■ TRAUMA

Development and validation of a trauma frailty scale in severely injured patients: the Nottingham Trauma Frailty Index

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Aims

Frailty greatly increases the risk of adverse outcome of trauma in older people. Frailty detection tools appear to be unsuitable for use in traumatically injured older patients. We therefore aimed to develop a method for detecting frailty in older people sustaining trauma using routinely collected clinical data.

Methods

We analyzed prospectively collected registry data from 2,108 patients aged ≥ 65 years who were admitted to a single major trauma centre over five years (1 October 2015 to 31 July 2020). We divided the sample equally into two, creating derivation and validation samples. In the derivation sample, we performed univariate analyses followed by multivariate regression, starting with 27 clinical variables in the registry to predict Clinical Frailty Scale (CFS; range 1 to 9) scores. Bland-Altman analyses were performed in the validation cohort to evaluate any biases between the Nottingham Trauma Frailty Index (NTFI) and the CFS.

Results

In the derivation cohort, five of the 27 variables were strongly predictive of the CFS (regression coefficient B = 6.383 (95% confidence interval 5.03 to 7.74), p < 0.001): age, Abbreviated Mental Test score, admission haemoglobin concentration (g/l), pre-admission mobility (needs assistance or not), and mechanism of injury (falls from standing height). In the validation cohort, there was strong agreement between the NTFI and the CFS (mean difference 0.02) with no apparent systematic bias.

Conclusion

We have developed a clinically applicable tool using easily and routinely measured physiological and functional parameters, which clinicians and researchers can use to guide patient care and to stratify the analysis of quality improvement and research projects.

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Introduction

Older people are at high risk of poor outcomes after major trauma due to both comorbidity and frailty. Frailty is the age-associated loss of resilience to challenge, due to multiple organ and system deficits. Frailty is an independent predictor of many adverse outcomes in trauma in older people, including in-hospital complications, length of stay, unfavourable discharge destination, and death.[1]

Many frailty detection tools are unsuitable for use in acute settings such as trauma. Tools based upon the Fried frailty phenotype require variables that are unavailable, such as a pre-injury gait speed,[2] and others using the Rockwood cumulative deficit[3] or hybrid approaches[4] require historical information about previous medical history of functioning that also might not be immediately or reliably available in the acute setting.

There are a range of prognostic tools for measuring outcomes in the hip fracture population, most notably work from our unit on the Nottingham Hip Fracture Score (NHFS).[5] The NHFS predicts death and length of stay in hip fracture and other

