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Development and Validation of a Frailty Risk Prediction Model for Community-Dwelling Elderly in Shanghai

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Abstract: *Background:* China is rapidly aging, increasing the burden on families, society, and public health services. The health of elderly individuals tends to deteriorate with age, and chronic conditions like frailty become more prevalent, driving up the use of healthcare services. Early screening and intervention for frailty are crucial in managing this demographic shift. While tools like the Fried Frailty Phenotype and Frailty Index assess frailty in communities, they are resource-intensive and only indicate frailty status without predicting risk or providing management recommendations. This study aims to develop a risk prediction model for frailty using real-world data, which can support the early detection of high-risk individuals in community settings. *Objectives:* To analyze the prevalence of frailty and its influencing factors in community-dwelling elderly, to construct a frailty risk prediction model and develop a nomogram, and to validate the model and assess its clinical utility. *Methods:* A cross-sectional survey of 420 elderly individuals in a Shanghai community health center was conducted (August 2022–March 2023). Data from various assessment tools were used to build a frailty prediction model through logistic regression, with validation conducted on 180 additional participants. The model's predictive performance was evaluated using the ROC, AUC, calibration curves, and decision curve analysis (DCA). *Results:* The frailty prevalence was 7.4%. Independent risk factors included social support, malnutrition, fatigue, sarcopenia, reduced grip strength, and sleep duration. The prediction model achieved an AUC of 0.968 in the training set and 0.939 in the validation set, indicating high discrimination and calibration. DCA confirmed the model's clinical utility. *Conclusion:* This study highlights a frailty prevalence rate of 7.4% among elderly individuals in Shanghai, with key risk factors identified. The validated frailty risk prediction model provides accurate and clinically effective frailty risk assessment, supporting targeted early interventions to prevent frailty in community settings.

Keywords: Frailty risk prediction; Community-dwelling elderly; Early intervention in aging

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1. Introduction

The United Nations Economic and Social Council defined the threshold for population aging in its 1957 report,

"Population Aging and Its Socio-Economic Implications," noting that a country or region is considered to have entered an aging society when the proportion of the population aged 65 and over exceeds 7%. By 2000, China's population aged 65 and reached 88 million, accounting for 7% of the total population, indicating that China had entered an aging society [1]. A country or region with 14% of its population aged 65 and over is considered an aged society, and a proportion of 20% defines a super-aged society. According to a 2022 announcement from China's National Bureau of Statistics, individuals aged 60 and over accounted for 19.8% of the total population, while those aged 65 and over accounted for 14.9%. China is expected to enter a super-aged society by 2031 [2]. As China moves toward a deeply aged society, promoting healthy aging has become a key objective [3].

The prevalence and incidence of frailty vary significantly across countries and regions. Surveys from the Survey of Health, Ageing, and Retirement in Europe (SHARE) found that Italy and Spain have a higher prevalence of frailty, while high-income countries generally show a lower prevalence [4]. Although the definition of frailty is not yet unified, most studies use the Frailty Phenotype assessment by Fried or the Frailty Index developed by Rockwood [5]. Frailty prevalence also differs based on assessment methods, with lower prevalence reported when using tools that measure only physical frailty, such as the Fried Frailty Phenotype (14.6%) [6]. Assessment tools focused on physical frailty provide a narrower, more specific definition of frailty and offer better comparability across studies.

Frailty prevalence also varies by setting. A meta-analysis of 56,407 elderly individuals highlighted differences in frailty prevalence across medical environments (community, outpatient, nursing home, hospitalization), finding the highest prevalence in hospitalized elderly people (39.3%) and the lowest in nursing homes (20%) [7]. This may relate to cultural and lifestyle differences across regions.

Frailty is a dynamic process influenced by multiple factors. Sociodemographic factors (age, gender, education level, income, living arrangements), physiological factors (weight, self-rated health, cognitive function, multimorbidity, polypharmacy), and behavioral factors (mobility limitations, smoking, drinking) are widely recognized as influencing frailty [8,9]. Although consensus exists on factors affecting frailty in community-dwelling elderly populations, differences in study design, region, population characteristics, and local medical levels continue to yield varied results, warranting further research.

Risk prediction models, also known as clinical prediction models, use statistical or machine learning methods to quantify health risks by analyzing patient characteristics, such as age, gender, medical history, and lifestyle [10]. These models include diagnostic models, which assess the likelihood of disease based on current symptoms and signs, and predictive models, which estimate future health outcomes [11].

The present study aims to examine the prevalence and risk factors of frailty in elderly individuals in Chinese communities and to construct a frailty risk prediction model using logistic regression analysis. Internal validation will be conducted to ensure model accuracy and reliability in clinical practice, thereby supporting elderly healthcare strategies, optimizing prevention and intervention measures, and ultimately enhancing the quality of life for the elderly.

2. Methods

2.1. Study design

This study selected community-dwelling elderly individuals aged 60 and above from a central urban district in Shanghai as research subjects, conducting the research from July 2022 to March 2023.

Inclusion criteria: (1) Community elderly population aged 60 and above; (2) Clear consciousness, normal understanding, and expression ability; (3) Informed consent and willingness to participate in the study.

Exclusion criteria: (1) Refusal to sign informed consent; (2) Severe hearing or vision impairment, impeding normal communication; (3) Patients with poorly controlled schizophrenia; (4) Patients with severe physical diseases, such as advanced cancer or severe heart failure, preventing frailty assessment. A total of 420 samples were collected for the modeling set.

