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Review

Frailty indices based on routinely collected data: a scoping review

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ABSTRACT

A frailty index (FI) is a frailty assessment tool calculated as the proportion of the number of health-related deficits an individual has to the total number of variables in the index. Routinely collected clinical and administrative data can be used as sources of deficits to automatically calculate FIs. This scoping review aimed to evaluate the current research landscape on routine data-based FIs. We searched seven databases to find literature published in 2013–2023. Main inclusion criteria were original research articles on FIs constructed from routine data, with deficits in at least two of the following categories: “symptoms/signs”, “laboratory values”, “diseases”, “disabilities”, and “others”. From 7526 publications screened, 218 were included. Studies were primarily from North America (47.7 %), conducted in the community (35.3 %), and used routine data-based FIs for risk stratification (51.4 %). FIs were calculated using various routine data sources; however, most were initially developed and validated using hospital records. We noted geographical differences in study settings and routine data sources. We identified 611 unique deficits comprising these FIs. Most were either “diseases” (34.4 %) or “symptoms/signs” (32.1 %). Routine data-based FIs are feasible and valid risk stratification tools, but research is confined to high-income countries, their routine adoption is slow, and deficits comprising these FIs emphasise a reactive and overtly medical approach in addressing frailty. Future directions include exploring the feasibility and applicability of using routine databases for frailty assessment in lower- and middle-income countries, and leveraging non-clinical routine data through data linkages to proactively identify and manage frailty.

1. Background

Frailty is a clinical syndrome characterised by an age-related decline in the physiological reserve and functioning of multiple organ systems, compromising the ability to resist minor stressor events [1]. As a result, there is increased vulnerability to severe adverse outcomes such as falls, fractures, disability, and dementia, leading to a higher incidence of emergency department visits, hospitalisation, and care home admissions [2]. Projections suggest that the proportion of the world’s population aged ≥65 will increase from 9.7 % (770 million) in 2022 to 16.4 % (1.6 billion) in 2050 [3]. As the risk of frailty and its associated adverse outcomes increase with both biological and chronological ageing, there is an urgent priority to address the heterogenous healthcare needs of frail older adults through timely identification and management [2].

Over the past two decades, several tools have been developed to identify and assess frailty, predominantly based on two conceptual models: the phenotypic and deficit accumulation models. The phenotypic model of frailty, posited by Fried et al. [4], states that the multiple components of frailty precede incident disability and can manifest clinically as the following signs and symptoms, i.e. *phenotypes*: shrinking (unintentional weight loss of ≥4.5 kg in the past year), weakness (low grip strength), exhaustion (self-reported), slowness (slow walking speed), and low physical activity. The deficit accumulation conceptual model, posited by Rockwood et al. [5], proposes that “the more things individuals have wrong with them, the higher the likelihood that they will be frail” [5, pp 722]. These “things that individuals have wrong with them” are deficits and can include health-related variables such as symptoms, signs, disabilities, and abnormal laboratory values [6]. This conceptual

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model can be operationalised as the frailty index (FI), a continuous score that is calculated as a proportion of the number of deficits to the total number of variables included in the index [5,7]. The FI has been validated in both hospital and community settings and has demonstrated high predictive validity for adverse clinical outcomes such as mortality and care home admission [8]. While both conceptual models may be considered complementary and useful markers of the need for intervention [9], key differences between the two prevail. The phenotypic model solely focuses on physical manifestations without considering psychosocial factors [8]; requires specialised equipment (such as a hand dynamometer) and some clinical expertise for assessment [8,10]; and can be applied before conducting a full comprehensive assessment [9]. In contrast, the deficit accumulation model allows the inclusion of deficits across different clinical, functional, and psychosocial domains but requires pre-existing records or a full comprehensive assessment to construct the FI. Hence, while the frailty phenotypes can help indicate the *need* for intervention in non-disabled people to prevent incident disability, the FI can help dictate the *type* of intervention based on the accumulated deficits and functional losses in both people with and without disability [9].

Another difference between the frailty phenotypes and FI is the mode of measurement. Frailty identification using the phenotypic model requires in-person assessments of grip strength and walking speed [4]. Although Mitnitski et al. [6] used survey-based data to construct their FI, retrospectively collected routine data can be leveraged to calculate FIs automatically with minimal effort [11,12]. Such data include symptoms, signs, diagnoses, laboratory test results, and socioeconomic and lifestyle information that are collected in different care settings and stored in electronic health records (EHRs) or administrative databases [11,13,14]. Thus, these databases store a plethora of discrete datapoints about a patient that can serve as variables for the automatic calculation of FIs [11].

Research has recently emerged on the development and validation of FIs based on routinely collected data stored in EHRs and administrative databases. Several reviews on utilising routine data for frailty assessment have been recently published [11,13,15–18]; however, all but one used a narrative approach [16]. These reviews signal the growing recognition of leveraging routine data for population health management and geriatric medicine, partly driven by recent monumental advances in data processing power and storage [18]. The number of publications on FIs based on routine data is continuing to rise, but how they fit in the context of previously reported research gaps and real-world clinical applications remains unclear.

This scoping review aimed to evaluate the breadth of the current evidence on FIs calculated from routinely collected data. By using a systematic approach to search and characterise peer-reviewed research, our review builds on previous literature reviews on the subject. Our scoping review also aimed to:

i) describe the characteristics of research on routine data-based FIs, including geographical trends, routine databases used, reasons for using the FIs, clinical areas, and outcomes assessed;
ii) present the characteristics of routine data-based FIs that have been developed in the last decade;
iii) summarise the deficits used in the FIs, how they overlap across different FIs, and the categories they fall under; and
iv) identify research and practice implications for developing and applying more robust FIs calculated from routine data.

2. Methods

We chose to conduct a scoping review as they help determine the coverage of literature based on an emerging topic, investigate research methodologies used in a particular topic, and identify knowledge gaps in the evidence [19]. As research using FIs calculated from routinely data is rapidly emerging, conducting a scoping review helped gain a clearer picture of the retrospective research landscape. We conducted this scoping review according to the Joanna Briggs Institute methodology for scoping reviews [20] and its reporting was guided by the Preferred Reporting Items for Systematic Reviews and Meta-analyses extension for scoping reviews (see Supplement 1, Supplementary Material 1) [21]. An initial protocol was registered in the Open Science Framework in February 2023 (https://doi.org/10.17605/osf.io/whcv6).

Table 1
Inclusion and exclusion criteria for studies in this scoping review.

