The deficit-accumulation electronic frailty index can predict patient safety events in adult patients of all ages using only structured data in the electronic health record.

Alex Bokov 1,✉, Sara Espinoza 1, Chandana Tripathy 1 , and Kathleen R. Stevens 1

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We have found that the electronic frailty index (EFI), a risk score developed using the Rockwood deficit-accumulation framework, is a strong predictor of patient safety events without relying on any predictors other than diagnoses, vital signs, and laboratory results from the electronic health record. Previous studies using electronic frailty indexes on claims data or electronic health records focused on older patients, but we found that for most of the patient safety outcomes we examined EFI is also predictive for patients in the 45-65 age range and even in the 18-45 age range.

# Introduction/Background

Frailty is the lifelong erosion of stress resistance and accumulation of impairments across multiple physiological systems. Among older community dwelling adults 32% have been classified as pre-frail and 24% have been classified as frail (Hoover *et al.*, 2013). Frailty predicts disability, injurious falls, and mortality (Pajewski *et al.*, 2019), emergency room visits and hospitalizations (Fried *et al.*, 2001), and long-term care admissions (Rockwood, 2005; Rockwood *et al.*, 2006; Pajewski *et al.*, 2019). The Fried phenotype (Fried *et al.*, 2001) and Rockwood deficit accumulation index (Mitnitski, Mogilner and Rockwood, 2001; Rockwood and Mitnitski, 2007), are two commonly used measures of frailty. There is reasonable convergence between these two approaches (Malmstrom, Miller and Morley, 2014; Li *et al.*, 2015) and Kulminsky Kulminski *et al.* (2008) found evidence for the index outperforming the phenotype. Furthermore, the but the deficit accumulation approach scales better to large populations and secondary use of data because it does not require individual questionnaires nor physical assessments. Recently Johnston et al. Johnston, Wen and Joynt Maddox (2020) reported that frailty can improve the accuracy of predicted annualized Medicare costs over Centers for Medicare & Medicaid Services Hierarchical Condition Categories (CMS-HCC) alone. To be pro-active health systems need to be able to replicate such analysis on their own electronic medical record (EMR) data. Several groups have adapted the Rockwood index to EMR-derived data (Clegg *et al.*, 2016; Stow *et al.*, 2018; Pajewski *et al.*, 2019). So far mainly patients older than 65 have been studied. Yet value-based care is broader than Medicare. As private payers start moving to the ACO model it is important to understand whether EFI generalizes to outcomes such as preventable safety events in other age groups.

Effective care of frail older persons is a public health priority for individuals and for the healthcare delivery system. Frailty identifies the vulnerability of a person to endogenous and exogenous stressors, exposing the individual to higher risk of negative health-related outcomes and a loss ofmarks a transition between successful aging and disability.

Accurate assessment of Frailty can inform clinical management decisions and assist with anticipating healthcare resource utilization. Such assessments are useful when validity of the Frailty Index scores are significantly associated with clinically relevant variables.

In order to mitigate the risks posed by frailty through case management, clinicians must be able to validly and efficiently assess the degree of frailty. While multiple approaches to frailty assessment in the elderly have been developed, these approaches remain inadequate in terms of efficiency (some are time intensive), clinical meaningfulness (predictive of negative outcomes), or both. Assessment approaches at the front line of care must be accurate and efficient to integrate into the clinical workflow.

The capability to leverage clinical data and harness its potential to generate knowledge rapidly to inform decisions can have transformative effects on complex systems that provide services. The Learning Health System (LHS) is one widely held vision for realizing this transformation. The LHS uses routine data from service delivery and patient care to generate knowledge to continuously improve healthcare. {Friedman C, Rubin J, Brown J, et al. Toward a science of learning systems: a research agenda for the high-functioning learning health system. J Am Med Inform Assoc.2015;22:43–50.doi:10.1136/amiajnl-2014-002977}

[NOTE FROM KS: The following paragraph is the more detailed background of the anchoring report on LHS from the IOM. Provided FYI, not necessarily to include in full narrative. KS]

