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**RESEARCH PAPER**

# How to construct a frailty index from an existing dataset in 10 steps

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## Abstract

**Background:** The frailty index is commonly used in research and clinical practice to quantify health. Using a health deficit accumulation model, a frailty index can be calculated retrospectively from data collected via survey, interview, performance test, laboratory report, clinical or administrative medical record, or any combination of these. Here, we offer a detailed 10-step approach to frailty index creation, with a worked example.
**Methods:** We identified 10 steps to guide the creation of a valid and reliable frailty index. We then used data from waves 5 to 12 of the Health and Retirement Study (HRS) to illustrate the steps.
**Results:** The 10 steps are as follows: (1) select every variable that measures a health problem; (2) exclude variables with more than 5% missing values; (3) recode the responses to 0 (no deficit) through 1 (deficit); (4) exclude variables when coded deficits are too rare (< 1%) or too common (> 80%); (5) screen the variables for association with age; (6) screen the variables for correlation with each other; (7) count the variables retained; (8) calculate the frailty index scores; (9) test the characteristics of the frailty index; (10) use the frailty index in analyses. In our worked example, we created a 61-item frailty index following these 10 steps.
**Conclusions:** This 10-step procedure can be used as a template to create one continuous health variable. The resulting high-information variable is suitable for use as an exposure, predictor or control variable, or an outcome measure of overall health and ageing.

**Keywords:** frail, frailty, morbidity, health measurement, health and retirement study, older people

### Key Points

- The frailty index approach is widely used to characterise overall health and ageing.
- The 10 steps can be used as a template for frailty index creation.
- The frailty index can be used as an exposure, predictor, control variable or outcome measure.

## Introduction

The frailty index, based on the accumulation of deficits approach, is used widely to condense many health variables into one continuous score that represents the overall health of an individual [1]. The health deficit accumulation model postulates that, as an organism ages, deficits accumulate, reflecting age-related physiologic vulnerability to adverse health outcomes [2].

Any properly constructed frailty index, covering a variety of physiological systems as well as multiple domains [3], using at least 30 health deficit variables (e.g. symptoms, signs, diseases and functional limitations), shows a dose-response increase in the risk for adverse outcomes [4]. These include all-cause mortality [5], disability [6], hospitalisation [7], institutionalisation [8] and falls [6]. A frailty index can be calculated retrospectively from data collected via survey, interview, performance test, laboratory report, clinical or

administrative medical record, or any combination of these [1, 8]. The frailty index is sensitive to change, even among very ill people [9], and accommodates individual missing values [10].

In the 15 years since its publication, our group's procedure for creating a frailty index [11] has been cited 2,500+ times (Google Scholar) and used by researchers all over the world in various settings. With over two decades using this method, and reflecting methodological advances and common issues, here we detail a step-by-step approach, illustrated with an example from an existing dataset, and discuss some variations in data and results that reflect decisions made in constructing a frailty index.

## Methods

An expert group of users (see Acknowledgements) met several times to review the evidence and discuss their experience with frailty index construction. Based on consensus in these meetings and correspondence throughout, we developed a 10-step guide to creating a frailty index. This procedure can be applied to clinical, administrative or population-based datasets.

Our example data come from the Health and Retirement Study (HRS) [12], the world's longest running longitudinal health database of middle-aged and older individuals. The HRS contains data collected every two years from 1992 to the present, on 20,000 people representative of the US population over the age of 50. We used two datasets: the RAND HRS longitudinal datafile and the Gateway to Global Aging's Harmonized HRS data, which is designed to supplement the RAND file. We analysed publicly available data from waves 5 to 12, covering the years 2000–2014. We included 19,022 individuals, mean age 67.8 years (standard deviation, SD 10.2); 57.9% were women.

Refer to Appendix A for the process we used to select all health-related variables, Appendix B for detailed information on each variable, Appendix C for complete, runnable SPSS syntax and Appendix D for a shortened syntax that, though not runnable, is more readable.

## Results

We identified the following 10 steps:

**1. Select every variable that measures a health problem.**
Review all variables in the dataset to select those that measure a health problem. Exclude demographic, economic, social, environmental and health behaviour variables; these can be considered separately. When using data from multiple waves of a longitudinal study, select only variables that were collected using the same questions and response options at each time point.

We found 109 HRS health deficit variables that were collected at each of eight time points (i.e. waves 5–12) that met the above criteria and did not duplicate data (e.g. we deleted height and weight, retaining categorical body mass index).