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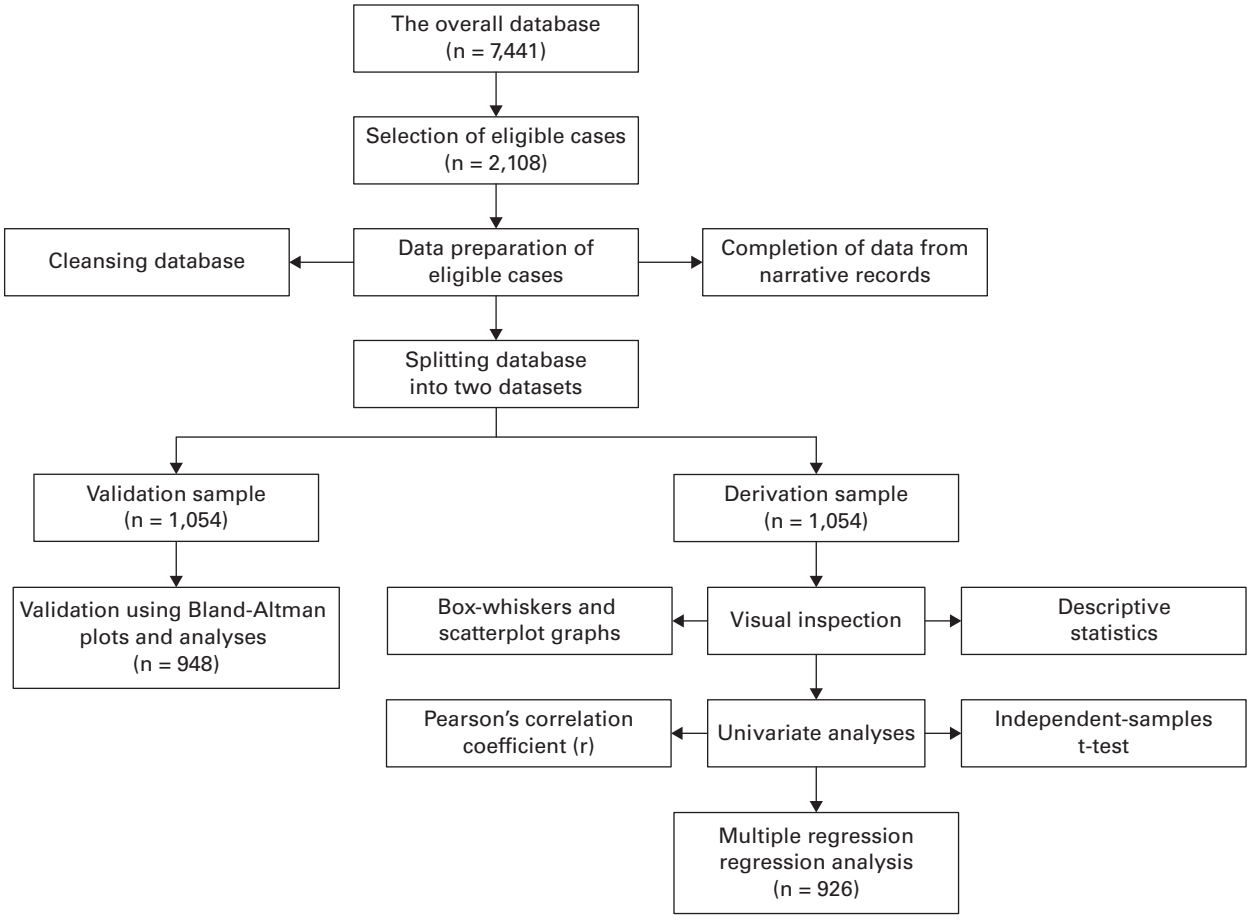

Fig. 1

Flowchart illustrating the overall procedure for participants.

fragility fracture patients.[6–8] However, measures of frailty are increasingly being used to guide management in populations with a high prevalence of frailty (such as in the National Hip Fracture Database[9] and in response to UK policy),[10] as they are better at taking account of the increased vulnerability due to multisystem deficits that characterizes the frailty state than other tools. The Clinical Frailty Scale (CFS)[11] is one of the most commonly used frailty tools in acute settings, with a score ranging from 1 to 9, and it has been shown to predict a range of outcomes in hip fracture and other trauma patients. The application of CFS requires staff to be uniformly trained in its use because it involves subjective judgement, otherwise its accuracy may be compromised when used by untrained personnel or different staff.[12] However, we have previously demonstrated that CFS in measuring frailty can provide useful predictive information for fitter patients, with a plateau in higher frailty hip fracture and potential difficulties in clinicians distinguishing between higher frailty grades in the acute setting.[13]

One potential way to improve the diagnosis and measurement of frailty in acute trauma in clinical practice is to use routinely collected clinical variables, as this would negate the need to train staff, reduce subjectivity, and would be likely to increase the proportion of patients with a frailty assessment. Researchers too could use such an approach to define patients with frailty in clinical datasets where there is no formal frailty measurement. We therefore set out to develop an easy-to-administer, reliable, and valid objective tool to measure frailty in the older trauma patient, as distinct from a prognostic score such as the NHFS.

In this study, we aimed to identify routinely collected variables that are predictive of frailty and, based upon these, develop a frailty scale suitable for use in older patients with traumatic injury.

Methods

We analyzed prospectively collected registry data from 2,108 patients admitted to a single major trauma centre over five years. We divided the sample equally into two, creating derivation and validation samples. In the derivation sample, we performed univariate screening followed by multivariate regression analyses using clinical variables to predict our gold standard, the CFS. From this, we created a model to calculate the Nottingham Trauma Frailty Index (NTFI). To assess for systematic measurement biases, we used Bland-Altman analyses in the validation cohort, comparing the NTFI and the CFS.

