($n = 5098$) and a validation cohort ($n = 1698$). Logistic regression models using the derivation cohort resulted in a c-statistic of 0.70 (95% CI 0.70, 0.73). The final regression model (including 21 main effects and 8 significant interaction terms) was applied to the validation cohort, resulting in a c-statistic of 0.69 (95% CI 0.66, 0.72).

Conclusion: interRAI data can be used to develop a model for identifying individuals at risk of cognitive decline. Identifying this group enables proactive clinical interventions and care planning, potentially improving their outcomes. While these results are promising, the model's moderate discriminative ability highlights opportunities for improvement.

1 | Introduction

Dementia is a global public health concern. Timely diagnosis of dementia can promote early access to services and optimal management, which might delay further cognitive decline and allow planning for the future (Livingston et al. 2017). However, early and accurate diagnosis of dementia is often challenging and requires clinical judgement (Johnson et al. 2021), including

Summary

- What does this paper contribute to the wider global clinical community
  - Twelve-month risk of cognitive decline can be predicted using routinely collected assessment data.
  - Such modelling could identify people at risk of developing cognitive impairment and facilitate discussions about preventative care or advanced care.
  - Routinely collected population-level assessment data could be used to inform the care of the individual.

history taking, cognitive testing and investigations to exclude other medical and psychiatric causes for cognitive impairment. It has been estimated that globally 75% of people with dementia are never diagnosed (Gauthier et al. 2021).

To reduce the personal, societal and economic impact of dementia, international research has begun to focus on identifying risk or predictive factors for dementia. For example, Livingston et al. identified 14 potentially modifiable risk factors for dementia, including those in later life: smoking, depression, social isolation, physical inactivity, diabetes and air pollution (Livingston et al. 2024). In addition, biomarkers such as neuroimaging features, amyloid-beta peptide concentration and apolipoprotein E genotype 4 can improve the prediction of progressive cognitive decline (Chen et al. 2022; Huang et al. 2020), a presenting feature of dementia. It has been argued that accurate predictive models could provide an opportunity to intervene by addressing dementia risk factors and preventing further cognitive decline (Hu et al. 2022; Zhou et al. 2020; Downer et al. 2016). Such models can be developed using multivariable logistic regression or Cox proportional hazard analyses (Lerner et al. 2007; Kattan et al. 1998).

Predictive tools are commonly used in oncology to estimate the likelihood of a cancer diagnosis and prognosis after treatment (Balachandran et al. 2015; Iasonos et al. 2008). They can be used to predict clinical outcomes, assess risk at an individual patient level, support personalised medicine and patient counselling and inform clinical decision-making (Lerner et al. 2007; Balachandran et al. 2015; Eastham et al. 2002). Predictive tools have also been used in cardiology to predict first coronary events and in neurology to predict survival time after dementia diagnosis (Haaksma et al. 2020; Eichler et al. 2007). In recent years, predictive tools have begun to be used in predicting cognitive decline (Hu et al. 2022; Zhou et al. 2020; Downer et al. 2016). For example, previous research has combined clinical assessments with assessments of functional well-being to construct a model with acceptable accuracy in predicting a 6-year risk of cognitive impairment in a cohort of older Chinese with normal cognition at baseline (Zhou et al. 2020).

interRAI home care (interRAI HC) is a comprehensive geriatric assessment aimed at providing a clinical assessment of medical, rehabilitation and support needs and abilities. interRAI HC collects information on 280 demographic, clinical and psychosocial items. interRAI HC has good psychometric properties (Schluter et al. 2016). In New Zealand, people accessing publicly funded home care services or prior to entering long-term care are required to have an interRAI HC assessment. Approximately 10% of New Zealanders aged ≥ 65 years and 40% aged ≥ 85 years have had an interRAI assessment (interRAI New Zealand n.d.). There are several clinical outcomes embedded within the interRAI assessments, including the Cognitive Performance Scale (CPS) (Morris et al. 1994), a global measure of cognitive function. Tracking CPS scores could potentially provide a mechanism for detecting cognitive decline early.

A recently published Canadian predictive model, the risk of CPS decline (RCD), was developed to identify a 6-month risk of decline in the CPS score in a large sample of interRAI home care clients (Guthrie et al. 2023). In this study, we report the development and validation of a similar predictive model, RCD-NZ, to predict a worsening of the CPS score within 12 months in home care clients without an existing diagnosis of dementia. The possibility of predicting cognitive decline in people who do not have cognitive impairment at intake is clinically important. A different predictive model is required for the New Zealand setting, where home care clients are typically reassessed every 12 months, whereas reassessments usually occur every 6 months in Canada.

2 | Method

2.1 | Sample: Eligibility Criteria

The sampling frame consisted of all community-dwelling adults aged 18 years or older who were assessed at least twice using the interRAI HC assessment between 1 January 2013 and 30 June 2021 anywhere in New Zealand ($N = 6796$ community-dwelling adults). Individuals were included if (i) they had an intake interRAI HC assessment and at least one follow-up assessment within 12 months (up to 390 days), and (ii) a CPS score of '0' or '1' at the intake interRAI assessment. Home care clients had to be alive and receiving home care throughout the entire duration of the 12-month period to be included. The CPS includes the following interRAI items: short-term memory, cognitive skills for daily decision-making, expressive communication and independence in eating. These items are combined into a hierarchical ranking scale providing scores from 0 to 6: 0 = intact, 1 = borderline intact, 2 = mild impairment, 3 = moderate impairment, 4 = moderately severe impairment, 5 = severe impairment and 6 = very severe impairment (Morris et al. 1994). The interRAI HC assessment routinely records whether a person has a diagnosis of Alzheimer's disease or another type of dementia. Individuals were excluded if they had a diagnosis of Alzheimer's disease/dementia at intake because their cognitive functioning is generally expected to decline.

2.2 | Primary Outcome

The primary outcome was significant cognitive decline as defined by an increase (deterioration) in CPS scores from '0' (intact) or '1' (borderline intact) at baseline to a score of '2', '3', '4', '5' or '6' at the follow-up assessment within 12 months. Previous research has shown that CPS score ≥ 2 has good sensitivity for the clinical diagnosis of dementia (Gee et al. 2021).