**2. Exclude variables with more than 5% missing values.**
To be included in the frailty index, a variable should have no more than 5% missing data. When constructing a frailty index for multiple waves, the 5% criterion applies to each time point (e.g. if a variable has 3% missing data in Wave 1 and 6% missing data in Wave 2, exclude the variable). If your dataset does not contain enough variables that meet this criterion, you can increase the threshold for missing data, but this might exclude more participants when you calculate the total frailty index scores in Step 8.

After we removed 34 variables with more than 5% missingness, 75 variables were retained. We excluded some variables for missingness, despite having enough answers. For example, when asked about difficulty preparing hot meals, more than 5% of interviewees reported that they 'don't' do it, not that they cannot do it. Since we could not interpret the *don't do* answer as a sign of difficulty, we coded the answer as missing. When a participant without a health condition was not asked follow-up questions about it, the *no* answer to the initial question was carried forward, not counted as missing.

**3. Recode the responses to 0 (no deficit) through 1 (deficit).**
The responses for each variable must be recoded to a scale from 0 to 1, with 0 representing no deficit and 1 representing the full deficit.

Dichotomous variables are coded 0 and 1 (e.g. no diabetes = 0, diabetes = 1). Interval or ordinal variables with three response levels are coded 0, 0.5 and 1. Those with four levels are coded 0, 0.33, 0.67 and 1, while those with five levels are coded 0, 0.25, 0.50, 0.75 and 1. Use a similar strategy for recoding interval and ordinal variables with more than five response levels.

Continuous variables can be broken into two or more groups using established cut points. Minus established cut points, you can rescale continuous variables to values between 0 and 1, either by dividing each score by the maximum score for that variable in the dataset, or by recoding the variable based on distribution frequencies (e.g. quartiles coded 0, 0.33, 0.67 and 1). Coding with the latter two options may not generalise to other samples. If you choose to divide individual scores by the maximum score, exclude outliers when determining the maximum score. For example, if 99% of the sample completed a walking test in 20 seconds, but an individual was timed at 50 seconds, then the denominator should be 20 for all participants, and the outlier should be scored as the maximum (20 seconds).

Variables with a U-shaped relationship with adverse health outcomes, where both extremes indicate poor health, should be coded accordingly. For example, resting heart rates that are too low or too high can both be considered health deficits and coded 1, while those within the normal range are coded 0.

All continuous variables were recoded by dividing by their 99th percentile value. For instance, the 99th percentile value for nights spent in a nursing home was 548. Therefore, we divided each score by 548; participants with values above 548 were scored as 1.

We recoded ordinal body mass index, which was categorised according to World Health Organization classifications, into two different variables: a dichotomous variable of persons either underweight or not, and an ordinal variable with underweight and normal weight coded as 0, overweight as 0.25, and the three levels of obesity coded as 0.5, 0.75 and 1. We used the two new variables instead of the original. At this point, we had retained 76 variables: 63 dichotomous, 7 ordinal and 6 continuous.

**4. Exclude variables when coded deficits are too rare (< 1%) or too common (> 80%).**
Exclude variables in which deficits are present in more than 80% of valid, non-missing responses. Exclude variables with less than 1% presence of a deficit, or, preferably, combine them with related variables (e.g. if presence of vascular dementia and/or Alzheimer's disease is less than 1%, combine them to create a dementia variable). For dichotomous variables, the proportion of people scoring 1 should be between 1 and 80%, inclusive. For non-dichotomous variables, the combined proportion of people with some level of the deficit (coded >0) should be at least 1%, and the proportion of people with a full deficit (coded 1) should be no more than 80%. For example, if a variable has three response options, coded 0, 0.5 and 1, the combined proportion of people coded 0.5 and 1 should be at least 1%, and the proportion of people coded 1 should be no more than 80%.

In our data, no deficit was too rare. Two deficits were too common: in the last 2 years, more than 80% of respondents had visited a physician, and more than 80% had used prescriptions regularly. After removing these, we retained 74 variables.

**5. Screen the coded variables for association with age.**
Assess each variable's relationship with age by plotting the mean (for dichotomous variables, this will be the proportion of people with a deficit), by age rounded to year. In small samples, combine individuals into age groups. Exclude variables where the mean deficit (for dichotomous variables, the proportion of people with a deficit) does not increase with age. It is acceptable for the proportion to plateau or decrease after a certain age (e.g. 80, due to survival bias). If in doubt, check for a positive correlation coefficient of this relationship.