The Hospital Audit Committee approved this study (approval number 21-040 C). We report our results in accordance with the

Table I. Candidate variables grouped by class.

Demographics	Mental health variables	Chronic diseases	Biological variables	Physical state
Age	Abbreviated Mental Test	Diabetes	Glomerular filtration rate	Residential home resident
Sex	Alzheimer's disease	Atrial fibrillation	Platelet count	Living alone
Mechanism of injury	Dementia	Hypertension	Lactate level	Nursing home resident
Alcohol excess		Osteoporosis	White cell count	Pre-admission mobility
Visual acuity		Malignancy	Haemoglobin level	
			Creatinine level	
			Urea level	
			Sodium level	
			Potassium level	
			Calcium level	

Table II. Characteristics of patients in the derivation and validation groups.

Characteristic	Derivation group	Validation group
Cases, n	1,054	1,054
Mean age, yrs (range)	83.58 (65 to 105)	83.60 (65 to 105)
Mean CFS (SD)	4.56 (1.671)	4.56 (1.686)
Median AMT (IQR)	8 (5 to 10)	8 (4 to 10)
Median haemoglobin, g/l (IQR)	123 (111 to 134)	122 (112 to 133)
Median urea, mmol/l (IQR)	7.1 (5.5 to 9.2)	6.8 (5.6 to 8.9)
Pre-admission mobility assistance, n (%)	665 (63.1)	673 (60.4)
MOI: fall from standing height, n (%)	988 (93.7)	990 (93.9)
Female sex, n (%)	746 (70.8)	743 (70.5)
Atrial fibrillation, n (%)	194 (18.4)	234 (22.2)
Dementia, n (%)	290 (27.5)	286 (27.1)
Residential home resident, n (%)	180 (17.1)	200 (19)
Nursing home resident, n (%)	100 (9.5)	109 (10.3)
Malignancy, n (%)	207 (19.6)	196 (18.6)
Median glomerular filtration rate, ml/min (IQR)	71 (32.3)	71 (54 to 85)

AMT, Abbreviated Mental Test; CFS, clinical frailty scale; IQR, interquartile range; MOI, mechanism of injury; SD, standard deviation.

Table III. Pearson correlation results for eligible continuous variables. Dependent variable: Clinical Frailty Scale.

Independent variables	Pearson correlation (95% CI)	Relationship*	p-value
Age, yrs	0.35 (0.30 to 0.40)	Moderate positive	< 0.001
Urea, mmol/L	0.11 (0.04 to 0.17)	Weak positive	< 0.001
Haemoglobin, g/l	-0.25 (-0.31 to -0.19)	Moderate negative	< 0.001
GFR, ml/min	-0.21 (-0.27 to -0.15)	Moderate negative	< 0.001
AMT (0 to 10)	-0.59 (-0.62 to -0.54)	Strong negative	< 0.001

*Weak: 0.01 to ≤ 0.20; moderate: > 0.20 to 0.50; strong: > 0.50.
AMT, Abbreviated Mental Test; GFR, glomerular filtration rate.

Transparent Reporting of a multivariable Prediction model for Individual Prognosis or Diagnosis.[14]

Source of data. The study used an anonymized data extract that included 7,441 trauma patients sequentially admitted to a level 1 trauma centre between 1 October 2015 and 31 July 2020. The data were extracted from the Nottingham Trauma Registry, which has been previously described and combined data from three routinely collected clinical patient groups: fragility fractures, hip fractures, and adult trauma. There were 7,441 adult fractures; 6,002 were fragility fractures, of which 3,801 were hip fractures. We included all datasets available locally to ensure the predictive score was generalizable to the whole available older population. While each dataset is heterogeneous, combining and linking the data yields the whole older population for our centre presenting with a fragility fracture.

Participants. We selected records used for this study from all those in the registry for the study period using the following eligibility criteria: age 65 years and above; presenting with a traumatic fracture requiring hospital admission; and a CFS completed on admission.

Outcome. We aimed to predict frailty as measured by the CFS score,[11] recorded on admission in clinical records by clinical staff and subsequently coded by audit staff, all of whom were unaware of this study. This score has nine distinct values, ranging from 1 (robust) to 9 (moribund).

