CONTRACTOR PROJECT REPORT

Identifying Frailty Using Existing Health Data

Challenges and Opportunities for Health Systems

Prepared for
the Office of the Assistant Secretary for Planning and Evaluation (ASPE)
at the U.S. Department of Health & Human Services

by
RAND Health Care

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ASPE Executive Summary

To support the project, *Validating and Expanding Claims-based Algorithms of Frailty and Functional Disability for Value-Based Care and Payment* funded by the Patient-Centered Outcomes Research Trust Fund (OS-PCORTF), the Office of the Assistant Secretary for Planning and Evaluation (ASPE) requested that RAND Health Care ASPE engage health systems, health care providers and researchers through an EHR Learning Network to share learnings on leading-edge frailty identification practices using EHR data, how the information is used in clinical care to identify and manage high-risk patients, factors that facilitate or prevent EHR data from being used, and to identify potential use cases from interviews.

This EHR Implementation Guide – *Identifying Frailty using Existing Health Data* is designed for use by health systems, shares learnings from this EHR Learning Network and a separate AHRQ-funded study evaluating a claims-based frailty index using EHR across health systems with varying degrees of delivery network open/closed-ness. It offers guidance to health systems on using EHR data to identify patients with frailty or functional impairment.

The guide describes the range of ways that EHRs are being used to capture data on frailty and functional impairment from primary to specialist care, and best practices for implementing algorithms using EHR data for population management and in support of patient-centered care. Key considerations are offered for providers and health systems as well as algorithm developers, researchers, practitioners and policymakers in using claims and EHR data to identify frailty and persons at risk of frailty.

The report concludes frailty indexes that are based on EHR data—EFIs—are promising and practical for health systems, but require considering data quality and completeness. Future research could explore tapping into unstructured EHR data, using standardized data on patient function and increased use of patient functional assessments.

Project Report

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About This Project Report

Frailty and functional impairment are associated with poor health outcomes in older adults, and there have been many efforts to use existing health data to identify or predict frailty. In this report, we describe the current state of the use of claims and electronic health record data for predicting and identifying frailty and functional impairment in older adults. We established a Learning Network for providers, health systems, and other interested parties to share their experience identifying frailty and using this information in clinical practice. We conducted interviews with clinicians and researchers developing and implementing frailty and functional impairment algorithms and held two webinars to share findings and identify areas for future research. We identify several potential next steps for algorithm developers, clinicians, and policymakers.

This research was funded by the Office of the Assistant Secretary for Planning and Evaluation and carried out within the Access and Delivery Program in RAND Health Care.
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Summary

This report summarizes the state of the use of claims and electronic health record (EHR) data for predicting and identifying frailty and functional impairment in older adults. Both frailty and functional impairment put older adults at risk for poor health outcomes, including falls, hospitalization, and mortality, so efforts to identify these conditions can be used to target clinical interventions and promote population health. This report is part of a project to develop, test, and support implementation of claims- and EHR-based algorithms to predict functional impairment and/or frailty in patients funded by the Patient-Centered Outcomes Research Trust Fund and coordinated by the Office of the Assistant Secretary for Planning and Evaluation (ASPE). There are many promising claims-based and EHR-based indexes for predicting and identifying frailty developed and used in research studies, but their use in routine clinical practice is limited. Given challenges with using claims data in real time, EHR-based frailty indexes are of particular interest to practitioners. These indexes generally draw on structured elements of the EHR (e.g., diagnoses, procedures, and lab results), but newer indexes are beginning to tap into unstructured data, such as clinical progress notes.

Approaches to implement these indexes in clinical practice have varied significantly across different health care systems. Several promising initiatives have implemented EHR-based indexes at the point of care in primary care or other outpatient clinics and use the results of these indexes to promote shared decisionmaking between patients and providers.

To improve the performance and increase the use of these indexes, we established an EHR Learning Network consisting of researchers, practitioners, and policymakers interested in sharing their experiences and lessons learned about the leading edge of the development and use of these indexes for novel clinical applications. We conducted interviews with several members of the EHR Learning Network and held two webinars in which network members shared their experiences putting these indexes into practice, the challenges they encountered, and the opportunities for future development.

Through this work, we identified many promising practices that could be widely adopted to improve the performance and increase the use of EHR-based indexes. Algorithm developers can continue refining these indexes to incorporate additional unstructured information and improve their predictive power. Researchers can study the incorporation of these indexes into clinical practice and their impact on patient outcomes. Practitioners should be mindful of data limitations associated with different data sources and take care to customize implementation into their health care system. Policymakers can encourage the development of standards to share these indexes across health care systems and to continue highlighting best practices for frailty identification using EHR-based indexes.

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Chapter 1. Introduction

Project Background

A person's level of physical and cognitive functioning is an important outcome to assess in patient-centered outcomes research. Physical or cognitive impairments that limit a person's ability to perform activities of daily living (ADL), especially among older adults, are associated with increased risk for poor health outcomes, including increased acute care utilization, longer length of inpatient stay, and increased mortality (Campbell, Seymour, and Primrose, 2004; Keeler et al., 2010; Miller and Weissert, 2000). *Frailty*, which is often defined as a state of vulnerability to stressors and identified by a set of signs that can be related to functional impairments, such as weakness, weight loss, and slow gait speed, is another condition that puts older adults at risk of poor outcomes, including falls, hospitalization, and mortality (Clegg et al., 2013). An estimated 15 percent of older U.S. adults are frail, corresponding to a population of millions of people (Bandeen-Roche et al., 2015). Identifying people with functional disabilities and/or frailty and those most at risk of developing these conditions is clinically important and would have value for researchers who focus on patient-centered outcomes, such as function, and practitioners treating older adults. Developing and widespread use of methods to predict patients' susceptibility to functional impairments or frailty would also support risk adjustment of performance measures and payments in value-based care programs. In addition, although claims data contain relevant information for identification of frailty and functional impairment, claims lack detailed clinical information, and there are often time lags associated with obtaining claims data. Given the rich clinical information available in electronic health records (EHRs), the near real-time access to that information, and the existence of several validated methods for using these data to identify patients with frailty and/or functional impairment, EHR-based approaches have considerable strengths over claims-based approaches if the goal is population management.

To support additional research to refine these methods and to move from research to practice in this area, the Patient-Centered Outcomes Research Trust Fund funded the U.S. Office of the Assistant Secretary for Planning and Evaluation (ASPE) to coordinate a four-year project to develop, test, and support implementation of claims- and EHR-based algorithms to predict functional impairment and/or frailty in patients. This overall project (of which the effort described here is one part) seeks to compare the advantages and disadvantages of these two different data sources, as well as their relative performance in predicting frailty and allowing clinicians to intervene and improve patient outcomes, including reducing unnecessary health care utilization.

Objectives of This Work

The objectives of the overall project are to develop and share:

1. a set of validated and refined claims-based algorithms using Medicare claims that predict patients' level of frailty, to be made available to the public through the Centers for Medicare & Medicaid Services' (CMS's) Chronic Conditions Data Warehouse (CCW)
2. validated EHR-based versions of the algorithms identified in objective 1
3. an EHR guidance report sharing experiences and lessons learned from an EHR Learning Network on collecting and extracting information on patients' frailty and/or functional status from the EHR.

ASPE engaged the RAND Corporation to achieve objectives 1 and 3, and the Agency for Healthcare Research and Quality (AHRQ) engaged Johns Hopkins University Center for Population Health Information Technology (JHU CPHIT) to meet objective 2 by extending the preliminary research on applying claims-based frailty indexes to EHR data conducted by ASPE and the Centers for Disease Control and Prevention. The first two objectives of the work are discussed briefly below, and the third is the topic of this report.

Prior and Ongoing Work

RAND Contract with ASPE

In fall 2019, ASPE contracted with RAND to address objectives 1 and 3. In the first component. RAND was charged with reviewing and refining algorithms based on Medicare fee-for-service claims to predict functional impairment as measured by patient assessment data from two postacute care providers: skilled nursing facilities and home health agencies. After reviewing existing algorithms, developing and testing new algorithms, and comparing algorithm performance, RAND recommended including Claims Frailty Index scores developed by Kim et al., 2018, in the CCW.

A second component of RAND's contract that corresponds to the overall project's third objective was to establish an EHR Learning Network to engage health care providers, systems, researchers, administrators, and vendors in learning how EHRs can be better utilized to identify patients' frailty and functional impairment. The EHR Learning Network consisted of an email list of interested researchers, practitioners, and policymakers recruited through existing research networks and snowball sampling (interested parties could email RAND to be added to the network). In September and November 2020, June and July 2022, RAND conducted two sets of individual interviews with providers and administrators in research and health care settings to better understand the current scope and utilization of EHR data for identifying patients with frailty or functional impairments. In May 2020 and May 2022, RAND has also held two informational webinars for the EHR Learning Network; these included implementation guidance based on the findings of the JHU CPHIT contract, opportunities to provide feedback on claims-and EHR-based algorithms, and invitations to share ideas about improving the use of EHR data more broadly. (Unless otherwise stated, the quotes in this report are from these events.)