In a 2013 report, the Institute of Medicine highlighted the use of routine data from service delivery (e.g., electronic health records) to generate knowledge to continuously improve healthcare. “The committee believes that achieving a learning health care system—one in which science and informatics, patient-clinician partnerships, incentives, and culture are aligned to prodownloadmote and enable continuous and real-time improvement in both the effectiveness and efficiency of care—is both necessary and possible for the nation.” (IOM, 2013, p. 21)

{Institute of Medicine (IOM). 2013. Best Care at Lower Cost: The Path to Continuously Learning Health Care in America. Washington, DC: National Academies Press.} <https://doi.org/10.17226/13444>. <https://www.nap.edu/catalog/13444/best-care-at-lower-cost-the-path-to-continuously-learning>

To address the need for assessment efficiency, we developed a Frailty Index that is calculated from readily available electronic health record data, reflecting a key improvement strategy from the Learning Healthcare System (LHS) paradigm.

# Methods

Following principles of implementation science {Meissner, Paul, Linda B. Cottler, and J. Lloyd Michener. “Engagement science: The core of dissemination, implementation, and translational research science.” Journal of Clinical and Translational Science 4, no. 3 (2020): 216-218.}, clinical stakeholders and experts (SE, CT) were directly engaged in the research design to identify key outcomes that were meaningful, relevant, and useful in guiding clinical care planning. We applied patient safety indicators used for routine large-scale surveillance of hospital and health system performance {Southern, Danielle A., Bernard Burnand, Saskia E. Droesler, Ward Flemons, Alan J. Forster, Yana Gurevich, James Harrison et al. “Deriving ICD-10 codes for patient safety indicators for large-scale surveillance using administrative hospital data.” Medical care 55, no. 3 (2017): 252-260} and extended the data set to include additional variables.

## Population

A random 1% sample (N=14,844) was drawn from the deidentified patient records of a large academic health center and its teaching hospital partner. Visits during which patient age was less than 18 years old were excluded and then patients who had fewer than three visits in the remaining data were excluded. To avoid bias, for each patient an index visit date was chosen and only data recorded on or after that date was used in analysis. To avoid distorted results in patients with sparse visit histories, those who had fewer than two visit-dates after index visit assignment were removed from the sample as were patients whose EFI was never higher than 0. Most patients had visits at the tails of their histories during which EFI was 0 and no diagnoses, procedures, nor lab results were recorded. These may have been missed appointments or accesses to patient data that did not physically involve the patient, so they were excluded also. Finally, the patients were randomly assigned to a development cohort (N= 2,497 patients, 50,609 visit-days) or a testing cohort (N=3,220 patients, 56,320 visit-days). Sensitivity analysis was done to see the effect of leaving in data from all visits by adult patients and the overall direction of EFI’s effect was the same but [the model performance was inflated, see supplement]. All decisions about data processing and statistical analysis were made using only the development cohort and blinded to the testing cohort. For publication, the same analysis scripts were run on the testing cohort and used to create all results reported here (the development version of each table and figure is available in the supplemental materials). The baseline characteristics of the testing cohort are shown in Table 1.

Table 1: Cohort demographics

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| . |  |  |  |  |  |  |  |

## Electronic Frailty Index

Clegg *et al.* (2016) developed an electronic frailty index (EFI) for UK health systems following the methodology of Mitnitsky, Rockwood, et al. (Mitnitski, Mogilner and Rockwood, 2001; Searle *et al.*, 2008; Song, Mitnitski and Rockwood, 2010). Recently, Pajewski *et al.* (2019) adapted the EFI to use ICD10 and ICD9. We further built on this work by also mapping laboratory tests to specific LOINC codes, de-duplicating several items, and omitting data elements which are not available in some EMR systems. We made the mapping tables and sample SQL code available for public use and discussion (Bokov, 2020). For each patient visit, all distinct diagnoses and abnormal lab results over the preceding two-year window for that patient were aggregated into a single EFI, a numeric value that can range from 0 to 1 (but in practice seldom exceeded 0.6). As mentioned above, we omitted all visits prior to a randomly select index visit for each patient. This did not interfere with EFI calculation because those EFI values were calculated separately for every distinct patient-date in our health system, and then joined to the EHR data.

