Supplementary Online Content

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This supplementary material has been provided by the authors to give readers additional information about their work.

eMethods. Latent Class Analysis and Relative Survival Analysis

Latent class analysis

A latent class analysis $(LCA)^{1}$ is a cluster analysis that groups binary objects so that objects in the same group are more similar to each other than those in other groups using their estimated probabilities of belonging to a specific group. This statistical clustering technique utilises maximum likelihood estimation to assimilate the observed specific comorbidities into unobserved classes that are statistically distinct and clinically meaningful². Importantly, LCA allows the comparison between all possible combinations of the variables of interest, which were the specific health conditions in our analysis to be statistically tested, making the selection of optimal clusters rigorous, objective and reproducible.²

Latent class analysis has been shown to be superior to the counts-based methods of measuring multimorbidity, which are usually not possible to distinguish between individuals with the same number but different types of diseases³. LCA is also more robust than the conventional clustering techniques²⁴ as not only does LCA provide rigorous statistical tests to assess model fit, class separation, but also formal criteria to make decisions to select the optimal clusters. LCA has been found to be also associated with significantly lower rate of misclassification than the k-means method, one of the most commonly used clustering methods $(1.3\%$ vs. 8%, P< 0.01 ⁵. However, as LCA assigns the participants to cluster based on their probability of being in the clusters¹², a risk of misclassification bias in LCA, though lower than the conventional clustering techniques cannot be completely eliminated. Additionally, the name of the identified clusters, usually assigned by researchers for convenience in interpretation sometimes leads to a "naming fallacy"⁶ wherein the cluster name might not accurately or fully reflect the cluster nature due to complexity of the cluster.

We conducted $LCA¹$ to determine the unique clusters of comorbidities presented at the time of fracture. Technically, we first developed a series of models in which we varied the number of latent classes from 2 to 10. We optimized the number of latent classes to provide the best fit for the data and the best separation among classes. Latent class enumeration was conducted without covariates to prevent problems related to class overestimation⁷. The optimal number of classes was chosen based on three criteria: (i) data fit, (ii) separation capacity and (iii) smallest meaningful class. We used the statistical model fit indices including log likelihood plot where the log likelihood starts to level off and other criteria, such as adjusted Bayesian Information Criterion (BIC) and Akaike Information Criterion

 (AIC) in which the smaller value indicates better fit⁸. An entropy statistic was used to quantify the degree of separation between latent classes, with the level of ≥ 0.6 suggesting good between-group separation⁹, whereas the smallest meaningful estimated class proportion was expected to be at least 5%⁸. Once the optimal latent class model was selected, each participant was assigned to the "best-fit" cluster for which he or she had the highest computed probability of membership.

Relative survival analysis

Relative survival analysis was originally developed to determine excess mortality attributable to a specific cancer by comparing the observed all-cause mortality rate in the cancer cohort with the expected mortality rate in a comparative age-, sex- and calendar period-matched general population. All-cause deaths in the cancer cohort result from two sources: the cancer *per se* and other causes; whereas the expected background time-related mortality rate in the comparative general cohort is assumed to reflect the contribution of "other causes" to mortality over time. As a result, the excess mortality is then considered a robust measure of mortality attributable to the cancer or a disease of interest¹⁰. Cause-specific mortality data are not needed in a relative survival analysis, making it especially relevant for examining the contribution of fracture to mortality as a fracture is rarely recognized as a contributing cause of death 1112 .

© 2022 Tran T et al. *JAMA Network Open*. We performed relative survival analysis to quantify excess mortality attributable to the interaction between specific multimorbidity clusters and individual fracture sites under similar assumptions originally used in oncology research¹⁰. Excess mortality for patients in a specific multimorbidity cluster who fractured at a specific site, calculated as 1 minus its relative survival ratio can be interpreted as the proportion of patients who would die due to the combination between the specific comorbidity cluster and the individual fracture site. The relative survival ratio is the ratio of observed survival among the cohort of individuals in a specific multimorbidity cluster who fractured at a specific site to the expected survival in a comparative age-, sex- and calendar period-matched general population¹⁰. The observed survival was calculated using all-cause deaths of the fracture cohort; whereas the expected survival is the survival probability of similar individuals from the general population of the same age, sex and calendar period as the fracture cohort¹⁰. We used the Ederer II method¹³ to estimate the expected mortality rate from the Danish population life tables stratified by sex, age and calendar period from the Human Mortality Database¹⁴. An excess mortality of zero

indicates that the mortality rate observed in the cohort of patients with specific fracture in a specific cluster of comorbidities is not different from that in a comparative background population and hence that no excess mortality is attributable to the combination of the cluster of comorbidity and the fracture site.

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eTable 1. List of *ICD-10* Codes Used to Define Specific Fractures and Comorbidities of Interest

eTable 2. Number of Comorbidities and Deaths by Specific Fracture Sites

	2-class	3-class	4-class	5-class	6-class	7-class	8-class	9-class	10-class
Men $(n=95372)$									
Number of parameters	65	98	131	164	197	230	263	296	329
Degree of freedom	95307	95274	95241	95208	95175	95142	95109	95076	95043
Maximal Log Likelihood	-595242	-588659	-583536	-578908	-576199	-575045	-574213	-573668	-573318
AIC	1190613	1177514	1167333	1158144	1152792	1150551	1148952	1147927	1147294
BIC	1191228	1178442	1168573	1159696	1154657	1152728	1151442	1150729	1150408
Adjusted BIC	1190514	1177365	1167134	1157894	1152493	1150201	1148552	1147477	1146793
Likelihood ratio	117347.5	104182.9	93936	84680.4	79263	76955.4	75290.6	74199.9	73500.8
Smallest class	31.3%	5.9%	2.0%	5.1%	2.0%	2.0%	2.0%	2.1%	1.2%
Entropy	0.673	0.686	0.711	0.725	0.677	0.677	0.639	0.641	0.637
Women (n=212498)									
Number of parameters	65	98	131	164	197	230	263	296	329
Degree of freedom	212433	212400	212367	212334	212301	212268	212235	212202	212169
Maximal Log Likelihood	-1123516	-1114338	-1105428	-1100572	-1096786	-1095184	-1093782	-1092826	-1091965
AIC	2247161	2228871	2211118	2201472	2193966	2190829	2188089	2186244	2184587
BIC	2247829	2229877	2212463	2203156	2195989	2193190	2190789	2189283	2187965
Adjusted BIC	2247065	2228725	2210923	2201228	2193673	2190486	2187698	2185803	2184098
Likelihood ratio	156969.8	138613.7	120794.8	111082.6	103510.6	100307	97501.5	95590.4	93867.8
Smallest class	26.5%	4.4%	5.0%	3.8%	0.9%	0.9%	1.0%	0.9%	0.8%
Entropy	0.643	0.651	0.697	0.653	0.645	0.626	0.600	0.590	0.591

eTable 3. The Parameters of Latent Class Models

AIC= Akaike Information Criterion; BIC= Bayesian Information Criterion

eTable 4. Probabilistic Distribution of All Comorbidities of Interest Within Each Multimorbidity Cluster

Data presented as probabilities (%) of each comorbidity of interest computed from the latent class analysis given the class membership.

eFigure 1. Flowchart of Follow-up

eFigure 2. The Model's Fit Indices of the Latent Class Models