Johns Hopkins University Center for Population Health Information Technology Project with the Agency for Healthcare Research and Quality

In 2020, AHRQ contracted with JHU CPHIT to address the second objective of the overall project. This included applying claims-based frailty algorithms to EHR data, validating the algorithms, and comparing the claims-based frailty index (CFI) with EHR-based frailty index (EFI) using EHR and claims data. JHU CPHIT assessed their value in predicting utilization and disseminated the findings. JHU CPHIT conducted this work using three separate data sources (Johns Hopkins Medical Institute [JHMI], OptumLabs Data Warehouse, and Kaiser Permanente Mid-Atlantic States [KPMAS]) that included previously linked EHR and claims records and provided the study team with various denominators to explore the CFI and EFI. Regression models included various predictors and weights to predict specific outcomes, including health care utilization. Findings of this work are anticipated to be made public by fall 2022.

Goals and Scope of This Report

This document addresses the third objective of the overall project: to share lessons learned from the EHR Learning Network members' experience collecting and extracting information on frailty and/or functional status impairment from claims and EHR data. The goals of this report are to

- describe how stakeholders collect and extract information on patients' functional status and/or frailty from structured and unstructured clinical data (e.g., traditional EHR databases, physician notes, and physical performance measures, such as gait speed assessments, that might not be entered into structured elements in the EHR
- illustrate how leveraging data contained in EHRs can be operationalized to inform clinical interventions
- identify promising practices in the standardized collection of data related to functional status in EHRs
- provide guidance on the use of the algorithms in EHR data to support quality improvement.

It is our hope that highlighting the barriers and facilitators of implementing EHR-based algorithms in this document, as well as sharing the experiences of our partners, will support health systems in adopting these approaches to identifying patients with frailty or functional impairment.

In the Chapters 2, 3, and 4, we draw on an environmental scan and key informant interviews to describe how frailty and functional impairment are defined clinically, how providers and health systems use clinical data to identify frailty and/or functional impairment in their patients, and how they use the resulting information. We also summarize the experience of project partners with regard to extracting frailty and functional status information from EHRs. In Chapter 5, we describe stakeholder insights from a series of interviews and an EHR Learning Network event in which we moderated a discussion of panelists with experience implementing claims- and EHR-based algorithms in clinical practice. Chapter 6 summarizes lessons learned from these activities and lists key questions that researchers and clinicians within health systems should consider before choosing or implementing an algorithm to predict frailty and/or functional impairment in patients. This chapter also discusses how claims and EHR algorithms can be used in practice and describes the final highlights, future areas for research, and methodological development.

We note throughout this report that the concepts of frailty, functional impairment, and ADLs are related, overlapping, but distinct concepts. Many researchers and practitioners working on these topics use the term *frailty*, and, in our algorithm development, we have specifically explored functional impairment. Therefore, when we broadly describe approaches to identify frailty or functional impairment, we use the term "frailty and/or functional impairment," but when describing a specific approach, we use the terms used by the developers of that approach. We also use the terms *identify* and *predict* to refer to the goals of these algorithms throughout this report; the term *identify* is used when frailty or functional impairment is directly assessed, whereas the term *predict* is used when an algorithm predicts frailty or functional impairment based on diagnoses or other data found in claims or EHRs.

Chapter 2. Conceptual and Operational Definitions of Frailty

The medical concept of frailty refers to decreased physiologic reserve and inability to withstand physical and psychological stressors (Clegg et al., 2013; Fried, Darer, and Walston. 2003). The term *frailty* has been used to unify the concepts of aging, disease, and other measures of risk that make some people more vulnerable than others to stressful events. Increasingly, frailty is considered a risk factor for adverse health outcomes that is independent of patient demographic characteristics and comorbidities. An estimated 10 percent of people over the age of 65 could be considered to have frailty, with the proportion increasing with age (British Geriatrics Society, 2014).

To support the identification of patients with frailty in both research and clinical practice, there have been many attempts to define frailty in terms of diagnoses, trajectories, function, or a combination of these factors. One approach, often called the *phenotypical model*, is to define frailty as a syndrome (Bouillon et al., 2013; Parker et al., 2017); patients who meet at least three of these characteristics—unintentional weight loss, fatigue, weakness, slow walking speed, and low physical activity—are considered frail (Fried et al., 2001). Some of these criteria are based on physical performance measures (e.g., walking speed or weakness as characterized by grip strength) and not routinely assessed in general primary care settings. Although this approach to assessing frailty is generally considered to be the gold standard, it is not practical for assessing frailty in the general older adult population because measuring physical performance is time-consuming (Bouillon et al., 2013). Furthermore, there is no consensus on which physical performance measures should be used, so a definition of frailty based on this method might not be equivalent or interoperable with other methods depending on which assessments were used (Parker et al., 2017).

Another approach to identifying frailty is to count an *accumulation of deficits*, including dependencies in ADLs such as the ability to bathe, eat, get dressed, use the bathroom, and move around, as well as other deficits including memory problems, falls, and heart problems (Rockwood et al., 2005). This deficit accumulation approach identifies frailty by counting impairments. Other researchers have used ADL dependencies alone as a proxy for frailty (Faurot et al., 2015). Although ADL dependencies can be assessed clinically, it is also possible to elicit this information directly from patients (e.g., via survey), shifting the collection burden from providers and health systems to patients and caregivers. Critics of this method of identifying frailty note that although functional impairments overlap with frailty, the two concepts are not equivalent (Morley et al., 2006; Morley, Perry, and Miller, 2002); frail patients might not have impairments, and not all patients with functional impairments are frail.

In practice, these definitions have been operationalized into many different assessments of frailty. There is a wide variety of domains that might be considered part of a frailty assessment

(Junius-Walker et al., 2018); in practice, a systematic review found 67 frailty instruments used in research, with nine instruments each cited more than 200 times (Buta et al., 2016). This variety of instruments means that, operationally, there are many different ways clinicians and researchers can define frailty.

Unfortunately, the information needed to define frailty through either a phenotype or a deficit accumulation approach is rarely available for all patients at a practice or health system level (Bery et al., 2020). In response, alternative specifications of frailty have been developed that adapt these approaches for use with administrative data (i.e., insurance claims) and the structured clinical data available in EHRs. In the sections that follow, we first review CFIs, then briefly discuss the differences between EHR and claims data and what makes EHR-based methods appealing for identifying frailty and functional impairment. Lastly, we review both basic and more advanced approaches to using EHR data to identify frailty and functional impairment.

Claims-Based Frailty Indexes

CFIs use the diagnosis and billing codes in health insurance claims data to predict frailty among insurance plan members. Several CFIs have been developed using health insurance claims—usually Medicare claims; see Shashikumar et al., 2020, for a recent review (Shashikumar et al., 2020). One strength of this approach is that claims data capture visits, diagnoses, and procedures for all providers seen by an individual; records are not limited to one provider's practice or even to a health system. CFIs therefore use complete information on a patient's diagnoses and health care utilization paid for by the observed insurer. However, the amount of clinical information submitted with claims is quite limited. Disease severity, for example, often needs to be inferred from utilization patterns, and information on symptoms and level of function is not consistently recorded in claims. Despite these limitations, CFIs have shown predictive value for various health outcomes (e.g., disability, mobility impairment, hospital days [Davidoff et al., 2013; Kim et al., 2018], and mortality [Ensrud et al., 2009; Graham et al., 2009]), making them potentially a key data element for health plans to improve care coordination and decrease unnecessary utilization (Shashikumar et al., 2020).

Multiple CFIs have been developed and validated. Some have been designed to predict disability or ADLs (Cuthbertson et al., 2018; Faurot et al., 2015), while others have adopted the phenotype concept (Ben-Shalom and Stapleton, 2016; Mitnitski, Mogilner, and Rockwood, 2001; Segal and Chang et al., 2017) or have used the deficit accumulation index as a standard (Davidoff et al., 2013; Shashikumar et al., 2020). Many CFIs were constructed using demographics, diagnosis codes, procedure codes, grouped CMS-specific procedure codes, and occasionally other information like enrollment data. The CCW's chronic conditions include 27 common chronic conditions and 40 other conditions that identify chronic health, mental health, and substance abuse conditions (Chronic Conditions Data Warehouse, undated).