2.3 | Covariates

Covariates were selected based on the recently published Canadian cognitive decline prediction tool (Guthrie et al. 2023). Baseline characteristics included demographic characteristics (e.g., age, sex and marital status), disease diagnoses (e.g., stroke, congestive heart failure and coronary artery disease), sensory and communication impairments, health conditions, responsive behaviours, physical functioning and health status, service utilisation, social functioning and informal caregiver status.

We included eight health index scales that are embedded within the interRAI HC assessment. Across all scales, a higher value indicates a greater degree of impairment.

1. The Activities of Daily Living (ADL) Self-Performance Hierarchy Scale includes items on bathing and dressing and is scored from 0 (no difficulty) to 6 (major difficulty), where a cut-point of 2 or higher was used to indicate at least moderate difficulty completing ADLs independently (Morris et al. 1999).
2. The Instrumental Activities of Daily Living (IADL) Involvement Scale is a summative scale across seven IADLs (e.g., meal preparation, housework, etc.), which ranges from 0 to 21, where a score of 14 or higher is used to indicate moderate difficulty completing these tasks independently (Morris et al. 1999).
3. The Depression Rating Scale (DRS) includes seven items related to mood and behaviour. The scale ranges from 0 to 13; there is evidence that a score of three or higher is predictive of a clinical diagnosis of depression (Martin et al. 2008).
4. The Pain Scale ranges from 0 (no pain/less than daily pain) to 4 (daily/severe pain) and a score of 2 or higher was used to indicate daily or severe pain. The scale has been validated against the vertical version of the Visual Analogue Scale (Fries et al. 2001).
5. The Changes in Health, End-Stage Disease, Signs and Symptoms (CHESS) Scale is scored from 0 to 5 and includes items such as shortness of breath and prognosis. For each 1-point increase on the scale, there is a nearly twofold increase in the risk of mortality (Hirdes et al. 2014).
6. The Pressure Ulcer Risk Scale (PURS) is scored from 0 to 8 and groups individuals into low, moderate, high and very high risk of experiencing a pressure ulcer. It includes items such as bowel incontinence, weight loss, history of a resolved pressure ulcer and impaired bed mobility (Poss et al. 2010).
7. The Method for Assigning Priority Levels (MAPLe) is scored from 0 to 5. It classifies individuals into levels of risk for experiencing adverse outcomes and the urgency to support them or review their current living situation. It also identifies caregiver distress and the risk of aged residential care placement (Hirdes et al. 2008).
8. The Caregiver Risk Evaluation (CaRE) algorithm is a decision-support tool that generates the risk of caregiver burden among informal caregivers. It assigns caregivers into one of four groups, ranging from low risk (score of 0) to very high risk (score of 4) of experiencing burden (Guthrie et al. 2021).

2.4 | Statistical Analysis

2.4.1 | Missing Data

interRAI HC assessors are not able to complete an assessment until all fields have been given a value and entered into the software program; therefore, missing data are rare. However, a missing category was created for the CaRE scale as the scale is only calculated when there are no missing data, and the person is recorded as having a primary caregiver. We did not impute or remove individuals from the analysis as there was no pattern within the missing data.

2.4.2 | Descriptive Analysis

All categorical variables were reported in frequencies and percentages, while variables with continuous-level data were reported using means and standard deviations.

2.4.3 | Developing the Prediction Model

The sample was randomly split into a derivation cohort ($n = 5098$ (75%)) and a validation cohort ($n = 1698$ (25%)). The derivation and validation cohorts were compared across baseline characteristics to ensure random sampling. Using the derivation cohort, a multivariable logistic regression model was used to predict deteriorating CPS score within 12 months of an individual's intake interRAI assessment. We examined collinearity using the variance inflation factor, where a cut-off of 5 was used to indicate collinearity; two variables (any psychiatric diagnoses and caregiver lives with client) were removed due to collinearity. Multiple model selection techniques were explored (e.g., backward, forward, stepwise procedures). The final model used the backward selection procedure for variable selection with a two-tailed p-value of 0.10 as the retention criterion. The p-value of 0.10 was chosen to create a model with the highest ability to accurately predict a decline. Continuous variables such as age were explored using both linear and quadratic terms. As decided a priori, all two-way interactions between age and sex were explored. Several of the odds ratios within the main effects model were counterintuitive (e.g., ADL impairment, pain, pneumonia, cancer, fractures and shortness of breath); we then explored all two-way interactions between these variables with other variables in Table 2. The rationale for examining the interaction terms was to provide insights, particularly for associations between variables with counterintuitive directions and deterioration of CPS scores.

2.4.4 | Validating the Prediction Model

The validation cohort was used to assess the performance of the model developed using the derivation cohort. The predicted

TABLE 1 | Comparison of the derivation and validation cohorts across all variables under consideration at baseline.

