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SUPPORTING INFORMATION

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Table S1 List of patient resources provided at the memory clinic and VMC.

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Availability of information on functional limitations in structured electronic health records data

INTRODUCTION

Data from electronic health records (EHR) are increasingly used for research, to inform clinical care decisions, assess quality of care, and identify patients at high-risk of poor outcomes.[1] Functional status—including mobility and the ability to perform activities of daily living (ADL)—are key indicators associated with mortality, healthcare use, ability to self-manage disease, and health-related quality of life of older adults.[2] However, EHR documentation of function is not standardized across vendors and health systems, limiting interoperability and information sharing.[3,4] The lack of standardization means that important measures of function are likely absent from EHR-integrated software and apps which often rely exclusively on standardized structured data fields.[5] The goal of this analysis was to quantify the extent that functional limitations are captured in a national pool of structured EHR data.

METHODS

This was a cross-sectional study using IBM Watson Health Explorys, a network of EHR data from 26 health systems comprising 360 hospitals and 64 million unique patients in the United States.[6] Explorys maps the standard elements of structured EHR data from each health system to SNOMED-CT concept codes, which were used to identify functional limitations into five categories: mobility and gross motor, fine motor, large muscle, ADL, and instrumental activities of daily living (IADL) (Table S1). The study sample included 7,662,030 adults age ≥65 with at least one healthcare encounter between 02/14/2017 and 02/14/2022. For benchmarking, the rates identified in EHR data were compared with the national prevalence rates of functional limitations among older adults in the community using the 2016 Health & Retirement Study (Text S1).[7] The study was deemed exempt by the authors' IRB.

Related presentations: Oral presentation at Gerontological Society of America 2020 annual research meeting.

RESULTS

Functional limitations were captured in just 11.5% of the EHR study population compared to 71.5% of the community-based survey population. The prevalence in EHRs was lower across all five categories of function with differences ranging from 9.6 percentage points (IADL limitations) to 62.7 percentage points (large muscle group limitations). The most common underrepresented functional limitation categories captured in structured EHR data were limitations in mobility (9.3%), followed by ADL limitations (3.5%), and IADL limitations (1.0%) (Table 1). Fine motor impairment and limitations in large muscle function were captured in ≤0.01% of patients in the structured data. Most ADL limitations captured in the data were related to difficulty walking (Table S1). Nearly all IADLs captured are due to non-compliance with medication, which could be for reasons other than functional limitation.

DISCUSSION

Structured EHR data are a poor source of information on functional limitations, with most, if not all, categories likely to be under-captured or missing completely. There are likely several reasons. First, forms to document function are not standardized and vary widely across vendors and health systems. Often functional limitations are documented in clinical notes, which are unstructured data and less amenable to analysis. Second, ICD-10-CM codes used for billing and the CORE Problem List Subset of SNOMED-CT used

TABLE 1 Percentage of older adults with documented functional limitations in electronic health records compared to estimated population prevalence in the United States

	Nationwide pool of electronic health records (Explorys)[a]		National community-based health survey on aging (Health & Retirement Study)[b]	
Characteristics	**No.**	**%**	**Weighted No.**	**% (95% CI)**
Total over age 65	7,622,030	100	48,419,000	100
Age group				
65–74	3,677,150	48.2	28,520,000	58.9 (57.1–60.7)
75–84	2,621,520	34.4	14,061,000	29.0 (27.7–30.4)
85+	1,413,540	18.5	5,838,000	12.1 (11.0–13.1)
Gender				
Male	3,333,380	43.7	21,496,000	44.4 (43.6–45.2)
Female	4,219,350	55.4	26,924,000	55.6 (54.8–56.4)
Unknown/other	113,910	1.5	–	–
Race				
Black/African-American	655,820	8.6	4,492,000	9.3 (8.3–10.2)
White/Caucasian	5,068,040	66.5	41,512,000	85.7 (84.4–87.0)
Other, unknown, or missing	1,850,440	24.3	2,416,000	5.0 (4.1–5.9)
Hispanic ethnicity	240,930	3.2	3,854,000	8.0 (5.8–10.1)
Functional limitations				
Any functional limitation	878,320	11.5	34,610,000	71.5 (70.3–72.7)
Mobility and gross motor impairment	750,300	9.8	26,128,000	54.0 (52.6–55.3)
Fine motor impairment	<10	<0.1	8,017,000	16.6 (15.8–17.3)
Large muscle group limitations	1030	<0.1	30,381,000	62.7 (61.4–64.1)
Limitations in activities of daily living (ADL)	327,980	4.3	8,518,000	17.6 (16.7–18.5)
Limitations in instrumental activities of daily living (IADL)	73,810	1.0	5,117,000	10.6 (9.8–11.4)

Note: Table compares the percentage of the study population with a documented functional limitation in a national network of electronic health records vs the estimated prevalence among adults age 65 and older in the U.S. population. Population weights were applied to the HRS study to provide national estimates (rounded to nearest 1000), and confidence intervals were calculated using Taylor series linearization.
Source: [a]IBM Watson Health Explorys platform, February 14, 2017–February 14, 2022. [b]RAND version of the Health & Retirement Study (HRS), 2016.

in problem lists and discharge diagnoses lack specificity to record detailed functional limitations and care dependence. Third, the assessment of functional limitations itself may vary across care settings and health systems.

The implication is that functional limitation measures are likely missing from health systems' initiatives to improve quality, safety, and value through "meaningful use" of EHR data, especially in smaller hospitals and clinics that do not have resources to develop custom software or collect additional data. For example, functional limitations are important predictors of hospital readmission, but these measures are likely absent from research and software/apps designed to identify high-risk patients prior to discharge.[8] Likewise, function is likely missing from population health management and learning health system efforts that rely on routinely collected structured EHR data.

Possible solutions include modifying EHRs to include a standardized place to document functional limitations and other disabilities such as the one recommended by HL7 International,[3] and/or allowing more detailed functional concepts as valid entries in the diagnosis or problem lists. Advances in natural language processing may allow for better use of clinical notes data in the future.[9] Adopting age-friendly models of care that incorporate routine functional assessment for older adults may improve documentation.[10]

Study limitations: the Health & Retirement Study collects self-reported measures in the community, while Explorys data are from EHR documentation in care settings, so some differences are expected. However, the rates are so low in the Explorys data that under-capture, rather than a healthier population, is the more likely explanation. Our study may miss functional limitations documented in non-standardized forms that are specific to a particular health system.

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CONFLICT OF INTEREST

Nicholas K. Schiltz's spouse is a former employee of IBM. The authors have no other conflicts to disclose.

AUTHOR CONTRIBUTIONS

Nicholas K. Schiltz conceptualized and designed the study, conducted the analysis, and drafted the manuscript. All authors contributed to interpretation of the data, participated in revising the manuscript for important intellectual content, and gave final approval of the submitted version.

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Appendix S1: Supporting Information.