Table 2.1 presents six well-known CFIs. Although they address a similar concept, there are notable differences in each approach. The Davidoff index uses Healthcare Common Procedure Coding System (HCPCS) and Current Procedural Terminology (CPT) codes in a 12-month look-back period to predict disability (Davidoff et al., 2013). This index does not include diagnosis codes or age. The Faurot index uses demographics, International Classification of Diseases (ICD), and HCPCS codes—but not CPT codes—in the past eight months to predict ADL disabilities (Faurot et al., 2015). The Ben-Shalom index combines six different claims-based disability indicators that use demographics and a variety of specialized diagnostic grouping codes to predict ADL disability as self-reported by patients (Ben-Shalom and Stapleton, 2016). The JEN Frailty Index (JFI) relies on diagnosis data in the form of ICD-9 and ICD-10 codes to calculate the sum of binary variables corresponding to 13 different diagnoses; a higher score indicates greater risk of need for long-term institutional support (JEN Associates, undated). The Segal index uses demographics, ICD codes, and comorbidity scores in the past six months to predict the frailty phenotype. This index excludes CPT and HCPCS codes (Segal, Chang, et al., 2017; Segal and Huang et al., 2017). The Kim index uses ICD, CPT, and HCPCS codes in the past 12 months to calculate a score that reflects accumulation of deficits. This index excludes demographic variables (e.g., sex and age) (Kim et al., 2019; Kim et al., 2018). The performance of each of these different CFIs depends on the population in question and the data set being used. In a comparison of four of these CFIs (Davidoff, Faurot, Segal, and Kim) in a Medicare population, C-statistics ranged from 0.73 to 0.78 at predicting a frailty phenotype defined by the researchers (weight loss, exhaustion, low activity, slowness, and weakness) (Kim et al., 2020).

Table 2.1. Six Common Claims-Based Frailty Indexes

Index	What It Identifies or Predicts	What It Uses	Lookback Period
Davidoff Index	Disability	HCPCS and CPT codes	12 months
Faurot Index	ADL disabilities	Demographics, ICD, and HCPCS codes	8 months
Ben-Shalom Index	Self-reported disability	Demographics, ICD, CPT, and HCPCS codes	2 years
JEN Frailty Index	Long-term institutionalization	ICD codes	Variable
Segal Index	Frailty phenotype	demographics, ICD codes, and comorbidity scores	6 months
Kim Index	Proportion of deficits present	ICD, CPT, and HCPCS codes	12 months

Research has shown that in addition to independently predicting utilization and clinical outcomes, CFIs can improve the predictive power of existing models that use demographic information and comorbidity scores alone. For example, compared with demographic characteristics and the Combined Comorbidity Index (CCI) (Gagne, 2011), Kim's index exhibited better prediction of disability, mobility impairment, recurrent falls, and skilled nursing facility stays among a sample of Medicare patients (i.e., patients in the Medicare Current Beneficiary Survey) (Kim et al., 2018). Such findings have propelled research on the potential utility of CFIs in improving risk stratification models of health care that use common comorbidity scores such as AHRQ's CCI, Charlson score (Charlson et al., 1987), or Elixhauser index (Elixhauser et al., 1998). Because of their predictive value, insurers have also shown interest in leveraging CFIs to improve care coordination and decrease unnecessary utilization and in using them as a risk adjustment factor in their internal predictive models.

What EHR Data Can Add to Frailty Algorithms

EHRs are inherently different from insurance claims. Despite the overlap between the types of data collected in claims and EHRs—for example, both contain major diagnoses, visit history, and procedures—they are designed for different purposes and therefore have different strengths and limitations. Claims are an artifact of reports submitted for reimbursement purposes, whereas EHRs are mainly used to support clinical care. Claims data cover a variety of events, diagnoses, and procedures that are collected across *all* providers seen by an individual, unlike EHRs, which are limited to clinical encounters with providers who share an EHR record, such as providers within a practice or within a specific health system. Therefore, a major limitation of using EHR data to assess frailty is that encounters and clinical documentation that occur outside a specific provider organization or health system are missing. Before pursuing EHR-based methods to identify patients with frailty, health system leaders should seek to understand how much care patients receive outside their system, and therefore how much clinical information will be missed by using an EHR-based method. Health systems with a large portion of patient care received outside the system might need to supplement their data with clinician assessments or claims data to gain a more complete picture of patients' frailty risk. There might also be more variation in EHR documentation across providers and health systems than is present in claims data (Cohen et al., 2019).

Despite these limitations, there are many reasons that researchers and health systems are eager to use EHR data for population management. EHRs provide robust clinical data and more-detailed information about utilization and procedures, such as symptoms, lab results, vital signs, and prescriptions ordered, than is available in claims. EHRs also provide more-timely data than claims data, making them a better choice for predictive models targeting outcomes requiring quick turnaround interventions or tasks (e.g., predicting and addressing 30-day hospital readmission).

EHR-Based Frailty Indexes

Although EHR data contain more-specific and richer clinical information than claims, as with claims, EHR data are not created for research or risk adjustment purposes and do not typically contain physical performance measures that would provide more-complete information on patient frailty. Consequently, EHR data are more suited to the accumulation of deficits model of frailty than to a phenotypical model, as some, but not all, types of deficits (e.g., weight loss and certain health conditions) are recorded in a structured way in the EHR (Bokovet al., 2021). The accumulation of deficits approach tallies deficits across a variety of physiologic and functional variables to produce a score.

EFIs use many data elements present in EHRs, including diagnosis information, problem lists, medication prescriptions, and information in clinical notes, to predict frailty in patients. Several EFIs have been developed and validated in recent years. Five common EFIs are shown in Table 2.2. The Lekan index focuses on inpatient encounters within the Medicare population. The index predicts mortality using diagnosis data captured in a 12-month look-back period (Lekan et al., 2017). The Anzaldi/Kharrazi index focuses on ambulatory care among older adults. The index uses unstructured EHR data, such as "free-text" clinical notes, to extract novel identifiers of frailty (Anzaldi et al., 2017). The Pajewski index is based on ambulatory care data of Medicare enrollees (Pajewski et al., 2019). This index predicts mortality using diagnosis and medication data captured in the past 24 months. The Shao index is limited to patients who receive health care through the Veterans Administration (VA) and has a 12-month assessment period. The Shao index uses EHR's unstructured data and predicts mortality (Shao et al., 2016). Lastly, the Clegg index focuses on ambulatory care among United Kingdom residents and uses a 12-month period. This index uses diagnosis, medication, and health services data from EHRs. The model both identifies clinical frailty and predicts mortality (Clegg et al., 2016).

Table 2.2. EHR-Based Frailty Indexes

Index	What It Predicts or Identifies	What It Uses	Lookback Period
Lekan Index	Mortality	Diagnosis data	12 months
Anzaldi/Kharrazi Index	Frailty	Diagnosis data and free-text clinical notes	12 months
Pajewski Index	Mortality	Diagnosis and medication data	24 months
Shao Index	Mortality	Free-text clinical notes	12 months
Clegg Index	Frailty and mortality	Diagnosis, medication, and health services data	12 months

The value of EFIs in predicting patients with frailty is similar to CFIs, in that both use readily available administrative data; no new data collection is required. The national trend toward increased harmonization of EHR data elements (e.g., through Meaningful Use certification

[Blumenthal and Tavenner, 2010] and Common Data [see the Observational Health Data Sciences and Informatics website]) could increase interest in EFIs, as interoperable EFIs could be established and applied across providers with different EHR platforms. Currently, because of differences in EHR software and local customization of EHR, an EFI developed in one health system or EHR would need to be customized to fit another health system. Because research on frailty using EHR data is a growing area, informaticists should collaborate with geriatricians and health services researchers when designing EHR structured data fields for the older adult population, as the strategic capture of frailty-related information could support patient-centered care and research goals. Promising movement toward interoperability for measures of functional status in EHRs and of applications of EFIs in real-world settings are discussed in Chapter 6.

Chapter 3. Operationalizing Frailty as a Measure in EHRs—the Promise of Natural Language Processing

There is general consensus that more-widespread tracking of measures of frailty and/or functional impairment in patient populations would be useful to improve quality of care. As discussed in Chapter 2, claims data can be a readily available source of diagnosis information but are limited in the clinical information they contain. EHR data are promising; however, there are many challenges to implementing EHR-based algorithms that have slowed the dissemination of this approach.

Limitations of Structured Data

A major challenge associated with developing EFI measures using EHRs is the lack of frailty-specific variables captured as structured codes in EHRs (e.g., there are not commonly used frailty ICD codes, though there are several codes that could be used to conceptualize something like frailty [Muscedere, 2020]). Most variables measured in common frailty instruments are not typically captured within a structured format in EHRs, thus limiting their use for population-level applications.

EHRs are frequently customized to capture specific data elements, but requiring providers to conduct standardized assessments can be burdensome. In thinking about what structured data elements would need to be added to the EHR to conduct frailty assessments, there are many potential approaches. Selecting and implementing in EHRs a small set of these data elements that would meet the needs of clinicians of different disciplines and population health managers would likely be challenging and possibly contentious, given the limited duration of a clinical visit and the time required to assess even one or two more data elements.