## Outcomes

The primary outcomes we predicted with EFI were hospital-acquired infections, non-operative hospital-acquired trauma, cardiac complications, and the occurrence of one or more of these or any other patient safety events defined in Southern *et al.* (2017). The advantage of using these PSI definitions is that they leverage the greater specificity of ICD10 codes (rather than a straight mapping from AHCR ICD9 codes) and the uniform denominator for all but maternal and fetal PSIs greatly simplifies calculation. Of the remaining PSIs defined by Southern *et al.* (2017), 2 were excluded because pregnancies were outside the scope of our protocol. Three (drug adverse event, CNS complications, and VTIs) were rare enough that they are difficult to interpret as survival curves but nevertheless are shown in supplementary table S1. The remaining 10 patient safety indicators were too rare to reliably analyze in a sample this size taken from a *general* patient population, but it is likely that more targeted samples will be more enriched for these events.

## Statistical Analysis

For each outcome of interest, we used a Cox proportional hazard model to estimate the risk of the first occurrences of the outcome after the patients’ respective index visits using EFI as the predictor. Unlike earlier studies, we treated EFI as a time-varying numeric predictor with multiple follow-ups per patient. Since only the first occurrence was being predicted, a recurring event model was not necessary. Patients were followed up to the first occurrences of the respective outcomes, so the standard form of the Cox model was sufficient. In order to determine whether predictive accuracy of EFI was only limited to some age subgroups, we repeated the analysis separately for the following age ranges: 18-45 years old, 45-65 years old, and 65 or above. These split the dataset into three roughly equal subgroups.

# Results

Table 2 shows the results of Cox proportional hazard models for each of the responses, with EFI as the predictor. For each 0.1 increase in EFI, we found at least a doubling of risk: 1.9 to 2.2 fold for Infections, 1.8 to 1.9 fold for Trauma, 1.9 to 2.7 fold for Cardiac, and 1.8 to 2.2 fold for Any PSI. In other words, a patient with a frailty of 0 would have a X% () chance of experiencing a patient safety compared to a patient with a frailty of 0.2, who would have a Y% () chance, while the overall risk is Z%(). The p-values shown have been adjusted for multiple comparisons (sixteen outcomes reported in one study) using the Holm (1979) method and in all cases are highly significant.