In a small population sample, clinical sample or sample with a limited age range, variables may not be correlated with age even when the conditions are known to be age-related. In this case, retain variables that have been included in validated frailty indices or that are established in the literature as positively associated with age.

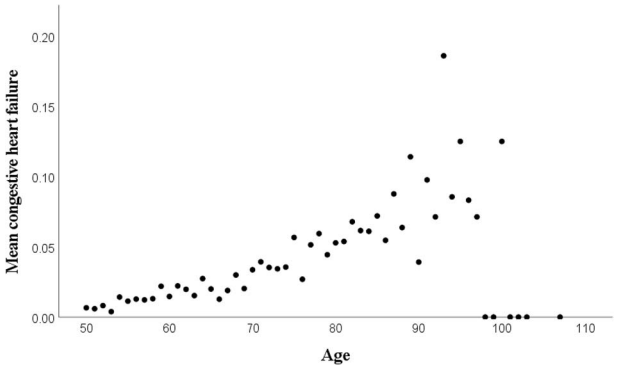


**Figure 1.** An example of increasing health deficit with age: Congestive heart failure, plotted by age rounded to year.

Trends of increasing health deficits with age were clear in 58 graphs (e.g. Figure 1), while 4 variables showed clear decreases and were removed (e.g. overweight and obese). We checked for statistically significant positive Spearman correlations with age for 12 variables with unclear graphs, retaining 7 (e.g. 3 diabetes variables), excluding 5 (e.g. 3 pain variables). This left a total of 65 variables.

**6. Screen the coded variables for correlation with each other.**
Assess the variables' relationships with each other. For coded variables that are too highly correlated ($r > 0.95$), exclude the variable with the lowest number of responses (the highest number of missing values).

Three hospital variables (hospital stay, number of hospital stays and number of nights in hospital) were correlated greater than 0.95, as were three nursing home variables. We removed 4 of the 6 variables, retaining 61 variables.

**7. Count the variables retained.**
Tally the remaining variables. A reliable frailty index requires at least 30 variables covering multiple domains (e.g. not only diseases) and several physiological systems (e.g. not only cardiovascular variables). For epidemiological datasets, frailty indices typically include items that measure symptoms, signs, diseases and functional limitations.

The HRS frailty index has 61 variables from multiple domains, covering health care utilisation, functional limitations and diseases.

**8. Calculate the frailty index scores.**
Frailty index scores can be calculated by dividing the sum of the variables' recoded values (the sum of the deficits) by the number of variables measured for that person. For example, in a dataset with 50 frailty index items, a person with a deficit sum of 3 and 48 valid items (i.e. 2 items with missing values) will have a frailty index score of 0.06 (3/48). In the same dataset, a person with a deficit sum of 5.5, and no missing values, will have a frailty index score of 0.11 (5.5/50). A frailty index score should not be calculated for individuals missing more than 20% of the frailty index items (e.g. > 10 items with missing values in a dataset with 50 frailty index items).

We calculated a frailty index score for all but 29 individuals (0.15%) who were missing more than 12 of the 61 frailty index items. Frailty index scores ranged from 0.00 to 0.84, mean 0.17, SD 0.14.

**9. Test the characteristics of the frailty index.**
Frailty indices constructed using population data share certain characteristics: a positive association with age, a right-skewed frequency distribution, higher mean frailty index scores in females than males and scores less than 0.7 for at least 99% of the samples. The frailty index that you construct should have similar characteristics. However, in small population samples, clinical samples or samples with a limited age range, the frailty index may show no correlation with age, a normal or Gaussian frequency distribution, and no sex difference. If most frailty index items are performance-based or laboratory tests, males may have higher frailty index scores than females, or there may be no sex differences.

In HRS, the relationship of the frailty index with age was non-linear (Figure 2). The frailty index increased 0.035 per year on a log scale. The Spearman correlation with age was 0.37, $P < 0.001$. The frailty index score frequency distribution had a long right tail (Figure 3). Mean scores were higher for females (0.18, SD 0.14) than for males (0.16, SD 0.13), $P < 0.001$. The 99th percentile score was 0.65.

**10. Use the frailty index in analyses.**
Use the frailty index as a continuous variable. If your research requires a categorical variable, maximise the number of categories (e.g. frailty groups in 0.1 increments). To increase replicability, report coding approaches, reasons for exclusion of variables and any changes from this standard procedure (e.g. using an 8% missing data criterion). Publish your syntax as an article supplement.