Predictors. We screened all available and feasible variables from the dataset for inclusion in the model. Of the 47 available variables, candidate predictors were 27 variables recorded on admission by clinicians and coded by audit staff, as shown in Table I.

Sample size. Different authors advise that multivariate analyses require at least ten to 20 cases per independent variable, and others advise a sample of at least > 500 cases.[15] In predictive modelling, however, larger sample sizes result in the development of more robust models, reduce the risk of overfitting, and enhance the precision and accuracy of predictions.[16] In our dataset, 2,108/7,441 patients fulfilled our inclusion criteria and had complete data, giving us 1,054 patients in each cohort, which we deemed sufficient for our purposes.

Missing data. Our analyses used complete cases only, because of the many biases introduced by imputation of missing data,[17,18] and because we had a sample size that made it unnecessary. We assumed that data in this clinical registry would be missing at random and hence a complete case analysis would not introduce systematic bias.[19]

Statistical analysis. We cleaned the dataset before we conducted any analyses, by identifying and repairing erroneous data such as outliers, duplicates, and where words rather than figures had been entered.[20] We then randomly divided the dataset equally into derivation and validation groups.

In the derivation sample, we initially examined the relationship between the CFS and the candidate variables by visually

Table IV. Independent-samples *t*-test results for eligible categorical variables. Dependent variable: Clinical Frailty Scale.

Variable	Mean (SD)		Independent-samples *t*-test	Cohen's d	p-value
	Yes	No			
Female sex	4.69 (1.65)	4.25 (1.69)	3.91	0.27	< 0.001
Atrial fibrillation	4.89 (1.53)	4.49 (1.70)	-3.02	-0.24	0.003
Dementia	5.90 (1.51)	4.05 (1.51)	-18.49	-1.28	< 0.001
Malignancy	4.79 (1.53)	4.50 (1.70)	-2.23	-0.17	0.026
Residential home resident	6.14 (1.20)	4.24 (1.57)	-15.39	-1.26	< 0.001
Nursing home resident	6.15 (1.23)	4.39 (1.62)	-10.50	-1.10	< 0.001
Falls from standing height	4.63 (1.64)	3.54 (1.82)	-4.69	-0.66	< 0.001
Pre-admission mobility assistance	4.94 (1.49)	3.51 (1.70)	-13.12	-0.92	< 0.001

SD, standard deviation.

Table V. Multiple linear regression to demonstrate relationship between Clinical Frailty Scale and significant patient characteristics.

Model	Unstandardized coefficient, B (SE; 95% CI)	Standardized coefficient, β	t	Collinearity statistics		p-value
				Tolerance	VIF	
Constant	6.383 (0.69; 5.03 to 7.74)		9.23			< 0.001
AMT	-0.234 (0.01; -0.26 to -0.21)	-0.50	-20.42	0.919	1.088	< 0.001
Hb	-0.011 (0.00; -0.02 to -0.01)	-0.12	-4.92	0.953	1.050	< 0.001
Age	0.021 (0.01; 0.01 to 0.03)	0.10	4.06	0.885	1.130	< 0.001
MOI	0.445 (0.20; 0.05 to 0.85)	0.05	2.19	0.991	1.009	0.029
Pre-admission mobility	-1.100 (0.09; -1.27 to -0.93)	-0.31	-12.64	0.927	1.079	< 0.001

Dependent variable: Clinical Frailty Scale.
AMT, Abbreviated Mental Test; CI, confidence interval; Hb, haemoglobin; MOI, mechanism of injury; SE, standard error; VIF, variable inflation factor.

examining the data using bar charts, and box and scatter plots. We excluded variables showing no obvious relationship to the CFS from further analysis. We conducted univariate analyses on remaining variables to screen for eligibility. As the CFS was normally distributed (Supplementary Figure a), continuous variables were analyzed using Pearson's correlation coefficient (r), and categorical (binary) variables using the independent-samples *t*-test. Multiple linear regression analysis was then conducted and included candidate variables with a significant ($p < 0.05$) univariate association with the CFS, and a good correlation ($r > 0.2$) for continuous variables or a good effect (Cohen's $d > 0.2$) for binary variables.

