A comparison of two national frailty scoring systems

Key Points

- Frailty is an important determinant of outcomes for older people
- It is now possible to measure frailty systematically in both primary care and secondary care, using electronic records (eFI in primary care, HFRS in secondary care)
- Whilst both the eFI and HFRS identify cohorts of older people at risk of adverse outcomes during and following an acute hospital admission, they identify different individuals
- The choice of which tool to use in secondary care will primarily be determined by feasibility of embedding the tool into secondary care systems

Keywords

- Frailty
- Risk stratification
- Electronic Health Records
- Primary care
- Secondary care

Abstract

Background

The electronic Frailty Index (eFI) has been developed in primary care settings. The Hospital Frailty Risk Score (HFRS) was derived using secondary care data.

Objective

Compare the two different tools for identifying frailty in older people admitted to hospital.

Design and setting

Retrospective cohort study using the Secure Anonymised Information Linkage Databank, comprising 126,600 people aged 65+ who were admitted as an emergency to hospital in Wales from January 2013 up until December 2017.

Methods

Pearson's correlation coefficient and weighted kappa were used to assess the correlation between the tools. Cox and logistic regression were used to estimate Hazard Ratios (HRs) and Odds Ratios (ORs). The Concordance statistic and Area Under the Receiver Operating Curves (AUROC) were estimated to determine discrimination.

Results

Pearson's correlation coefficient was 0.26 and the weighted kappa was 0.23. Comparing the highest to the least frail categories in the two scores the HRs for 90-day mortality, 90-day emergency readmission and care home admissions within 1-year using the HFRS were 1.41, 1.69, and 4.15 for the eFI 1.16, 1.63 and 1.47. Similarly, the ORs for inpatient death, length of stay greater than 10 days and readmission within 30-days were 1.44, 2.07 and 1.52 for the HFRS, and 1.21, 1.21 and 1.44 for the eFI. AUROC was determined as having no clinically relevant difference between the tools.

Conclusions

The eFI and HFRS have low correlation between their scores. The HRs and ORs were higher for the increasing frailty categories for both the HFRS and eFI.

Introduction

People aged 65+ are frequent users of urgent care (encompassing acute and emergency care), and have poor short, medium and longer term outcomes, which worsen with increasing degrees of frailty [1-4].

NHS policy [5] encourages early identification of frailty during an urgent care episode to inform prognosis, guide clinical decision making, and activate evidence based interventions such as Comprehensive Geriatric Assessment (CGA) [6]. The Clinical Frailty Scale has been validated in the urgent care context [7-9], and is quick simple and easy to use [10]; yet as with any manual scale, imposes an implementation burden, and reliability is often sub-optimal [11].

An alternative approach to manual scales is to take advantage of routine data and the growing use of Electronic Health Records (EHRs), to provide clinicians with automated frailty scores. The advantage of such an approach includes greater reliability, and potentially dynamic, real-time updates. There are only two systematic frailty score available for use in the NHS: the electronic Frailty Index (eFI - derived from primary care Read codes) [12, 13] and the Hospital Frailty Risk Score (HFRS - derived from secondary care International Classification of Disease version 10 (ICD-10) codes) [14]. If either (or both) of these could be implemented into EHRs, they could provide robust and reliable frailty measures available to guide clinical decision making 24 hours per day. However, the relationship between these two scales has not been studied, so it is unclear which scale, might best predict outcomes in the urgent care context.

Aside from influencing clinical care, advantages of a frailty identification tool in secondary care include:

- Informing service provision
- Linkage to Patient Reported Outcome Measures
- Informing commissioning and reimbursement decisions
- Research and quality improvement

This study aimed to compare and contrast the HFRS and the eFI in urgent care cohorts, and their ability to predict hospital-related outcomes.

Methods

Study design

We undertook a retrospective cohort study using routinely collected primary and secondary care data. Routinely Collected Data (RCD) are increasingly used for research. RCD collected under real-world circumstances maximises representativeness of the study

population and generalisability of findings, maximises resource efficiencies and allows the capture of information in large populations with continuously collected clinical events across long time periods [15].