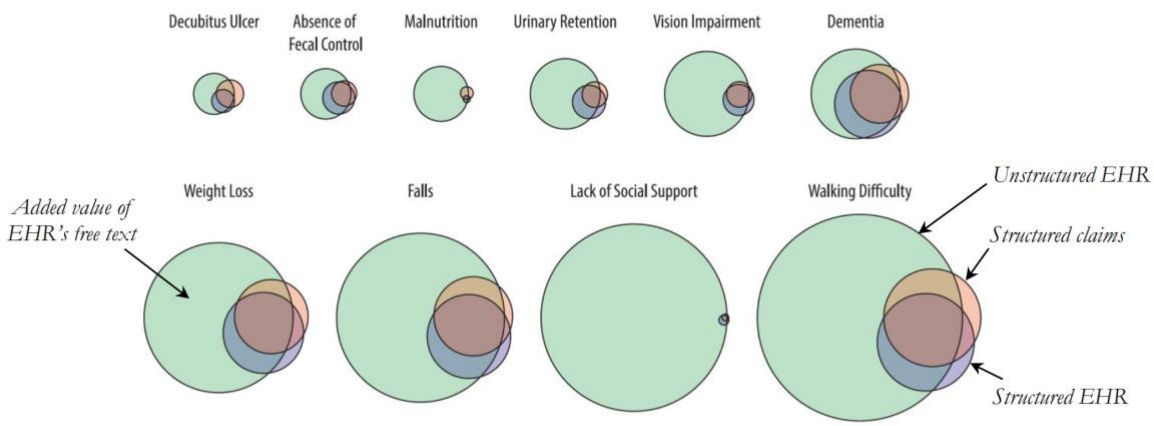
Challenges of Using Unstructured Data

Most of the currently available EFIs that are suitable for widespread use rely on only the structured data captured in the EHR. That is, the relatively straightforward methods for modeling structured data do not lend themselves to using the valuable information that is contained in free-text notes fields.

Unstructured data in EHRs (e.g., clinical notes) can be algorithmically mined to enhance the measurement of frailty on a population level; two of the EFIs described in Chapter 2 (the Anzaldi/Kharrazi index and the Shao index) use these notes as part of their approach. *Natural language processing* (NLP) refers to statistical and other computational approaches to analyze text—in this case, the free-text notes made by clinicians in EHRs. NLP is a type of machine learning; the “learning” refers to the ability of these advanced programs to use the relationships and patterns of the text in the data set to inform how to classify different inputs without direct human involvement.

A study by Kharrazi and colleagues assessed the value of unstructured EHR data in identifying several constructs of frailty (Kharrazi et al., 2018). An NLP algorithm was used to identify individuals at high risk of experiencing frailty. The study found that claims and structured EHR data yield an incomplete picture of burden related to frailty constructs, and frailty variables recorded in the EHR are likely to be missed if unstructured data are not analyzed (see Figure 2.1, taken from this study). Notably, the frailty-related construct rates extracted from structured data in the EHR were substantially lower than published epidemiological rates, suggesting the limitation of structured data. Incorporating unstructured EHR notes, enabled by applying the NLP algorithm, led to identification of considerably higher rates of frailty-related constructs than using claims and structured EHR data alone (ASPE, undated). This suggests that applying this method to unstructured data is a more-sensitive approach for identifying frailty. Additional work is needed to explore the specificity of this approach. However, as noted earlier, there is variability in how physicians and health systems populate EHRs, so, as this approach is applied to more health systems with different practices for data entry, results might vary.

Figure 2.1. Value of Unstructured EHR Data in Identifying Frailty Constructs



SOURCE: Kharrazi et al., 2018.
NOTE: “Overlaps and sizes of circles are scaled to represent actual sizes or overlaps of underlying patient populations used in study. In each Venn diagram, the top right circle represents claims data (red [sic]), the bottom right circle represents structured EHR data (blue), and the left circle represents unstructured free-text EHR data (green) extracted using an NLP approach. Diagrams are sorted based on absolute frequency of cases found from all data sources (including free text) for each geriatric syndrome in the study population (not sorted based on relative added value of free text). The blue or red areas not encompassed by the green area indicate that a condition has been captured using encoded data but was not mentioned in the free text as a clinical note” (Kharrazi et al., 2018).

Suitability of NLP for Population Health Management

NLP refers to using statistical and other computational approaches to analyze text—in this case, the free-text notes made by clinicians in EHRs. As described above, the unstructured data contained in the clinicians’ notes is a rich source of information about patients. NLP might be the key to leveraging these data for population management. Unfortunately, there are two types of barriers to using NLP to process EHR data. First, NLP requires resources—both human resources, in the form of experts in machine learning, and computing resources to process large datasets—that are currently beyond what is available to most health systems (Roski et al., 2018). In addition, because of both the computational approach and the size of the datasets involved, applying NLP to EHR notes data is time-consuming, especially if any manual validation or input is needed (Zeng, 2018). Computing time might improve incrementally with advances in hardware, and cloud computing is making high-powered computing resources more affordable and widely available.

The second major barrier to using NLP to analyze EHR data relates to variations in how frailty or functional impairment is assessed and documented. Similar to challenges in creating claims- or EHR-based algorithms to predict frailty, there is no gold standard for how clinicians define and measure frailty and, presumably, for how they would document this information in notes in the EHR. Because of the lack of standardization in conventions for describing frailty within and across health systems, there is little hope for scalability of an NLP approach to identifying frailty: Each set of clinical notes would form its own corpus for training, limiting the portability of the approach to other health systems (Sohn et al., 2018). Researchers have called on the field to move toward improved methods and standards that would address these issues (Velupillai et al., 2018; Wen et al., 2019), but, at this time, many obstacles exist.

Chapter 4. Promising Practices for EHR-Based Tracking and Identification of Frailty and Functional Impairment

In this chapter, we highlight examples of health systems that have effectively implemented claims- and EHR-based frailty and/or functional assessment indexes and used them for clinical practice and research. These examples are drawn from the academic and gray literature and supplemented with the results of interviews with clinical practitioners and researchers working on implementing claims- and EHR-based frailty indexes. The interview methods are described in Chapter 5.

Johns Hopkins University Center for Population Health Information Technology

JHU CPHIT has conducted many analyses of linked claims and EHR data from several health care systems to assess the completeness of frailty information in structured EHR and claims data, as well as to compare the performance and concordance of claims- and EHR-based frailty indexes. One key insight from their work relates to the degree of *openness* of the health care system and its impact on the performance of EFIs. For example, KPMAS is a highly closed health care system; most patients get nearly all their care from this system. This results in the claims- and EHR-based indexes performing similarly, as almost all the patient claims have corresponding EHR records in the KPMAS system. However, in a more-open system like the JHMI, patients receive care from other external health systems that do not share an EHR. This means that for many patients, key EHR-based information about their frailty might not be present in the JHMI EHR, and the EFI will be less accurate relative to the CFI. Understanding the degree of openness and the context of the health system where one is implementing the EFI is key to setting expectations about its performance; more-closed health systems are likely to have better-performing EFIs.

Veterans Health Administration

In the United States, the VA has a long history of developing geriatric assessments and implementing processes based on the results. For example, the Care Assessment Need is a well-known tool that was deployed in the 2010s to identify patients at risk of hospitalization and death using EHR data from primary care medical records (Fihn and Box, 2013; Wang et al., 2013). More recently, the JFI has been implemented to support patient care and population management (Kinosian et al., 2018). The JFI is a proprietary claims-based tool that is calculated using 13 categories of diagnostic codes that cover geriatric syndromes, functional impairments, and comorbidities. The JFI score captures the sum of these risk factors. The JFI has been validated against claims- and survey-based measures and found to have good ability to predict concurrent functional impairment and future long-term institutionalization (area under the curve around 0.8 across models). The next chapter discusses one research project comparing frailty indexes in the VA by one of the webinar panelists, Bruce Kinosian. The VA also has developed an intervention called the Surgical Pause for patients undergoing surgery; VA providers assess frailty before the surgery, and, if a patient is identified as frail, the provider can implement additional interventions or even reconsider the surgery (Center for Health Equity Research and Promotion, 2021).

Regional EHR Integration with EHR-Based Patient Identification in Primary Care

In an interview with one member of the EHR Learning Network, we learned about a multiyear collaboration among primary care providers and long-term care facilities at Primary Care Partners in Grand Junction, Colorado. The champion of this effort, Pat Page, was an early adopter of EHR technology in primary care; many of his relationships with other primary care practices were built when he served as a mentor to them in the 1990s during the adoption of EHR systems. In 2002, his practice, along with the other physician-owned practices comprising Primary Care Partners, supported the development a regional Health Information Exchange (HIE), which led to the establishment of the current HIE serving western Colorado, Quality Health Network. Around the same time, this primary care physician began focusing on the postacute and long-term care needs of his patients, which led to efforts to identify frailty patients. In his words, “My innovation was to assert that care for the frail should be ‘safe, simple, and respectful’ for patients, families, and providers.”