2.2. Data collection

2.2.1. General information questionnaire

A self-designed General Information Survey Questionnaire was used, including variables such as gender, age, education level, self-assessed health status, marital status, children, type and manner of residence, average monthly household income, number of chronic diseases, walking speed, grip strength, and lifestyle factors such as alcohol consumption, smoking, exercise habits, social support networks, and social activities.

2.2.2. Frailty assessment

The Fried Frailty Phenotype, a widely used clinical frailty assessment tool focused on biological indicators of multi-system decline, was employed. This study used a modified version of the Fried Frailty Phenotype for frailty assessment.

2.2.3. Nutrition status assessment

The Mini Nutritional Assessment (MNA) [12,13], developed by Vellas *et al.* in 1990, evaluates nutritional status comprehensively, without invasive examination. Although the simplified MNA-SF [14] exists, this study employed the full MNA due to its higher sensitivity and comprehensiveness.

2.2.4. Cognitive status assessment

The Mini-Mental State Examination (MMSE) [15] is widely used clinically to assess cognitive function, covering 11 items across five cognitive domains.

2.2.5. Depression status assessment

The Geriatric Depression Scale (GDS-5) [16], comprising five items and with a total score of 5 points, served as a screening tool for depressive symptoms. A score above 2 indicates depression, with higher scores suggesting increased severity.

2.2.6. Daily living ability assessment

The Assessment of Activities of Daily Living (ADL) [17] includes two scales: the Basic Activities of Daily Living (BADL) scale and the Instrumental Activities of Daily Living (IADL) scale.

2.2.7. Sarcopenia screening

The Strength, Assistance with Walking, Rising from a Chair, Climbing Stairs, and Falls (SARC-F) Scale [18] screens for sarcopenia risk with five items, each scored from 0 (none) to 2 (a lot or unable). A score of ≥ 4 suggests a need for further evaluation.

2.2.8. Social support assessment

The Social Support Rating Scale (SSRS) [8] measures social support across three dimensions: subjective support, objective support, and utilization of support, totaling ten items.

2.3. Statistical methods

Data normality was first assessed using the Shapiro-Wilk test. Normally distributed data were expressed as mean ± standard deviation (SD) and analyzed using the two-sample *t*-test, while non-normally distributed data were described using the median and interquartile range, analyzed with the Wilcoxon rank-sum test. Categorical data were presented with frequencies and percentages, compared across groups using the chi-squared or Fisher's exact test. Variables with significant differences ($P < 0.05$) in univariate analysis were selected. Stepwise forward logistic regression was used to address multicollinearity and identify predictive factors from the significant univariate variables. A multivariable logistic regression equation was developed, with results expressed as odds ratios (OR) and 95% confidence intervals (CI). A nomogram was constructed for visual analysis.

The model's discrimination was assessed using the area under the receiver operating characteristic curve (AUC), and a calibration curve evaluated the goodness of fit. Clinical benefit was evaluated with a decision curve. All analyses used two-tailed tests with $P < 0.05$ as statistically significant.

For the validation set, the model's diagnostic ability was analyzed with the AUC, and calibration was assessed with a calibration curve. Clinical benefit was evaluated with a decision curve analysis (DCA).

Data analysis and visualization were performed using R software (R Version 4.3.1), including the "glmnet," "rms," "gplots," "Matrix," "pROC," and "ResourceSelection" packages, with *P*-values interpreted using two-tailed tests and $P < 0.05$ as the significance threshold.

3. Results

A total of 420 community-dwelling elderly individuals participated in the modeling set for this study, divided into a frail group and a non-frail group, as shown in **Table 1**.

Table 1. Prevalence of frailty in community-dwelling elderly individuals in the modeling set ($n = 420$)

Frailty scale	Grouping	Categorization	Number	Proportion (%)
Frailty phenotype	Non-frail group	Health status	203	48.3
		Pre-frailty	186	44.3
	Frail group	Frailty	31	7.4

3.1. Univariate analysis

3.1.1. Sociodemographic data

A Wilcoxon test was conducted to analyze sociodemographic data between the frail and non-frail groups, with detailed results shown in **Table 2**.

Table 2. Univariate analysis of socio-demographic data

Item		Non-frailty (n = 389)	Frailty (n = 31)	Z / χ^2	P
Gender	Male	150 (38.6%)	14 (45.2%)	0.526	0.567
	Female	239 (61.4%)	17 (54.8%)		
Age		72 (68, 76)	77 (75, 83)	-4.434	< 0.001
Education	Elementary school or below	31 (8.0%)	2 (6.5%)	2.649	0.449
	Junior high school	109 (28.0%)	6 (19.3%)		
	High school / Vocational high school	130 (33.4%)	15 (48.4%)		
	College degree or above	119 (30.6%)	8 (25.8%)		
Marital status	Married	313 (80.5%)	26 (83.9%)	0.214	0.643
	Unmarried / Widowed / Divorced	76 (19.5%)	5 (16.1%)		
Income situation (Chinese Yuan)	< 2,000	13 (3.0%)	1 (3.2%)	2.135	0.477
	2,000–4,999	117 (30.1%)	12 (38.7%)		
	5,000–9,999	237 (60.9%)	18 (58.1%)		
	≥ 10,000	22 (6.0%)	0 (0.0%)		
Social Support Rating Scale		14 (12, 16)	15 (13, 18)	-2.083	0.037

3.1.2. Physical health-related data

The univariate analysis results of physical health conditions between frail and non-frail groups are presented in **Table 3**.