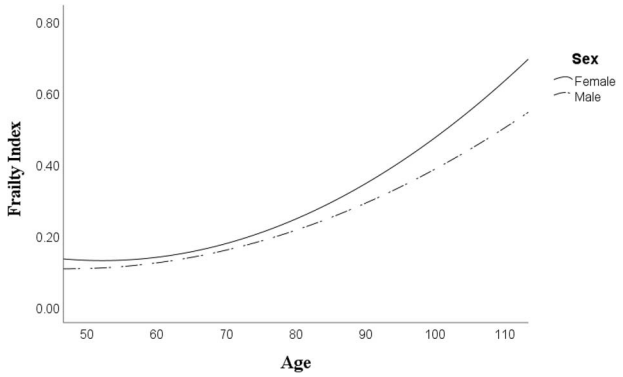


**Figure 2.** Mean frailty index scores, plotted by age rounded to year.

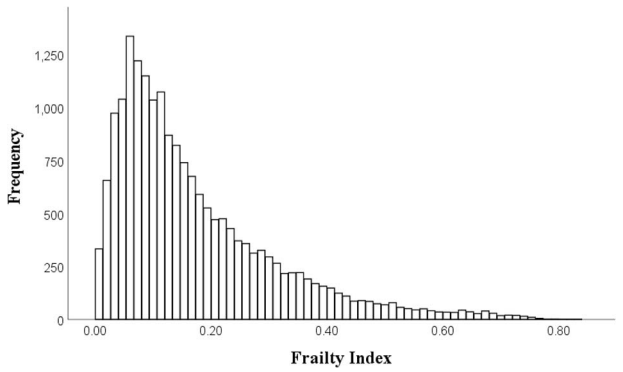


**Figure 3.** Frequency distribution of frailty index scores.

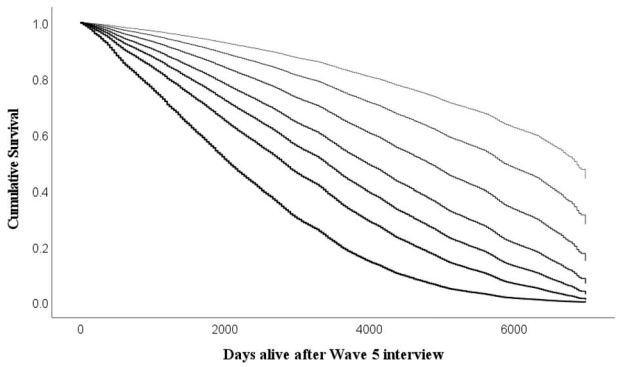


**Figure 4.** Survival by frailty index category. From top to bottom, the lines represent frailty index scores grouped from 0.0 to <0.1, 0.1 to <0.2, 0.2 to <0.3, 0.3 to <0.4, 0.4 to <0.5, 0.5 to <0.6 and 0.6 to 1.0.

Frailty was associated with mortality, as a continuous or categorical score, after adjusting for age and sex (Table 1, Figure 4).

## Discussion

We developed a 10-step approach to creating a frailty index, illustrated using the HRS. From 109 candidate variables, we created a 61-item frailty index that increases with age, is

**Table 1.** Association of frailty with mortality, after adjusting for age and sex

| | Frequency | | Hazard ratio | 95% confidence interval | | |
|---|---|---|---|---|---|---|
| | | | | Lower | Upper | *P*-value |
| **Continuous frailty index** | | | | | | |
| Frailty score (per 0.01) | | | 1.04 | 1.04 | 1.04 | < 0.001 |
| Age (per year) | | | 1.09 | 1.08 | 1.09 | < 0.001 |
| Female | | | 0.63 | 0.61 | 0.66 | < 0.001 |
| **Categorical frailty index** | | | | | | |
| | ***N*** | **%** | | | | |
| 0.0 to <0.1 | 6,796 | 37.3 | 1.00 | | | |
| 0.1 to <0.2 | 5,591 | 30.7 | 1.56 | 1.48 | 1.65 | < 0.001 |
| 0.2 to <0.3 | 2,811 | 15.4 | 2.34 | 2.20 | 2.48 | < 0.001 |
| 0.3 to <0.4 | 1,558 | 8.6 | 3.30 | 3.08 | 3.54 | < 0.001 |
| 0.4 to <0.5 | 740 | 4.1 | 4.34 | 3.97 | 4.75 | < 0.001 |
| 0.5 to <0.6 | 389 | 2.1 | 5.76 | 5.14 | 6.45 | < 0.001 |
| 0.6 to 1.0 | 336 | 1.8 | 8.93 | 7.91 | 10.09 | < 0.001 |
| Age (per year) | | | 1.09 | 1.08 | 1.09 | < 0.001 |
| Female | | | 0.63 | 0.61 | 0.66 | < 0.001 |

higher in females, has a right-skewed frequency distribution and predicts mortality, consistent with frailty index reports from other ageing cohorts [13].