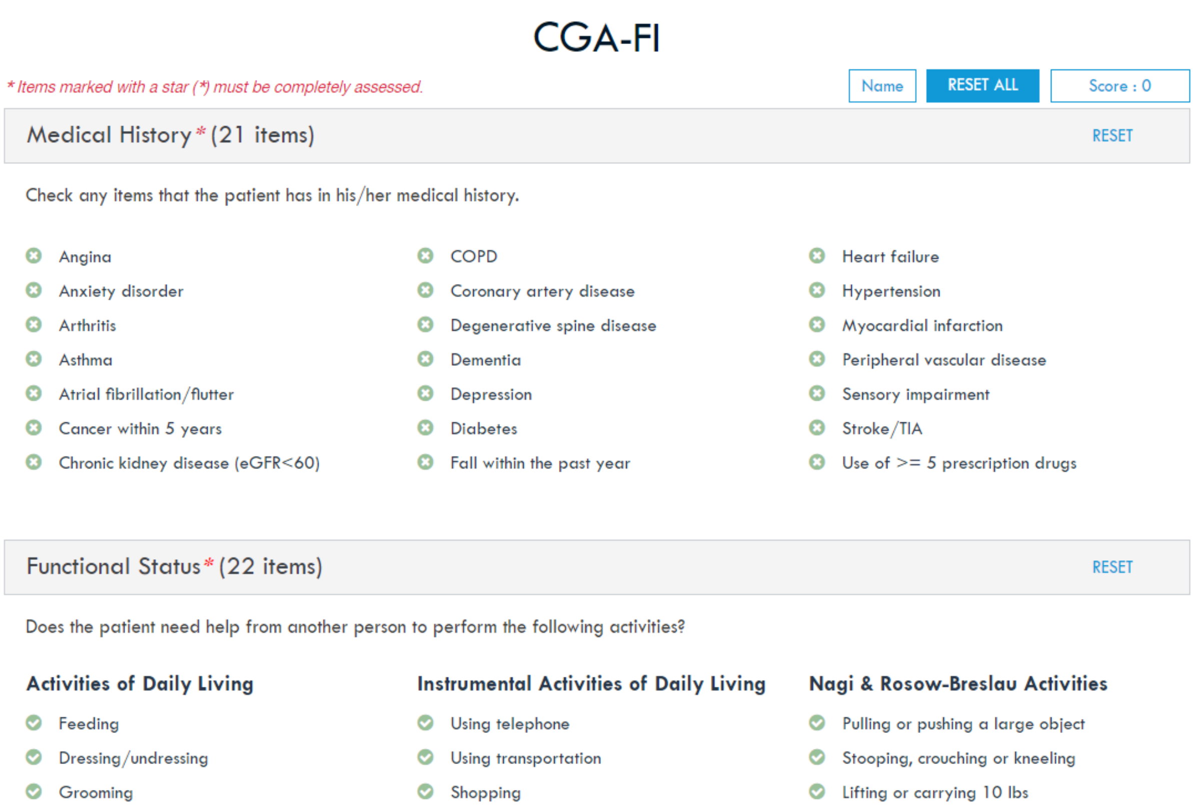
To advance these goals, Primary Care Partners, and eventually partners in the HIE, first used Kenneth Rockwood’s seven-point Clinical Frailty Scale to identify frailty (Rockwood et al., 2005), and then later, the commercial software Patient Pattern which uses data from the Minimum Data Set nursing home assessment to identify at-risk patients. This early adopter’s opinion was that “. . . the use of the scale was not sufficient. I needed the score and the process of eliciting the comprehensive geriatric assessment questions in Patient Pattern to migrate [the clinician’s] dialogue to a frailty-based dialogue. The score alone was not enough for a generalist, hospitalist, rehab doctor [to initiate meaningful risk-assessment and goals of care conversations].” Regarding mechanism of change, when this provider described the high quality of care that he believes results from a frailty score being displayed in the EHR, his explanation was that “it leads to honest communication of risk, which leads to alignment of care plan to patient values.”

This multipractice collaboration is currently funded to expand the use of Patient Pattern to more providers and settings of care. The next chapter also describes some of Page’s insights during an EHR Learning Network webinar.

Comprehensive Geriatric Assessment—Frailty Index

Beth Israel Deaconess Medical Center has implemented an online tool to assess frailty that blends EHR data with physician assessment, known as the Comprehensive Geriatric Assessment—Frailty Index (CGA-FI). Providers can enter diagnoses, patient- (or proxy-) reported functional status; mental state; nutritional status; and performance test values, such as gait speed, grip strength, and repeated chair stands (see Figure 2.2); for patients seen in its health care system, information can be pulled automatically from the patient's EHR, drawn from functional status information collected in comprehensive geriatric assessments. The look-back period used for laboratory and assessment data is 12 months, but everything on the problem list (an electronic list of all active health problems the patient is managing) is presented, including resolved issues if they have not explicitly been removed from the list. In practice, providers have found the problem lists are often not accurate, so those can be changed by the physician when assessing the patient's history.

Figure 2.2. Screenshot of the First Items from the Senior Health Calculator



SOURCE: Beth Israel Deaconess Medical Center, undated.

After inputting the required information and optional assessment scores, the CGA-FI calculator produces a score on a scale from 0 to 1, representing the proportion of deficits present, and scores in multiple domains: medical, mobility, muscle strength, ADL disability, instrumental activities of daily living (IADL) disability, cognition, and nutrition. The calculator also produces an estimate of biological age that might or might not correspond to the patient’s chronological age.

The calculator is currently used by geriatrics consultants for care of patients in the hospital and as part of the preoperative process for older patients. The tool highlights which aspects of the patient’s condition are most problematic and allows physicians to target interventions to patients. However, the frailty assessment, including both the calculation and the shared decisionmaking that follows, can take 30 to 60 additional minutes. The calculation can be used if a patient is planning to undergo a procedure; the procedure might be reconsidered given their frailty. Some patients are very interested in this information, and most appreciate having the discussion as part of their care.

Other areas in the medical center, including primary care, have been slower to adopt this tool, but clinicians from other inpatient departments and outpatient settings in the health system have expressed interest in using it in other settings, and it is becoming part of the training for residents. One other potential value of the tool is to use traditional claims- and EHR-based frailty indexes to screen for frailty on a population level and then use this tool to perform more-detailed assessments at the point of care for confirmation, for treatment plan development, and to support prognostic discussions.

England’s National Health Service

The National Health Service (NHS) is the publicly funded health system in the United Kingdom. Across NHS England—the branch of the NHS that covers England—general practitioners are required to screen individuals aged 65 and over with the NHS electronic frailty index (commonly called the eFI, but, to avoid confusion with the general term EFI, in this report, this specific index will be referred to as NHS-eFI) (National Health Service England, undated). The NHS-eFI uses electronic primary health care records and a cumulative deficit model to identify patients who are at risk of moderate to severe frailty. The NHS stresses that the NHS-eFI is a population risk stratification tool rather than a diagnostic tool and requires the input and judgment of clinicians to determine diagnosis and care plan, which might vary depending on clinical processes. The NHS-eFI has been standardized and is widely available in all practices throughout NHS England. The index aims to promote access to appropriate care across care settings—supported by supplemental information available in the patient’s medical record—and overall well-being, as measured by improved medication management, fewer unnecessary hospitalizations, and reduced risk of falls or accidents.

Adapted EFI in a Medicare Accountable Care Organization

Researchers from Wake Forest Medical School adapted the NHS-eFI for use in the population of patients who participate in their Medicare Accountable Care Organization, with the goals of associating the NHS-eFI with mortality, health care utilization, and fall risk (Pajewski et al., 2019). One additional goal of the research was to understand how frequently missing EHR data prevents calculation of the NHS-eFI. Because this is a deficit-based model, the researchers treated data from patients who had no diagnosis codes in the past two years as different from patients who had some diagnosis codes; to be included in the model, patients were required to have at least 30 pieces of relevant data. The resulting model drew from the EHR, including functional assessment data collected in Medicare Annual Wellness Visits, to predict injurious falls, inpatient hospitalizations, emergency room visits, and all-cause mortality. Beyond the empirical findings, this research demonstrates that it is feasible to develop a site-adapted EFI for patient identification. This study stopped short of integrating the resulting score into the EHR, but the authors note that using the NHS-eFI for population health management would be a good next step for this work.