Data sources

To construct both the HFRS and eFI, access was required to linked data containing primary and secondary care patient records. Our cohort was created using the Secure Anonymised Information Linkage (SAIL) Databank [16-18]. The SAIL Databank has a unique individual anonymised person identifier known as an Anonymous Linking Field (ALF) and unique address anonymised identifier known as a Residential Anonymous Linking Field (RALF) [18] that are used to link between data sources at individual and residential levels, respectively. Individual linking fields, nested within residences are both contained in the anonymised version of the Welsh Demographic Service Dataset (WDSD), replacing the identifiable names and addresses of people who are registered with an NHS General Practitioner service. The databank also contains the Welsh Longitudinal General Practice (WLGP) primary care dataset. We used the Emergency Department Data Set (EDDS) and the Patient Episode Database for Wales (PEDW) for details of events in emergency departments and emergency hospital admissions respectively. We used the Annual District Death Extract (ADDE) to determine deaths. We used the WDSD to check if individuals had moved out of Wales in the follow up period, and to confirm the date of death.

We created an index for anonymised care home addresses in the Welsh Demographic Service Dataset (WDSD). The WDSD contains details of address changes declared to the NHS for the population of Wales. We therefore determined the date of a care home move by anonymously observing changes in residence for everyone in our cohort into any of the residences indexed as a care home in the WDSD. An anonymised care home index was created by using the Care Inspectorate Wales (CIW) data source and assigning a Unique Property Reference Number (UPRN) to each address. The UPRN was double encrypted into a project level RALF and uploaded into SAIL to create a deterministic match to the WDSD.

Electronic Frailty Index

The eFI is based on the internationally established cumulative deficit model, and assigns a frailty score to an individual calculated using 36 variables from primary care data including symptoms, signs, diseases, disabilities and abnormal laboratory values, referred to as deficits [19]. The eFI score is the number of deficits present, expressed as an equally weighted proportion of the total. An individual with a single deficit would be assigned an eFI of 1/36 (0.03); another with nine deficits would be assigned an eFI of 9/36 (0.25). The eFI score is then used to categorise individuals as: fit (eFI value of 0-0.12), mild (>0.12 – 0.24), moderate (>0.24 – 0.36), or severely frail (>0.36) [12, 13].

Hospital Frailty Risk Score

The HFRS was developed using Hospital Episode Statistics (a database containing details of all admissions, A&E attendances and outpatient appointments at NHS hospitals in England), and validated on over one million older people (75+) using hospitals in 2014/15. The HFRS uses ICD-10 codes to search for specific conditions from secondary care. A weight is then applied to the conditions and a cumulative sum is used to determine a frailty risk of: Low, Intermediate or High [14].

Inclusion criteria

We included patients that met the following criteria:

- Individuals aged over 65 years at the time of hospital admission.
- Individuals having been admitted as an emergency to hospital from January 2013 up until December 2017. For those with more than one emergency admission a single admission was selected randomly.
- Individuals were registered with a general practice contributing data to SAIL at the time of admission.
- Individuals with a residential history in the WDSD.

The 'unit of analysis' was individual patients, with their service outcomes (e.g. readmissions) being those occurring after their 'index' emergency admission.

Sample size

We included patients admitted to hospital as an emergency from January 2013 to December 2017, for individuals who were admitted more than once a random admission was chosen. We used information from the previous 10 years to construct the eFI and two years prior to the emergency admission date for the HFRS. The index admission date data was omitted for the calculation of the HFRS to ensure only prior knowledge was used to determine the HFRS score. The sample sizes used were sufficiently large to detect even very small statistical differences in the predictive accuracy of the tools. Specifically, our *a priori* approach was that at a difference in the Area Under the Receiver Operator Curve (AUROC) of 0.05 would be considered the minimum clinically important difference.

Data analyses

To determine if the eFI and HFRS identify the same groups of individuals we calculated the continuous and categorical scores of both tools for each patient on the day before their index admission date. We then analysed the correlation of the continuous scores using Pearson's correlation coefficient, and the categorised scores using weighted kappa scores.