Inclusion criteria
(1) Population – if the publication included adults aged ≥18 years. (2) Concept – if the FI was constructed from routinely collected data. Although not a comprehensive list, such data could include those from EHRs, medical claims databases, administrative databases, disease registries, and prescription databases. (3) Context – any geographical location and any clinical setting. (4) If they were published, peer-reviewed, original research articles. (5) Published from 2013 onwards. (6) If the FI scores were reported as proportions from 0 to 1. (7) If the routine data-based FI was the main tool investigated or main tool used to measure frailty. (8) If the publications were in English. (9) Any study design.
Exclusion criteria
(1) If the frailty assessment tool was not specified. (2) Primary research that investigated FIs constructed from survey-based data, as surveys typically collect data that are not recorded in routine databases. (3) If the routine data-based FI was only used to validate another frailty assessment tool or used to investigate the performance or accuracy of another frailty assessment tool. (4) Reviews, study and review protocols, commentaries, conference abstracts, theses, editorials, reviews, and opinion pieces. (6) If full texts were not found.

2.1. Eligibility criteria

As this review aimed to gain a broad, holistic picture of research on FIs calculated from routine data, we formulated our inclusion criteria based on the *Population, Concept, Context* (PCC) framework [20]. The eligibility criteria are presented in Table 1.

2.2. Databases

We used the following databases to ensure the search strategy had a broad subject coverage and captured multiple disciplines: MEDLINE, EMBASE, PsycINFO, CINAHL, Web of Science, Scopus, and ProQuest. We also conducted citation searches of the shortlisted articles during full-text screening to identify additional relevant publications.

2.3. Search terms

The scoping review title contains two core concepts: the FI and routinely collected data. Hence, the search strategy involved using terms related to the frailty syndrome in general, the FI, and routinely collected data, combined with the Boolean operator OR. This helped ensure the search strategy captured all relevant literature. We conducted a preliminary scoping of the literature on PubMed to identify related index terms and keywords:

(frail* OR “frailty syndrome” OR “frailness” OR “frailties”) OR ("frailty index” OR “frailty score” OR “electronic frailty”)

AND

(“electronic frailty” OR “laboratory-based” OR “electronic medical record” OR “electronic health record” OR “EMR-based” OR “EHR-based” OR “administrative data” OR “medical claims” OR “prescription data” OR “patient records” OR “medical records" OR "routinely collected health data" OR “computeri?ed medical record” OR “computeri?ed medical records” OR “routine data”)

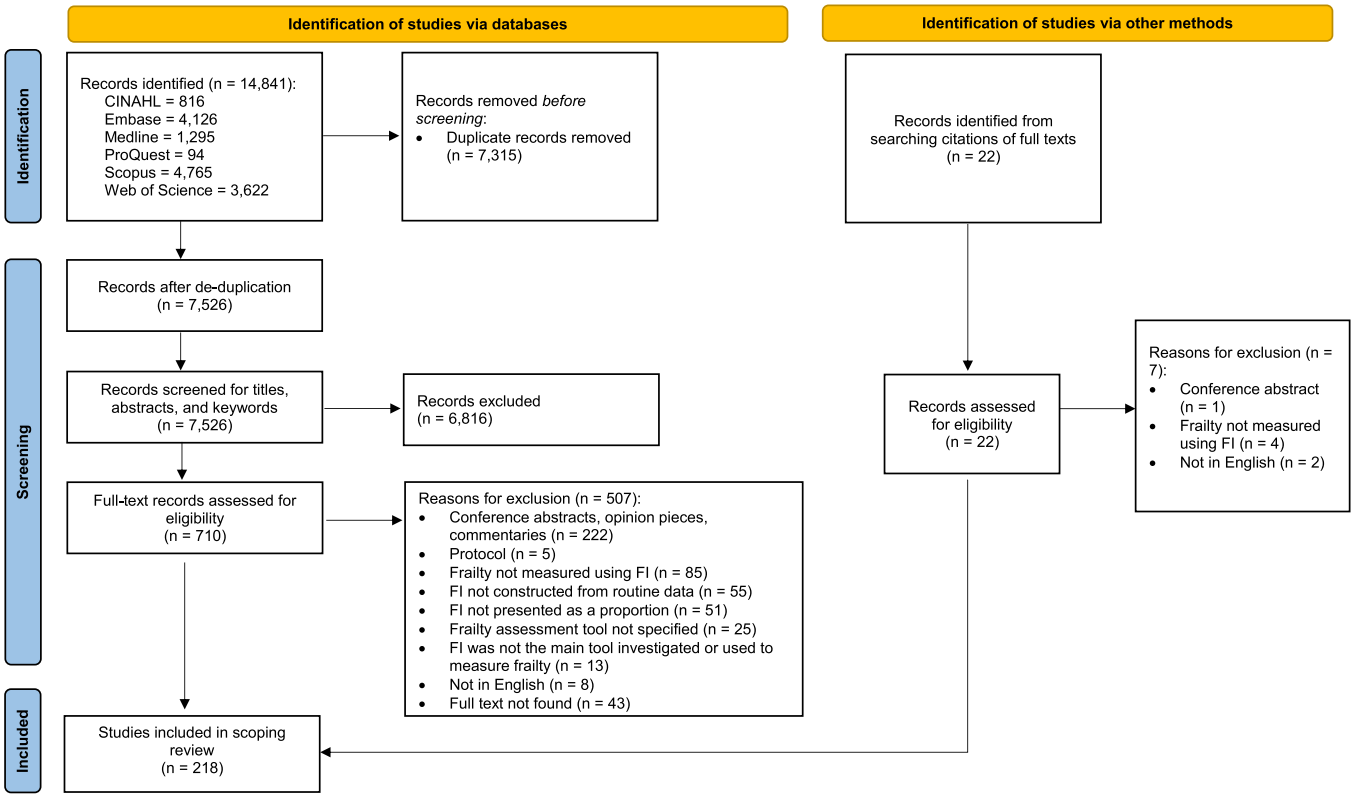

Fig. 1. PRISMA flowchart showing the study selection process for this scoping review.

We consulted a librarian to finalise the search terms and strategy for each database/information source (see Supplement 2, Supplementary Material 1). We conducted the last searches in April 2023.

2.4. Study selection process

We imported all the references from the databases into the reference management software EndNote for de-duplication. We then imported the remaining references into the Rayyan.ai system [22]. Two independent reviewers (SDD and DH) screened the publications using the pre-determined eligibility criteria. A pilot screening was first conducted; both reviewers screened the titles, abstracts, and keywords of 25 publications, as suggested by Peters et al. [20]. This helped ensure consistent interpretation of the eligibility criteria. The reviewers continued screening for concordance with the eligibility criteria. The reviewers then screened the full texts, and reasons for exclusion were documented in the Rayyan.ai system. Any disagreements on the final publications were resolved through discussions between the reviewers.

As the primary aim of this review was to examine the breadth of scientific evidence on FIs constructed from routine data, we did not conduct critical appraisals of the shortlisted publications and risk of bias assessments [19].

2.5. Data extraction, charting, and analysis

Data extraction and charting were conducted in two stages by two reviewers (SDD and DH): (1) for all the final studies; and (2) for only those studies that developed a routine data-based FI (see Supplement 3, Supplementary Material 1 for more details).