Key Takeaways

These examples demonstrate wide variation in the EFI landscape. Although some large health systems, and, in the case of England, an entire country, have adopted EFIs to support population management and patient care, other initiatives, such as those focused on a single geriatric consultancy service in a hospital, are tailored or much more modest in scope. The EHR-based frailty indexes are used to identify frail patients at risk for injurious falls, inpatient hospitalizations, emergency room visits, and all-cause mortality. This information is used to inform patient-centered care across the care continuum, such as suitability for surgery or other procedures based on individual risks, and potential postacute care and long-term care needs that reflect patient goals and preferences. Clinicians have indicated they have used a frailty-based framework for discussing care planning with patients and their caregivers based on the frailty scores.

The differences between the adopted approach (i.e., claims versus EHR) and how it is being used are likely due to the variety of goals, technical capabilities, and resources at each site. The use of these indexes in clinical practice also depends on buy-in from clinicians. Health systems researchers have also evaluated the comprehensiveness and completeness of data in EHR-based frailty indexes to provide a longitudinal history of a patient, which might affect the accuracy and validity of the derived frailty scores. The research suggests adaptations as well as claims data might improve these frailty indexes. However, meaningful implementation of EFIs in such varied settings and variety of use cases argues for the flexibility of these methods to accomplish system- or population-specific goals and the ability of practitioners to adapt EFIs to meet the needs of their specific contexts. Further work to describe the implementation of these indexes in a variety of health systems is described in Chapter 5.

Chapter 5. Stakeholder Insights

Interviews with Subject-Matter Experts

Throughout this project, we have gathered insights from stakeholders participating in the EHR Learning Network about their experiences capturing patients’ functional status and/or frailty risk factors in the EHR through semistructured interviews. We have described our interview methods and identified common content in the completed interviews that are summarized below.

Interview Methods

We conducted eight semistructured interviews with clinicians and researchers who were implementing claims- and EHR-based frailty indexes. The goal of these interviews was to identify promising practices for the use of these indexes. We sent emails to the EHR Learning Network email list to recruit interviewees. Members of the EHR Learning Network (researchers and practitioners) who indicated that they were using these indexes in practice were asked to participate in interviews; we also conducted snowball sampling by asking interviewees if they knew of any other novel uses of these indexes in clinical practice or research. These interviews were completed in two rounds. The goal of the first round was to identify promising approaches and help plan future webinars, and the goal of the second round was to obtain more information on documented efforts to use EFIs in clinical practice. The first round of five interviews took place between September and November 2020, and the second round of three interviews took place in June and July 2022, with each interview lasting approximately 45 minutes. Each interview was led by a researcher who was experienced in qualitative methods; between one and three members of the project team were present for each interview. We developed an interview guide that consisted of a series of open-ended questions with probes to follow up on points raised by the interviewee and to provoke additional discussion. The interview guide covered the interviewee’s current practices for capturing functional status and frailty in the medical record, how the interviewee was using that data, and any potential best practices they had identified for future efforts to capture frailty data in the EHR. When possible, interviews were recorded, transcribed, and analyzed using a conventional content analysis approach. If not recorded, we took detailed notes. We did not seek to achieve content saturation in these interviews; each was considered a case study and we looked for commonalities across each case study. These interviews were deemed exempt from Institutional Review Board review by the RAND Human Subjects Protection Committee.

Potential for EHR-Based Frailty Index

In general, respondents did not think that providers are currently documenting in the EHR, in a structured way, the type of information that would be needed to identify patients with functional impairment and/or frailty. However, they did think that agreement could be reached in the geriatrics community on a small set of measures that ought to be collected (e.g., gait speed, grip strength, and "timed up and go" [the amount of time it takes a patient to stand up from an armchair, walk a predetermined distance, turn around, walk back, and sit back down]). One respondent was emphatic that it was only lack of political will (i.e., to engage with the idea of appropriate but low-intensity care for patients who are declining) that kept the United States from doing what the United Kingdom and other countries have done with regard to widespread use of geriatric frailty indexes.

Challenges to Data Collection

Respondents mentioned several challenges to collecting and recording the type of geriatric assessment data that would be needed to calculate a frailty index for older patients. One respondent noted that some patients do not complete forms; he cited a 50 percent completion rate for health questionnaires that patients are asked to complete before a visit and thought that additional data collection would be a challenge. Another respondent suggested the idea of having community health workers complete geriatric assessments in nonclinic settings. When presented with this idea, another respondent disagreed with this approach, stating his belief that performance tests should be performed in a controlled setting—such as a clinic—but also noting that primary care clinics are often pressed for space: It would be difficult to keep a patient "roomed" for an extra 15 minutes to complete assessments when there is pressure on a clinic to maintain a certain cadence of visits.

Commercial Products for Frailty Assessment Through EFIs

Patient Pattern, an EHR add-on to calculate a geriatric frailty score for patients, is well-known among the respondents, but it is by no means universally known (see Patient Pattern, undated). This frailty score is described as the physiologic age of an individual, an age that might be different from their numeric age. Patient Pattern can be tailored to pull existing data from the EHR, but one respondent described it as being able to prepopulate about 60 percent of what is needed to complete the geriatric assessment. The other 40 percent of information would need to be collected through a patient exam. The respondent felt that prepopulating the 60 percent of data is a good head start, but the geriatric assessment can still be time-consuming and is not likely to be feasible to complete for all patients.

Trade-Off Between Perfect Measures and "Good Enough" Algorithms

One geriatrician described collecting ADL and IADL information in a check-box format for his patients, but he also captures functional status in the notes (not in an extractable format), and he noted that there is not uniformity in the way that providers in his practice capture this information. Two respondents noted that subspecialists (e.g., cardiologists and orthopedists) tend to collect this information more systematically than primary care physicians (possibly because these measures have known relationships to patient outcomes relevant to their practice); in health systems where specialists and primary care physicians share an EHR, this information would be available to all clinicians. One respondent discussed how providers or specialties sometimes favor one similar measure over another—for example, to assess mobility, some providers might use a timed up and go, in which a patient must stand from a chair, walk six meters, and sit back down in under 12 seconds, compared with other providers who favor a "sit to stand," in which a patient must stand from a chair without using their arms repeatedly during a 30-second time frame—but discussed how, at a crude level, either might be good enough for detecting a concerning level of impairment in the general population.

On this theme, one respondent made the analogy of needing a *PHQ-2* for frailty. The PHQ-2 is a two-item depression-screening tool with high sensitivity and relatively low specificity. That is, the PHQ-2 is very good at identifying people with depression but less good at identifying people without depression. The respondent used this analogy in the frailty-screening context to express his desire for a short but high-sensitivity means to identify those who are likely to be experiencing frailty or impairment so that they can be identified for further assessment. This respondent added the example of Cologuard screenings for colon cancer, which have been set up in a way that the lab results flow automatically back to the EHR, with established workflows for prescribing (primary care physician), filling (pharmacist), analyzing (vendor or lab), and reporting back (EHR), with follow-up mail and phone scripts for each party.

Webinars

In addition to the interviews, we also held two webinars for the members of the EHR Learning Network. The first of these webinars kicked off the EHR Learning Network. It took place in May 2020 and involved presentations from ASPE, RAND, and JHU CPHIT. Staff from ASPE presented on the motivation for the Patient-Centered Outcomes Research Trust Fund–funded project and the establishment of the EHR Learning Network, as well as the overall goals for the project of developing claims-based frailty algorithms and testing them using EHR and claims data in a health system. Researchers from RAND then presented their proposed process to refine and validate claims-based algorithms to identify and predict frailty and/or functional impairment, along with the goal of adding these indicators to the CCW. Finally, researchers from JHU CPHIT presented their plans to validate this claims-based algorithm using EHR data.

RAND convened the second webinar in May 2022, where panelists from the EHR Learning Network shared their experiences implementing claims- and EHR-based frailty indexes in practice and discussed some of the complications associated with using these data in practice.

Bruce Kinosian (associate director, Geriatric and Extended Care Data Analysis Center, U.S. Department of Veterans Affairs, and associate professor of medicine at the Hospital of the University of Pennsylvania) presented findings from his experience implementing the JFI in the VA Medical Center in Philadelphia, where he practices as an internist and geriatrician. The JFI has been used by the VA since 2012. One current project he discussed is an evaluation of several different claims-based indexes in the claims data for the VA patient population to determine which patients are picked up by each. Among 2.5 million veterans, the indexes identified 144,000 frail veterans with the highest risk for long-term institutionalization (Huan et al., 2022). Early findings suggest that performance in terms of area under the curve is similar for all the indexes, but each index identifies a slightly different set of individuals.

