ATTRITION IN A LONGITUDINAL STUDY OF DEPRESSION

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Lifecourse, mental health and well-being (TAM project)

- A follow-up study of 16-year-old adolescents in Tampere at 22, 32 and 42 years (Aro, Huurre et al.)
- Data on:
  - Gender
  - Family backgroud factors (SES, parental divorce or death)
  - Education (school, studies)
  - Health (depression, self-perceived health, psychosomatic symptoms, self-esteem)
  - Health behaviour (daily smoking, heavy use of alcohol)
- Attrition: 2194 (96.7%) $\rightarrow$ 1656 (75.5%) $\rightarrow$ 1471 (67%)
- Is the data still valid for estimating the **prevalence of depressive symptoms** in the follow-up years?

Information and uncertainty

- Before study termination at each panel, missingness is as uncertain as is the value of the outcome, and has some probability
- *"What would the outcome of the non-respondents be, had the stayed in the study for the whole follow-up?"*
- The more information on this question is available, the better the problem of missingness can be handled by statistical methods
- The same data set can be informative for one question but not for another
- In this study, the high initial response rate provided information for non-respondents

Two ways of correcting for attrition

1. Inverse probability weighting (IPW)
   - Correct the estimating equations by weighting the score functions of observed cases with the inverse probability of responding

$$\sum_i \frac{R_i U_i(\beta)}{P(R_i = 1 | Y_i, Z_i)} = 0$$

2. Likelihood-based methods
   - Augment the estimating equations by predicting the outcomes of non-respondents from the distribution of $Y = (Y_{obs}, Y_{mis})$ given Y_{obs}

$$\sum_i [R_i U_i(\beta) + (1 - R_i) E_{Y_i|R_i}(U_i(\beta))] = 0$$

   - If $Y \perp R$ then $E_{Y_i|R_i}(Y_i) = E_{Y_i}(Y_i)$

Both depend on MAR!

Longitudinal MAR assumption

- Given the history of observed outcomes, responding and covariates, the probability of R_t does not depend on their *future* values
- Noninformative non-response (Diggle and Kenward, 1994, Laird,1988)
- Cf. Noninformative censoring in survival analysis

Model-based weights in IPW: propensity scores

- Estimates of conditional probabilities of responding

$$p_{it}(z) = P(R_{it} = 1|\{Y_{i,t-1}\}, \{R_{i,t-1}\}\{Z_{i,t-1}\})$$

(Rosenbaum and Rubin, 1983, Robins et al., 1995)

- Longitudinal weights for panels t=1,2,3
  - $w_{i1} = 1/p_{i1}(z)$
  - $w_{i2} = w_{i1} \times 1/p_{i2}(z)$, given that $R_{i2} = 1$
  - $w_{i3} = w_{i2} \times 1/p_{i3}(z)$, given that $R_{i3} = 1$

assuming that $p_{it}(z) > 0,$ for all i, t

- Holds for monotone missingness
- Depression prevalence was estimated with weighted logistic regression with normalized weights

Likelihood based methods: longitudinal Bayes model

- Under MAR, can ignore the missing mechanism in the joint distribution

$$P(Y, R|Z, \theta, \phi) \propto p(Y|Z, \theta)p(R|Y, \phi)$$

for complete data $Y = (Y_{obs}, Y_{mis})$

- Need to average over Y^{mis} in the complete data distribution
- Several ways to estimate, we used Bayesian inference and MCMC
- Need the assumption of distinct θ, ϕ in estimation (prior and posterior)
- Individual random effect = propensity not to respond

Observed prevalence within the confidence and credible intervals

Table 4. Observed, weighted (propensity scores and adjustment class) and simulated (MCMC) estimates of depression prevalence at ages 22 and 32 years (95% CI)

	Observed prevalence	Propensity score	Adjustment class	MCMC
Age 22	0.1122 (0.097, 0.1275)	0.1145 (0.0977, 0.1337)	0.1167 (0.0992, 0.1369)	0.1107 (0.1006, 0.1208)
Age 32	0.1497 (0.1324, 0.1669)	0.1524 (0.1309, 0.1767)	0.1527 (0.1305, 0.1778)	0.1563 (0.1446, 0.1685)

Sensitivity, specificity and positive predictive value

- **Sensitivity** $P(+|R=0)$: the proportion of those who have the model characteristics (+), given that they are non-respondents
- **Specificity** $P(-|R=1)$: the proportion of those who do not have the model characteristics (-), given that they are respondents
- **Positive (negative) predictive value** $P(R=0|+)$: the proportion of non-respondents who actually (do not) have the model characteristics (+).