Table 2: Cox-proportional hazards with EFI as a predictor

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| predictor | Outcome | β^ (95% CI) | fold-change (95% CI) | SE | Z | P, adjusted | # Events | # Visits |
| Frailty | Infections | 0.70 (0.58, 0.81) | 2.01 (1.79, 2.25) | 0.0583 | 11.9 | 1.09e-30 | 162 | 45164 |
| Frailty, age:18-45 | Infections | 0.78 (0.56, 1.00) | 2.18 (1.75, 2.71) | 0.111 | 7.02 | 3.29e-10 | 63 | 15253 |
| Frailty, age:45-65 | Infections | 0.67 (0.48, 0.86) | 1.95 (1.61, 2.36) | 0.0968 | 6.89 | 7.67e-10 | 59 | 18401 |
| Frailty, age:65+ | Infections | 0.66 (0.44, 0.88) | 1.93 (1.55, 2.40) | 0.111 | 5.92 | 4.29e-07 | 40 | 11510 |
| Frailty | Trauma | 0.61 (0.48, 0.73) | 1.83 (1.61, 2.08) | 0.0645 | 9.39 | 9.78e-19 | 145 | 46223 |
| Frailty, age:18-45 | Trauma | 0.66 (0.41, 0.91) | 1.94 (1.51, 2.48) | 0.126 | 5.26 | 1.78e-05 | 63 | 15168 |
| Frailty, age:45-65 | Trauma | 0.64 (0.43, 0.84) | 1.89 (1.54, 2.31) | 0.104 | 6.13 | 1.16e-07 | 54 | 18895 |
| Frailty, age:65+ | Trauma | 0.60 (0.33, 0.87) | 1.82 (1.40, 2.38) | 0.136 | 4.42 | 0.0011 | 28 | 12160 |
| Frailty | Cardiac | 0.92 (0.78, 1.05) | 2.50 (2.18, 2.86) | 0.0685 | 13.4 | 1.8e-38 | 108 | 45368 |
| Frailty, age:18-45 | Cardiac | 0.98 (0.60, 1.36) | 2.67 (1.83, 3.91) | 0.194 | 5.06 | 5.01e-05 | 14 | 16160 |
| Frailty, age:45-65 | Cardiac | 0.87 (0.67, 1.08) | 2.39 (1.95, 2.93) | 0.104 | 8.37 | 8.97e-15 | 53 | 17886 |
| Frailty, age:65+ | Cardiac | 0.62 (0.40, 0.84) | 1.86 (1.50, 2.32) | 0.112 | 5.56 | 3.42e-06 | 41 | 11322 |
| Frailty | Any PSI | 0.73 (0.66, 0.81) | 2.08 (1.93, 2.25) | 0.0393 | 18.6 | 2.66e-75 | 404 | 37036 |
| Frailty, age:18-45 | Any PSI | 0.79 (0.64, 0.94) | 2.20 (1.89, 2.57) | 0.0773 | 10.2 | 2.55e-22 | 146 | 13750 |
| Frailty, age:45-65 | Any PSI | 0.74 (0.62, 0.86) | 2.10 (1.85, 2.37) | 0.0634 | 11.7 | 2.93e-29 | 157 | 14436 |
| Frailty, age:65+ | Any PSI | 0.59 (0.44, 0.73) | 1.80 (1.55, 2.08) | 0.0751 | 7.83 | 7.54e-13 | 101 | 8850 |