Patrick Page (family physician in Primary Care Partners in Grand Junction, Colorado, and adjunct professor for aging studies at Colorado Mesa University) presented the work his primary care medical group has done to integrate frailty assessment into primary care using the proprietary Patient Pattern software that pulls data from the EHR and is supplemented by direct clinical assessments. Their group has found clinicians in the practice to be quite interested in the use of this frailty assessment, with most able to integrate the direct assessment into a visit by adding less than 20 minutes to the overall visit time. The combined information generates a frailty score that goes into the EHR and prompts a geriatric consultation as a task based on the score. The frailty score and related consultation information from the EHR also goes to the regional HIE, which is available to providers in emergency rooms and hospitals to support patients' advance care plans.

Hadi Kharrazi (associate professor of health policy and management at Johns Hopkins Bloomberg School of Public Health and codirector of JHU CPHIT) presented work, funded by the Patient-Centered Outcomes Research Trust Fund, that JHU CPHIT has done to explore health system "leakage" and its implications for EHR-based frailty assessment (i.e., how much of a patient's care is delivered in various health systems with different EHRs). In systems that were more closed or less "leaky," patients received a greater percentage of their care from the system and EHR-based frailty assessments were more accurate, whereas with patients from more open health systems, frailty was more accurately identified using claims-based frailty algorithms.

Finally, David Hill, principal software systems engineer at The MITRE Corporation, presented its work on the PACIO Project, a collaborative effort sponsored by CMS to develop Fast Healthcare Interoperability Resources guides for promoting data exchange between postacute care and other providers ("PACIO Project," 2020). This effort focuses on using the Health Level 7 (HL7) standards to develop transmission processes for six use cases: functional status, advanced directives, reassessment time points, cognitive status, quality measures, and "SPLASCH" (speech, language, swallowing, cognitive communication, and hearing). In the future, the implementation guides produced through this effort can be used by other health systems and providers to speed up data sharing and possibly address issues regarding aggregation of frailty data from multiple sources (e.g., different EHRs in different health systems).

The panelists discussed some of the barriers and challenges with identifying frailty in their projects. Several panelists cited difficulty with data access and data lags, especially when integrating data from different sources or different health systems. Much of the data varies because of distortions in diagnosis coding; some health systems have different cultures of coding and others are more subject to upcoding, often due to financial incentives. The quality of diagnosis information varies by source; some health systems place more emphasis on accurate problem lists, while others do not. This variation in data affects identification of frailty using claims and/or EHR data. The panelists also discussed the importance of sharing frailty results with patients but noted that these must be patient-centered discussions that avoid potentially stigmatizing language around frailty.

In addition, members of the EHR Learning Network were encouraged to ask questions and share their experiences using these indexes at the end of the webinar. There was substantial discussion about the identification of what one attendee called *pre-prefrailty*. Eleanor Simonsick from the National Institute on Aging and an associate professor in the Division of Geriatric Medicine and Gerontology at the Johns Hopkins University School of Medicine referenced studies from the Baltimore Longitudinal Study on Aging that suggest fatigue during activities is a marker of impending decline, or pre-prefrailty (Simonsick et al., 2016). Traditionally, *prefrailty* is defined as a person who has some of the indicators of frailty but not enough to be considered frail. If patients who were at risk for becoming prefrail could also be flagged and detected by these or other indexes, health care systems and providers could target these patients for intervention and prevent or slow their progression into a prefrail or frail state and alter the course of the aging trajectory. Panelists expressed interest in identifying those at risk and deploying early interventions. There might also be opportunities to assess frailty or prefrailty in continuing care communities for seniors or housing authorities. This idea sparked a larger discussion of the need to translate basic science and clinical research findings more quickly into clinical practice to prevent frailty and improve the lives of patients. Some research is being conducted to implement these early screenings and tools in clinical practice and provide early help to seniors under an early detection and prevention paradigm. Supporting interoperability of functional status data through the PACIO Project can also help these early identification and prevention efforts and could be a potential use case for functional status data.

Chapter 6. Key Considerations for Providers and Health Systems

After reviewing measures to assess frailty using claims and EHR data and gathering practitioner input through interviews and webinars, we identified several key considerations for algorithm developers, researchers, practitioners, and policymakers working to identify frailty and/or functional impairment through EHR- and claims-based indexes.

Algorithm Developers: Identify and Understand the Strengths and Limitations of These Approaches

In this report, we identified many validated claims- and EHR-based frailty indexes. However, given the value of unstructured data, there is the potential to improve the performance of these indexes.

Clearly Define the Use Case(s)

EFIs have been developed to predict utilization, mortality, functional impairment, and other markers of vulnerability or risk. Although there is overlap in predictors and populations, clinicians and population health managers should be clear on the purpose and goals of EFI development and implementation and where patient care protocols might vary. For example, an algorithm to identify patients at risk of high health care utilization might need to account for different environmental or social factors from those included in an algorithm to identify functional impairment only (e.g., the presence of a caregiver could mitigate the risk of high health care utilization in an otherwise high-risk patient, so a health system using an algorithm might not necessarily need to target additional services for this patient or recommend them for a nursing home stay). Algorithms might also be used to identify those in the patient population who might need further in-depth clinical assessment or performance tests to evaluate risk of frailty. Another potentially different use case beyond the scope of this project might be for EFIs to identify risk of prefrailty or pre-prefrailty for early prevention and lifestyle modifications, such as exercise or strength training, rather than changes in care. This might require different types of clinical assessments or performance tests in addition to those that help identify and distinguish moderate to severe frailty.

Ask: Could Existing Algorithms Be Applied or Adapted to Meet the Need?

The proliferation of homegrown EFIs, partly due to local differences in data availability and system architecture, has serious implications for the development of an algorithm. Some EFIs are created as part of quality improvement efforts or are codeveloped with clinicians who want to improve their practice. However, before starting from scratch, health systems should consider the benefits of using an existing EFI. These benefits might include prior testing and validation, established EHR workflows, and ideas on how to integrate the results of the EFI into clinical practice and broader population health management efforts.

Include Informaticists and Clinicians in EFI Selection

Implementation and uptake are important for any quality improvement intervention; for an EFI to be used, clinicians and administrators need to agree on its validity and potential to support care delivery. Especially if the goal of an EFI is to prompt provider action—such as a response to an alert or dashboard in the EHR—developers should partner with clinicians early to get buy-in from the end users and feedback on the types of actionable information that would be useful to inform care. One example of successful collaboration between developers and clinicians is the CGA-FI used at Beth Israel Deaconess Medical Center that provides a report that helps clinicians understand the relevant types of interventions, such as mobility, cognition, or nutrition.

Researchers: Gaps in Knowledge

There are many areas in which researchers interested in improving the quality of the data used in these indexes, and the use of these indexes in practice can fill gaps in knowledge. The claims-based frailty indexes are relatively well-documented, and many of these indexes have successfully been adapted across clinical settings. These indexes might have reached a plateau in terms of performance given the limited information in claims data. EHR-based frailty indexes are more novel, and significant portions of data in many EHRs or data that could be linked to the EHR (such as health risk assessments or performance tests) remain relatively untapped. We believe that the most pressing gaps in knowledge with the most potential to improve patient outcomes relate to EHR data use to assess frailty, especially the use of unstructured data.

Accuracy of EHR Data

Several respondents cited problem list data as relatively inaccurate and not as useful for frailty identification as other structured elements of the EHR. Ideally, a problem list in an EHR would contain all active health problems that a patient is dealing with, but, in practice, many problem lists are not up to date, as resolved problems are not removed and new problems are not always added. More research is needed to systematically assess the quality of data on problem lists, including whether all relevant active problems are on the list and whether problems that are resolved are removed from these lists. This research could also include analysis of potential variation in diagnostic coding practices, including the impact of upcoding on data accuracy. There is likely significant variation across health systems and potentially even within specific clinical departments or services in a health system. Strategies to increase the accuracy of problem lists are likely to result in improved identification of frailty among patients.

Benefits of Unstructured Data

The use of free-text or unstructured data in these indexes has significant potential to improve their performance. Notes might be able to provide valuable information about specific aspects of frailty, including lack of social supports and malnutrition, that are not captured in diagnosis codes, procedures, or problem lists. More research into NLP and other text analysis approaches is needed to validate their performance across various health care systems with different cultures of note writing and clinical documentation. However, as these approaches are often labor intensive and technically difficult, more research into how these approaches can be exported and more easily built into different EHR systems is needed.

Application of Indexes in Clinical Practice

The use of these indexes in clinical practice can be a rich target for research. Although we cite several examples of clinicians using EFIs in practice, the impact of the standardized use of these indexes on patient outcomes is largely unknown. Researchers could conduct studies comparing outcomes among practitioners using these indexes to those who do not. For example, the Beth Israel experience suggests that standardized use of this index before surgery would improve outcomes for patients by avoiding surgery in high-risk patients. The results of a clinical trial conducted at Beth Israel and 13 other centers show that frailty assessment before a transcatheter aortic valve replacement or surgical aortic valve replacement procedure can be used to identify frail patients at higher risk for complications or death after the procedure (Afilalo et al., 2017). As mentioned earlier, the VA has developed a similar intervention called the Surgical Pause, in which frailty is assessed before surgery and additional interventions could be deployed (Center for Health Equity Research and Promotion, 2021).