	Derivation cohort ($n=5098$)	Validation cohort ($n=1698$)	p
	% (n)		
Age (years)			
18–64	5.9 (299)	5.8 (98)	0.6587
65–74	16.2 (825)	16.3 (276)	
75–84	35.2 (1794)	36.8 (624)	
85+	42.8 (2180)	41.2 (700)	
Sex			
Male	39.2 (2000)	40.9 (694)	0.2313
Female	60.8 (3098)	59.1 (1004)	
Marital status			
Never married/widowed/separated/divorced/other	63.7 (3250)	63.3 (1075)	0.7437
Married/de facto/civil union	36.3 (1848)	36.7 (623)	
Who the client lived with at referral			
Alone	53.1 (2709)	51.2 (869)	0.1611
Lives with others (e.g., spouse, spouse and others, child, etc.)	46.9 (2389)	48.8 (829)	
Baseline CPS score			
0	64.2 (3272)	62.7 (1065)	0.2778
1	35.8 (1826)	37.3 (633)	
Health index scales			
Activities of Daily Living (ADL) Self-Performance Hierarchy Scale			
No or minor difficulty (0–1)	84.5 (4308)	84.5 (1434)	0.8723
Moderate difficulty (2, 3)	11.7 (598)	12.0 (204)	
Major difficulty (4–6)	3.8 (192)	3.5 (60)	
Instrumental Activities of Daily Living (IADL) Capacity Scale			
None/minor difficulty (0–13)	77.8 (3966)	76.7 (1303)	0.1683
Moderate difficulty (14–18)	16.9 (860)	18.6 (316)	
Major difficulty (19–21)	5.3 (272)	4.7 (79)	
Depression Rating Scale (DRS)			
No signs/symptoms (0–2)	88.7 (4524)	87.6 (1488)	0.0075
Some signs/symptoms (3–5)	9.3 (473)	9.1 (154)	
Severe signs/symptoms of depression (6–14)	2.0 (101)	3.3 (56)	
Pain Scale			
No pain/less than daily pain (0)	33.5 (1709)	34.6 (588)	0.6930
Less than daily pain (1, 2)	49.3 (2512)	48.7 (826)	
Severe/daily pain (3, 4)	17.2 (877)	16.7 (284)	
Change in Health, End-Stage Disease Signs and Symptoms Scale (CHESS)			
None/mild health instability (0–1)	51.0 (2599)	49.9 (848)	0.5548
Moderate health instability (2, 3)	46.4 (2364)	47.7 (810)	
Severe health instability (4, 5)	2.7 (135)	2.4 (40)	

(Continues)

TABLE 1 | (Continued)

	Derivation cohort ($n = 5098$)	Validation cohort ($n = 1698$)	p
Pressure Ulcer Risk Scale (PURS)			
Low risk (0–2)	92.0 (4690)	91.5 (1554)	0.6733
Moderate risk (3)	5.9 (300)	6.0 (102)	
High/very risk (4–7)	2.1 (108)	2.5 (42)	
Method for Assigning Priority Levels (MAPLe)			
Low risk (1)	40.2 (2049)	42.2 (716)	0.0147
Mild risk (2)	14.4 (736)	11.4 (193)	
Moderate risk (3)	28.6 (1456)	29.6 (503)	
High/very risk (4, 5)	16.8 (857)	16.8 (286)	
Informal caregiver status			
Caregiver lives with client			
No	52.8 (2694)	51.8 (879)	0.5892
Yes	39.9 (2034)	41.3 (701)	
No caregiver	7.3 (370)	7.0 (118)	
Caregiver risk evaluation (CaRE)			
Low risk	44.6 (2276)	43.1 (732)	0.4128
Moderate risk	25.4 (1296)	25.4 (431)	
High risk	22.6 (1152)	24.5 (416)	
Very high risk[a]	—	—	
Missing	7.3 (374)	7.0 (119)	
Client openly expresses conflict or anger with family/friends			
Never	88.2 (4494)	87.5 (1486)	0.7800
1–29 days ago/more than 30 days ago	7.4 (378)	7.8 (132)	
Unable to determine	4.4 (226)	4.7 (80)	
Disease diagnoses (reference = not present)			
Stroke	14.1 (721)	12.1 (206)	0.0365
Congestive heart failure	16.4 (834)	18.9 (321)	0.0156
Coronary artery disease	30.1 (1532)	27.5 (465)	0.0367
Hemiplegia/hemiparesis	2.1 (109)	2.3 (39)	0.6979
Parkinson disease	4.9 (250)	6.2 (105)	0.0401
Bipolar disorder	1.2 (600)	1.2 (21)	0.8440
Anxiety and/or depression	15.9 (810)	15.8 (269)	0.9638
Schizophrenia and/or bipolar	2.1 (108)	1.9 (33)	0.6612
Pneumonia	1.7 (84)	2.2 (37)	0.1516
Cancer	15.7 (798)	16.6 (282)	0.3514
Hip fracture	1.0 (53)	1.2 (20)	0.6322
Other fractures	2.4 (123)	1.8 (31)	0.1592
Diabetes	21.4 (1090)	21.2 (360)	0.8757

(Continues)

TABLE 1 | (Continued)

	Derivation cohort ($n=5098$)	Validation cohort ($n=1698$)	p
Communication and sensory impairments			
Hearing impairment	71.2 (3627)	71.8 (1219)	0.6109
Vision impairment	89.5 (4560)	90.5 (1537)	0.2081
Dual sensory impairment	86.6 (4414)	85.2 (1446)	0.1403
Ability to understand others			
Understands	89.8 (4578)	90.5 (1537)	0.3932
Usually/often/sometimes/rarely/never understands	10.2 (520)	9.5 (161)	
Health conditions and behaviours			
Chest pain	4.8 (247)	5.2 (88)	0.5779
Dizziness or light headedness	16.1 (820)	16.8 (285)	0.4986
Oedema	29.0 (1477)	27.2 (462)	0.1633
Shortness of breath	52.4 (2670)	53.1 (902)	0.5930
Smoked/chewed tobacco daily	6.4 (325)	7.7 (130)	0.0674
Highest number of alcoholic drinks in any single setting in last 14 days			
0	77.9 (3972)	76.3 (1296)	0.2973
1–4	20.8 (1062)	22.1 (375)	
5+	1.3 (64)	1.6 (27)	
Physical functioning and health status			
Client believes they are capable of increased functional independence	36.4 (1854)	34.6 (587)	0.1813
Number of falls in last 90 days			
No falls	64.3 (3279)	66.1 (1123)	0.1112
1 fall	26.9 (1371)	24.4 (414)	
2 or more falls	8.8 (448)	9.5 (161)	
Unsteady gait	53.5 (2727)	57.3 (973)	0.0063
Number of days client went out of house in last 3 days			
No days	18.8 (956)	19.0 (332)	0.2325
No days, but usually goes out	6.7 (342)	5.5 (94)	
1–3 days	74.5 (3800)	75.5 (1282)	
Bladder incontinence in last 7 days	36.0 (1836)	33.6 (570)	0.0680
Client has conditions or diseases that make cognition, ADL, mood or behaviour patterns unstable	49.5 (2525)	52.4 (889)	0.0436
Client experienced a flare-up of a recurrent/chronic problem	21.6 (1110)	20.0 (339)	0.1590
Self-rated health			
Excellent/good	43.2 (2204)	43.1 (731)	0.8523
Fair	41.1 (2097)	40.5 (687)	
Poor	13.0 (662)	13.6 (231)	
Could not (would not) respond	2.7 (135)	2.9 (49)	
Client has a prognosis of less than 6 months to live	1.6 (83)	2.5 (43)	0.0167