We used a narrative synthesis approach to summarise the characteristics of the final studies. For studies that developed FIs, we calculated descriptive statistics for the distinct deficits that comprised the FIs. To summarise the frequency of deficits used in the FIs, we presented the deficits that were used in >50 %, 20–50 %, and <20 % of the FIs.

We conducted the statistical analyses and created plots using Microsoft Excel and R statistical programme.

3. Results

Fig. 1 presents the PRISMA flowchart of the study selection process. Our initial database search identified 7526 publications after de-duplication. We identified 710 potentially eligible publications after screening the titles, abstracts, and keywords. We also searched the citations of the 710 publications. After full-text screening, we finally included 218 publications.

3.1. Characteristics of the included studies

Table 2 presents the study characteristics stratified by setting. Approximately 62 % of the studies were published from 2020. Most studies were conducted in the USA ($n = 74$), the UK ($n = 40$), Canada ($n = 32$), and Australia ($n = 15$). Routine data-based FIs were used predominantly in community settings (35.3 %; $n = 77$), followed by hospital settings (23.9 %; $n = 52$). Most studies used an observational analytic study design (92.2 %; $n = 201$). Hospital records were the most used routine data source for deficits comprising the FIs (28.9 %; $n = 63$), followed by primary care (19.3 %; $n = 42$) and linked (17.4 %; $n = 38$) records. Approximately half the studies used routine data-based FIs for risk stratification (51.4 %; $n = 112$). For studies that categorised the FI scores, most used either four (28.0 %; $n = 61$) or two (24.8 %; $n = 54$) categories. The full data extraction table and citations of the included articles are provided in Supplementary Material 2.

The clinical areas of the research studies on routine data-based FIs are presented in Supplement 1, Supplementary Material 3. Most studies used the FI to understand frailty prevalence, incidence, and progression in different populations and settings, including in surgical settings. Types of surgery varied; some examples include primary debulking surgery for cancer [23], aortic valve replacement [24], artificial uri-

Table 2
Study characteristics of the 218 publications stratified by setting.

Study characteristics	Community	Hospital	Hospital and Community	Long-Term Care	Mixed	Outpatient	Total
Year of publication							
2013 to 2016	5 (26.3 %)	8 (42.1 %)	2 (10.5 %)	2 (10.5 %)	0 (0 %)	2 (10.5 %)	19 (8.7 %)
2017 to 2019	24 (38.1 %)	14 (22.2 %)	14 (22.2 %)	6 (9.5 %)	2 (3.2 %)	3 (4.8 %)	63 (28.9 %)
2020 to April 2023	48 (35.3 %)	30 (22.1 %)	27 (19.9 %)	15 (11.0 %)	3 (2.2 %)	13 (9.6 %)	136 (62.4 %)
Geographical region of origin							
Americas	31 (29.8 %)	22 (21.2 %)	27 (26.0 %)	16 (15.4 %)	4 (3.8 %)	4 (3.8 %)	104 (47.7 %)
Europe	42 (53.8 %)	17 (21.8 %)	8 (10.3 %)	2 (2.6 %)	1 (1.3 %)	8 (10.3 %)	78 (35.8 %)
Western Pacific	4 (12.5 %)	13 (40.6 %)	8 (25.0 %)	5 (15.6 %)	0 (0 %)	2 (6.2 %)	32 (14.7 %)
Multi-country	0 (0 %)	0 (0 %)	0 (0 %)	0 (0 %)	0 (0 %)	4 (100.0 %)	4 (1.8 %)
Study design							
Observational analytic	68 (33.8 %)	49 (24.4 %)	42 (20.9 %)	20 (10.0 %)	4 (2.0 %)	18 (9.0 %)	201 (92.2 %)
Observational descriptive	8 (50.0 %)	3 (18.8 %)	1 (6.2 %)	3 (18.8 %)	1 (6.2 %)	0 (0 %)	16 (7.3 %)
Experimental	1 (100.0 %)	0 (0 %)	0 (0 %)	0 (0 %)	0 (0 %)	0 (0 %)	1 (0.5 %)
Data source for deficits							
Hospital	2 (3.2 %)	37 (58.7 %)	18 (28.6 %)	1 (1.6 %)	0 (0 %)	5 (7.9 %)	63 (28.9 %)
Primary care	38 (90.5 %)	0 (0 %)	1 (2.4 %)	0 (0 %)	0 (0 %)	3 (7.1 %)	42 (19.3 %)
Linked	14 (36.8 %)	4 (10.5 %)	12 (31.6 %)	6 (15.8 %)	1 (2.6 %)	1 (2.6 %)	38 (17.4 %)
Claims/insurance	19 (63.3 %)	4 (13.3 %)	4 (13.3 %)	1 (3.3 %)	2 (6.7 %)	0 (0 %)	30 (13.8 %)
Long-term care	0 (0 %)	1 (5.0 %)	3 (15.0 %)	15 (75.0 %)	1 (5.0 %)	0 (0 %)	20 (9.2 %)
Registry	4 (23.5 %)	4 (23.5 %)	5 (29.4 %)	0 (0 %)	1 (5.9 %)	3 (17.6 %)	17 (7.8 %)
Specialist care	0 (0 %)	2 (25.0 %)	0 (0 %)	0 (0 %)	0 (0 %)	6 (75.0 %)	8 (3.7 %)
Reasons for FI use							
Risk stratification	31 (27.7 %)	32 (28.6 %)	24 (21.4 %)	13 (11.6 %)	2 (1.8 %)	10 (8.9 %)	112 (51.4 %)
Development/validation	14 (32.6 %)	9 (20.9 %)	8 (18.6 %)	6 (14.0 %)	1 (2.3 %)	5 (11.6 %)	43 (19.7 %)
Others/mixed	9 (45.0 %)	5 (25.0 %)	6 (30.0 %)	0 (0 %)	0 (0 %)	0 (0 %)	20 (9.2 %)
Comparison with other frailty instruments	4 (33.3 %)	3 (25.0 %)	3 (25.0 %)	2 (16.7 %)	0 (0 %)	0 (0 %)	12 (5.5 %)
Outcome measure	7 (63.6 %)	0 (0 %)	0 (0 %)	2 (18.2 %)	0 (0 %)	2 (18.2 %)	11 (5.0 %)
Validation only	6 (75.0 %)	1 (12.5 %)	0 (0 %)	0 (0 %)	0 (0 %)	1 (12.5 %)	8 (3.7 %)
Descriptive only	3 (42.9 %)	2 (28.6 %)	1 (14.3 %)	0 (0 %)	1 (14.3 %)	0 (0 %)	7 (3.2 %)
Eligibility criterion	3 (75.0 %)	0 (0 %)	0 (0 %)	0 (0 %)	1 (25.0 %)	0 (0 %)	4 (1.8 %)
Clinical decision based on frailty	0 (0 %)	0 (0 %)	1 (100.0 %)	0 (0 %)	0 (0 %)	0 (0 %)	1 (0.5 %)
Number of FI categories used							
2	9 (16.7 %)	17 (31.5 %)	17 (31.5 %)	3 (5.6 %)	0 (0 %)	8 (14.8 %)	54 (24.8 %)
3	14 (29.2 %)	11 (22.9 %)	5 (10.4 %)	14 (29.2 %)	2 (4.2 %)	2 (4.2 %)	48 (22.1 %)
4	38 (62.3 %)	8 (13.1 %)	9 (14.8 %)	3 (4.9 %)	1 (1.6 %)	2 (3.3 %)	61 (28.0 %)
5	5 (83.3 %)	1 (16.7 %)	0 (0 %)	0 (0 %)	0 (0 %)	0 (0 %)	6 (2.8 %)
Not specified	11 (22.4 %)	15 (30.6 %)	12 (24.4 %)	3 (6.1 %)	2 (4.0 %)	6 (12.2 %)	49 (22.5 %)
Total	**77 (35.3 %)**	**52 (23.9 %)**	**43 (19.7 %)**	**23 (10.6 %)**	**5 (2.3 %)**	**18 (8.3 %)**	**218 (100.0 %)**