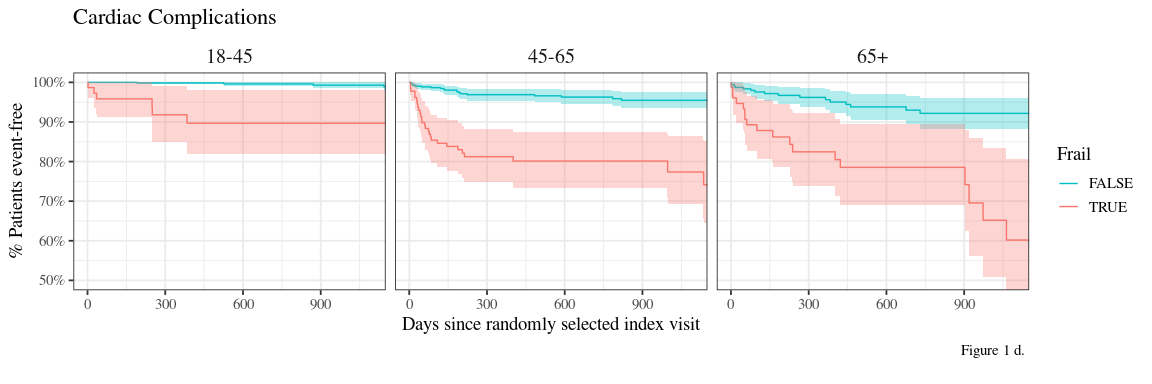
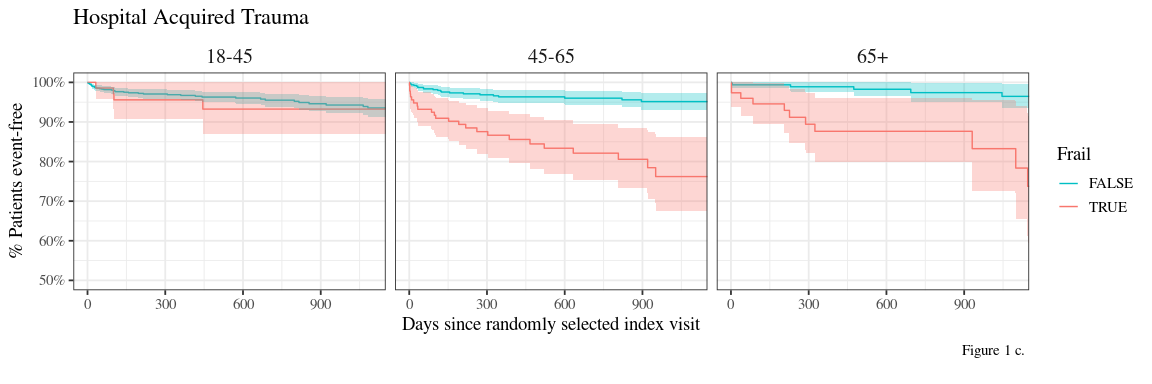
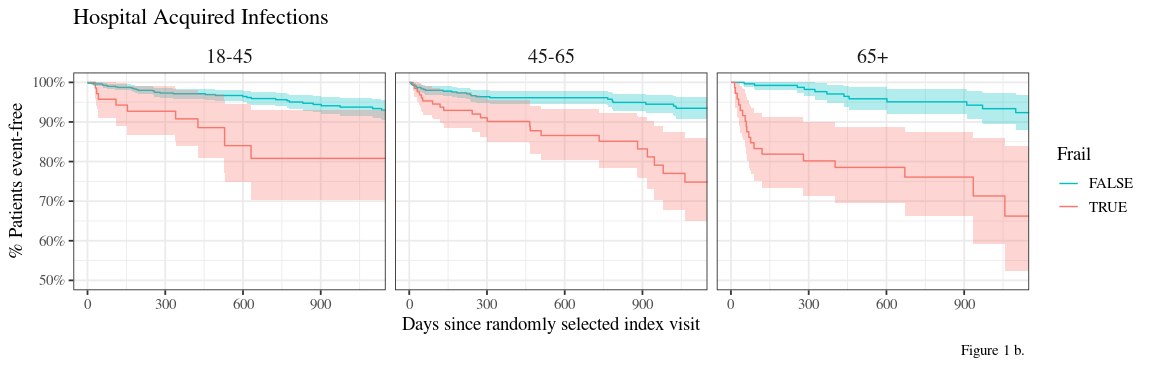
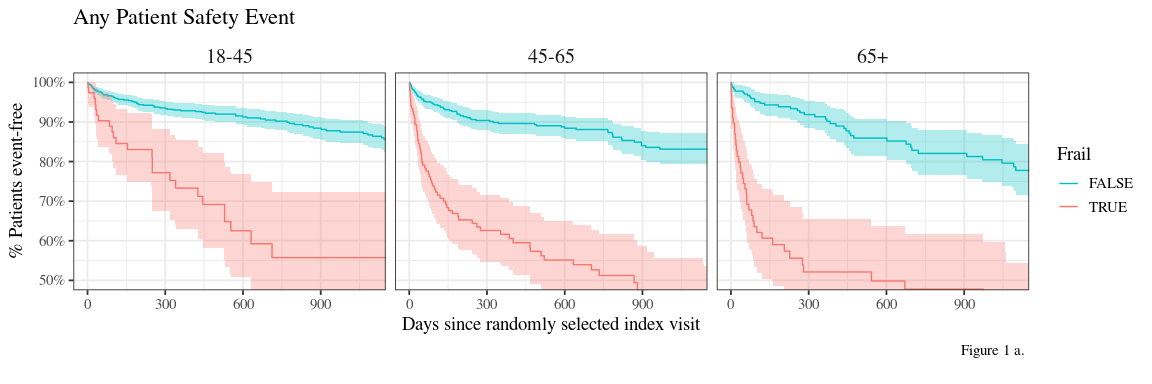
For each outcome, we re-fit the same Cox proportional on subsets of the data separated by age at visit: 18-45 years old, 45-65 years old, and 65 or older. We found that for most of the primary outcomes (as well as for most of the analyzable outcomes, see supplementary table S1) EFI was a good predictor in all three age groups.