We used data from January 2013 to December 2017 to test and compare the predictive validity of the eFI and HFRS for the following hospital-related outcomes:

- Mortality: in-patient deaths, and deaths within 90 days of the emergency admission.
- Hospital resource use: extended length of stay (greater than 10 days), 30-day readmission rates, readmission within 90 days (censored for deaths).
- Care home admissions: for patients living in their own homes on admission, we measured admissions to a care home from hospital within 1-year of the index admission.

Cox regression models were used to predict Hazard Ratios (HRs) for 90-day time-to-event outcomes; mortality and emergency readmissions to hospital, and care home admissions within 1-year. Logistic regression models were used to predict binary outcomes (Inpatient mortality, length of stay greater than 10-days and readmission within 30-days). All models were adjusted for age and gender. Discrimination was assessed using the adjusted concordance statistic and Receiver Operating Characteristic (ROC) curves to estimate areas under the curve (AUC) for the Cox and logistic regression models respectively.

Results

The data included 126,600 individuals admitted to hospital as an emergency between January 2013 and December 2017. To identify new care home moves, people that were already resident in a care home were removed from the cohort for the care home analysis (N = 11,294 removed). The baseline characteristics for included participants are shown in Table 1.

Table 1 Baseline characteristics

	Emergency admissions	Not resident in a care home at time of admission
Cohort size, N	126,600	115,306
Mean age (SD)	79.3 (8.4)	78.7 (8.2)
Gender: Female (%)	53.1%	52.0%
eFI		
Fit	12.6%	13.4%
Mild	38.3%	39.5%
Moderate	34.0%	33.4%
Severe	15.2%	13.7%
HFRS		
Low	53.6%	56.9%
Intermediate	33.5%	32.4%
High	12.9%	10.6%
Welsh Index of Multiple Deprivation (WIMD) 2014*		
Least Deprived 1	19.7%	20.0%
2	18.3%	18.3%
3	20.9%	20.6%
4	21.5%	21.3%
Most deprived 5	19.7%	19.8%

* WIMD is the official measure of relative deprivation for small areas in Wales.

Overall the Pearson's correlation coefficient for the continuous measures was 0.26 (95% CI 0.252-0.262). Table 2 shows the agreement between the two categorised measures (using original categories); Table 3, with a combined eFI fit & mild category, matches the following groups from the eFI and HFRS: eFI fit and mild (combined) to low HFRS, eFI moderate to intermediate HFRS, and the eFI severe to high HFRS. Table 3 shows that, with a combined eFI 'Fit & Mild' category, the two marginal distributions are quite similar – both have just over half of cases in the lowest category and approximately an eighth in the highest category. Table 3 also indicates low agreement between the two measures – relatively large numbers of people are in the highest category for one measure but in the

lowest for the other. More formally, the weighted kappa scores for these categories was 0.23 (95% CI 0.22-0.24) – slight agreement.

Table 2 Two way cross-tabulation of eFI and HFRS categories – original categories.

		eFI				
		Fit	Mild	Moderate	Severe	Totals
HFRS	Low	11393 (9.0%)	29256 (23.1%)	20526 (16.2%)	6727 (5.3%)	67902 (53.6%)
	Intermediate	3757 (3.0%)	14855 (11.7%)	15953 (12.6%)	7846 (6.2%)	42411 (33.5%)
	High	780 (0.6%)	4343 (3.4%)	6516 (5.1%)	4648 (3.7%)	16287 (12.9%)
	Totals	15930 (12.6%)	48454 (38.3%)	42995 (34%)	19221 (15.2%)	126600 (100%)

Table 3 Two way cross-tabulation of eFI and HFRS categories, with combined eFI 'Fit & Mild'

		eFI			
		Fit & Mild	Moderate	Severe	Totals
HFRS	Low	40649 (32.1%)	20526 (16.2%)	6727 (5.3%)	67902 (53.6%)
	Intermediate	18612 (14.7%)	15953 (12.6%)	7846 (6.2%)	42411 (33.5%)
	High	5123 (4.0%)	6516 (5.1%)	4648 (3.7%)	16287 (12.9%)
	Totals	64384 (50.9%)	42995 (34%)	19221 (15.2%)	126600 (100%)

In addition, we categorised frailty into a composite binary measure, the non-frail category contained individuals who were defined as fit from the eFI and Low from the HFRS. The kappa coefficient for the binary frailty indicator was 0.085 (95% CI 0.082-0.089) – again slight agreement.