Abbreviations: FI, frailty index.

nary sphincter placement and removal [25], hip and knee arthroplasty [26], liver transplantation [27], and tracheostomy [28]. Studies also explored associations between FI scores and treatment/medication outcomes such as anti-cancer agents [29], cholinesterase inhibitors [30], anticoagulants [31], anti-psychotic use [32], and glucose-lowering medications [33].

The outcomes used in the studies are presented in Supplement 2, Supplementary Material 3. The most common outcomes were mortality, healthcare utilisation, and patient-centred outcomes. Outcomes related to healthcare utilisation included length of hospital stay, costs associated with hospitalisation, unplanned hospital readmissions, and discharge destination. Examples of patient-centred outcomes included quality of life, days alive at home after discharge or an adverse health event, and functional recovery after discharge or an adverse health event.

3.2. Geographical trends in research on routine data-based FIs

Fig. 2 presents the study settings, data source to calculate the FIs, and reasons for FI use stratified by geographical region of origin. Most studies conducted in the "community" were from Europe (n = 42; 54.5 %), while most conducted in "hospital and community" (62.8 %; n = 27) and "long-term care" settings (69.6 %; n = 16) were from the Americas. Notably, there were within-region differences; half the studies conducted in "long-term care" and "hospital and community" settings were from Canada (n = 11) and the USA (n = 16), respectively.

Geographical trends in data sources to calculate the FIs echoed those in study settings. Studies using primary care records were predominantly from Europe (85.7 %; n = 36). Almost all studies using claims/insurance records were from the USA (93.3 %; n = 28). Over half the studies using long-term care data were from Canada (52.9 %; n = 9), followed by Australia (29.4 %; n = 5). Studies using registries predominantly originated from the Americas (82.4 %; n = 14), particularly from the USA (n = 13). Half the studies (n = 4) that used specialist care records were conducted by the Systemic Lupus Erythematosus International Collaborating Clinics (SLICC).

Reasons for FI use in the studies appeared to be consistent between the Americas and Europe. Risk stratification was the most common reason for using routine data-based FIs, and over half these studies were from the USA (51.8 %; n = 43), followed by the UK (26.5 %; n = 22) and Canada (19.3 %; n = 16). For studies that developed or validated FIs, there was a balanced geographic representation across the Americas (34.9 %; n = 15), Europe (34.9 %; n = 15), and the Western Pacific region (27.9 %; n = 12).

3.3. Characteristics of the included studies by reasons for FI use

The most common reasons studies used routine data-based FIs were for "risk stratification" (n = 112), "development/validation" (n = 43), "comparison with other frailty instruments" (n = 12), "outcome measure" (n = 11), and "others/mixed" (n = 20). Regarding "others/mixed" reasons, most used the FI for a combination of reasons, as a proxy for comorbidities [34], or as a covariate or confounder in the statistical analyses [34–38].