(Continues)

TABLE 1 | (Continued)

	Derivation cohort (n = 5098)	Validation cohort (n = 1698)	p
Swallowing			
Normal	93.2 (4750)	93.1 (1580)	0.8619
Requires modifications to swallow (e.g., diet, tube feeding, etc.)	6.8 (348)	6.9 (118)	
Ate one or fewer meals a day in last 3 days	3.5 (179)	3.7 (63)	0.7014
Unintended weight loss of 5% or more in last 30 days	14.4 (734)	14.9 (253)	0.6110
Service utilisation			
Hospital admissions (last 90 days)			
0	57.2 (2914)	57.3 (973)	0.3741
1	32.6 (1662)	31.4 (533)	
2 or more	10.2 (522)	11.3 (192)	
Emergency department visits (last 90 days)			
0	83.4 (4250)	83.5 (1417)	0.4691
1	13.3 (678)	12.7 (215)	
2 or more	3.3 (170)	3.9 (66)	
Social functioning			
Client indicates that he/she feels lonely	21.9 (1118)	21.7 (369)	0.8638
Change in social activities in last 90 days			
No decline	59.2 (3020)	59.5 (1011)	0.5456
Decline, not distressed	32.0 (1629)	30.9 (525)	
Decline, distressed	8.8 (449)	9.5 (162)	

[a]The high-risk group cannot be calculated for CaRE as it includes baseline CPS scores > 2.

probability of deteriorating CPS score within 12 months was calculated for each individual in the validation cohort based on their specific covariate values and the beta estimates from the regression model developed from the derivation cohort. The model was calibrated by grouping individuals into deciles of lowest and highest risk, then plotting the observed proportion of individuals who experienced deteriorating CPS scores against the corresponding mean predicted risk within each score. Points closer to the 45° line indicate better calibration (Figure 2).

The model's ability to discriminate (i.e., the ability to discriminate between those with a deteriorating CPS score and those without) was measured via the concordance statistic (c-statistic): c-statistic < 0.5 indicates a poor model, > 0.7 indicates a reasonably good model and > 0.8 indicates a strong model (Austin and Steyerberg 2012).

All analyses were performed using SAS software, version 9.4. The study followed the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) reporting guidelines (File S1) (Collins et al. 2015). The Research Ethics Board at Wilfrid Laurier University provided ethics approval for this study (REB #: 6504).

3 | Results

A total of 6796 community-dwelling adults were identified based on our eligibility criteria. The mean age of the sample was 82.5 (SD = 8.7); over half were female (60.4%), 63.6% were not in a relationship and 52.6% lived alone. The mean time between assessments was 7.6 months (SD = 3.7) and 7.0 months (SD = 3.5) for those individuals who declined cognitively (n = 1621) and those who did not decline (n = 3477). The sample was randomly split into a derivation cohort (75%, n = 5098) and a validation cohort (25%, n = 1698). Table 1 shows the baseline characteristics of these two cohorts. Nearly two-thirds (64.2%) of the derivation cohort and 62.7% of the validation cohort had a CPS score of '0' at baseline. Only 2 of the 54 baseline characteristics differed between the derivation and validation cohorts (Depression Rating Scale, p = 0.0075; unsteady gait: p = 0.0063).

Table 2 illustrates the results of the main effects in the logistic regression model using the derivation cohort to predict a deterioration of CPS score (CPS ≥ 2) within 12 months of an individual's baseline assessment.

The final model included 21 main effects and eight significant interactions between age and ability to understand others, ADL

TABLE 2 | Regression model[a] predicting a decline in the Cognitive Performance Scale (CPS) score within 12 months of an individual's baseline assessment.

Parameter	Adjusted odds ratio (95% CI)[b]	*p*
Age (5-year increments)	1.15 (1.10, 1.19)	< 0.0001
Sex		
Male	Reference	Reference
Female	0.88 (0.77, 1.00)	0.0505
Baseline Cognitive Performance Scale (CPS) score		
0	Reference	Reference
1	3.11 (2.73, 3.55)	< 0.0001
Activities of Daily Living (ADL) Self-Performance Hierarchy Scale		
No/minor difficulty (0–1)	Reference	Reference
Moderate difficulty (2, 3)	0.81 (0.65, 1.02)	0.0700
Major difficulty (4–6)	0.64 (0.44, 0.93)	0.0184
Pain Scale		
No pain (0)	Reference	Reference
Less than daily pain (1, 2)	0.75 (0.65, 0.86)	< 0.0001
Daily/severe pain (3, 4)	0.80 (0.66, 0.98)	0.0263
Changes in Health, End-Stage Disease Signs and Symptoms (CHESS) Scale		
No/minor health instability (0–1)	Reference	Reference
Moderate health instability (2, 3)	0.98 (0.78, 1.05)	0.1772
Severe health instability (4, 5)	1.27 (0.85, 1.92)	0.2485
Method for Assigning Priority Levels (MAPLe)		
Low risk	Reference	Reference
Mild risk	0.91 (0.75, 1.11)	0.3535
Moderate risk	1.02 (0.86, 1.20)	0.8627
High/very high risk	1.28 (1.03, 1.58)	0.0235
Stroke		
Not present	Reference	Reference
Present	1.24 (1.03, 1.49)	0.0214
Hemiplegia/hemiparesis		
Not present	Reference	Reference
Present	0.67 (0.42, 1.07)	0.0943
Parkinson disease		
Not present	Reference	Reference
Present	1.42 (1.07, 1.87)	0.0155
Anxiety and/or depression		
Not present	Reference	Reference
Present	1.23 (1.04, 1.47)	0.0182
Pneumonia		