The Cox regression models in Table 4 show an increased HR for 90 day mortality, 90 day emergency readmission or 1-year care home admission, as the severity of frailty scores increases for both the HFRS and the eFI. Similarly, the Odds Ratios (ORs) for the logistic regression models were higher for increased frailty severity. The AUC for the models was slightly higher for the HFRS. However, the difference in AUC between the HFRS and eFI did not exceed the *a priori* minimum clinically important difference of 0.05 for any of the models.

Table 4. Cox Regression models for 90-day mortality, 90-day emergency readmissions to hospital, and care-home admissions within 1-year.

Outcome		90 day mortality HR (95% CI)	90 day emergency readmission HR (95% CI)	1-year care home admission HR (95% CI)
	Reference: Low			
HFRS	Intermediate	1.29 (1.26,1.32)	1.37 (1.33,1.41)	2.52 (2.38,2.66)
	High	1.41 (1.36,1.45)	1.69 (1.63,1.75)	4.15 (3.89,4.42)
	Age	1.03 (1.03,1.03)	1.00 (0.99,1.00)	1.09 (1.08,1.09)
	Male	1.29 (1.26,1.32)	1.15 (1.12,1.18)	0.82 (0.78,0.86)
Concordance		0.595 (SE 0.002)	0.555 (SE 0.002)	0.776 (SE 0.002)
	Reference: Fit			
eFI	Mild	1.00 (0.96,1.04)	1.15 (1.10,1.21)	1.07 (0.98,1.18)
	Moderate	1.08 (1.03,1.12)	1.38 (1.32,1.45)	1.22 (1.11,1.34)
	Severe	1.16 (1.10,1.21)	1.63 (1.55,1.72)	1.47 (1.33,1.63)
	Age	1.03 (1.03,1.03)	1.00 (1.00,1.00)	1.10 (1.10,1.10)
	Male	1.29 (1.26,1.32)	1.16 (1.13,1.19)	0.79 (0.76,0.83)
Concordance		0.588 (SE 0.002)	0.543 (SE 0.002)	0.737 (SE 0.003)
Concordance difference		0.007	0.012	0.039

Table 5 Adjusted Logistic Regression models for: inpatient deaths, long lengths of stay (greater than 10 days) and 30 day emergency readmission.

Outcome		Inpatient death OR (95% CI)	Length of Stay >10 days OR (95% CI)	30-day readmission OR (95% CI)
	Reference: Low			
HFRS	Intermediate	1.34 (1.29,1.38)	1.68 (1.63,1.72)	1.31 (1.25,1.37)
	High	1.44 (1.37,1.51)	2.07 (1.99,2.14)	1.52 (1.43,1.61)
	Age	1.04 (1.03,1.04)	1.03 (1.03,1.03)	0.99 (0.99,0.99)
	Male	1.24 (1.20,1.29)	0.94 (0.92,0.97)	1.15 (1.10,1.19)
AUC		0.615	0.636	0.548
	Reference: Fit			
eFI	Mild	1.04 (0.98,1.10)	1.04 (1.00,1.09)	1.11 (1.04,1.18)
	Moderate	1.12 (1.06,1.19)	1.14 (1.09,1.19)	1.28 (1.20,1.37)
	Severe	1.21 (1.13,1.29)	1.21 (1.15,1.27)	1.44 (1.34,1.55)
	Age	1.04 (1.04,1.04)	1.04 (1.04,1.04)	0.99 (0.99,1.00)
	Male	1.24 (1.20,1.28)	0.93 (0.91,0.96)	1.16 (1.11,1.20)
AUC		0.608	0.609	0.536
AUC difference HFRS vs eFI		0.007	0.027	0.012

Discussion

This is the first study to compare and contrast the eFI and HFRS. The eFI and HFRS identify different individuals within frailty strata (as shown by Tables 2-3) and the low/slight agreement between categories – this indicates potential for using these measures in combination to obtain more useful individual-level information. Whilst discrimination at key time points was broadly similar for a range of important outcomes (longer stays, readmission, care home admittance, mortality), the HFRS had higher HRs and ORs than the eFI; this may reflect the different cut points used for each tool. Overall neither tool had especially high discrimination when looking at the AUCs; this is an important reminder that whilst such tools can be helpful at the population level (for example, system mapping), they should not be used to guide individual patient clinical decisions.