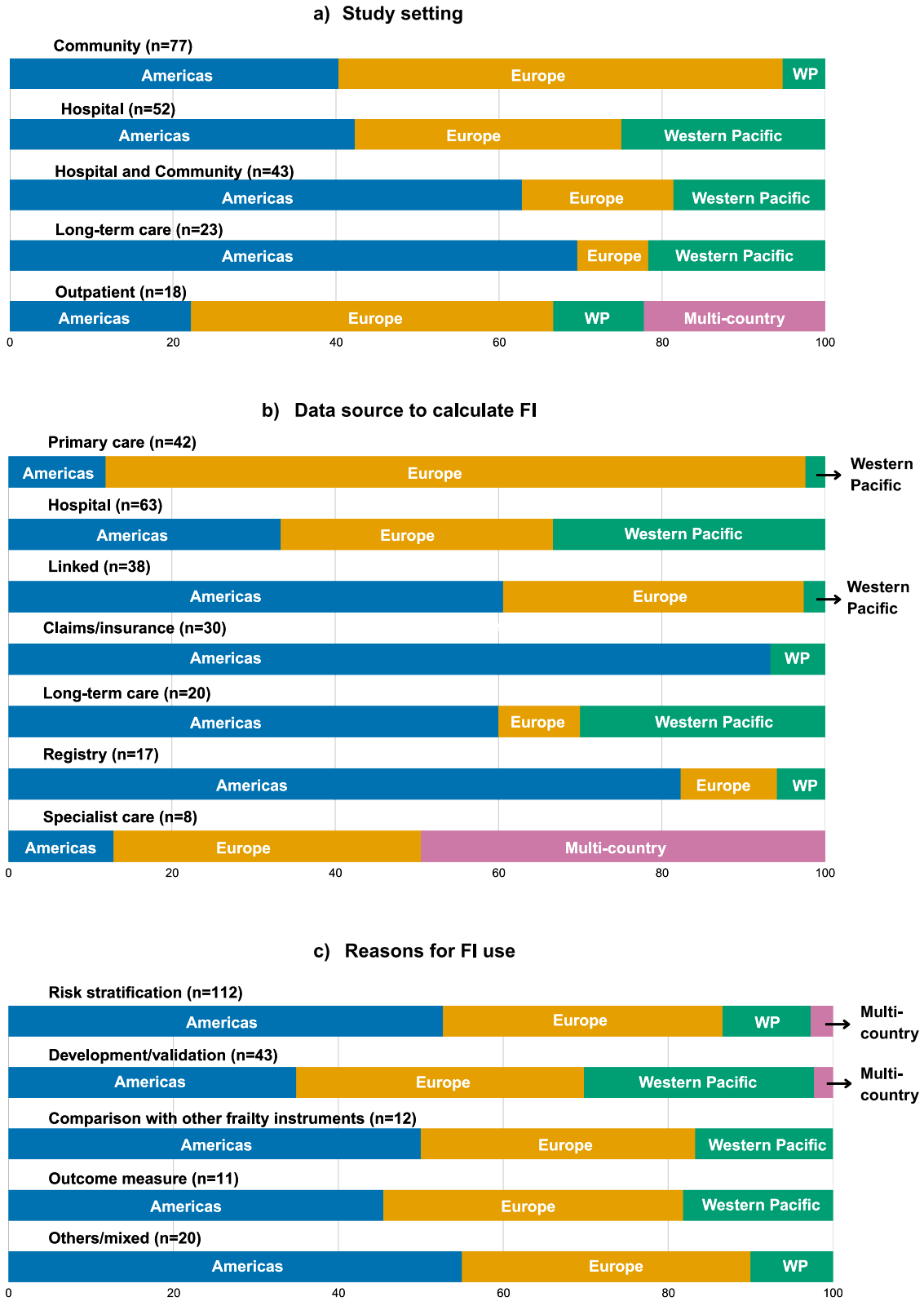

Fig. 2. Stacked bar charts showing geographical trends in research on routine data-based frailty indices. (a) Study settings by geographical region. (b) Data source to calculate the frailty index by geographical region. (c) Reasons for frailty index use by geographical region. Abbreviations: FI, frailty index; MC, Multi-country; WP, Western Pacific.

3.3.1. Clinical areas by reasons for FI use

The clinical areas of the included studies stratified by reason for FI use are presented in Supplement 3, Supplementary Material 3. Studies that used routine data-based FIs for risk stratification spanned different clinical areas, such as surgery, infectious diseases, mental health disorders, and community care. The most common clinical areas for using routine data-based FIs for risk stratification were surgery ($n = 36$), treatment/medications ($n = 18$), and circulatory system disorders ($n = 16$). Regarding the other reasons for FI use, frailty identification/progression and surgery were generally the most frequent clinical areas.

3.3.2. Outcomes assessed by reasons for FI use

The outcomes assessed stratified by the reason for FI use are shown in Supplement 4, Supplementary Material 3. For studies that used routine data-based FIs for risk stratification and development/validation, a range of outcomes across several clinical areas were assessed, including patient-centred, post-procedural, and disease-specific outcomes. Mortality was again the most common outcome assessed in studies that used the FI for risk stratification ($n = 51$), developed routine data-based FIs ($n = 28$), and compared routine data-based FIs with other frailty instruments ($n = 7$). Healthcare utilisation was the next most common outcome assessed in studies that used the FI for risk stratification ($n = 48$), development/validation ($n = 23$), and comparison with other frailty instruments ($n = 5$).

3.4. Characteristics of the original FIs

Of the 7562 publications screened, 65 included studies contained 67 unique FIs. The deficits were not reported for five FIs [39–43]. In one study, deficits were reported for only one of the two FIs [44]. Thus, we finally included 61 FIs across 60 studies in the analysis.

3.4.1. Descriptive characteristics of the studies that developed the FIs

Table 3 presents the descriptive characteristics of the studies that developed FIs. Most FIs were developed in the USA ($n = 16$), followed by Canada and Italy (both $n = 8$). The most dominant mean or median age categories were 70–79 years ($n = 22$) and ≥80 years ($n = 16$) (for 54 FIs). The median proportion of women was 55.6 % (for 53 FIs). Seven FIs included <25 % women, while three FIs included 100 % women. Twenty FIs were developed in hospital settings, followed by community and outpatient settings (both $n = 10$). The most common data sources of deficits were hospital records ($n = 23$), registries ($n = 11$), and long-term care data ($n = 8$). Twenty-six FIs were developed for specific diseases and/or populations.

We categorised the deficits as “symptoms/signs”, “abnormal laboratory values”, “diseases”, “disabilities”, and “others”. Most FIs had deficits that fell under either four categories ($n = 25$) or three categories ($n = 22$). Eleven FIs had deficits that fell under all the categories.

Regarding criteria for deficit selection, most FIs ($n = 44$) used those put forward by Searle et al. [45]. These were as follows:

(1) deficit should be associated with health status;
(2) prevalence of the deficit should increase with age;
(3) deficit must not saturate too early;
(4) deficits should cover a range of physiological systems; and
(5) the same deficits should be used in the FI for all people in the sample.

Authors also used the publications by Clegg et al. [46] (researchers who developed the electronic frailty index [eFI]) and Mitnitski et al. [6] (researchers who posited the deficit accumulation model of frailty) to select their deficits.

Sixteen of the 61 FIs were validated by either using a different dataset [37,46–52], using a subset of individuals from the development cohort [46,52,53], or comparing with other frailty assessment methods [44,53–55]. Rockwood et al. [56] investigated construct, content, and criterion validity.

Table 3
Descriptive characteristics of the studies that developed routine data-based frailty indices.

Characteristics	Number of FIs (n)
Geographical region of origin	
North America (USA, Canada)	24
Europe (Austria, Denmark, Finland, France, Italy, Spain, Sweden, Switzerland, The Netherlands, the UK)	20
Asia (China, Hong Kong, South Korea, Taiwan)	8
Australia / New Zealand	7
Multi-country	2
Mean or median age categories (for 54 FIs)	
<50 years	3
50–59 years	5
60–69 years	8
70–79 years	22
≥80 years	16
Proportion of women in study samples (for 53 FIs)	
<25 %	7
25–49 %	11
50–74 %	31
≥75 %	5
Setting	
Hospital	20
Community	10
Outpatient[a]	10
Hospital and community	7
Long-term care	6
Mixed	1
Data source of deficits	
Hospital records	23
Registries	11
Long-term care data	8
Claims/insurance data	6
Primary care records	6
Linked	4
Specialist care records	3
Disease- or population-specific FIs	
Yes [b]	26
No	35
Criteria for deficit selection	
Searle et al. [45]	44
Clegg et al. [46]	6
Mitnitski et al. [6]	4
Rockwood et al. [58]	2
Guaraldi et al. [59]	1
Hogan et al. [60]	
Howlett et al. [61]	
Kim et al. [62]	
Kim et al. [63]	
McNallan et al. [64]	
Pajewski et al. [65]	
Rockwood and Mitnitski [66]	
Schoufour et al. [67]	
Segal et al. [68]	
Velanovich et al. [69]	
Not reported	7
Binary scores for deficits	
Yes	31
No	30
Outcomes assessed (most frequent)	
Mortality	37
Hospitalisation	32
Transition to long-term care	14

[a] Outpatient settings included HIV clinics [59,70,71], a cognitive impairment centre [72], academic centres comprising the Systemic Lupus International Collaborating Clinics (SLICC) [73], receipt of chronic renal replacement therapy [74], outpatient clinics of a cancer hospital [75], a geriatric outpatient clinic [48], and centres contributing to the Canadian Scleroderma Research Group (CSRG) database [56].

[b] Diseases and populations included cancer, systemic sclerosis, mental health diseases (dementia and schizophrenia), HIV, receipt of treatment (such as haemodialysis), musculoskeletal conditions (such as hip fractures and systemic lupus erythematosus), geriatric psychiatry, organ transplantation, intellectual and developmental disabilities, type 2 diabetes, veterans, heart failure, and kidney disease.