Table 3. Univariate analysis of physical health-related data

Item		Non-frailty (n = 389)	Frailty (n = 31)	Z / χ^2	P
Meditation time	< 2 h	75 (19.3%)	5 (16.1%)	0.286	0.867
	2–4 h	135 (34.7%)	12 (38.7%)		
	> 4 h	179 (46.0%)	14 (45.2%)		
Sleep time		6.9 (5.8, 8.1)	5.3 (5.1, 6.5)	-5.336	< 0.001
Body mass index	Underweight	16 (4.1%)	3 (9.7%)	6.032	0.088
	Healthy weight	192 (49.4%)	20 (64.5%)		
	Overweight	142 (36.5%)	7 (22.6%)		
	Obesity	39 (10.0%)	1 (3.2%)		
Walking pace	Slow pace	110 (28.3%)	22 (71.0%)	24.280	< 0.001
	Normal pace	279 (71.7%)	9 (29.0%)		
Grip strength	Decreased grip strength	99 (25.4%)	26 (83.9%)	46.878	< 0.001
	Normal grip strength	290 (74.6%)	5 (16.1%)		
MNA	Risk of malnutrition	15 (3.9%)	9 (29.0%)	33.778	< 0.001
	Good nutrition	374 (96.1%)	22 (71.0%)		

Table 3 (Continued)

Item		Non-frailty (n = 389)	Frailty (n = 31)	Z / χ^2	P
ADL	Normal	357 (91.8%)	22 (71.0%)	12.168	0.002
	Decreased functionality	24 (6.2%)	6 (19.4%)		
	Dysfunction	8 (2.0%)	3 (9.6%)		

3.1.3. Chronic disease and complication data

Results of univariate analysis for chronic diseases and complications are detailed in **Table 4**.

Table 4. Univariate analysis of chronic diseases and complications [n (%)]

Item		Non-frailty (n = 389)	Frailty (n = 31)	χ^2	P
> 5 chronic diseases	Yes	82 (21.1%)	11 (35.5%)	3.455	0.063
	No	307 (78.9%)	20 (64.5%)		
Fatigue	Yes	132 (33.9%)	23 (74.2%)	19.987	< 0.001
	No	257 (66.1%)	8 (25.8%)		
Five Times Sit to Stand Test	Risk-free	177 (45.5%)	7 (22.6%)	6.128	0.014
	Fall risks	212 (54.5%)	24 (77.4%)		
Reduced food intake	Yes	52 (13.4%)	9 (29.0%)	5.675	0.030
	no	337 (86.6%)	22 (71.0%)		
Vision problems	Yes	76 (19.5%)	14 (45.2%)	11.197	0.001
	No	313 (80.5%)	17 (54.8%)		
Hearing issues	Yes	46 (11.8%)	11 (35.5%)	13.701	0.001
	No	343 (88.2%)	20 (64.5%)		
SARC-F	No sarcopenia	367 (94.3%)	19 (61.3%)	42.164	< 0.001
	Sarcopenia	22 (5.7%)	12 (38.7%)		

3.1.4. Cognitive function

Univariate analysis indicates statistically significant differences in cognitive function between frail and non-frail groups (P = 0.014), as shown in **Table 5**.

Table 5. Univariate analysis of cognitive function

Item		Non-frailty (n = 389)	Frailty (n = 31)	χ^2	P
GDS-5	Normal	349 (89.7%)	27 (87.1%)	0.210	0.552
	Depression	40 (10.3%)	4 (12.9%)		
MMSE	Normal cognition	247 (63.5%)	13 (41.9%)	9.945	0.014
	Mild cognitive impairment	104 (26.7%)	13 (41.9%)		
	Moderate cognitive impairment	25 (6.4%)	1 (3.2%)		
	Severe cognitive impairment	13 (3.3%)	4 (12.9%)		

3.2. Multivariate logistic regression analysis

Binary logistic regression analysis was employed to further assess the factors influencing the degree of frailty. The dependent variable was the occurrence of frailty, and the independent variables were the 17 factors selected from the univariate analysis ($P < 0.05$). A forward stepwise logistic regression method based on the partial maximum likelihood estimation was used for the multivariate logistic regression analysis. The assignment table of independent variables is shown in **Table 6**.

Table 6. Assignment table of independent variables

Item	Assignment
Age	Continuous variable
SSRS	Continuous variable
Sleep duration	Continuous variable
Hemoglobin	Continuous variable
Blood urea nitrogen (BUN)	Continuous variable
Blood glucose	Continuous variable
Fatigue	1 = Yes, 2 = No
Fall risk	0 = No risk of falling, 1 = Risk of falling
Reduced food intake	1 = No reduction in eating, 2 = Reduction in eating
Vision problems	1 = No, 2 = Yes
Hearing issues	1 = No, 2 = Yes
Decreased walking pace	0 = No, 1 = Yes
Decreased grip strength	0 = No, 1 = Yes
SARC-F	0 = Negative screening, 1 = Positive screening
MNA	0 = Good nutritional status, 1 = Risk of malnutrition
MMSE	1 = Normal cognitive function, 2 = Mild cognitive impairment, 3 = Moderate cognitive impairment, 4 = Severe cognitive impairment
ADL	0 = Completely normal, 1 = Decreased functionality, 2 = Significant dysfunction

The multivariate analysis results (**Table 7**) indicate that positive sarcopenia screening (OR = 20.625, 95% CI: 4.822–88.216), risk of malnutrition (OR = 16.899, 95% CI: 3.008–94.927), decreased grip strength (OR = 29.837, 95% CI: 7.010–126.996), and presence of fatigue (OR = 16.326, 95% CI: 4.18–63.768) are risk factors for the occurrence of frailty, while extended sleep duration is a protective factor against frailty. Notably, increased social support appears to be a risk factor for the development of frailty.