Table 3: Performance of EFI models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Outcome | Predictor | Concordance | Log Likelihood | AIC |
| Infections | Frailty | 0.7252 | -1036 | 2075 |
| Infections | Frailty, age:18-45 | 0.6582 | -345.4 | 692.9 |
| Infections | Frailty, age:45-65 | 0.7233 | -325.8 | 653.6 |
| Infections | Frailty, age:65+ | 0.7851 | -190.2 | 382.5 |
| Trauma | Frailty | 0.7085 | -945.4 | 1893 |
| Trauma | Frailty, age:18-45 | 0.6912 | -357.3 | 716.6 |
| Trauma | Frailty, age:45-65 | 0.7104 | -310.2 | 622.4 |
| Trauma | Frailty, age:65+ | 0.7606 | -127.1 | 256.2 |
| Cardiac | Frailty | 0.7978 | -686.3 | 1375 |
| Cardiac | Frailty, age:18-45 | 0.8718 | -69.41 | 140.8 |
| Cardiac | Frailty, age:45-65 | 0.7921 | -295.2 | 592.5 |
| Cardiac | Frailty, age:65+ | 0.6779 | -203.1 | 408.3 |
| Any PSI | Frailty | 0.741 | -2622 | 5247 |
| Any PSI | Frailty, age:18-45 | 0.7071 | -810.3 | 1623 |
| Any PSI | Frailty, age:45-65 | 0.7468 | -884.7 | 1771 |
| Any PSI | Frailty, age:65+ | 0.7239 | -491.9 | 985.9 |

In Table 3 we report the performance of EFI as the predictor for each combination of age group and outcome, as well as for the cohort overall (Frailty).

In figures 1 a-d we show Kaplan-Meier plots for each of the outcomes stratified by whether EFI is greater than 0.19 (Frail=TRUE) or less (Frail=FALSE), the cut-point established by (Stow *et al.*, 2018).



# Discussion

We implemented an electronic Frailty Index using the Rockwood deficit-accumulation framework and used it to predict patient safety events in real-world data from an EHR system. Our results add to the evidence that Rockwood indexes are a rapid, low-effort method of risk assessment that scales to large patient populations. As yet there is no gold standard method to assess Frailty in clinical practice. Currently available frailty assessment tools geriatric practice have good validity (for example Fried et al. (2001)) are time intensive and often difficult to implement in a busy general practice. Assessing frailty helps clinicians identify high risk patients and tailor interventions to preserve function and prevent health decline and poor outcomes and impact cost of care. Because of the simplicity of the Rockwood Frailty Index, it is more likely to be adopted by clinicians in a busy practice.

Unlike previous studies, we did not restrict our sample to older patients. We found a highly significant relationship in all age groups between frailty and hospital-acquired infections, hospital-acquired trauma, cardiac complications, and overall occurrence of patient safety events even after a very conservative multiple comparison correction. [go through the rest, mention which ones were not significant]. Moreover, except the 18-45 year old group for infections and trauma, all the models had a concordance greater than 0.7.

Our sample population amounts to making predictions about randomly selected patients assessed only on EHR data available up to a randomly selected encounter for each of these patients. As a consequence some clinically relevant events such as pressure ulcers, post-surgical complications, and ICU stays were less frequent than they would be in a more narrowly focused sample (e.g. only geriatric patients or only inpatients). Nevertheless frailty does predict patient safety events that may be less anticipated in younger patients. As the next step toward clinical deployment we intend to repeat this analysis with patients seen at the internal medicine department of our health system, who tend toward older ages and more comorbidities but are not solely geriatric patients.