Practitioners: Potential Barriers

We have identified several potential barriers that practitioners looking to implement more-standardized frailty assessment into clinical practice might face. First, there is still a lack of consensus among clinicians on how to define frailty; this lack of a standard definition and measurement approach is a limiting factor that is likely preventing the widespread use of any specific index. Anytime that practitioners want to add a new assessment to be completed as part of routine outpatient visits or standardized inpatient care, the time it takes to conduct the assessment must be justified in terms of clinical impact and improvement in patient outcomes. Without belief among practitioners that these assessments will improve patient care, health systems are unlikely to see significant use of these assessments. Even when health risk assessments, such as those used by health plans, are conducted, these data do not always feed back into the EHR. In addition, without any provider reimbursement for frailty assessment, there is little economic incentive for practices to add a potentially lengthy frailty assessment to routine care.

The greatest potential for increased use of frailty assessment is likely in specialized geriatrics services in hospitals or outpatient clinics for older, potentially frail patients and those who are considering high-risk treatments for cancer, invasive procedures, or surgery. Integrated health systems that are responsible for more of a patient's care and are reimbursed in part using value-based payment models are also more likely to see benefits to these assessments—they will likely already have more of the necessary data in their EHR and will have more incentive than more-fragmented health care systems to improve outcomes for their patients because better outcomes could result in lower overall costs of care, particularly in value-based payment systems. Age-friendly health systems, which focus on providing quality care to older adults, might also benefit from increased use of frailty assessments, which align well with their goals of maintaining function in older adults.

Understand the Context of the EHR

Procedures, diagnoses, and utilization captured in the EHR generally reflect only care received within one health system. Even within health systems, the inpatient and outpatient EHRs might not be fully integrated, and/or integration of key information (e.g., lab results) might be included as unstructured data (e.g., PDF attachments). Before implementing EHR-based methods for population identification, health system administrators should attempt to understand the limitations of their EHR through close review and comparison with insurance claims data, where possible.

Data Quality Issues

Practitioners will also need to address data quality issues. Inaccurate electronic health data can result in both over- and underdiagnosis of frailty, both of which have the potential to negatively affect patient outcomes (Predmore and Fischer, 2021). Full automation of these indexes based on EHR data will be less successful than indexes that prepopulate with data from the EHR but allow practitioners to adjust or enter new information at the point of care.

Patient Engagement

Finally, when communicating the benefits of the use of these frailty indexes to patients, practitioners need to be mindful of how these results are communicated. Discussions on frailty and functional impairment should be handled respectfully as part of a shared decisionmaking process, not in a judgmental way. Patients might feel stigma around discussing frailty and functional impairment with clinicians, as well as concern that these assessments and discussions could lead to a loss of independence, for instance, if they go to a nursing home. Older patients might be skeptical of the use of algorithms and electronic data as replacements for clinical acumen. These indexes and their outputs should be framed as tools that support a physician's judgement, not as hard-and-fast rules that dictate patient care.

Policymakers: Implications

Policymakers looking to improve the performance of EFIs and increase the use of these indexes to improve patient outcomes could take several different approaches. We outline several of these below.

Health Information Technology Standards

Given the relative ease of using structured EHR data elements, such as coded diagnoses and procedures for frailty identification, efforts to code frailty or functional impairment directly would likely improve the performance of these indexes. If there was a standard code for frailty, then any provider who interacts with a patient could code them as frail and provide that information for all future providers treating the patient. This information would need to be periodically reassessed to verify that the patient was still frail. The new version of the ICD coding system (ICD-11) has a supplementary section for functioning assessment based on the World Health Organization's International Classification of Functioning, Disability and Health (ICF) (Harrison et al., 2021). Although it will likely take many years for ICD-11 to be implemented in the United States (and there are other definitions of frailty that might not be captured by the ICF), better integration of standard ICF elements into ICD could better support the use of structured data elements to describe the impacts of frailty on mobility and cognitive functions (Escorpizo et al., 2013).

PACIO and Other Efforts to Promote Interoperability

Efforts to share information about patient functioning across health systems are a promising way to address the limits of EHR and other electronic sources of data. The CMS-funded PACIO Project is a collaborative effort that uses the HL7 standards to promote the transfer of functional status information among various health system stakeholders ("PACIO Project," 2020). Building off this effort, HIEs and health systems could use these guides to promote the transfer of this information and the use of this information for frailty assessment. The U.S. Office of the National Coordinator for Health Information Technology (ONC) plays an important role in promoting interoperability between EHRs and other health data repositories. Under the 21st Century Cures Act, ONC promulgated rules intending to prevent "information blocking," in which EHR vendors and health systems prevent others from accessing their data. However, a survey of HIEs found that there was still some resistance to sharing patient data from both EHR vendors and health systems (Everson, Patel, and Adler-Milstein, 2021); there is still more that policymakers can do to promote interoperability and hold stakeholders that are not sharing data accountable. HIEs could be an important mechanism for interoperability and sharing of clinical data across health systems that can help prevent unnecessary care and poor outcomes, especially in frail seniors, whose standard care protocols might be too aggressive and might not contribute to their quality of life. HIEs can also help address the limited reach of EHRs that reflect only care experiences within a particular health system or health care provider. For seniors who see multiple providers, integrated EHR data that includes frailty status and other information shared across an HIE might be more likely to affect the care they receive.

Promoting Research and Learning from Practitioners

Policymakers could fund and promote the work of algorithm developers, researchers, and practitioners working on these topics. Federal funding agencies could look for ways to move research findings into practice by supporting pilot efforts to assess frailty as part of standard practice in clinical settings or look for other models for incorporating EHR information about frailty into care at health systems across the country. Convenings and webinars are good ways to bring together stakeholders interested in frailty assessment and publicize findings from promising pilot efforts and other implementations.

Conclusion

The routine record keeping and billing practices of modern medical care have resulted in a trove of information about patients' health and health care that can be mined for quality improvement and population management purposes, including identifying patients at risk of frailty and/or functional impairment. There is not consensus on how to operationalize the concept of frailty in administrative data; as a result, various approaches have been used. The approaches that have drawn from claims data have been moderately successful in identifying frailty, but different approaches identify different patient populations and are limited in clinical utility as a result.

Frailty indexes that are based on EHR data—EFIs—are more promising and practical for health systems. However, the levels of data quality and completeness have limited the accuracy of many EFIs. There are many barriers to developing EFIs or replicating existing models outside the system in which they were developed, but there are some promising examples of large-scale use of EFIs for population management and patient care that demonstrate their feasibility and benefits. Future developments in processing unstructured EHR data could vastly increase the amount of clinical information available and thus the accuracy of EFIs. In addition, data-sharing efforts can increase the amount of information available for EFIs, going beyond a single health system's EHR to include more electronic information about a patient.

Clinicians and health system leaders who are interested in leveraging EHRs to identify patients at risk of poor outcomes due to frailty or functional impairment should consider the completeness of their EHRs for their patient population, clearly define the goals of the EFI, familiarize themselves with existing EFIs so as to not spend time recreating what has already been done, and ensure that informaticists collaborate with clinicians to produce a workflow that is feasible in the clinical environment. Policymakers could take many different steps to increase the use of these assessments to improve the quality of patient care and improve patient outcomes.

Abbreviations

ADL	activities of daily living
AHRQ	Agency for Healthcare Research and Quality
ASPE	U.S. Office of the Assistant Secretary for Planning and Evaluation
CCI	Combined Comorbidity Index
CCW	Chronic Conditions Data Warehouse
CGA-FI	Comprehensive Geriatric Assessment—Frailty Index
CMS	Centers for Medicare & Medicaid Services
CFI	claims-based frailty index
CPT	Current Procedural Terminology
EFI	EHR-based frailty index
EHR	electronic health record
HCPCS	Healthcare Common Procedure Coding System
HIE	Health Information Exchange
IADL	instrumental activities of daily living
ICD	International Classification of Diseases
ICF	International Classification of Functioning, Disability and Health (World Health Organization)
JFI	JEN Frailty Index
JHMI	Johns Hopkins Medical Institute
JHU CPHIT	Johns Hopkins University Center for Population Health Information Technology
KPMAS	Kaiser Permanente Mid-Atlantic States
NHS	National Health Service
NHS-eFI	electronic frailty index (National Health Service)
NLP	natural language processing

ONC	Office of the National Coordinator for Health Information Technology
VA	Veterans Administration

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