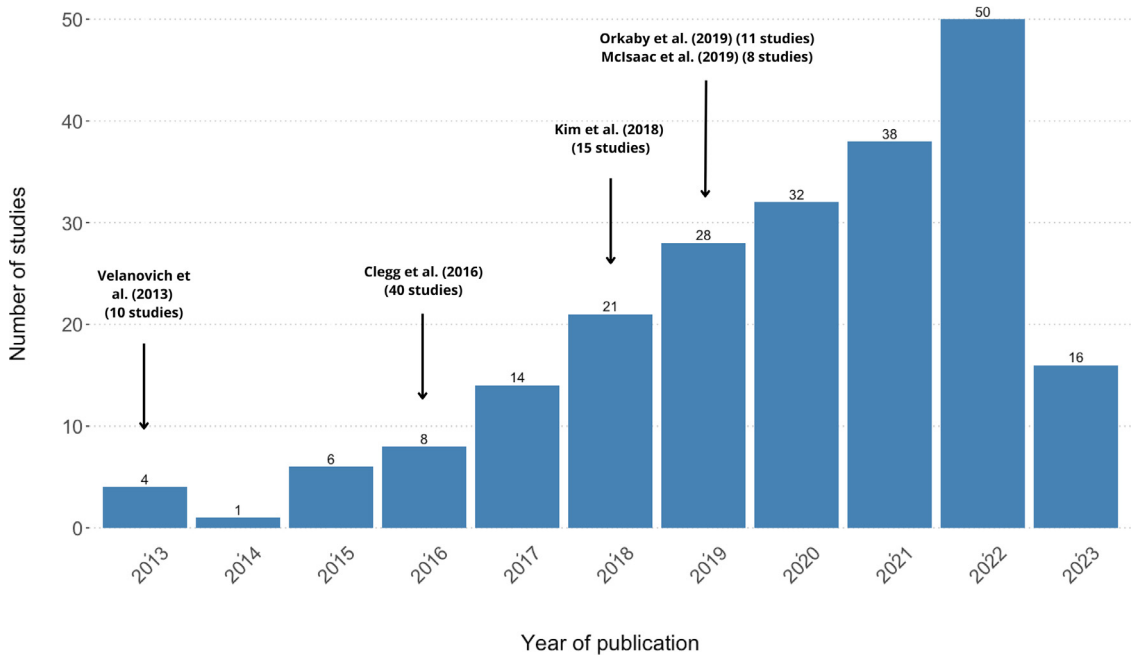

Fig. 3. Frailty indices that were cited the most by the 218 studies included in this scoping review.

Approximately half the FIs (n = 31) had binary scores for deficits. This means that the presence of a deficit was assigned a score of 1. The remaining FIs had ordinal scores for some deficits. For example, in the Frailty-VIG index developed by Amblàs-Novellas et al. [57], dependency for activities of daily living (ADLs) could be scored from 0 to 3, determined by the Barthel index scores.

Fig. 3 presents the FIs that were most frequently used in the 218 studies. The most common was the eFI developed by Clegg et al. [46] in the UK (40 studies), followed by the claims-based FI developed by Kim et al. [76] in the USA.

3.4.2. *Deficits used in the FIs*

We identified 611 unique deficits that comprised the FIs across all categories (see Supplementary Material 4). The median deficits used in the FIs was 36 (range = 5–72). Most deficits were either diseases (34.4 %; n = 205) or symptoms/signs (32.1 %; n = 196), followed by disabilities (17.0 %; n = 101), others (10.1 %; n = 60), and abnormal laboratory values (8.3 %; n = 49).

Table 4 presents the median deficits under each category used in the FIs and the most common deficits used in the FIs. "Diseases" were the most frequent; the FIs used a median of 17 "diseases" as deficits. This was followed by "symptoms/signs" (median = 8) and "disabilities" (median = 6). The dominance of "diseases" as deficits was also underscored by how they were the most common deficits used across the 61 FIs: diabetes (49 FIs), hypertension (42 FIs), and heart failure (34 FIs).

Deficits used in more than half the FIs (31 or more FIs) and in 20–50 % of the FIs (12–30 FIs) are presented in Supplement 5, Supplementary Material 3. Only five deficits were used in over half of the FIs, and these were all "diseases". Twelve "symptoms/signs", two "abnormal laboratory values", 20 "diseases", and eight "disabilities" were used as deficits in 20–50 % of the FIs.

Table 4
Most common deficits from each category used in routine data-based frailty indices.

Category	Median deficits and ranges from each category used across the 61 FIs	Most common deficits from each category	Number of FIs using the deficit
Symptoms/signs	8 (0–38)	Depression	29
		Weight loss and anorexia	28
		Falls	27
Abnormal laboratory values	1 (0–28)	Anaemia & haematinic deficiency	17
		Haemoglobin	12
		Albumin	11
Diseases	17 (0–30)	Diabetes (current / history)	49
		Hypertension (general)	42
		Heart failure (current / history)	34
Disabilities	6 (0–28)	Hearing loss	28
		Vision problems / blindness	27
		Toilet use	20
Others	0 (0–19)	Hospital admission	5
		Smoking	3
		Age	
		Male sex	2
		Race	
		Emergency room visit	
		Home visit	

4. Discussion

Our review provides an overview of the breadth of the evidence landscape on FIs constructed from routine data. Of the 218 studies, most were from North America; conducted in the community; and used routine data-based FIs for risk stratification. FIs were constructed using various routine data sources; however, most were initially developed and validated using hospital records. Routine data-based FIs were used in various clinical areas, including in identifying frailty in different settings, surgery, and assessing impacts of treatments and medications. Mortality and healthcare utilisation were the most common outcomes. We noted geographical differences in study settings and routine data sources. We identified 611 unique deficits comprising routine data-based FIs. Most deficits were either "diseases" or "symptoms/signs".

The following sub-sections triangulate the results and describe overall trends in research on routine data-based FIs and the deficits com-

prising these FIs. We then present research, practice, and policy implications.

4.1. Geographical trends in research reflect healthcare system structures and policy priorities

The rising trend in this research area, especially since 2020, signals a growing interest in harnessing routine data to develop and validate FIs in different populations and settings. The most frequently cited FIs [37,46,69,76,77] were all developed before 2020, which may have driven the rapidly rising trend thereafter. However, research in this area appears to be restricted to high-income countries, apart from China, where six studies were conducted. Geographical differences in the study settings and data sources used to calculate the FIs highlight where in the care pathway frailty identification takes place in different geographical regions. In most European countries, primary care is typically the first point of contact in the healthcare system and acts as a gatekeeper for more specialised diagnostic tests and care. This may explain why studies in Europe were primarily conducted in the community and used primary care records as data sources, indicating frailty case-finding is more primary care oriented. In contrast, studies from the USA used claims/insurance databases, hospital records, and registries as their data sources to calculate FIs. This reflects the USA's healthcare provision; government-funded insurance programmes targeted at specific populations, such as the Veterans Affairs (VA) Healthcare System [78] (for eligible veterans) and Medicare [76] (a public insurance programme for people aged ≥65), can be valuable information sources to determine older people's frailty states. These trends are reflected in the most cited FIs. The eFI developed in the UK by Clegg et al. [46] used primary care data. In the USA, the claims-based FI was developed using data from Medicare [76], while the Veterans Affairs FI was developed using data in the VA healthcare system [77]. Most studies that used long-term care data were from Canada. In Canada, older people's formal care needs are assessed using the interRAI Resident Assessment Instrument [79]. The RAI-HC assessment is conducted twice a year for all long-stay home care clients by trained professionals [32], making it a reliable source of health and functional data pertinent to older people.