Our data shares the fundamental limitation of the EHR system from which it was obtained: like all EHR systems, it only has information that providers and coders put into it. Events taking place outside the health system or at un-connected health systems are not visible to our analysis. On the other hand, providers who rely on EHR systems at point of care are also working under these limitations on. The data we used is representative of this scenario, and despite the limitations EFI provides accurate predictions of poor patient outcomes. Because our implementation of the Rockwood index real EHR data, it is more directly transferable to clinical use than implementations based on curated registries and more immediate than claims data. EFI is most accurate for patients who have accumulated a reasonable in-system visit-history but further work is needed to find a more precise relationship between the length of a patient’s visit-history and the accuracy of EFI and to better distinguish genuinely non-frail patients from those who have a lot of missing data because they are often seen outside the researchers’ health system.

There is no gold standard method to assess Frailty in clinical practice. Currently available frailty assessment tools used in geriatric practice have good validity (for example Fried *et al.* (2001)) but these are time intensive and often difficult to implement in a busy general practice. Assessing frailty helps clinicians identify high risk patients and tailor interventions to prevent health decline and poor outcomes. Because of the simplicity of the Rockwood Frailty Index, it is more likely to be adopted by clinicians in a busy practice.

# Conclusions

Results from our Cox proportional hazard models in Table 2 demonstrate a statistically significant association of EFI with clinically meaningful outcomes from EHR data. The c-statistics in Table 3 demonstrate that the Cox models are well fitted to this data. This contributes to a growing body of evidence that risk scores built using the Rockwood framework (Mitnitski, Mogilner and Rockwood, 2001) will be a valuable tool for clinical decision support not restricted to any one illness or specialty. The variables used to calculate EFI are ones that are in some form available in every EMR system. If there are EMR systems where a few of these variables are not available, Rockwood deficit accumulation indexes have been shown to continue giving consistent results despite variations in what individual codes are available as long as there is a sufficiently large and representative collection of deficits into which these variables can be binned [ref].

To facilitate adoption and refinement of EFI, we are publishing not only the code mappings but also scripts that implement the mapping algorithm with detailed notes on adapting them to local environments. We intend to evolve these scripts into a self-contained app that interfaces with EMR systems (via FHIR) to provide real-time frailty assessment at the clinical point of care and assist clinicians in developing care plans to mitigate the risks of frailty.

NOTE FROM KS: Can we make a parallel statement in our CONCLUSIONS? KS: AN INTERESTING QUOTE FROM Southern: “The methodological work presented here utilizes the unique potential of diagnosis timing information to produce a clinically relevant listing of diagnosis codes that have potential as PSIs that may overcome some of the notable shortcomings of existing PSI systems. The resulting work has great potential to inform future approaches to monitoring health system performance and quality/safety improvement internationally.”

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# References

Bokov, A. (2020) ‘Bokov/FreeFI: First Release’. Zenodo. doi: [10.5281/ZENODO.4053088](https://doi.org/10.5281/ZENODO.4053088).

Clegg, A. *et al.* (2016) ‘Development and validation of an electronic frailty index using routine primary care electronic health record data’, *Age and Ageing*, 45(3), pp. 353–360. doi: [10.1093/ageing/afw039](https://doi.org/10.1093/ageing/afw039).

Fried, L. P. *et al.* (2001) ‘Frailty in older adults: Evidence for a phenotype’, *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 56(3), pp. M146–M157. doi: [10.1093/gerona/56.3.M146](https://doi.org/10.1093/gerona/56.3.M146).

Holm, S. (1979) ‘A simple sequentially rejective multiple test procedure.’, *Scandinavian Journal of Statistics*, 6, pp. 65–70.

Hoover, M. *et al.* (2013) ‘Validation of an index to estimate the prevalence of frailty among community-dwelling seniors’, *Health Reports*, 24(9), pp. 10–17.

Johnston, K. J., Wen, H. and Joynt Maddox, K. E. (2020) ‘Relationship of a Claims-Based Frailty Index to Annualized Medicare Costs: A Cohort Study’, *Annals of Internal Medicine*, 172(8), p. 533. doi: [10.7326/M19-3261](https://doi.org/10.7326/M19-3261).