We used the results of the multiple regression analysis to derive an equation to compute the NTFI, and performed verification tests for homoscedasticity and multicollinearity. We examined homoscedasticity (to determine if the variance of the residual, or error term in a regression model is constant) using a scatter plot of the predicted values and residuals. We looked for multi-collinearity by analyzing variable inflation factors (VIFs) in the results of collinearity statistics.

We subsequently tested the regression model derived from the derivation cohort in the validation cohort, by comparing scores generated by the multiple regression model (the NTFI) with the CFS scores using Bland-Altman plots and analyses.[21] We initially tested the normality of the difference between the NTFI and the CFS by histogram (Gaussian), then performed an independent-samples *t*-test to determine whether there was a statistically significant difference between zero and the mean difference between the two instruments. We then created scatter plots where the x-axis represented the mean of the two measures and the y-axis represented the difference between the two paired measures.[21] We analyzed the data using SPSS Statistics v. 28 (IBM, USA).

Results

There were 7,441 records in the register over the study period, of which 2,108 (1,054 in both the derivation and validation groups) were selected for this study using the inclusion criteria (Figure 1). In the derivation and validation samples, 926 and 948 complete records were available for regression analysis, respectively.

Univariate analysis. Following visual inspection of distributions, 14/27 variables (alcohol excess, osteoporosis, Alzheimer's disease, potassium level, platelet count, visual acuity, hypertension, diabetes, living alone, sodium, creatinine, calcium, lactate, and white cell count) had no apparent relationship with CFS and were not analyzed. Univariate analyses were conducted on the remaining 13 variables (age, sex, pre-admission mobility, mechanism of injury, urea (U), abbreviated mental test (AMT), haemoglobin (Hb), glomerular filtration rate (GFR), atrial fibrillation, dementia, residential care home resident, nursing home resident, malignancy) that were eligible (Tables II to IV). All 13 variables demonstrated a significant relationship with the CFS and were put forward to the multiple regression analysis, with the exception of urea ($r = 0.1$) and malignancy ($d = -0.17$) due to the low strength of correlation with CFS.

Multiple regression analysis. Five of the 11 variables included in the multiple regression analysis (age, mechanism of injury, haemoglobin, AMT, and pre-admission mobility) remained significantly associated with CFS scores (Table V), but six (sex, atrial fibrillation, dementia, care home resident, nursing home resident, and GFR) were non-significant (Figure 2).