The geographical trends demonstrate how FIs can be adapted to different healthcare system structures, public health priorities (such as addressing the health needs of veterans in the USA), and databases available.

4.2. Routine data-based FIs are valuable risk stratification tools, but limitations prevail

Studies used routine data-based FIs predominantly for risk stratification across diverse settings and clinical areas, and this was consistent across geographies. Many studies also investigated the correlations of frailty states with disease-specific outcomes related to atrial fibrillation [80,81], type 2 diabetes [33], cancer [82,83], HIV [59], lupus erythematosus [84], dementia [36,72], anorexia [85], and COVID-19 [86,87]. This demonstrates the clinical utility of frailty indices in stratifying risk in disease populations and predicting outcomes related to treatment/medication, surgery, and healthcare utilisation, influencing clinical decision-making and facilitating optimal disease management [13].

Despite the promise demonstrated by routine data-based FIs in research, their limitations in clinical and social care practice should be considered. These FIs rely on historical data that may not be consistently updated, especially for individuals who do not seek healthcare frequently. The choice of routine database also limits the deficits that can be used and may not provide a complete picture of a person's frailty state. Administrative databases, such as those used for billing purposes, lack laboratory data and nuanced disease-specific and patient-reported information [15,88]. In EHRs, data related to sociodemographic characteristics, economic status, lifestyle and psychological behaviours, and social care utilisation may be absent or inconsistently captured [11,17,89]. Regarding the constructions of the FIs, dichotomised and unweighted deficits may lose granular clinical information and over- or underestimate frailty levels. For example, the presence of type 2 diabetes, a long-term condition, and dyspnoea, a vital sign, are assigned the same score. However, the cumulative deficit theory postulates that the FI self-weights if it comprises deficits that significantly affect multiple body systems and frailty domains, such as type 2 diabetes [31], helping override this limitation. Thus, although routine data-based FIs can be valuable for frailty identification, these scores may be more useful as a risk stratification rather than a diagnostic tool [17], as underscored in most studies included in this review. For those at high risk, these scores should be supplemented with clinical judgements and patient-reported information to inform diagnoses and tailored care plans [90].

4.3. Routine data can be leveraged to develop disease- and population-specific FIs

Our review found that 26 of the 61 distinct FIs were developed for specific diseases or populations, such as HIV [59,70,71], cancer [75,82,91–93], systemic lupus erythematosus [73], dementia [72,94], veterans in the USA [77], and organ transplant recipients [27,95]. Routine data-based FIs can be useful tools to understand disease- and population-specific dynamics and outcomes for several reasons. First, their adaptability allows for the selection of deficits most pertinent to the disease or population of interest. These deficits can reach high levels of granularity; example deficits include whether anti-retroviral therapy started before 1 January 1997 (for HIV) [59] and type of displacement in hip fracture (for surgery following hip fracture) [96]. Second, FIs can help track trajectories of long-term conditions such as HIV, systemic lupus erythematosus, schizophrenia, cancer, and intellectual disabilities as individuals age. Although such long-term conditions may have heterogenous manifestations and clinical courses, a single composite score encompassing variables across multiple organ systems can help quantify vulnerability and guide disease management and timely intervention [7]. Moreover, geriatric syndromes may occur earlier in certain vulnerable populations or individuals with long-term conditions. Thus, FI scores can determine outcomes related to accumulated age-related physiological changes, while accounting for nuanced population and disease factors if relevant deficits are present. Third, the prognostic value of routine data-based FIs can help determine eligibility for procedures such as transplants [27,95], predict risks associated with procedures and treatments [23,38,96,97], and inform treatment and care plans [74,98]. Finally, disease- and population-specific FIs that use registries as routine data sources can be reliable clinical tools. Registries contain variables highly relevant to the population of interest and may be less subject to data incompleteness and inaccuracies, given that individuals contributing to these registries use healthcare services more frequently [18,99].

Despite the opportunities disease- and population-specific FIs present, their external validation is warranted before routine implementation in understanding population health trends and influencing clinical decisions.

4.4. Deficits comprising routine data-based FIs highlight a reactive approach in assessing frailty

Our sub-analysis of the deficits comprising routine data-based FIs found that approximately two-third of all deficits were either "diseases" or "symptoms/signs". Furthermore, only long-term diseases were used as deficits in more than half the FIs. This finding, in addition to how most FIs were developed in hospital settings, indicates frailty identification may be disproportionately prioritised in acute care settings. Hospital records are most likely to have up-to-date patient data, owing to routine assessment of vital signs during admission and pre-existing records of a patient's disease status. Given how FIs can be automatically calculated, existing patient data and those collected in real time during

admission can yield FI scores to help assess risk and inform clinical decisions. For example, if an older person with type 2 diabetes is admitted to emergency care with a hip fracture, data related to their diabetes status (such as current medications), past medical history (such as history of cerebrovascular accident), and assessments conducted during admission (such as presence of dyspnoea) can be used to automatically calculate an FI score. This FI score can subsequently be used to predict post-operative risk and develop a tailored post-discharge plan.

Despite the valuable clinical utility of routine data-based FIs in acute hospital settings, their disproportionate inclusion of diseases and symptoms/signs may not capture the multi-dimensional risk factors and manifestations of frailty in older people in community and long-term care settings. It should be noted that we classified deficits related to social frailty and mood as "symptoms/signs", but their frequencies were low. Based on data from developed countries, deficits have been reported to accumulate annually at an exponential rate of 3.5 % to 4.5 % [100,101]. Mitnitski and Rockwood [100] demonstrated that deficit accumulation doubles every 15.4 years independent of age, and this doubling occurs twice between ages 50 and 80. These reports highlight frailty progression outside clinical settings and the importance of proactively monitoring frailty from early mid-life. Deficits such as loneliness, social isolation, cognitive problems, financial difficulties, nutritional status, and performance in ADLs may be more feasible to routinely assess through comprehensive geriatric assessments at other points of care, such as primary and long-term care. Such non-physical deficits are important to consider, especially given the emerging emphasis of social frailty [102], cognitive frailty [103], and psychological frailty [104] in the literature. However, we found FIs that included the most disabilities as deficits used different routine databases: claims databases [76], long-term care records [105], and hospital records [23]. It should be noted that the FI developed by Kumar et al. [23] included some data collected during a routine assessment of ADLs and assistance needs in patients with ovarian cancer in an outpatient setting. Deficits in the FI developed by Kim et al. [76] were also extracted from multiple Medicare datasets related to inpatient, outpatient, skilled nursing, homecare, and durable medical equipment services. Thus, harmonising data collected at different points of care can facilitate a proactive approach to identify and manage frailty, both in community and post-discharge settings.

