**Supplementary File 3:** Handling missing data

Missing data were handled following the guidance described in Faria et al., (1). Missing values were imputed using multiple imputations at the endpoint level, specifically for total healthcare and non-healthcare costs, utilities, and total anxiety and depression HADS scores. Briggs et al. indicate this as an appropriate method when missing data patterns are relatively simple and the missing data rates are similar across cost items (2), which was the case for this study as there were less than 2% missing single items (n=5) across all baseline and follow-up observations. Initially, the missing data were tested and classified as either “missing-not-at-random, “missing-at-random”, or “missing-completely-at-random”. Logistic regression analyses were conducted to test the association of missing endpoints with baseline covariates (age, sex, and baseline HADS) and follow-up characteristics (follow-up costs, utilities, and HADS). The multiple imputation process involved chained equations using predictive mean matching to impute the endpoint outcomes and it was stratified by study arm (3). Age, sex, education, marital status, HADS anxiety and depression scores, EQ5D utility, and healthcare and non-healthcare costs at baseline were used as baseline predictors in the multiple imputation model: A total of 15 imputed datasets were generated, following the recommendation by White et al., which suggests creating imputed datasets in a quantity equal to the percentage of incomplete data observed during the trial (3). The STATA code of the multiple imputation model can be consulted below.

\* Set MI

mi set flong

mi register imputed ///

**var**HADS anxiety at T1 **var**HADS anxiety at T2 **var**HADS anxiety at T3 ///

**var**HADS depression at T1 **var**HADS depression at T2 **var**HADS depression at T3 ///

**var**utility at T1 **var**utility at T2 **var**utility at T3 ///

**var**healthcare costs at T1 **var**healthcare costs at T2 **var**healthcare costs at T3 ///

**var**non-healthcare costs at T1 **var**non-healthcare costs at T2 **var**non-healthcare costs at T3 ///

\* Impute

mi impute chained ///

(pmm, knn(3)) ///

**var**HADS anxiety at T1 **var**HADS depression at T1  **var**utility at T1  **var**healthcare costs at T1  **var**non-healthcare costs at T1 ///

**var**HADS anxiety at T2 **var**HADS depression at T2  **var**utility at T2  **var**healthcare costs at T2  **var**non-healthcare costs at T2 ///

**var**HADS anxiety at T3 **var**HADS depression at T3  **var**utility at T3  **var**healthcare costs at T3  **var**non-healthcare costs at T3 ///

= **var**baseline HADS anxiety **var**baseline HADS depression **var**baseline utility **var**baseline healthcare costs ///

**var**baseline non-healthcare costs **var**age **var**sex **var**educational level **var**marital status ///

, by(**var**study arm) add(15) burnin(20) rseed(10001) chaindots dots

*Abbreviations: T1 = 3-month follow-up, T2 = 7-month follow-up, T3 = 12-month follow up, MI = multiple imputation, var = variable, and pmm = predictive mean matching.*

**SOURCES**

1. Faria R, Gomes M, Epstein D, White IR. A guide to handling missing data in cost-effectiveness analysis conducted within randomised controlled trials. Pharmacoeconomics. 2014 Dec;32(12):1157-70.

2. Briggs A, Clark T, Wolstenholme J, Clarke P. Missing... presumed at random: cost-analysis of incomplete data. Health Econ. 2003 May;12(5):377-92.

3. White IR, Royston P, Wood AM. Multiple imputation using chained equations: Issues and guidance for practice. Stat Med. 2011 Feb 20;30(4):377-99.