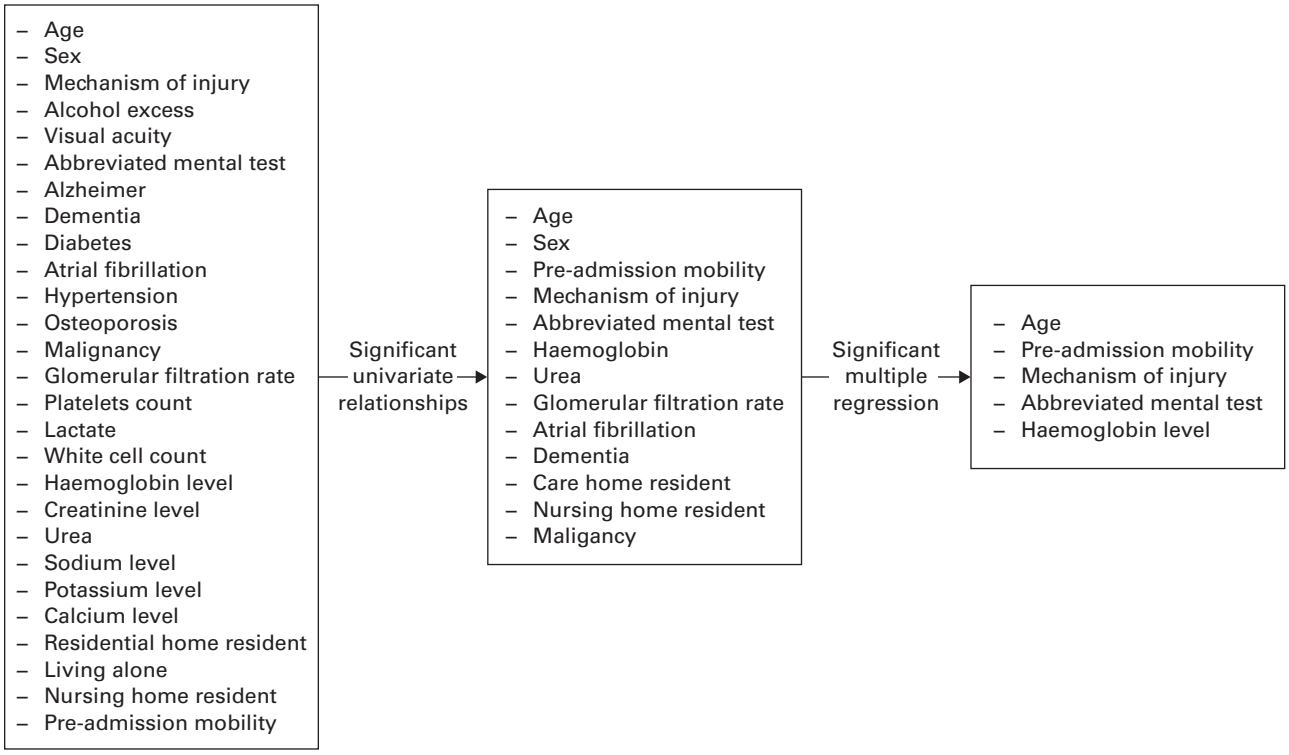

Fig. 2

Variables selection processes.

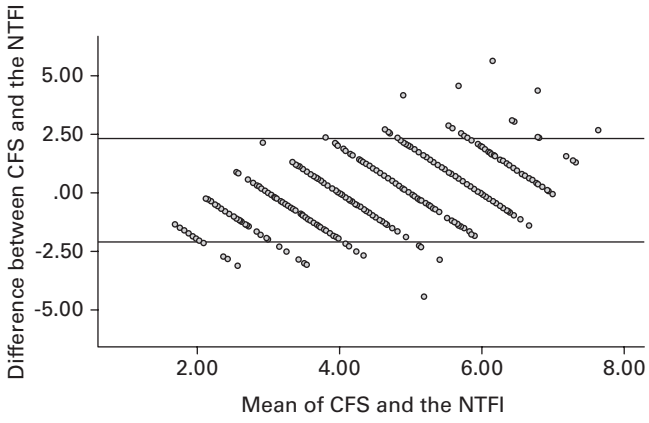

Fig. 3

Bland-Altman plot. CFS, Clinical Frailty Scale; NTFI, Nottingham Trauma Fracture Index.

NTFI specification. The significant regression equation ($F(5,920) = 176.74$; $p < 0.001$; $\beta = 6.383$ (95% CI 5.028 to 7.740); $p < 0.001$, $R^2 = 0.49$) was used to generate a predicted frailty score (the NTFI) using the following equation:

NTFI = 6.383 + 0.021 (age) − 1.100 (pre-admission mobility) + 0.445 (MOI) − 0.234 (AMT) – 0.011 (haemoglobin)

where pre-admission mobility is coded as 1 = requires mobility aid(s) and 2 = freely mobile without aids; MOI is coded as 1 = other MOI and 2 = falls from standing height; AMT is the ten-point Abbreviated Mental Test score; and haemoglobin is measured in g/l. The NTFI can be treated in a similar way to the CFS; while the values are continuous, the same bounds range from 1 (robust) to 9 (moribund).

Verification. The standardized residuals from the multiple regression were calculated and displayed using Q-Q plots, which indicated homoscedasticity and the normal distribution of standardized results: the scatter plot assumed (approximately) rectangular shape, with scores clustered in the centre (around 0) and dispersed in a rectangular pattern (Supplementary Figure b). Multicollinearity was not present, as indicated by the collinearity statistics columns of Table V.

Bland-Altman analysis. The NTFI was validated in the validation cohort. The histogram graph showed that the difference between the NTFI and CFS was normally distributed (Gaussian), as illustrated in Supplementary Figure c). There was no significant difference between the measurements and zero ($t(947) = 0.51$; $p = 0.612$, independent-samples *t*-test). Figure 3 shows a Bland-Altman plot, including the 95% CIs, illustrating the high level of agreement between the NTFI and the CFS (mean difference 0.02 (SD 1.14)).

