Comment on "Current Issues and a "Wish List" for Conjoint Analysis"

Magidson, J.; Vermunt, J.K.

Published in:
Applied Stochastic Models in Business and Industry

Publication date:
2005

Document Version
Publisher's PDF, also known as Version of record

Link to publication in Tilburg University Research Portal

Citation for published version (APA):
Magidson, J., & Vermunt, J. K. (2005). Comment on "Current Issues and a "Wish List" for Conjoint Analysis". *Applied Stochastic Models in Business and Industry*, *21*(4-5), 327-328.

APPLIED STOCHASTIC MODELS IN BUSINESS AND INDUSTRY
Appl. Stochastic Models Bus. Ind., 2005; **21**:327–328
Published online in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/asmb.561

Comment on

Current issues and a 'wish list' for conjoint analysis

Jay Magidson[1,*,†,§] and Jeroen K. Vermunt[2,‡,¶]

[1] *Statistical Innovations, 375 Concord Avenue, Belmont, MA 02478, U.S.A.*
[2] *Department of Methodology and Statistics, Tilburg University, The Netherlands*

Conjoint analysis has its underpinnings in the late 1960s. In his 'Current Issues' article, Eric Bradlow points out that conjoint analysis has now come of age and is entering 'midlife'. We believe that the midlife analogy is a good one as each of Eric's nine directions represents an important opportunity for continued growth. We will comment briefly on four of these opportunities where latent class (LC) choice models have already moved the conjoint field in these directions.

First on his list is the important issue of stability of the estimated partworths. Since conjoint studies typically attempt to predict the future, it is essential that the partworth estimates not only predict *current* preferences/choices and underlying values/utilities accurately, but also that these estimates are sufficiently stable to allow for successful introductions of new products. Incorporating respondent heterogeneity is the single most important way to assure that the partworth accurately reflects the individual consumer's values, as opposed to just some aggregate measure that fails to account for the different utilities associated with different market segments. Beyond this is the question of how consumer choices may change over time.

From a LC perspective, modelling change (or learning) allows respondents to be in different latent states (or segments) at different measurement occasions. This involves specifying a model with multiple latent variables; that is, a model with one categorical latent variable per occasion. The correlations between the time-specific states may be modeled by an auto-regressive structure, yielding what is known as a LC or hidden Markov model. An alternative is to model the dependencies between the occasion-specific latent states using a random-effects or multilevel structure, as is done in the multilevel LC model recently proposed by Vermunt [1]. In both the Markov and multilevel specifications, it is possible to model the pattern of change over time, which may be used to improve prediction of future choices.

Issue #4 deals with the related need to extend beyond the simplistic aggregate linear model to represent adequately non-compensatory 'latent decision rules' that may be used by consumers in making choices. The psychometrics literature contains many examples of how LC models can be

*Correspondence to: Jay Magidson, Statistical Innovations, 375 Concord Avenue, Belmont, MA 02478, U.S.A.
† E-mail: jay@statisticalinnovations.com
‡ E-mail: j.k.vermunt@uvt.nl
§ President.
¶ Professor.

used to estimate the proportion of the population for which pre-specified decision rules apply. For example, persons in some (latent) segment might require attribute A to be present, or that the price be no higher than x before they would consider buying. The key to implementing this in practice would be to operationalize such a decision rule by specifying those *combinations* of attribute levels which are ruled out.[‖]

We agree that data fusion (issue #5) is an important future direction. Since the ordinal (adjacent category) logit model can be expressed as a restricted multinomial logit model, it is possible now to have a set of stated choices, one or more revealed choices, and a set of ordinal attitude questions all be analysed as part of one large LC choice model. Future software will exploit this fact and make it easy for the user to estimate such models.

Regarding issue #6, CAT is a useful procedure when testing persons using an *existing* model. Without a model, it does not help in the administration of a conjoint survey. The way that CAT works in educational testing is that the best predicting item is selected to determine a person's latent trait, given a known latent trait model and the information already collected for the respondent. Thus, once a conjoint model that captures the unobserved heterogeneity has been estimated and we want to administer the same survey to a *new* sample (say in a telephone interview), one may apply CAT techniques to minimize the number of questions that are needed per respondent. For example, if the model is a LC choice model, the purpose is to predict to which class or segment a person belongs. Given the recorded responses at any point in time, the model can be used to select the best next choice set to administer. This set could be selected from among predefined choice sets, or it could be a *new* choice set that is generated at that moment. For example, if after the fifth question the posterior membership probabilities indicate that the person belongs to either class 2 or 3, we know that it would be best to present a choice set that discriminates as much a possible between these two classes.

We look forward to these and other extensions as midlife promises to be an exciting time for conjoint analysis.

REFERENCES

1. Vermunt JK. Multilevel latent class models. *Sociological Methodology* 2003; **33**:213–239.
2. Vermunt JK, Magidson J. *Latent GOLD Choice 4.0 User's Manual*. Statistical Innovations: Belmont, MA, 2005.

[‖] This type of model could then be estimated using a program such as Latent GOLD Choice [2] by specifying an offset of minus infinity for a particular latent class to represent a zero probability of occurrence for such attribute combinations.