In population-based samples, the frailty index is typically highly correlated with age [14], whereas age and frailty are not consistently correlated in clinical samples [1, 8], where health is by definition compromised for every individual and less likely to be a function of age. Frailty indices with mostly self-report items (e.g. disease symptoms) are typically positively correlated with being female, while frailty indices with mostly physical signs (e.g. abnormal heart rate) and laboratory-based items (e.g. high cholesterol) are not [3, 6, 7, 15, 16]. Missing entire domains can undermine predictive performance [3]. In population-based samples, the frequency distribution is typically right-skewed whereas, in clinical samples and in frailty indices with mostly physical signs and laboratory-based items, the frequency distribution is normal [17, 18]. The 99th percentile score less than 0.7 is typical of all sample types [19]. This suggests that, as an individual accumulates about two-thirds of possible deficits, key functions fail and the individual dies. Late-life deficit acceleration can also portend death, but this needs further verification [20]. In longitudinal studies, frailty increases with varying rates, mostly 3–6% per year [8, 20, 21]. These consistent mathematic characteristics allow comparison across studies, even with indices created from different sets of variables.

There are some limitations to our study. The HRS data are from the United States and may not generalise to other countries, although our findings are consistent with reports from other regions. The steps presented here are an elaboration of a previous frailty index creation procedure [11] and are informed by expert opinion and evidence to date. The purpose was to create step-by-step practical guidance based on best practices from experience. Even so, we did not include the views of all who have employed the frailty index in their work. As more research is published, updates to this protocol will be made and further issues will be accounted for. One such issue that our team is working on is understanding how the length of time someone experiences a health deficit should be reflected in the frailty index. Another example is that a multiple imputation approach may mitigate bias in samples with much missing data (which was not the case in the HRS), but future research is needed to refine this approach [22]. We do not provide the rationale for each step here and instead refer to previous papers that justify the approach. Future work will continue to refine these steps. Finally, we recognise that frailty is only one source of risk that many people face. Also important are age [23], sex [24], social vulnerability [25–29], ethnicity, race and how they intersect [30, 31]. Quantifying the degree of frailty and other relevant factors are essential steps in being able to identify risk, and mitigate it.

The frailty index approach is robust and flexible when the 10 steps are followed. Using judgement is necessary during the construction of a frailty index; therefore, researchers should be explicit in their description of the process. Frailty index items can be gathered from surveys, interviews, medical charts, records or tests, from clinical, convenience or representative samples. The frailty index approach also has important potential for translational research [32]. Here we offer a reliable, validated procedure to create one continuous health variable, suitable for use as a predictor, control variable or outcome measure, to quantify overall health and ageing.

**Supplementary Data:** Supplementary data mentioned in the text are available to subscribers in *Age and Ageing* online.

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and Arnold Mitnitski to our understanding of the frailty index characteristics presented here.

**Declaration of Conflicts of Interest:** Kenneth Rockwood has asserted copyright of the Clinical Frailty Scale and, with Olga Theou, the Pictorial Fit-Frail Scale, which are made freely available for education, research and not-for-profit health-care. Licences for commercial use are facilitated through the Dalhousie Office of Commercialization and Industry Engagement. In addition to academic and hospital appointments, Kenneth Rockwood is the Co-founder of Ardea Outcomes, which (as DGI Clinical), in the last 3 years, has contracts with pharma and device manufacturers (Danone, Hollister, INmune, Novartis, Takeda) on individualised outcome measurement. In 2020, he attended an advisory board meeting with Nutricia on dementia, and chaired a Scientific Workshop & Technical Review Panel on frailty for the Singapore National Research Foundation. Otherwise any personal fees are for invited guest lectures, rounds and academic symposia, received directly from event organisers, for presentations on frailty. He is the Associate Director of the Canadian Consortium on Neurodegeneration in Aging, itself funded by the Canadian Institutes for Health Research, the Alzheimer Society of Canada and several other charities.

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