(Continues)

Parameter	Adjusted odds ratio (95% CI)[b]	p
Not present	Reference	Reference
Present	0.55 (0.31, 0.97)	0.0388
Cancer		
Not present	Reference	Reference
Present	0.83 (0.69, 0.97)	0.0379
Other types of fractures		
Not present	Reference	Reference
Present	0.62 (0.39, 0.98)	0.0396
Diabetes		
Not present	Reference	Reference
Present	1.10 (0.94, 1.28)	0.2552
Ability to understand others		
Always understands	Reference	Reference
Usually/often/sometimes/rarely understands	1.35 (1.11, 1.65)	0.0027
Shortness of breath		
No	Reference	Reference
Yes	0.88 (0.76, 1.02)	0.0784
Smoking		
No	Reference	Reference
Yes	1.11 (0.85, 1.46)	0.4498
Client believes that they are capable of increased functional independence		
No	Reference	Reference
Yes	0.87 (0.76, 1.00)	0.0543
Bladder incontinence		
Continent	Reference	Reference
Incontinent	1.17 (1.02, 1.34)	0.0210
Change in social activities		
No decline	Reference	Reference
Decline, not distressed	0.94 (0.81, 1.08)	0.3585
Decline, distressed	1.14 (0.90, 1.44)	0.2836

Note: Interaction terms of the regression model were examined; details are presented in the Supporting Information.
[a]Final main effects model for the derivation cohort following backward elimination.
[b]The odds ratio estimates are from the main effects-only model (without the interactions with age, ADL impairments, pain, MAPLe, stroke and fractures).

and diabetes, ADL and ability to understand others, ADL and change in social activities, pain and change in social activities, pneumonia and MAPLe, pneumonia and stroke and fractures and incontinence (Supporting Information S1). The most significant predictors ($p<0.0001$) were a baseline CPS score of '1' (OR = 3.11, 95% CI = 2.73, 3.55), any difficulty understanding others (OR = 1.35, 95% CI = 1.11, 1.65) and age (OR = 1.15, 95% CI = 1.10, 1.19). Several factors were negatively associated with CPS ≥ 2 within 12 months, including major difficulty in completing ADLs (OR = 0.64, 95% CI = 0.44, 0.93), less than daily pain (OR = 0.75, 95% CI = 0.65, 0.86) and daily/severe pain (OR = 0.80, 95% CI = 0.66, 0.98), pneumonia (OR = 0.55, 95% CI = 0.31, 0.97), cancer (OR = 0.83, 95% CI = 0.69, 0.97) and fractures (OR = 0.62, 95% CI = 0.39, 0.98). The resulting model has a c-statistic of 0.70 (95% CI 0.70, 0.73) indicating a good model. The equation to calculate the predicted risk of CPS decline is presented in Supporting Information S2.

The final regression model was applied to the validation cohort. As shown in Figure 1, the discrimination in the validation

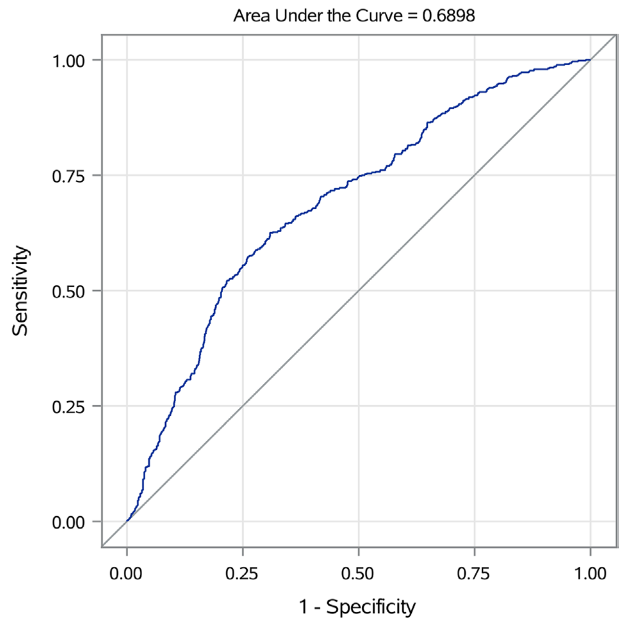

FIGURE 1 | Receiver operating characteristic (ROC) curve for the validation cohort (c-statistic = 0.69).

cohort was good, with a c-statistic of 0.69 (95% CI 0.66, 0.72). Across the three plots shown in Figure 2, the calibration plots for the 10-, 25- and 50-decline bins were acceptable.

The lowest and highest deciles for the 10-bin calibration plot for the validation sample are presented in Supporting Information S3. The calibration plots show that model discrimination in the validation cohort was moderate, with both under- and overestimating the observed rate of a worsening on the CPS.

4 | Discussion

This study used routinely collected health data to develop a model to predict a deteriorating CPS score in home care clients without a diagnosis of dementia. The prediction model, RCD-NZ, has reasonably good discriminative ability, c-statistic = 0.69, which is similar to the recently published model from Canada (discriminative ability c-statistic = 0.66) (Guthrie et al. 2023). Our result is comparable to recent efforts to predict Alzheimer's disease utilising clinical data (Revathi et al. 2022), and arguably more clinically promising as our outcome is related to functional cognitive ability. Nonetheless, there is room for improvement in