The study used a national cohort of linked primary and secondary care data along with death records and residential history. This allowed us to generate a large cohort for our analyses which afforded greater precision. The ability to capture institutionalisation at scale is a strength, as this outcome is likely to be very relevant for this population [20]. The study used retrospectively collected administrative data, this data was not specifically generated for research and potentially has errors in the records. It is possible that some clinically relevant, historical (i.e. >two years) primary care diagnoses may not have been captured in the hospital dataset (and therefore the HFRS), which may have affected the agreement between the two scores. HFRS scores are only available for individuals who have had a hospital admission, although this is the majority of older people (75+) over a four year period [21]. Patients were only included if they had been admitted to hospital in the previous two years, which may have affected the sample selection. It is possible that the different time periods for examining records (10 years for eFI vs. two years for HFRS) may have contributed to the poor correlation, though we think this is unlikely. Whilst drawn from multiple areas within Wales, we cannot be sure how the results might generalise to different healthcare settings, especially where there are differences in coding practice.

The advantage of system wide frailty identification, covering primary and secondary care, is that it allows clinicians to think about likely outcomes for patients at the time they are being assessed, informed by robust, objective evidence. For example, an older person with frailty and urgent care needs who has a high frailty score might have an in-patient mortality risk of 30% - management for this individual might be very different to the approach for a similarly aged person with a low frailty score and a 1% risk of death. An accurate prognosis helps inform evidence based treatment decisions, for example using the 'Annualised Number Needed to Treat' data provided in the NICE multi-morbidity

guidelines [22]. We observed a high hazard ratio (4.15) for institutionalisation with the HFRS; sadly the clinical pathway is all too often increasing frailty leading to hospitalisation, deconditioning and admission to long term care [23, 24]. Interventions such as CGA[6] may attenuate this trajectory somewhat, so capturing frailty allows systems to observe this 'hidden epidemic' and adjust clinical pathways accordingly. Importantly, clinicians using these scores should be aware of their limitations for predicting outcomes for any individual patient; whilst higher frailty might sensitise clinicians to the likely risk of adverse outcomes, clinical decision should only be taken after a more holistic assessment, and using the principles of shared decision making.

Frailty mapping might also be used to inform service design – for example guiding the need for geriatric interventions, as well as commissioning. An automated frailty identification process allows systems to evaluate large scale changes to clinical pathways with a particular focus on older people with frailty, who are amongst the most vulnerable, but also account for the majority of resource use. Frailty identification also has the potential to be used by trusts and commissioners to inform on service provision and urgent care needs for this target population and guide strategic decisions at the public health level.

Systems considering implementing systematic frailty risk scoring into their Electronic Health Records could reasonably use either the eFI or the HFRS, given the small differences in the AUC between the two tools for the outcomes studied; which tool to use will depend upon the ease of implementation. The advantage of the HFRS is that it uses routine hospital data, and has slightly higher accuracy for predicting time to events such as death or readmission. As many countries have adopted international norms for coding diagnoses (ICD-10), it might be that the HFRS has greater generalisability – although the eFI Read codes have the potential to be mapped to ICD-10 codes.

Future research could explore combining eFI and HFRS scores as well as introducing further refinements to enhance their predictive accuracy. It would also be interesting explore the potential for using dynamic scores enhanced by real time data during hospital admissions, such as early warning scores [3] or laboratory data [4]. Artificial intelligence [5] might offer some new insights on risk stratification, but it is likely that the complexity of frailty (with multiple combinations and permutations of comorbidities, ageing physiology and socioeconomic factors all contributing to frailty) means that we will never achieve sufficient precision at the individual patient level.

Conclusions

The eFI and HFRS are weakly correlated, indicating that the two scores identify different levels of frailty in the same individuals. The risk of adverse outcomes was higher for the increased frailty risk for both the HFRS and the eFI.

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