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Aims
- Review the properties and assumptions of methods for population-adjusted treatment comparisons, including Matching-Adjusted Indirect Comparisons (MAIC) and Simulated Treatment Comparisons (STC).
- Provide guidance on their use in health technology appraisal (HTA).

Background
In HTA submissions, a company wishes to compare their treatment with that of a competitor. C. Standard indirect comparison and related methods involve a meta-analysis to assure that there are no differences in effect modifiers between the populations, and require a common comparator or network of treatments — neither of which are assured. The use of population-adjusted methods for health technology appraisal

Effect modification is present on a gender scale, relative effects \( \frac{\exp(\hat{\beta} X)}{\exp(\hat{\beta} X)} \) between treatments that are scale specific. A population \( P \) with \( \hat{\beta} X \) and \( \hat{\beta} X \) are the mean

Recommendations

Valid only if:
- No effect modifiers in the outcome model
- No effect modifiers in the outcome model
- No effect modifiers in the outcome model
- No effect modifiers in the outcome model

Figure 1: Forms of indirect comparisons and constancy assumptions

Figure 1c: Anchored

Figure 1d: Unanchored

Anchored population adjusted indirect comparisons

Unanchored population adjusted indirect comparisons


Propensity score reweighting

1. Create a logistic propensity score model, \( P(U) \), which includes all effect modifiers that improve model fit.
2. Weight each individual by \( \exp(T(U)) \), where \( T(U) \) is the logistic regression equation for the propensity score model.
3. Calculate standard errors using a robust standard error estimator, bootstrapping, or Bayesian techniques.
4. Provide evidence that absolute outcomes can be predicted with sufficient accuracy in relation to the

Processes for population-adjusted indirect comparison

Anchored

Unanchored

Figure 1b: Anchored

Figure 1a: Unanchored


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Table of methods for population adjustment

Population adjustment methods are broadly of two types:
- Propensity score reweighting, such as Matching Indirect Comparison (Cappellini et al., 2017), where individuals in the \( \hat{\beta} \) are weighted by a thorough review of the subject area or discussion with experts in the clinical discipline.

The focus of the following recommendations is statistical and clinical validity, transparency, and consistency in the use of population adjustment methods for health technology appraisal.

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