Dr. Bradlow has provided an invaluable road map for important and necessary future research in Conjoint Analysis (CA). Particularly, and using his terminology, I reinforce his call for research in a) within-task learning/variation, b) massive number of attributes (albeit I believe the number of attributes needed for “massive” categorization needs to be increased somewhat above the 15-20 level he mentions), c) non-compensatory decision rules and d) true integration of profile conjoint data with other data sources.

Before elaborating on two topics in his list, I would like to address an overarching need for this research area. It is my belief that CA has lagged in theoretical development in part because it lacks a framework that goes beyond its functional measurement origins in psychology. The use of random utility theory in economics and transportation can and has furnished such a theoretical framework for CA ([1]), but it has not been widely adopted in the marketing field. Not least among the benefits of such a theoretical development is the integration to CA of such concepts as consideration and choice set formation, decision rule modeling, non-compensatory evaluation rules, market structure, measurement reliability, and, very importantly, an error theory. More needs to be done to integrate CA and random utility theory.

To build on Dr. Bradlow’s call for research on the integration of CA data with other data sources, it is necessary to point out that an active research stream ([1, Chapter 13]) already exists along these lines in transportation ([2]), environmental economics ([3]) and marketing ([4]), where it is known under the rubric of “data fusion.” For economy of space I have cited only a few exemplars of this work, but it is important to highlight this well-developed literature to CA practitioners.

Both academics and practitioners need to better understand the impacts of context complexity (certainly number of attributes and levels, as well as products) on choice behavior ([5], [6], [7]). The need is particularly acute in terms of being able to distinguish between measurement task effects and those operating in real markets: separating “artificial” task complexity responses from “real world” complexity responses, and/or discovering under what conditions task complexity responses are transferable to the forecasting context, is crucial to lending credibility to forecasts based on CA.

REFERENCES