Table 7. Multivariate logistic regression analysis

Variable	β	Standard error	Distinctiveness	OR	95% Confidence interval	
					Lower limit	Upper limit
SSRS	0.336	0.100	0.001	1.399	1.15	1.702
Sleep time	-1.230	0.320	< 0.001	0.292	0.156	0.547
Fatigue	2.793	0.695	< 0.001	16.326	4.18	63.768
Grip strength	3.396	0.739	< 0.001	29.837	7.010	126.996
MNA	2.827	0.881	0.001	16.899	3.008	94.927
SARC-F	3.026	0.741	< 0.001	20.625	4.822	88.216
Constant	-7.016	2.573	0.006			

The logistic regression identified six independent frailty-related factors: SSRS score, sleep duration, fatigue, grip strength, MNA, and SARC-F. Based on these factors, the frailty risk prediction model equation is:

$$Logit = 0.336 \times SSRS - 1.230 \times Sleep\ duration + 2.793 \times Fatigue + 3.396 \times Grip\ strength + 2.827 \times MNA + 3.026 \times SARC\text{-}F$$

3.3. Frailty risk prediction nomogram

3.3.1. Construction of a frailty risk prediction nomogram

Based on the community elderly frailty risk prediction model as described, a nomogram was developed. This nomogram assigns scores to six independent variables: SSRS, sleep duration, fatigue, grip strength, MNA, and SARC-F, according to the magnitude of their regression coefficients in the model, reflecting the importance of each variable in predicting frailty occurrence, as shown in **Figure 1**.

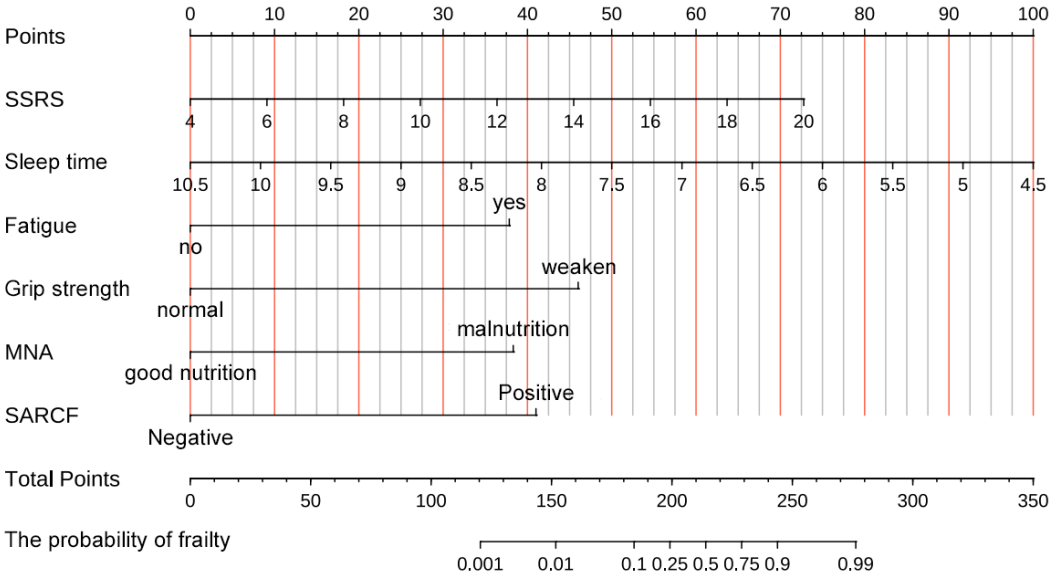

Figure 1. Nomogram for community elderly frailty risk prediction model

3.3.2. ROC curve of the community elderly frailty risk prediction model in the modeling set

The nomogram model's performance was evaluated using modeling set data, with the ROC curve plotted and the AUC calculated. The model's AUC in the training set was 0.968 (95% CI: 0.938–0.988), with a sensitivity of 0.968, specificity of 0.817, Youden's index of 0.785, and an accuracy of 0.829 in identifying frailty, as shown in **Figure 2**.

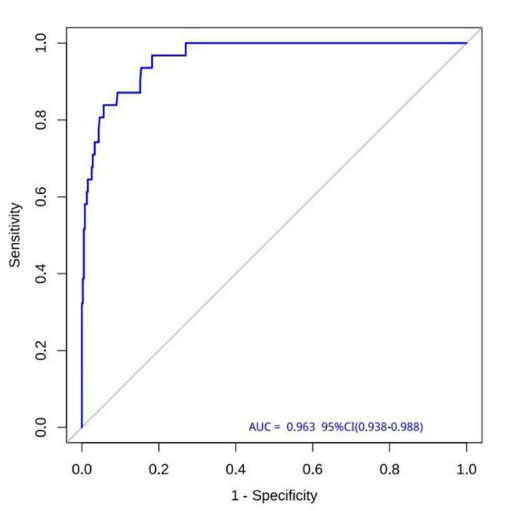

Figure 2. ROC curve of the community-based frailty risk prediction model for the elderly

3.3.3. Calibration curve of the community elderly frailty risk prediction model in the modeling set

The predicted probabilities of frailty are closely aligned with actual occurrences, indicating high accuracy, as shown in **Figure 3**.

