This supplement provides some statistical details of the models for estimating individual-level utilities in the manuscript.

Bayesian Latent Utility Model

Formulation and interpretation: Individual patient preferences for different attributes of Personalized Trials were estimated using empirical Bayesian latent utility modeling on all conjoint responses of the participants. Under this model, the latent utility of trial prototype *j* to a participant *i* (denoted as u_{ij}) was postulated to follow a logistic distribution in which the mean depended on a linear combination of trial attributes. Specifically, having $u_{ij} = \beta_i^T x_{ij} + \varepsilon_{ij}$, where ε_{ij} is a standard logistic error and the design x_{ij} indicated the presence/absence of attributes in prototype *j* presented to the participant, for *i=1, ..., n,* and *j=1,..., J.* In our application, n = 500 and J = 2. We note that x_{ij} is a vector of length equal to the number of binary attributes. For attributes with more than 2 levels (e.g. treatment types), we code x_{ij} using dummy variables. To illustrate and unpack the model formulation, consider the simplified case where we only have two binary attributes, namely, blinding (denoted as $x_{blind,i,j}$) and cost (denoted as $x_{cost,i,j}$) for individual i and scenario j in a question. The vector $x_{ij} = (x_{blind,i,j}, x_{cost,i,j})^T$. Then $\beta_{blind,i}$ denotes the contribution to the utility u_{ij} due to blinding, and $\beta_{cost,i}$ due to cost. For example, suppose the first scenario (j=1) in a conjoint question is presented with blinding ($x_{blind,i,j} = 1$) and no cost ($x_{cost,i,j} = 0$), whereas the second question with no blinding ($x_{blind,i,j} = 0$) and cost ($x_{cost,i,j} = 1$). Then the utility for the first scenario: $u_{i1} = \beta_{blind,i} x_{i1} + \beta_{cost,i} x_{i1} + \varepsilon_{i1} = \beta_{blind,i} + \varepsilon_{i1}$ and the utility for the second scenario: $u_{i2} = \beta_{blind,i} x_{i2} + \beta_{cost,i} x_{i2} + \varepsilon_{i2} = \beta_{cost,i} + \varepsilon_{i2}$. Thus, by comparing u_{i1} and u_{i2} based on the conjoint response, we can directly compare the coefficients, with mean zero noise. In other words, the conjoint utilities provide the relative preferences between two attributes.

Estimation method: In a conjoint survey, while we do not observe u_{ij} directly (i.e., a latent utility), we do observe $d_i = I(u_{i1} > u_{i2})$, the conjoint question response. It can be easily show that d_i is binomial variable with probability that is logit-linear in β_i , and thus a mixed effect logistic regression *likelihood* function can be used for inference. Using the empirical Bayes formulation similar to Laird and Ware (1982), we postulate β_i are distributed as N(0,**D**), independently of each other, where **D** is a positive-definite covariance matrix. Instead of prescribing what **D** is, we estimate it from the marginal likelihood of $\{d_i\}$ after integrating out β_i . We note that while the formulation in Laird and Ware (1982) is described for linear mixed model, the principle naturally extends to generalized linear mixed model and the estimation method of **D** is implemented in the glmer function of the R library lme4 (Bates et al., 2015).

General statistical analyses: All statistical analyses in the article were performed using R Statistical Software (R Core Team, 2020).

Reference:

1. Laird NM, Ware JH. Random effects models for longitudinal data. Biometrics 1982;38:963-974.
2. Bates D, Mächler,M, Bolker B, Walker S. Fitting linear mixed-effects models using lme4. *Journal of Statistical Software* 2015;67:1-48. doi:10.18637/jss.v067.i01
3. R Core Team (2020). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://urldefense.proofpoint.com/v2/url?u=https-3A__www.R-2Dproject.org_&d=DwIFaQ&c=G2MiLlal7SXE3PeSnG8W6_JBU6FcdVjSsBSbw6gcR0U&r=3S92mR9RS-V17crZs5I3JmRGPmLU0biAr1TT1vi652U&m=CCAo-miRazlCZOshMn1kObLD243PdOUZgWuJ0-TYYng&s=G7h8-ub2atPynW6x9FSlJcLMe-acT95jnSq0lgzjQOc&e= .