Analysis of Data from Method Comparison Studies Using *R*, **merror**, and **OpenMx**

Richard A. Bilonick[1,2,*]

1. University of Pittsburgh School of Medicine, Dept. of Ophthalmology
2. University of Pittsburgh Graduate School of Public Health, Dept. of Biostatistics
*Contact author: rab45@pitt.edu

Keywords: measurement error, bias, imprecision, structural equation model, latent variable

Method comparison studies are used to compare the measurements made of the same quantity using different instruments, monitors, devices or methods. Researchers often try to compare the measurements made by just two devices, in some cases using regression analysis. As is well known, when both devices are subject to measurement error (ME), regression analysis presents a distorted view of the actual bias (or shows bias when none exists). Analogously, correlation is often used to describe the agreement even though correlation only measures linear association and cannot provide any insight into agreement of the two instruments. Other researchers resort to the use of Bland-Altman plots (paired differences versus paired averages). This approach is useful if there is good agreement but provides no way to determine the cause of poor agreement.

A more fruitful and general approach is provided by using the classic ME model (Jaech, 1985):

$$X_{ij} = \alpha_i + \beta_i \mu_j + \epsilon_{ij}$$

where μ denotes the "true" but unknown value of the j^{th} item being measured (often assumed to be Normally distributed with mean $\bar{\mu}$ and standard deviation σ), X_{ij} denotes the observed measurement from instrument *i* for item *j*, α_i and β_i describe the bias introduced by the instrument (assumed to be a linear function of μ), and ϵ_{ij} denotes a Normally distributed random error of instrument *i* and item *j* with mean of 0 and standard deviation of σ_i . The instrument imprecision adjusted for differences in scale is given by σ_i / β_i . The ME model can be described using a path diagram with μ as a latent variable and X_i as manifest variables, and represented as a structural equation model (SEM). SEM path analysis readily explains the deficiencies of using only two devices and the necessity of including repeats and/or 3 or more devices. SEMs can easily include repeated measurements, or, for example as in ophthalmology, having measurements from both eyes. Parameter estimates can be made using the method of moments (MOM) or the method of maximum likelihood (ML). Using these estimates, calibration equations relating measurements from different instruments can be easily derived.

The **merror** package (Bilonick, 2003) provides the function `ncb.od` for computing ML estimates of the ME imprecision standard deviations for unclustered data and least squares estimates of β_i . The function `lrt` tests whether $\beta_i = \beta_{i'}$. Other functions are available for Grubbs (MOM) estimators. For clustered data, the more flexible **OpenMx** (SEM) package (Boker, et al., 2010) can be used for ML estimates of any desired (functions of) model parameters. When using **OpenMx** for ME models, **merror** can be used to provide good starting values for the parameter estimates. These methods will be illustrated using data from ophthalmic studies and from air pollution studies.

References

Richard A. Bilonick (2003). **merror**: Accuracy and Precision of Measurements. R package version 1.0.

Steven Boker, Michael Neale, Hermine Maes, Paras Metah, Sarah Kenny, Timothy Bates, Ryne Estabrook, Jeffrey Spies, Timothy Brick and Michael Spiegel (2010). **OpenMx**: The OpenMx Statistical Modeling Package. R package version 0.2.3-1006. http://openmx.psyc.virginia.edu.

John L. Jaech (1985). **Statistical Analysis of Measurement Errors**, John Wiley & Sons, New York.