Mixed Linear Modeling: a Very Short Introduction

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Update ~2020. A slideshow that includes the first four slides from the slideshow below, plus slides from an earlier slideshow (2003) explaining the "hat metaphor" for random effects, is available here. This slideshow is included in the suite of materials for mixed modeling with SAS Studio and for mixed modeling with SPSS.

For a succinct summary of how mixed linear models work in four slides, including the best ever explanation of fixed and random effects, download this slideshow (4.5 MB) presented at the 2013 annual conference of the European College of Sports Science. My topic was using mixed linear modeling to estimate and adjust for environmental effects on competitive performance, and the very short introduction to the method is followed by examples of recent research by my colleagues and students. Some results of unpublished projects have been deleted to avoid any issues about prior publication with journals (even though the results shown were only a small fraction of the findings for illustrative purposes). I will restore the results once the manuscripts have been accepted.

The results of Ken Quarrie's analysis of goal kicking in international rugby union includes tables of the rankings of the kickers. We have published the rankings as a spreadsheet here, to avoid any issues a journal might have with showing names of athletes, even though the original data were in the public domain.

Update: Sample-Size/Meta-Analysis Tool

Will G Hopkins, Sport and Recreation, AUT University, Auckland, New Zealand. **Email**. Sportscience 17, i-ii, 2013 (sportsci.org/2013/inbrief.htm#updates). Reviewer: Alan M Batterham, University of Teesside, Middlesbrough, UK. Published July 2013.

To estimate sample size for a crossover or parallel-groups controlled trial, you need an estimate of the typical error (aka error of measurement or within-subject standard deviation) of the dependent variable over a period of time and with subjects similar to those in your intended study. Finding such an estimate in published reliability studies is difficult, especially if you are planning a long-term intervention, because reliability studies generally don't go beyond a week between trials and the subjects may be quite different (sedentary vs active vs competitive). However, you can usually find another intervention with a time frame and subjects similar to yours, so I have worked out how to extract the typical error from such studies. The authors will need to have provided not only the magnitude of their effect and the sample size (in the control and experimental groups for a parallel-groups trial), but also inferential information in the form of either an exact p value or confidence limits. The design doesn't have to be exactly the same: you can use data from a controlled trial for an intended crossover or vice versa.

It doesn't matter that the intervention was different from what you intend to use. Any intervention may be better than a reliability study, because any individual responses to the intervention will increase the typical error. Hence if your intervention produces individual responses, the estimate of sample size based on a reliability study will be too low. Of course it's not quite that simple, because the individual re-

sponses to different interventions will differ, and if there are individual responses there is probably a substantial mean effect, in which case the sample size in your study can be smaller. But estimates of sample size are always approximate, and the approach I am presenting here is, in my opinion, as good as it gets. I have updated the spreadsheet and article on sample-size estimation accordingly.

You can also use this approach when meta-analyzing crossovers or controlled trials when the authors of a given study have not provided enough inferential information to derive the standard error for their estimate of the effect. In previous meta-analyses (e.g., Vandenbogaerde and Hopkins, 2009) we have imputed the standard error in what we believe is the best way possible: from the typical error in comparable studies. The relevant cells in the sample-size spreadsheet now provide you with the typical error. You will have to convert it to a standard error yourself by dividing by $\sqrt{n}$ for a crossover or multiplying by $\sqrt{(1/n_1 + 1/n_2)}$ for a parallel-groups trial, where n, n_1 and n_2 are appropriate sample sizes in the study for which you are imputing the standard error.

Vandenbogaerde TJ, Hopkins WG (2011). Effects of acute carbohydrate supplementation on endurance performance: a meta-analysis. Sports Medicine 41, 773-792

Update: Meta-Analysis Slideshow

Will G Hopkins, Sport and Recreation, AUT University, Auckland, New Zealand. **Email**. Sportscience 17, ii, 2013 (sportsci.org/2013/inbrief.htm#metaslides). Reviewer: Alan M Batterham, University of Teesside, Middlesbrough, UK. Published Oct 2013.

I have streamlined the slideshow in the article on meta-analysis and made substantial modifications to take into account the unified approach to effects represented by ratios of risks or proportions, odds, hazards and counts in the article on linear models and effect magnitudes. A novel approach of including separate effects for each group from controlled trials or other studies with control, reference or other comparison groups is also described.

Statistical Analysis and Data Interpretation: an Introduction

Will G Hopkins, Sport and Recreation, AUT University, Auckland, New Zealand. **Email**. Sportscience 17, ii, 2013 (sportsci.org/2013/inbrief.htm#metaslides). Reviewer: Alan M Batterham, University of Teesside, Middlesbrough, UK. Published Oct 2013.

I recently recorded a one-hour lecture on basic statistics for a new post-graduate diploma in sports medicine organized by Prof. Ron Maughan for the International Olympic Committee. The lecture, minus the recorded commentary and with minor edits, is available at this link.

The title supplied by Ron was *Statistical Analysis and Data Interpretation What is significant for the athlete, the statistician, and team doctor?* As you will see in the slideshow, I replaced *significant* with *important* to focus attention on the need for sport clinicians and other practitioners to consider the clinical or practical importance of effects in published studies.

The lecture is a highly condensed version of the slideshows on magnitude-based inference and linear models and effect magnitudes. I included no explanation of linear models and mixed models, but a condensed version of these topics is available in the first four slides of the slideshow mentioned in the first In-Brief item above.

In the first few slides I present an overview of the different kinds of statistic (simple, effect, inferential). I then explain the meaning of statistical significance and the p value, followed by clinical and non-clinical magnitude-based inference. The rest of the lecture details the smallest and other clinically important magnitudes of the most common kinds of effect statistic in sports medicine and science (differences and changes in means; correlations; slopes or gradients; ratios of proportions, risks, odds, hazards, and counts).