The models did not detect non-respondents

Table 1. Logistic regression of non-response at age 22 years adjusted for gender and school performance

Missing at age 22	OR	95% CI
Gender (male)	1.95	(1.58, 2.42)
School performance at age 16 (4–10)	0.67	(0.60, 0.75)
Sensitivity Prob(+ | M)	0.39%	
Specificity Prob(− | ~M)	100.00%	
Positive predictive value Prob(M | +)	100.00%	
Negative predictive value Prob(~M | −)	76.01%	
Correctly classified	76.03%	

M = missing, ~M = response, + = model characteristics present, − = model characteristics absent.

Non-response cannot be explained

- Sensitivity of the models, regardless of covariates, was extremely poor; at best approximately 2%.
- The ability of the predictive covariates to *discriminate* between respondents and non-respondents was poor
- The opposites of the characteristics were *specific* to those who responded
- This reflects the fact that non-response is caused by a multiplicity of different factors, which cannot be modelled exhaustively.

Earlier depression did not predict non-response

Table 3. Logistic regression of non-response at age 32 years adjusted for gender, school performance and depression

Missing at age 32	OR	95% CI
Gender (male)	1.48	(1.16, 1.87)
School performance at age 16 (4–10)	0.74	(0.65, 0.85)
Depression at age 22 (yes)	0.99	(0.68, 1.43)
Sensitivity Prob(+ | M)	0.0%	
Specificity Prob(−|~M)	100.00%	
Positive predictive value Prob(M| +)	0.0%	
Negative predictive value Prob(~M| −)	76.56 %	
Correctly classified	76.56%	

M = missing, ~M = response, + = model characteristics present, − = model characteristics absent.

Missingness predicted missingness

- Earlier depression at age 22, or its predictive covariates, had no apparent effect on the probability of responding (distinct parameters)
- Around 76% of the subjects could be classified correctly by this model, all of them respondents.
- Around 72% of those missing at age 32 could be predicted by non-response at age 22 alone in the model
- From a purely predictive point of view not much is gained by adding other significant covariates
- Earlier non-response also increases sensitivity to 40

Missingness predicted missingness

Table 2. Logistic regression of non-response at ag[e]
32 years adjusted for earlier non-response

Missing at age 32	OR	95% CI
Missing at age 22	5.04	(4.10, 6.20)
Sensitivity Prob(+ | M)	45.50%	
Specificity Prob(−|~M)	85.79%	
Positive predictive value Prob(M| +)	61.15%	
Negative predictive value Prob(~M| −)	76.21%	
Correctly classified	72.52%	

M = missing, ~M = response, + = model characteris tics present, − = model characteristics absent.

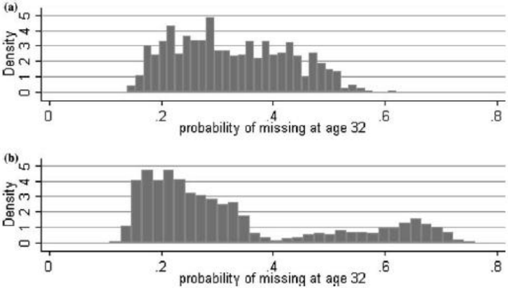

Figure 1. Estimated probability of non-response at age 32: (a) adjusted for gender and school performance at age 16; (b) additionally adjusted for non-response at age 22.

Assessing plausibility of MAR with modelling

- Pattern-mixture model: the outcome is a mixture of outcome probabilities weighted by response pattern proportions
- Response patterns at panels 2 and 3:
  - $R = 0$, if $R_{22} = 0$ & $R_{32} = 0$
  - $R = 1$, if $R_{22} = 1$ & $R_{32} = 0$
  - $R = 2$, if $R_{22} = 0$ & $R_{32} = 1$
  - $R = 3$, if $R_{22} = 1$ & $R_{32} = 1$
- Compare $P(Y|R, Z)$ between patterns $R = 1$ and $R = 3$ (age 22) and $R = 2$ and $R = 3$ (age 32)

Identifiability restrictions

- Need identifiability restrictions:

$$P(Y_{22} = 1 | R = 0, Z_{22}) = P(Y_{22} = 1 | R = 1, Z_{22})$$

$$P(Y_{32} = 1 | R = 0, Z_{32}) = P(Y_{32} = 1 | R = 1, Z_{32})$$

$$P(Y_{22} = 1 | R = 2, Z_{22}) = P(Y_{22} = 1 | R = 3, Z_{22})$$

- Depression probability is now modelled by including pattern indicators and their interaction terms with other covariates into the model
- Nonsignificant interaction terms suggested that there was no informative missingness

Conclusions

- Effective use of the longitudinal data is vital when evaluating the effect of missingness
- Non-response models are likely to have poor predictive ability
- The models merely reveal characteristics that are absent from those who respond
- Careful sensitivity analysis is needed to assess plausibility of the missing at random (MAR) assumption
- *Eerola, M, Huurre, T, Aro, H. The problem of attrition in a Finnish longitudinal survey on depression. Eur. J Epid. 2005, 20: 113-120.*