4.5. Implications for research, practice, and policy

Our scoping review highlights the growing recognition of routine data-based FIs as useful tools in identifying frailty and stratifying risk in real time across various populations and settings. However, research in this area appears to be restricted to specific geographies (North America and Europe) and economic areas (high-income countries). Although this research trend reflects national priorities to address ageing populations in high-income countries, lower-income countries (which collectively includes upper middle-income, lower-middle income, and low-income countries) have approximately 69 % of the global population aged ≥65 [106]. Given that frailty is an age-related condition, its increasing incidence in lower-income countries, compounded by lack of geriatric workforces and standard clinical guidelines to screen and manage the condition, will strain resource-limited health and social care systems. Leveraging existing routine data to automatically calculate FI scores can be useful in such contexts, but several challenges persist. These include fragmented care delivery and data systems [107]; lack of standardised monitoring and supervision processes [108]; lack of legal and ethical considerations [109]; and limited training and motivation in the workforce [108,110]. It should be noted that conducive policy environments in high-income countries such as the USA and UK facilitated the standard adoption of publicly funded EHRs and implementation of routine data-based FIs [17]. Thus, policies that recognise frailty as a population ageing concern and the potential of using routine data to address the needs of the older population can drive resource investments and relevant research in lower-income countries.

Despite the growing recognition of routine data-based FIs as risk stratification tools in research, their adoption in clinical practice has been slow. This is partly attributed to the lack of consensus on the most appropriate "next steps" following frailty identification; Orkaby et al. [17] highlighted how routine data-based FIs can be clinically worthwhile in different settings only if their use aids in clinical decision-making and delivering tailored care. Reports suggest how the frailty research landscape is saturated with studies on screening rather than management and gaps in designing and delivering services for older people with frailty [111,112]. The USA and UK have integrated routine data-based FIs in practice, albeit at different levels (national-level English National Health Service and state-level Atrium Health–Wake Forest Baptist hospital network, respectively), and there is ongoing research in further implementation and testing intervention pathways following frailty identification [17]. Thus, routine data-based FIs show promise as a vulnerability marker to guide subsequent clinical assessments (such as gait speed or grip strength tests), surgical and treatment decisions, and personalisation of interventions. Rather than developing new FIs, we recommend validating existing routine data-based FIs in populations of interests. Given how they can be applied to any database and allow flexibility in the deficits comprising them, existing routine data-based FIs can serve as blueprints to adapt these tools to population- and context-specific needs, helping accelerate their implementation in routine practice.

Our review highlighted a reactive approach in assessing frailty, which may lead to frailty identification at later and potentially irreversible stages. Frailty is a dynamic condition, and timely identification is important as reversal in early stages is likelier than in severe stages [10,113]. Given the multitude of clinical, behavioural, and social factors that contribute to frailty [114,115], harmonising data routinely collected at different points of care can provide valuable insights into an older person's frailty state and risk of adverse outcomes, facilitating an anticipatory care approach. Moreover, a proactive approach in monitoring the intrinsic and extrinsic factors that contribute to frailty onset is key in frailty prevention. Data linkages can help in understanding these multi-dimensional factors and plugging in missing and inaccurate data, providing a complete picture a person's health and living status [116]. However, such linked records are still primarily used for research purposes rather than in practice. There are several challenges in linking different routine datasets, including privacy and security concerns, significant financial investment, and need for large computational power and skilled data analytics workforce. Moreover, social and long-term care data differ in consistency and quality owing to lack of standard data recording protocols, impeding interoperability and transferability across different care systems. Newer data analytics approaches related to machine learning and natural language processing can be used to manage and process large volumes of data across different routine datasets. A recent systematic review highlighted studies that explored machine learning-based predictive tools to assess frailty, but the authors noted issues in integrating such models into existing healthcare systems, such as lack of a standard frailty definition, limited research on testing algorithms using EHRs, and explainability of model results to practitioners [117]. Hence, further work on assessing the feasibility and applicability of linked records, standardising social care data collection, and harnessing recent data processing advancements in linking routine records is warranted in the research and policy space to proactively prevent and manage frailty.

4.6. Strengths and limitations of this scoping review

Our scoping review analysed studies published in the last decade to identify research trends and present practice and policy implications for developing and applying routine data-based FIs. We also extracted and systematically mapped the deficits comprising the FIs, highlighting the skewed inclusion of clinical deficits. However, our review is limited by lack of statistical syntheses to determine the predictive ability of rou-

tine data-based FIs for adverse outcomes. We also did not assess the quality of the included studies as our primary aim was to provide an overarching view of the research landscape. We only included studies that used multi-dimensional FIs where deficits fell across at least two categories. This criterion disregarded studies that used laboratory FIs; however, a recent scoping review has already summarised the development and validation of these FIs [118]. We also excluded studies that did not present the FIs as proportions and where the FI was not the main frailty tool investigated, which may have missed relevant studies. Despite these exclusion criteria, our review found 218 eligible articles, ensuring adequate representation of research in this area.

5. Conclusions

Our scoping review summarises the characteristics of primary research on routine data-based FIs and the deficits comprising them. Our findings underscore routine data-based FIs as useful risk stratification tools that can be adapted to various populations and settings, but they suggest an overly medical and reactive approach in identifying and assessing frailty. We also highlighted the geographical skewness of research to certain geographies and economic areas and slow adoption of these FIs in clinical practice. Given the increasing incidence of frailty in ageing populations, the adaptability of routine data-based FIs, and continuing rise in research on these FIs, future directions include: (i) exploring opportunities in using routine data-based FIs in lower-income contexts through research; (ii) developing and implementing tailored care pathways after identifying frailty identification using routine data-based FIs; and (ii) leveraging linkages of routine health, social care, and administrative data sources to gain a holistic view of a person's frailty state, thereby facilitating proactive frailty assessment and management.

Abbreviations

ADL – activity of daily living
eFI – electronic frailty index
EHR – electronic health record
FI – frailty index
HFRS – Hospital Frailty Risk Score
SLICC – Systemic Lupus Erythematosus International Collaborating Clinics

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Declaration of competing interest

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CRediT authorship contribution statement

Schenelle Dayna Dlima: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Danielle Harris:** Writing – review & editing, Methodology. **Abodunrin Quadri Aminu:** Writing – review & editing, Methodology. **Alex Hall:** Writing – review & editing, Methodology. **Chris Todd:** Writing – review & editing, Methodology. **Emma RLC Vardy:** Writing – review & editing, Methodology.

Supplementary materials

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