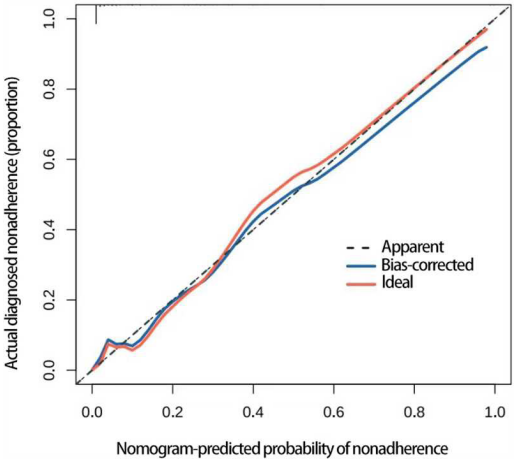

Figure 3. Calibration curve of the community-based frailty risk prediction model for the elderly

3.3.4. Decision Curve Analysis for predicting frailty risk in the modeling set

Decision Curve Analysis (DCA) visually assesses clinical applicability by showing changes in net clinical benefit across various thresholds. The DCA curve for the modeling set is positioned above both extremes, indicating good clinical utility with considerable net benefit. This is demonstrated in **Figure 4**. Internal validation resulted in a Brier Score of 0.056, showing the model's high predictive accuracy.

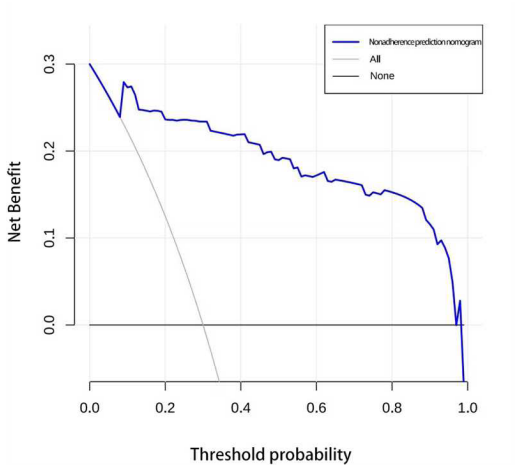

Figure 4. DCA for a community-based frailty risk prediction model for the elderly

3.4. Comparison of sociodemographic data between the modeling set and validation set

The study presents a univariate analysis of sociodemographic data between the modeling cohort (n = 420) and the validation cohort (n = 180), as detailed in **Table 8**.

Table 8. Univariate analysis of sociodemographic data of community elderly people in the modeling set and the validation set [n (%)]

Item		Modeling set (n = 420)	Validation set (n = 180)	χ^2	P
Gender	Male	164 (39%)	61 (33.9%)	1.431	0.232
	Female	256 (61%)	119 (66.1%)		
Education	Elementary school and below	26 (6.2%)	9 (5.0%)	0.435	0.933
	Junior high school	116 (27.6%)	48 (26.7%)		
	High school / vocational high school	147 (35.0%)	65 (36.1%)		
	College degree or above	131 (31.2%)	58 (32.2%)		
Marital status	Married	339 (80.7%)	142 (78.9%)	0.264	0.607
	Unmarried / widowed / divorced	81 (19.3%)	38 (21.1%)		
Income	< 2,000	3 (0.7%)	2 (1.1%)	5.469	0.242
	2,000–4,999	129 (30.7%)	47 (26.1%)		
	5,000–9,999	255 (60.7%)	116 (64.4%)		
	≥10,000	22 (5.2%)	14 (7.8%)		
≥ 5 chronic disease	Yes	93 (22.1%)	42 (23.3%)	0.102	0.749
	No	327 (77.9%)	138 (76.7%)		
BMI	Underweight	19 (4.5%)	9 (5.0%)	4.573	0.206
	Normal weight	213 (50.7%)	99 (55.0%)		
	Overweight	148 (35.2%)	64 (35.6%)		
	Obesity	40 (83.3%)	8 (4.4%)		

Table 8 (Continued)

Item		Modeling set (n = 420)	Validation set (n = 180)	χ^2	P
Walking pace	Slow pace	130 (31.1%)	53 (29.4%)	0.162	0.687
	Normal pace	288 (68.9%)	127 (70.6%)		
Grip strength	Decreased grip strength	125 (29.8%)	54 (30.0%)	0.003	0.953
	Normal grip strength	295 (70.2%)	126 (70.0%)		
Meditation time	< 2 h	80 (19.0%)	38 (21.1%)	4.309	0.230
	2–4 h	131 (31.2%)	65 (36.1%)		
	> 4 h	193 (46.0%)	67 (37.2%)		
Age	60–69 year	131 (31.2%)	65 (36.1%)	1.632	0.442
	70–79 year	222 (52.9%)	91 (50.6%)		
	≥ 80 year	67 (16.0%)	24 (13.3%)		
Sleep time	< 7h	231 (55.0%)	111 (61.7%)	2.285	0.131
	≥ 7h	189 (45.0%)	69 (38.3%)		

3.5. Internal validation of the frailty risk prediction model

3.5.1. Discriminative performance of the model in the validation set

Using validation set data (n = 180), the model achieved an AUC of 0.939 (95% CI: 0.890–0.990) with a sensitivity of 0.909, specificity of 0.876, Youden's index of 0.785, and an accuracy of 0.878. These metrics indicate good generalizability and predictive performance. See **Figure 5** for details.