Kulminski, A. M. *et al.* (2008) ‘Cumulative Deficits Better Characterize Susceptibility to Death in Elderly People than Phenotypic Frailty: Lessons from the Cardiovascular Health Study: FRAILTY, CUMULATIVE DEFICITS, AND SURVIVAL’, *Journal of the American Geriatrics Society*, 56(5), pp. 898–903. doi: [10.1111/j.1532-5415.2008.01656.x](https://doi.org/10.1111/j.1532-5415.2008.01656.x).

Li, G. *et al.* (2015) ‘Comparison between Frailty Index of Deficit Accumulation and Phenotypic Model to Predict Risk of Falls: Data from the Global Longitudinal Study of Osteoporosis in Women (GLOW) Hamilton Cohort’, *PLOS ONE*. Edited by A. M. Chamberlain, 10(3), p. e0120144. doi: [10.1371/journal.pone.0120144](https://doi.org/10.1371/journal.pone.0120144).

Malmstrom, T. K., Miller, D. K. and Morley, J. E. (2014) ‘A Comparison of Four Frailty Models’, *Journal of the American Geriatrics Society*, 62(4), pp. 721–726. doi: [10.1111/jgs.12735](https://doi.org/10.1111/jgs.12735).

Mitnitski, A. B., Mogilner, A. J. and Rockwood, K. (2001) ‘Accumulation of Deficits as a Proxy Measure of Aging’, *The Scientific World JOURNAL*, 1, pp. 323–336. doi: [10.1100/tsw.2001.58](https://doi.org/10.1100/tsw.2001.58).

Pajewski, N. M. *et al.* (2019) ‘Frailty Screening Using the Electronic Health Record Within a Medicare Accountable Care Organization’, *The Journals of Gerontology: Series A*. Edited by A. Newman, 74(11), pp. 1771–1777. doi: [10.1093/gerona/glz017](https://doi.org/10.1093/gerona/glz017).

Rockwood, K. (2005) ‘A global clinical measure of fitness and frailty in elderly people’, *Canadian Medical Association Journal*, 173(5), pp. 489–495. doi: [10.1503/cmaj.050051](https://doi.org/10.1503/cmaj.050051).

Rockwood, K. and Mitnitski, A. (2007) ‘Frailty in Relation to the Accumulation of Deficits’, *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 62(7), pp. 722–727. doi: [10.1093/gerona/62.7.722](https://doi.org/10.1093/gerona/62.7.722).

Rockwood, K. *et al.* (2006) ‘Long-Term Risks of Death and Institutionalization of Elderly People in Relation to Deficit Accumulation at Age 70: LONG-TERM RISK OF DEATH DEFINED BY AGE 70’, *Journal of the American Geriatrics Society*, 54(6), pp. 975–979. doi: [10.1111/j.1532-5415.2006.00738.x](https://doi.org/10.1111/j.1532-5415.2006.00738.x).

Searle, S. D. *et al.* (2008) ‘A standard procedure for creating a frailty index’, *BMC Geriatrics*, 8(1). doi: [10.1186/1471-2318-8-24](https://doi.org/10.1186/1471-2318-8-24).

Song, X., Mitnitski, A. and Rockwood, K. (2010) ‘Prevalence and 10-year outcomes of frailty in older adults in relation to deficit accumulation’, *Journal of the American Geriatrics Society*, 58(4), pp. 681–687. doi: [10.1111/j.1532-5415.2010.02764.x](https://doi.org/10.1111/j.1532-5415.2010.02764.x).

Southern, D. A. *et al.* (2017) ‘Deriving ICD-10 Codes for Patient Safety Indicators for Large-scale Surveillance Using Administrative Hospital Data:’ *Medical Care*, 55(3), pp. 252–260. doi: [10.1097/MLR.0000000000000649](https://doi.org/10.1097/MLR.0000000000000649).

Stow, D. *et al.* (2018) ‘Evaluating frailty scores to predict mortality in older adults using data from population based electronic health records: Case control study’, *Age and Ageing*, 47(4), pp. 564–569. doi: [10.1093/ageing/afy022](https://doi.org/10.1093/ageing/afy022).