Discussion

We have developed a novel score to predict frailty in major trauma patients using five variables from routinely collected data (age, mechanism of injury, haemoglobin level, AMT score, and pre-admission mobility) and shown that it can accurately replicate the CFS.

A strength of this study is that we used data collected by clinicians rather than research tools collected by staff, which means that our results are likely to be applicable in routine clinical practice. The large sample size increases reliability, and we did not need to use imputation, which reduced the risk of bias. Testing the generated model in a large different dataset from the one we used to derive it reduced the risk of over-fit. However, we could only examine routinely collected variables in this particular dataset: it is possible that there are other routinely collected data items that could improve upon our model. Another limitation is that the derivation and validation samples were collected in the same centre: it is possible that the model could perform less well in a dataset from a different hospital. This study has not tested the predictive value of the NTFI against frailty outcomes following trauma.

We believe we are the first to develop a frailty index for patients with trauma using routinely collected clinical data. Age, cognitive function, and mobility are commonly used in frailty assessment,[2,11,22–29] but the haemoglobin level and mechanism of injury are novel indicators of frailty. Mechanism of injury (falling from a standing height) is likely to reflect frailty in this trauma population because robust people usually require stronger forces to produce injury: bony injuries caused by a fall from a standing height are often referred to as fragility fractures and to indicate osteoporosis, which often accompanies frailty.[30,31] It is clearly acting here as a trauma-specific frailty variable, confirming a frailty role in the widely known association between ground-level falls and poor outcomes in older trauma patients.[32–34] Haemoglobin level is also likely to be trauma-specific because it reflects not only generic frailty deficits, such as the degree of pre-morbid anaemia and malnutrition, but also the blood loss from injury. Haemoglobin has previously been found to be predictive of outcome in trauma, and is included in the NHFS.[5] Because of these two trauma-specific items, the NTFI is a trauma-specific score and would not be expected to predict the presence of frailty in non-trauma populations.

The NTFI can be used to identify frailty in trauma patients using routinely collected clinical data, without the need to train staff in the use of a specific frailty tool (Supplementary Material 4). This could be useful in clinical services where there are large numbers of frequently changing staff, in whom training in the reliable use of frailty tools is difficult. This is an important addition to the range of assessment tools available, as assessment of frailty has been identified as an important component of managing the older trauma population[35] and part of policy.[36] Our new frailty index (NTFI) overlaps with the Nottingham Hip Fracture Score used for the prediction of outcomes such as survival, because they have two common items (haemoglobin level and age), which presumably are related both to frailty and survival. But the NTFI includes measures of musculoskeletal performance and independence in ADLs (pre-admission mobility), cognitive function (AMT), and the fact that an injury was sustained after low-velocity trauma (fall from standing height): these factors are more closely related to the frailty concept and hence may best guide management that depends upon the frailty state of the patient and better predict frailty outcomes. The integration of NHFS and NTFI in older trauma patients with hip fractures could assist clinicians in predicting potential outcomes and addressing frailty. Future research may investigate the interplay between these two tools.

NTFI scores could be used not only to guide patient management, but also to stratify patients in quality improvement projects. The NTFI could also be used in existing clinical and research datasets where frailty has not been measured, to explore the impact of frailty. An important implication is that NTFI would quickly enable clinicians to stratify frailty risk, thereby reducing intervention and waiting times, and facilitating the triage of severely injured frail patients. Further work could aim to automate the calculation of the NTFI score from electronic patient records so as to provide a frailty assessment in real time. Further research is also required to examine its performance in other datasets, including whether it is predictive of frailty outcomes such as the complication rate, length of stay, need for long-term care, and survival.

Take home message

- We developed a novel automated tool that can accurately and efficiently assess frailty in trauma settings.
- The use of the Nottingham Trauma Frailty Index has the capacity to modify the decision-making process in trauma treatment by offering clinicians a rapid and unbiased assessment of frailty.
- This assessment may then be used to tailor therapies to individual patients, ultimately leading to improved outcomes.

Social media

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Supplementary material

Supplementary graphs for Nottingham Trauma Frailty Index (NTFI) construction and validation, and the NTFI calculator.

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