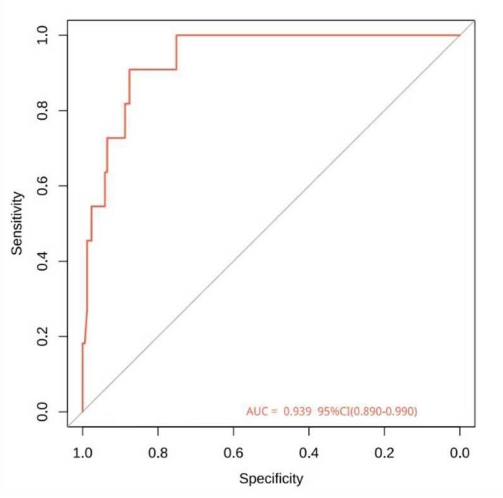

Figure 5. ROC curve of frailty risk prediction model for the elderly in the community validation set

3.5.2. Calibration of the model on the validation set

The calibration curve aligns closely with the ideal line, indicating acceptable calibration (Hosmer-Lemeshow test, χ^2 = 2.321, P = 0.970), as shown in **Figure 6**.

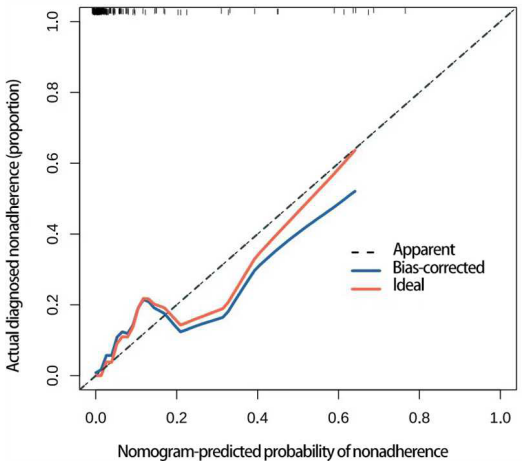

Figure 6. Calibration curve of frailty risk prediction model for the elderly in the community validation set

3.5.3. Clinical effectiveness evaluation of the model in the validation set

DCA curves for the validation set are positioned above the extreme thresholds of "no clinical intervention for any patients" and "clinical intervention for all patients," suggesting high clinical utility and net benefit, as detailed in **Figure 7**. The Brier Score of 0.034 in internal validation indicates the model's strong predictive accuracy.

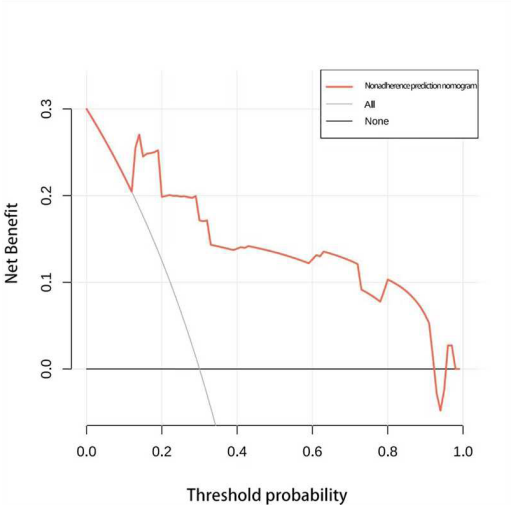

Figure 7. ROC curve for the frailty risk prediction model in the community elderly validation set

4. Discussion

Currently, China is gradually entering a stage of deep population aging, with the issue of aging becoming increasingly severe. As the proportion of the elderly population continues to rise, effectively improving the quality of health and elderly care services has become an urgent societal issue to address.

The ultimate goal of this research is to provide scientific evidence for improving and refining health and elderly care services through early prediction of frailty risks, thereby laying the foundation for preventing

adverse clinical events in the elderly. The first part of the study has completed the construction of the frailty risk prediction model, and further data collection is needed to complete model validation.

4.1. The clinical significance of building a frailty risk prediction model

4.1.1. The importance of constructing a frailty risk prediction model

Appropriate interventions may improve frailty status; however, interventions implemented in community-dwelling older adults have generally shown limited effectiveness. Many older adults are reluctant to be labeled as "frail," and even if they have been identified as such, they still strive to appear healthy [19]. Some intervention studies targeting frailty have demonstrated that timely intervention and management can reduce the risk of frailty. This suggests that taking preventive measures in the early stages before frailty develops is crucial [20]. Therefore, one of the key strategies to address frailty is to identify high-risk but non-frail older adults and implement preventive interventions for them [21].

4.2. Analysis of the incidence of frailty in community-dwelling elderly

This study assessed the prevalence of frailty in the study population using the Fried Frailty Phenotype, with the frailty prevalence in the modeled community-dwelling elderly population being 7.4%. As seen in Table 1.1, a considerable proportion of the population is in the pre-frail stage. Although these individuals have not yet entered the frailty state, they are already exhibiting some early symptoms of frailty, indicating a decline in their health status that warrants close attention.