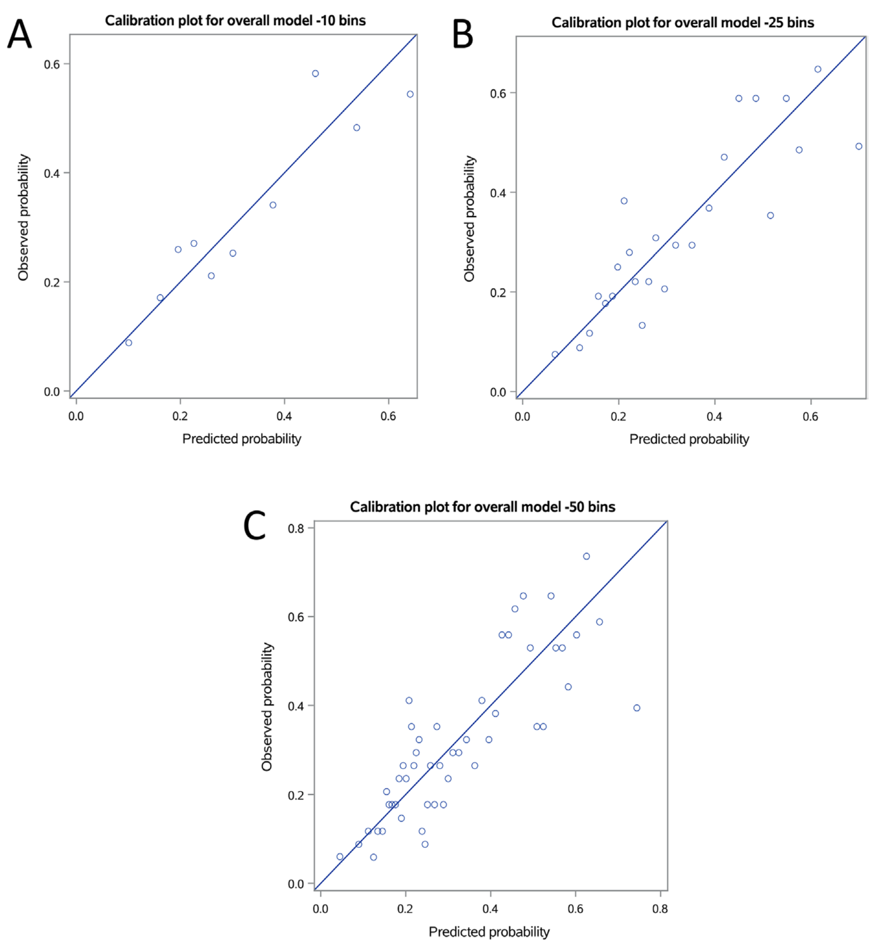

FIGURE 2 | Calibration plots for 10 (A), 25 (B) and 50-decline (C) bins for the validation sample. $^{\beta}$The model's predicted probability is on the *x*-axis and the observed rate of cognitive decline is on the *y*-axis. The 45° line represents a perfect calibration. Dots represent the deciles of individuals observed 12-month probability of decline plotted against their 12-month predicted probability of decline.

the discriminative ability of this model. For example, predictive models for heart failure routinely report c-statistics of ≥ 0.8 (Razaghizad et al. 2022). The results presented here demonstrate that developing a predictive model for cognitive decline is possible using routinely collected assessment data. Using a nationally representative dataset may mean that our results have the potential to inform national healthcare policy and planning. In addition, the results provide a possible pathway to leverage routinely collected data to develop useful models for informing clinical care.

Our modelling identified that significant ADL impairment, pain, pneumonia, cancer and fractures were negatively associated with a deterioration of the CPS, a similar finding in the Canadian cognitive decline prediction tool (Guthrie et al. 2023). Possible explanations for these counterintuitive observations in this study may be attributed to the survival effect; for example, those with cancer are more likely to die before they experience cognitive decline. In another study utilising NZ interRAI HC data, it was reported that cancer diagnosis has the highest mortality risk among eight other chronic conditions, but the risk of mortality decreases with age (Abey-Nesbit et al. 2023). This may be attributed to the cancer type, which is not included in the interRAI assessment. Those with difficulty performing activities for daily function may receive earlier and/or more structured social support, for example, home care support, than may alleviate daily stressors that in turn reduce cognitive load. A systematic review showed the role of functional social support in the preservation of cognitive health (Mogic et al. 2023). These insights, while interesting, are unlikely to fundamentally change or enhance the clinical care of home care clients, with the possible exceptions of circumstances where cognitive decline is not expected or where circumstances suggest the need for advance care planning. Our study included a heterogeneous sample; for example, we included people who are not expecting to experience changes in cognitive functioning (e.g., younger people and people with a cancer diagnosis). A predictive model could provide a 'flag' for further assessment and early intervention in these circumstances. A recent review suggested that 4–6 months of aerobic exercise, combined cognitive and motor challenges (such as Tai Chi, dance or dumb bell training), creative art or art and storytelling groups could reduce cognitive decline in older adults (Whitty et al. 2020). It is important to recognise that some home care clients or their families may not be interested in learning about future cognitive decline and, in some settings, resources to support patients may not be available to support patients or modify management. Alternatively, early identification of cognitive decline in the presence of other life-limiting conditions may create an opportunity for advance care planning. There is strong international evidence that advance care planning for people with dementia is acceptable and is associated with decreased hospitalisation and alignment between care delivered and the expressed wishes of the person (Wendrich-van Dael et al. 2020).

