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| Method | Type/data | Output | Notes | refs |
| Cox PH | Cause-specific, continuous surv time | HR | Censoring for competing risks – may violate noninformative censoring,  KM used for survival function, 1-KM can be used for cumulative incidence function (CIF), if there are competing risks -> upward bias of incidence estimation, KM estimates the prob of event in the absence of competing risks, that probability is larger the probability in the presence of competing risks  -model the cause-specific hazard rate, rate at which events occur over time |  |
| Fine & Gray | Subdistribution, continuous survival time | sHR | -The direction of the subdistribution hazard ratio describes the direction of the effect of the covariate on the risk or incidence of the outcome, but not the magnitude of this effect  -model the cumulative incidence function (ie the cumulative incidence of event occurring)  -cumulative incidence of event by specific time depends on accumulated hazards over time of both events of interest and the competing event  “The Cumulative Incidence Function (CIF), as distinct from 1 – S(t), allows for estimation of the incidence of the occurrence of an event while taking competing risk into account. This allows one to estimate incidence in a population where all competing events must be accounted for in clinical decision making.  The cumulative incidence function for the kth cause is defined as: CIFk(t) = Pr(T ≤ t,D = k), where D is a variable denoting the type of event that occurred. A key point is that, in the competing risks setting, only 1 event type can occur, such that the occurrence of 1 event precludes the subsequent occurrence of other event types.” Austin, Lee, Fine 2016  Fine and Gray (1999) proposed a Cox type regression model for the subdistribution hazard. This gives a model where the complementary log-log transformed cumulative incidence function is linear in the covariates, i.e. g(x) = log(−log(1−x)) in (4). They used inverse probability of censoring weighting of the ordinary proportional hazards estimating equations with modified risk sets for inference from right-censored data. Eriksson 2015 Biometrics    Subdistribution hazard model ~ CIF regression model  -esstimate effects on CIF for the event of interestin | Introduction to the Analysis of Survival Data in the Presence of Competing Risks Peter C. Austin, Douglas S. Lee and Jason P. Fine Circulation. 2016  Austin PC, Fine JP. Practical recommendations for reporting Fine-Gray model analyses for competing risk data. Stat Med. 2017 <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5698744/#:~:text=The%20direction%20of%20the%20subdistribution,the%20magnitude%20of%20this%20effect>. |
| Multinomial logistic regression  Baseline category logit model | Cause-specific, discrete survival time, person-period data | Odds ratio    Cause-specific log odds | In the literature, there exists a variety of models for discrete time-to-event data, see e.g., Tutz and Schmid (2016).  A common approach for discrete competing risks analysis is to model the cause-specific discrete hazard function P(T=t,ϵ=j|T≥t,x)⁠, t=1,2,…⁠, by use of a regression model for multi-categorical response (Tutz, 1995). | Tutz, G. (1995). Competing risks models in discrete time with nominal or ordinal categories of response. Quality and Quantity 29, 405–420.  Federico Ambrogi, Elia Biganzoli, Patrizia Boracchi,  Estimating crude cumulative incidences through multinomial logit regression on discrete cause-specific hazards,  Computational Statistics & Data Analysis,  Volume 53, Issue 7,  2009  Tutz, G. and Schmid, M. (2016). Modeling Discrete Time-to-Event Data. New York: Springer. <https://link.springer.com/content/pdf/10.1007/978-3-319-28158-2.pdf> |
| Proportional odds model/ complementary log-log | Cause-specific, discrete surv time | HR | Discrete time analog to proportional hazards with continuous time  similar to logit results when events rare | Eriksson F, Li J, Scheike T, Zhang MJ. The proportional odds cumulative incidence model for competing risks. Biometrics. 2015 |
| Discrete-time subdistribution hazard function | Subdistribution, discrete survival time, person-period data | sHR | Model discrete cumulative inc. function w/ right censored data, weighted binomial regression – based on censorship survival function  Model in terms of subdistribution hazard function for event of interest   * Weighted ML estimation for binary regression * Life-table estimates of censoring survival function – applies it to those who experience competing event | Moritz Berger and others, Subdistribution hazard models for competing risks in discrete time, Biostatistics, Volume 21, Issue 3, July 2020, Pages 449–466, |
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Cause-specific hazard vs subdistribution hazard

“The cause‐specific hazard function for a given event type is the instantaneous rate of occurrence of the given type of event in subjects who are currently event‐free. The subdistribution hazard function, introduced by Fine and Gray, for a given type of event is defined as the instantaneous rate of occurrence of the given type of event in subjects who have not yet experienced an event of that type. Note that for the subdistribution hazard function, we are considering the rate of the event in those subjects who are either currently event‐free or who have previously experienced a competing event. The cause‐specific hazard model estimates the effect of covariates on the cause‐specific hazard function, while the Fine‐Gray subdistribution hazard model estimates the effect of covariates on the subdistribution hazard function.” Austin, Fine Stat Med 2017

Columbia SPH <https://www.publichealth.columbia.edu/research/population-health-methods/competing-risk-analysis>

R <https://cran.r-project.org/web/views/Survival.html>

Mlogit/cloglog <https://www.iser.essex.ac.uk/wp-content/uploads/files/teaching/stephenj/ec968/pdfs/ec968st8.pdf>

More on to use competing risks:

Marlies Noordzij et al. When do we need competing risks methods for survival analysis in nephrology?, Nephrology Dialysis Transplantation, Volume 28, Issue 11, November 2013, Pages 2670–2677, <https://academic.oup.com/ndt/article/28/11/2670/1823847>

Highlights how inferences can change ->> Buzkova P. Competing risk of mortality in association studies of non-fatal events. PLoS One. 2021 Aug 13;16(8)