A comparison of frailty prevalence among elderly individuals across different economic regions in China and studies using various assessment tools shows that a 2019 systematic review by Han *et al.*, involving community-dwelling elderly from five regions—Beijing, Hong Kong, Jinan, Langfang, and Taiwan—reported an average frailty prevalence of 10% in China's community elderly population [22]. In 2023, Zhou *et al.* expanded the regions included in their study to 23 provinces, and a meta-analysis indicated that the overall frailty prevalence among Chinese community residents was 10.1% [23]. The frailty incidence in this study is lower than in the above studies; however, another cross-sectional study conducted in Shanghai reported a frailty prevalence of 8.0% among community-dwelling elderly [24].

Currently, there is no gold standard for measuring frailty, and most studies use the Fried Frailty Phenotype and Frailty Index (FI) to assess frailty [25]. Different frailty assessment tools may also lead to variations in frailty incidence. The frailty prevalence derived from the Fried Frailty Phenotype tends to be lower compared to other multidimensional frailty assessment tools [26]. A meta-analysis of the multidimensional frailty screening tool Tilburg Frailty Indicator (TFI) showed that the frailty incidence assessed using TFI was 41% [27].

4.3. Selection of modeling elements for community frailty risk prediction model

4.3.1. Sleep duration

4.3.1.1. Shortened sleep duration as an important risk factor for frailty

Previous studies have shown that short sleep duration and poor sleep quality are significant risk factors for developing frailty. Frailty, characterized as a state of age-related decline in physiological reserve and increased vulnerability, often progresses alongside deteriorating sleep quality, potentially leading to various adverse health outcomes [28]. Sleep problems are a multidimensional concept, including aspects such as poor sleep quality, daytime sleepiness, short sleep duration, and insomnia symptoms [29]. The Pittsburgh Sleep Quality Index (PSQI)

is commonly used to quantify sleep quality in older adults. A cross-sectional study involving 392 older adults over the age of 65 found that participants reporting poor subjective sleep quality were more likely to exhibit symptoms of frailty [30], emphasizing the direct link between sleep quality and frailty.

This study utilized validated sleep monitoring tools to examine the impact of sleep duration on frailty. The analysis indicated that extended sleep duration (OR = 0.292) was associated with a reduced risk of frailty, highlighting the importance of adequate sleep in preventing frailty and suggesting that optimizing sleep patterns may be an effective approach to reducing frailty risk.

4.3.2. Malnutrition

4.3.2.1. Malnutrition as a risk factor for frailty in the elderly community

Malnutrition includes both overnutrition and undernutrition, but in the elderly population, it predominantly refers to undernutrition. Approximately one-quarter of individuals over 65 are at risk of malnutrition [31]. Malnutrition can be classified into three categories based on its causes: malnutrition due to inflammatory diseases, malnutrition due to non-inflammatory diseases, and malnutrition due to non-disease factors [32].

This study used the MNA to assess the nutritional status of elderly community residents. Results showed that 396 (94.3%) of the elderly were classified as having good nutritional status, while 24 (5.7%) were at risk of malnutrition. Although most elderly individuals in the community have good nutritional status, a small portion face undernutrition, which requires further attention and intervention.

Univariate analysis revealed a higher proportion of frailty among older adults at risk of malnutrition. Specifically, 9 (29.03%) of those at risk exhibited frailty, compared to only 22 (5.67%) of those with good nutritional status. This statistically significant difference ($P < 0.001$) demonstrates a clear association between nutritional status and frailty, with findings consistent with previous research.

4.3.3. Fatigue

4.3.3.1. The close relationship between fatigue and frailty in chronic diseases among the elderly

Frailty, a state of gradual physical function decline, is characterized by core features such as fatigue, reduced grip strength, unintentional weight loss, and decreased physical activity [10]. Fatigue, described as extreme tiredness or drowsiness from insufficient sleep, prolonged labor, or stress, may signal age-related depletion of physiological reserves, posing risks for adverse health outcomes [33]. Although not yet considered a specific disease of old age, fatigue's strong association with chronic diseases in the elderly has garnered increased attention.

4.3.3.2. Fatigue as an independent risk factor for frailty

This study further confirmed that increased fatigue is an independent risk factor for frailty onset, with a weight of 16%, aligning with findings from most prior studies. A longitudinal aging study in Finland, spanning nine years, demonstrated that fatigue could be observed as an early marker of frailty, up to nine years before frailty manifests [34]. This finding underscores the critical role of fatigue in frailty onset and progression.

4.3.4. Sarcopenia and grip strength

4.3.4.1. Sarcopenia and decreased grip strength as risk factors for frailty in community-dwelling older adults

Grip strength, a key indicator of muscle strength, reflects changes in overall muscle strength. A cross-sectional

study found that decreased grip strength is a significant predictor of sarcopenia in older adults, with lower grip strength correlating with higher sarcopenia incidence [35]. Another study linked reduced grip strength with physical activity, balance ability, and cognitive function, making it an important indicator for assessing the health of this population [36]. These findings suggest that declining grip strength may serve as an early warning sign of muscle weakness and muscle mass reduction in older adults, which is crucial for the timely detection and management of sarcopenia.

This study found that decreased grip strength and positive screening for sarcopenia were independent risk factors for frailty in community-dwelling older adults. Data from **Tables 3** and **4** show that 29.8% of older adults had decreased grip strength, indicating that reduced grip strength is relatively common in this group. Additionally, the proportion of positive sarcopenia screenings was 8.1%, which, though relatively low, still requires attention.