4.1 | Strengths and Limitations

The use of a large and reliable national interRAI dataset means that the prerequisites for predictive model development are present (i.e., a defined population and outcome of interest and a pathophysiological framework associated with the clinical outcome). Our sample size is in excess of the recommended sample size of 6443 (116 events) for an outcome event of 0.018 (Riley et al. 2021); however, this is likely to overestimate the incidence of cognitive decline. Future research should seek to obtain a larger sample size if possible (Riley et al. 2021) and inclusion of minority ethnic groups who are also at risk of dementia (Livingston et al. 2024). The development of a predictive model is dependent on the quality of the underlying data. In this study, we have drawn on internationally validated assessment instruments with data collected by trained assessors. It is possible that there is some level of multicollinearity between several of the assessment scales, as differing assessments have different ways of assessing functional data, that is, MAPLe contains items to assess a person's ability to independently perform activities of daily living, as does IADL. In this model, we account for the risk of multicollinearity by using the variance inflation factor; however, it is an acknowledged limitation. Time assumption is a limitation of using a model to predict risk. Our sample came from an interRAI HC cohort from 2013 to 2021. The overall rates of cognitive impairment in the New Zealand population over time are unknown. Our model also did not include other biomarkers (e.g., neuroimaging features, amyloid-beta peptide concentration and apolipoprotein E genotype 4) that could improve its accuracy, with the acknowledgement that the model presented here requires further refinement and that domain-specific clinical knowledge is central to the further development of models and use in clinical practice. While the model has been validated in Canada (Guthrie et al. 2023) with a different assessment point, that is, 6 monthly versus 12 monthly in New Zealand, both studies had similar results. However, we recommend that the current prediction model be further validated in other cohorts in countries with access to interRAI assessment, which may foster wider utility of the prediction model. This is limited to clinicians where interRAI is not a regular care assessment. Finally, the interRAI home care data available to us were already deidentified and we could not link them to other outcomes such as mortality and admission to long-term care. However, our study was not aimed at assessing cognitive decline in individuals who experienced rapid deterioration leading to other outcomes within 12 months. We believe our results are generalisable to New Zealand home care clients who have had two interRAI home care assessments conducted within a 12-month period living in the community.

5 | Conclusion

We have demonstrated that routine interRAI assessment data can be effectively used to develop a predictive model for identifying home care clients without a diagnosis of dementia who are at risk of cognitive decline within 12 months. While these results are promising, the model's moderate discriminative ability highlights opportunities for improvement, especially through more advanced machine learning techniques and using multiple routinely collected health datasets and clinical data. Clinicians can use this model to identify at-risk individuals in home care settings. Identifying this vulnerable group enables proactive clinical interventions and advanced care planning, potentially improving outcomes for clients in the community. Dementia is underdiagnosed in the community, and prediction models may support the healthcare workforce and create possibilities for targeted services.

Author Contributions

Study concept and design: All authors. Acquisition of data: Gary Cheung and Dawn M. Guthrie. Analysis of data: Nicole Williams. Interpretation of data: All authors. Drafting of the manuscript: Gary Cheung, Ruth Teh and Eamon Merrick. Critical revision of the manuscript for important intellectual content: All authors.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from Health New Zealand - Te Whatu Ora. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from https://www.interrai.co.nz/ with the permission of Health New Zealand - Te Whatu Ora.

Patient/Public Contributions

Patients who had an interRAI Home Care assessment within our sampling frame contributed their data to this research.

References

Abey-Nesbit, R., H. A. Jamieson, H. U. Bergler, N. Kerse, J. W. Pickering, and R. Teh. 2023. "Chronic Health Conditions and Mortality Among Older Adults With Complex Care Needs in Aotearoa New Zealand." *BMC Geriatrics* 23: 318.

Austin, P. C., and E. W. Steyerberg. 2012. "Interpreting the Concordance Statistic of a Logistic Regression Model: Relation to the Variance and Odds Ratio of a Continuous Explanatory Variable." *BMC Medical Research Methodology* 12: 82.

Balachandran, V. P., M. Gonen, J. J. Smith, and R. P. DeMatteo. 2015. "Nomograms in Oncology: More Than Meets the Eye." *Lancet Oncology* 16, no. 4: e173–e180. https://doi.org/10.1016/S1470-2045(14)71116-7.

Chen, Y., X. Qian, Y. Zhang, et al. 2022. "Prediction Models for Conversion From Mild Cognitive Impairment to Alzheimer's Disease: A Systematic Review and Meta-Analysis." *Frontiers in Aging Neuroscience* 14: 840386.

Collins, G. S., J. B. Reitsma, D. G. Altman, and K. G. M. Moons. 2015. "Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD): The TRIPOD Statement." *BMJ* 350: g7594.

Downer, B., A. Kumar, S. P. Veeranki, H. B. Mehta, M. Raji, and K. S. Markides. 2016. "Mexican-American Dementia Nomogram: Development of a Dementia Risk Index for Mexican-American Older Adults." *Journal of the American Geriatrics Society* 64, no. 12: e265–e269.

Eastham, J. A., M. W. Kattan, and P. T. Scardino. 2002. "Nomograms as Predictive Models." *Seminars in Urologic Oncology* 20, no. 2: 108–115.

Eichler, K., M. A. Puhan, J. Steurer, and L. M. Bachmann. 2007. "Prediction of First Coronary Events With the Framingham Score: A Systematic Review." *American Heart Journal* 153, no. 5: 722–731.

Fries, B. E., S. E. Simon, J. N. Morris, C. Flodstrom, and F. L. Bookstein. 2001. "Pain in U.S. Nursing Homes: Validating a Pain Scale for the Minimum Data Set." *Gerontologist* 41, no. 2: 173–179. https://doi.org/10.1093/geront/41.2.173.

Gauthier, S., P. Rosa-Neto, J. A. Morais, and C. Webster. 2021. *World Alzheimer Report 2021: Journey Through the Diagnosis of Dementia*. Alzheimer's Disease International.

Gee, S., M. Croucher, and G. Cheung. 2021. "Performance of the Cognitive Performance Scale of the Resident Assessment Instrument (interRAI) for Detecting Dementia Amongst Older Adults in the Community." *International Journal of Environmental Research and Public Health* 18, no. 13: 6708.

Guthrie, D. M., N. Williams, C. Beach, et al. 2021. "Development and Validation of Caregiver Risk Evaluation (CaRE): A New Algorithm to Screen for Caregiver Burden." *Journal of Applied Gerontology* 40, no. 7: 731–741.

Guthrie, D. M., N. Williams, H. M. O'Rourke, et al. 2023. "Development and Validation of Risk of CPS Decline (RCD): A New Prediction Tool for Worsening Cognitive Performance Among Home Care Clients in Canada." *BMC Geriatrics* 23: 297.

Haaksma, M. L., M. Eriksdotter, D. Rizzuto, et al. 2020. "Survival Time Tool to Guide Care Planning in People With Dementia." *Neurology* 94, no. 5: e538–e548.

