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Nursing Science Research Consulting: A Multidisciplinary Framework

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Abstract

Nursing science research is at the intersection of the social and medical sciences and statistical developments in many different disciplines are relevant. A framework for nursing science statistics which recognizes and builds upon the statistical contributions from biostatistics, quantitative psychology, epidemiology, econometrics, survey research, computer science and statistics is presented. A broad eclectic framework is necessary to take advantage of new developments in statistical and research design methodology addressing specific problems common to a given area. This framework recognizes that awareness of differences in established expectations (conventions, guidelines, regulations, etc.) with regard to statistical methodology across different research areas is an important aspect of successful consulting. It is hoped that this framework will facilitate interdisciplinary collaboration so nurse scientist statisticians will take a leading role in advancing methodology and research design.

Key Words: Nursing research, methodology, research design

1. Introduction

The idea for an interdisciplinary framework came out of a growing realization that there is a need for a more systematic look at the diversity of statistical methods and research design methodology that is being used across the different disciplines.

1.1 Motivating Example

NIH peer reviewers often raise questions about the research design and statistical methodology in the applications they review. These scientific peer review groups are typically multidisciplinary. The question that occurred was, “Does it appear that researchers from different academic backgrounds raise different kinds of methodological and statistical questions”? While it is impossible to know if objections come from statisticians or researchers with content expertise, there are many ways misunderstanding can occur and my bias is that issues are more often raised by researchers who have always done things a certain way rather than by statisticians. Regardless, a better understanding of the different perspectives of statisticians and methodologists in different research areas will improve our ability to communicate different and novel methodological approaches more effectively.

2. The Framework

I am proposing *cross disciplinary statistics* as a framework for methodological research with goals in three areas:

- Consensus
- Awareness
- Understanding

Before discussing these goal areas, a note on terminology: the terminology of team science distinguishes different kinds of cross disciplinary research—multidisciplinary, interdisciplinary, and transdisciplinary. In order to avoid confusion, the more general term, cross disciplinary, is used here rather than multidisciplinary even if though that is consistent with the title of this talk.

2.1 What differences of consensus exist among researchers within and across disciplines and research areas on statistical issues in sampling, measurement, research design, and data analysis?

Table 1 contrasts some design and analysis decisions that differ across research areas or disciplines. This list is not systematic or exhaustive but based on my consulting experience. For example, with a background in cognitive psychology complex factorial designs are very familiar to me yet the single factor analysis of variance (ANOVA) design appears to be preferred in clinical trials. The reason for this might be the high stake decision at hand, “They must avoid false effect claims that would introduce costly, useless, and possibly toxic interventions into society” (Goetghebeur & Loeys, 2002, p. 85). This convention has merited some recent attention (Collins et al, 2011).

Table 1: Examples of Statistical Conventions that Differ Across Research Areas or Disciplines

Primary, secondary, and surrogate end points	Analysis of mediation
Adjustment of alpha for multiplicity	Multivariate tests to control Type 1 error
Design based adjustment for clustering	Model based adjustment for clustering
Single factor ANOVA design	Complex factorial ANOVA
Rubin causal model	Structural equation modeling
Okay to dichotomize continuous endpoint	Avoid dichotomization
Phase 1 trial	Pilot study
Subgroup analysis	Interaction effects

2.1.1 The role of role of guidelines and regulations

Guidelines, regulations and methodological critiques (when available) provide a way to know what is expected. This is useful when proposing less conventional solutions that could draw criticism. The advantages of the novel solution can be explained in terms of what the more conventional solution lacks.

2.2 Awareness

Some statistical developments in different disciplines and research areas that could have relevance to nursing science and not often used in nursing research include the following:

- Research designs used in Phase 1 clinical trials that make use of very small N
- Nonlinear regression models similar to those used in pharmaceutical research
- Compartment and other nonlinear models of biological processes.

With regard to measurement, developments in the following areas are important:

- Measurement theory that includes psychometric and biometric constructs
- Precisely calibrated item banks (Fries et al, 2005)
- Multidimensional scaling

Computer intensive methods and the use of statistical simulation to estimate power and sensitivity are rapid becoming more the norm than the exception. A useful example is the R program to estimate power of liner trends in a longitudinal design with a fixed or random exposure variable (Basagaña & Spiegelman, 2010).

2.3 Understanding

Comparing different approaches to the same design challenge will increase understanding and improve communication of alternative design options from those that might be expected. This is likely to result in better scores when applications are judged by a multidisciplinary panel.

3. Background

The framework takes clues from two classic texts, R. A. Fisher's, *Statistical Methods for Research Workers* (14th edition, 1970), and Cook & Campbell's, *Quasi-Experimentation: Design & Analysis Issues for Field Settings* (1979).

3.1 Statistical Methods for Research Workers

In the opening paragraph Fisher stated: "As in other mathematical studies, the same formula is equally relevant to widely different groups of subject-matter. Consequently the unity of the different applications had usually been overlooked, the more naturally because the development of the underlying mathematical theory had been much neglected. We shall therefore consider the subject-matter of statistics under three different aspects ...Statistics may be regarded as (i) the study of **populations**, (ii) as the study of **variation**, (iii) as the study of method of **reduction of data**" (1970, p1).

He described one of problems of data reduction as follow: "Problems in **specification**, which arise in the choice of the mathematical form of the population. This is not arbitrary, but requires an understanding of the way in which the data are supposed to, or did in fact, originate. Its further discussion depends on such fields as the theory of Sample Survey, or that of Experimental Design" (p 8).

Two points are to be made here. The first is the dependence of valid inference on getting the *data generating process (DGP)* correct. The second is on the dependence of valid inference on Sample and Design. The other two types of problems in data reduction were **estimation** and **distribution**. There are problems that clearly fall in the domain of **mathematical statistics**.

3.2 Quasi-Experimentation

Cook and Campbell's conceptualization of four threats to validity-- statistical conclusion validity, internal validity, construct validity, and external validity-- are the core of this seminal work and arguably the reason for its continued relevance (see updated edition by W. Shadish et al.).

3.2.1 Threats to validity as guidelines

These threats to validity remain a useful heuristic. Many design and research area specific guidelines are available today. Guidelines can have unintended consequences. For example, one-arm trial design may still be perceived as nearly always unacceptable (Clay, R. A., 2010). Guidelines, of course, don't replace understanding though they are useful in discussing the design strengths and limitations

4. Discussion and Conclusions

The practice of statistics involves a judicious blend of abstract concepts, practical constraints, and substantive knowledge. Statistical consultants and nurse scientists face the multidisciplinary challenges described here apart from the research implications suggested by the framework.

Some additional questions of interest follow:

- Would a cross disciplinary instrument to measure statistical knowledge at a level suitable to make judgments on research proposals be useful?
- What consensus is there on how to handle subject self selection and noncompliance in comparative effectiveness trials?
- What consensus is there on the validity of self report for different kinds of exposures like cigarette smoking, physical activity, hours worked per week?
- Would clinical trials benefit by including mediation constructs and/or more complex factorial designs?
- What are the underlying statistical concepts that bring coherence to the variety of methods being used today?

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