4.3.5. Social support

4.3.5.1. Social support is closely related to the health of the elderly

Social support is a complex, multidimensional concept that includes various forms of support individuals gain through relationships with others, encompassing emotional support, informational support, practical assistance, and social belonging. These elements, forming the Social Support Scale, highlight the importance of subjective support [37]. Research indicates that increased social support significantly reduces mortality rates among the elderly [38], demonstrating its critical role in maintaining their health.

4.3.5.2. Frail elderly in the community require more social support

This study found a negative correlation between the level of social support and frailty occurrence, differing from prior research conclusions. Frail older adults reported higher levels of social support in the questionnaire, possibly reflecting the increased support needs among frail individuals, who may require assistance from family, the community, and social institutions to cope with frailty. By contrast, those with active social lives might report a smaller discrepancy between subjective expectations and reality, resulting in lower questionnaire scores. For example, an elderly person with an SSRS score of 20 might need more social support than one with a score of 10. The SSRS score could represent the gap between actual support received and the objective circumstances of frail individuals.

In conclusion, social support plays a vital role in preventing and managing frailty from a multidimensional perspective, encompassing family care, community programs such as elder education, and multidisciplinary medical teams involving general practitioners, nurses, and rehabilitation therapists to provide comprehensive, multi-level support [39].

4.4. The application and discussion of line graphs in medical research

4.4.1. Definition and uses of a nomogram

Based on the previously constructed frailty risk prediction model for community-dwelling elderly individuals, a nomogram was developed. This nomogram assigns scores to six variables—SSRS, sleep duration, fatigue, grip strength, MNA, and SARC-F—to visually reflect the significance of each variable in determining frailty risk. In practical clinical use, healthcare professionals can determine the score for each variable based on the patient's actual condition, sum these scores, and then calculate the total. This total score corresponds to a probability

value for frailty, thus providing an estimate of the patient's frailty risk.

4.4.2. Analysis of the variables in the nomogram for this study

The nomogram results in this study highlight six major variables: SSRS, sleep duration, fatigue, grip strength, MNA, and SARC-F. Each variable is assigned a score based on its levels, and these scores collectively determine the total score, which corresponds to a specific probability of frailty.

By summing the scores from various health variables in the nomogram, a total score is obtained, which summarizes an individual's health status across multiple dimensions. This total score is directly proportional to frailty risk; the higher the total score, the greater the frailty risk. In the lower score range (below 100 points), the probability of frailty remains relatively low, while in the higher score range (above 150 points), the probability of frailty increases significantly.

4.4.3. Visual presentation of multivariable analysis using the nomogram

The study further validated the constructed frailty risk prediction model by collecting health check-up data from elderly individuals in the same community over different time periods. During validation, the model's discrimination, calibration, and effectiveness in clinical settings were comprehensively analyzed. Results showed that the frailty risk prediction model performed well across key metrics, exhibiting high discrimination, good calibration, and strong clinical applicability. These validation results affirm the model's reliability and practical value, establishing a foundation for its potential widespread application.

Applying this model in community healthcare practice enables early identification of elderly individuals at risk of frailty, providing a scientific basis for enhancing elderly health care. Early intervention can help lower the probability of frailty in elderly individuals, prevent adverse clinical events, improve quality of life, and reduce the healthcare burden on families and society.

4.5. Evaluation of internal consistency and clinical performance of a frailty risk prediction model for community-dwelling elderly

The model constructed in this study, after internal validation correction, achieved a C-statistic of 0.939 (95% CI: 0.890–0.990) in the validation set, a Brier score of 0.034, and the calibration curve demonstrates that the model's predicted frailty occurrence aligns with actual frailty incidence. With a specificity of 0.876, a Youden's index of 0.785, and an accuracy of 0.878, the model exhibits strong clinical effectiveness as reflected in the DCA curve, which remains above the two extreme threshold curves.

Overall, the frailty risk prediction model for the community-dwelling elderly developed in this study shows strong internal consistency and clinical performance. It can effectively differentiate between high- and low-risk elderly individuals for frailty and offers valuable decision-support information for clinicians.

5. Conclusion

(1) Frailty in community elderly is affected by six factors: The prevalence of frailty among elderly individuals aged 60 and above in Shanghai communities is 7.4%. Independent risk factors for frailty include short sleep duration, malnutrition, fatigue, sarcopenia, and decreased grip strength, while extended sleep duration serves as a protective factor. Frail elderly individuals especially require

adequate social support.

(2) The frailty risk prediction model constructed in this study shows good discrimination, calibration, and clinical utility for preliminary frailty risk assessment: The risk prediction model developed for frailty is defined as Logit = 0.336 × SSRS - 1.230 × Sleep Time + 2.793 × Fatigue + 3.396 × Grip Strength + 2.827 × MNA + 3.026 × SARC-F. This model has been validated for discriminative ability, calibration, and clinical utility, providing a personalized frailty risk assessment in community settings. Early targeted interventions based on this model hold significant value in preventing frailty.

6. Limitations

The study scope is limited to Shanghai, China, with samples drawn from a single community, thus requiring further research with larger samples and multicenter studies to assess the model's applicability in other regions or countries. Since model data is sourced exclusively from community residents' health check-ups, it is currently suitable only for preliminary frailty assessment of community residents in Shanghai.

Disclosure statement

The authors declare no conflict of interest.

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