Hirdes, J. P., J. W. Poss, and N. Curtin-Telegdi. 2008. "The Method for Assigning Priority Levels (MAPLe): A New Decision-Support System for Allocating Home Care Resources." *BMC Medicine* 6: 9.

Hirdes, J. P., J. W. Poss, L. Mitchell, L. Korngut, and G. Heckman. 2014. "Use of the interRAI CHESS Scale to Predict Mortality Among Persons With Neurological Conditions in Three Care Settings." *PLoS One* 9: e99066.

Hu, M., Y. Gao, T. C. Y. Kwok, Z. Shao, L. D. Xiao, and H. Feng. 2022. "Derivation and Validation of the Cognitive Impairment Prediction Model in Older Adults: A National Cohort Study." *Frontiers in Aging Neuroscience* 14: 755005.

Huang, K., Y. Lin, L. Yang, et al. 2020. "A Multipredictor Model to Predict the Conversion of Mild Cognitive Impairment to Alzheimer's Disease by Using a Predictive Nomogram." *Neuropsychopharmacology* 45, no. 2: 358–366. https://doi.org/10.1038/s41386-019-0551-0.

Iasonos, A., D. Schrag, G. V. Raj, and K. S. Panageas. 2008. "How to Build and Interpret a Nomogram for Cancer Prognosis." *Journal of Clinical Oncology* 26, no. 8: 1346–1354.

interRAI New Zealand. Annual report 2018/19 Updated 2019.

Johnson, J. C. S., L. McWhirter, C. J. D. Hardy, et al. 2021. "Suspecting Dementia: Canaries, Chameleons and Zebras." *Practical Neurology* 21, no. 4: 300–312.

Kattan, M. W., J. A. Eastham, A. M. F. Stapleton, T. M. Wheeler, and P. T. Scardino. 1998. "A Preoperative Nomogram for Disease Recurrence Following Radical Prostatectomy for Prostate Cancer." *Journal of the National Cancer Institute* 90, no. 10: 766–771.

Lerner, S. P., B. Bochner, and A. S. Kibel. 2007. "The Use and Abuse of Data: Nomograms and Talking to Patients About Clinical Medicine." *Urologic Oncology: Seminars and Original Investigations* 25, no. 4: 333–337.

Livingston, G., J. Huntley, K. Y. Liu, et al. 2024. "Dementia Prevention, Intervention, and Care: 2024 Report of the Lancet Standing Commission." *Lancet* 404, no. 10452: 572–628.

Livingston, G., A. Sommerlad, V. Orgeta, et al. 2017. "Dementia Prevention, Intervention, and Care." *Lancet* 390, no. 10113: 2673–2734.

Martin, L., J. W. Poss, J. P. Hirdes, R. N. Jones, M. J. Stones, and B. E. Fries. 2008. "Predictors of a New Depression Diagnosis Among Older Adults Admitted to Complex Continuing Care: Implications for the Depression Rating Scale (DRS)." *Age and Ageing* 37, no. 1: 51–56.

Mogic, L., E. C. Rutter, S. L. Tyas, C. J. Maxwell, M. E. O'Connell, and M. Oremus. 2023. "Functional Social Support and Cognitive Function in Middle- and Older-Aged Adults: A Systematic Review of Cross-Sectional and Cohort Studies." *Systematic Reviews* 12, no. 1: 86.

Morris, J. N., B. E. Fries, D. R. Mehr, et al. 1994. "MDS Cognitive Performance Scale (C)." *Journal of Gerontology* 49, no. 4: M174–M182.

Morris, J. N., B. E. Fries, and S. A. Morris. 1999. "Scaling ADLs Within the MDS." *Journals of Gerontology Series A, Biological Sciences and Medical Sciences* 54, no. 11: M546–M553.

Poss, J., K. M. Murphy, M. G. Woodbury, et al. 2010. "Development of the interRAI Pressure Ulcer Risk Scale (PURS) for Use in Long-Term Care and Home Care Settings." *BMC Geriatrics* 10: 67.

Razaghizad, A., E. Oulousian, V. K. Randhawa, et al. 2022. "Clinical Prediction Models for Heart Failure Hospitalization in Type 2 Diabetes: A Systematic Review and Meta-Analysis." *Journal of the American Heart Association* 11, no. 10: e024833.

Revathi, A., R. Kaladevi, K. Ramana, R. H. Jhaveri, M. Rudra Kumar, and M. Sankara Prasanna Kumar. 2022. "Early Detection of Cognitive Decline Using Machine Learning Algorithm and Cognitive Ability Test. Security and Communication." *Networks* 2022: 1–13.

Riley, R. D., T. P. A. Debray, G. S. Collins, et al. 2021. "Minimum Sample Size for External Validation of a Clinical Prediction Model With a Binary Outcome." *Statistics in Medicine* 40, no. 19: 4230–4251.

Schluter, P. J., A. Ahuriri-Driscoll, T. J. Anderson, et al. 2016. "Comprehensive Clinical Assessment of Home-Based Older Persons Within New Zealand: An Epidemiological Profile of a National Cross-Section." *Australian and New Zealand Journal of Public Health* 40, no. 4: 349–355.

Wendrich-van Dael, A., F. Bunn, J. Lynch, L. Pivodic, L. Van den Block, and C. Goodman. 2020. "Advance Care Planning for People Living With Dementia: An Umbrella Review of Effectiveness and Experiences." *International Journal of Nursing Studies* 107: 103576.

Whitty, E., H. Mansour, E. Aguirre, et al. 2020. "Efficacy of Lifestyle and Psychosocial Interventions in Reducing Cognitive Decline in Older People: Systematic Review." *Ageing Research Reviews* 62: 101113.

Zhou, J., Y. Lv, C. Mao, et al. 2020. "Development and Validation of a Nomogram for Predicting the 6-Year Risk of Cognitive Impairment Among Chinese Older Adults." *Journal of the American Medical Directors Association* 21, no. 6: 864–871.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.