Optimal Data Analysis
Vol. 2, Release 2 (December 5, 2013), 232-234

2155-0182/10/$3.00

# Statistical Evaluation of the Findings of Qualitative Comparative Analysis

Paul R. Yarnold, Ph.D.
Optimal Data Analysis, LLC

Qualitative data analysis is a structured observational and clustering methodology which facilitates hypothesis development and variable generation for quantitative research, fruitfully employed in agriculture, anthropology, astronomy, biology, forensic investigation, education, history, marketing, medicine, political science, psychology, sociology, and zoology, to name a handful of diciplines.[1-6] The method known as qualitative comparative analysis (QCA) is adept in producing evidence in complex policy problems involving interdependencies among multiple causes.[7] Recent research used QCA to study factors underlying high rates of teenage conceptions in high-risk areas in England. Nine binary attributes reflecting five different "variable constellations" were identified. Variable constellations are putatively associated with areas with teenage conception rates which are narrowing versus not narrowing (the outcome or class variable) with respect to the national average. This article discusses use of UniODA and CTA to ascertain which attributes are statistically reliable predictors of outcome.

UniODA is used to investigate the relationship between each attribute considered individually and the outcome.[8,9] Table 1 presents the data for nine binary attributes available for 11 areas with narrowing conception rates, and 16 areas with not-narrowing conception rates.[7] Also shown are the exact Type I error rate, ESS and ESP for the UniODA model.[10]

Higher minority ethnic population was statistically significant ($p<0.05$) considered at the experimentwise criterion (nine tests of statistical hypotheses were conducted): the model had strong accuracy and very strong predictive value.[8-10]

A higher proportion of teens younger than 18 years, and fair, poor, or mixed leadership were statistically significant ($p<0.05$) at the generalized "per-comparison" criterion: the models had moderate accuracy and predictive value. And, availability of major programmes was statistically marginal (generalized $p<0.10$), with moderate accuracy and predictive value.

For all remaining variables the UniODA model was not statistically significant (generalized $p>0.10$), and all of the accuracy and predictive value indices were weak.

2155-0182/10/$3.00

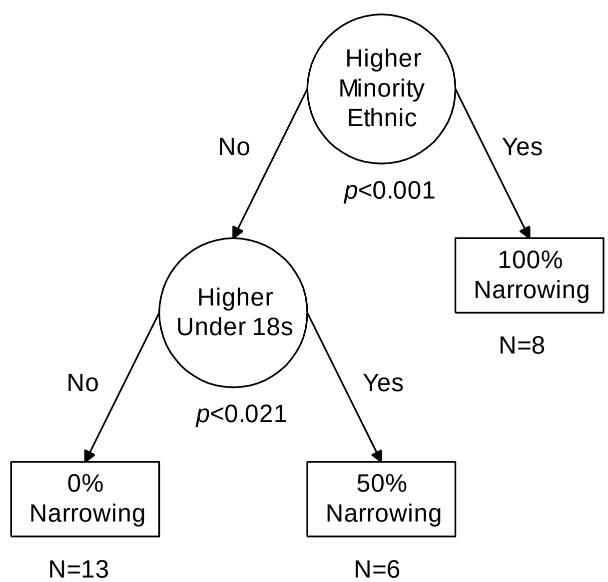
Table 1: QCA-Based Conception Rate Data

| Attribute | Narrowing | Not Narrowing | Exact *p*< | ESS | ESP |
|---|---|---|---|---|---|
| Higher minority ethnic population | 72.7% | 0% | 0.000074 | 72.7 | 84.2 |
| Lower drug treatment | 72.7% | 50% | 0.43 | 22.7 | 22.7 |
| Higher under 18s | 63.6% | 18.8% | 0.041 | 44.9 | 46.5 |
| Basic commissioning of services | 72.7% | 50% | 0.43 | 22.7 | 22.7 |
| Fair, poor or mixed leadership | 81.8% | 37.5% | 0.048 | 44.3 | 43.3 |
| Intervention focuses on community settings | 54.5% | 37.5% | 0.46 | 17.1 | 16.7 |
| Major programmes | 54.5% | 18.8% | 0.097 | 35.8 | 38.9 |
| Lower deprivation | 36.4% | 56.3% | 0.45 | 19.9 | 19.2 |
| Higher educational achievement | 36.4% | 56.3% | 0.45 | 19.9 | 19.2 |

Hierarchically optimal *c*lassification *t*ree *a*nalysis (CTA) identifies the (non)linear model which consists of a set of UniODA models that together achieve the maximum possible overall accuracy using one or more attributes to predict the class variable: statistical and ecological significance; jackknife, hold-out, and generalizability validity; and theoretical clarity and parsimony serve as criteria and objectives in the modelling process.[11,12] Applied to the data in Table 1, CTA returned the two-attribute model illustrated in Figure 1. The model yields very strong accuracy (ESS=81.2) and very strong predictive value (ESP=78.6). As seen, the only endpoint in the model for which accuracy can be improved (the others are errorless) is the non-higher minority ethnic areas having more teens under 18 years of age. Future research in this area should thus concentrate on increasing the sample size for this less-than-perfect model endpoint, and conduct secondary QCA using only this new sample in an effort to identify the variable which perfects the CTA model.

The objective of this note was to show how UniODA and CTA may be used to test statistical hypotheses, evaluating individual variables and "sorting-out" multiple variables which were developed via qualitative data analysis including QCA. The specific application used presently involved a time-ordered series, but data were reported as a scaler (a ratio indicating change over time), so ipsative standardization—needed to avoid confounded spurious results attributable to Simpson's Paradox—is not possible with these data: this may be remedied by measuring data using more sensitive fixed time intervals.[13-16] In addition, the methodology used to dichotomize the attributes[1] likely induced paradoxical confounding.[17] Finally, the more complex the data, the greater the relative performance of CTA versus suboptimal methods.

Figure 1: CTA Model for QCA Example



2155-0182/10/$3.00

## References

[1]Barbour R (2008). *Doing focus groups*. Sage.

[2]Flick U (2008). *Designing qualitative research*. Sage.

[3]Rapley T (2008). *Doing conversation, discourse, and document analysis*. Sage.

[4]Steadman E, Raisch DW, Bennett CL, Esterly JS, Becker T, Postelnick M, McKoy JM, Trifilio S, Yarnold PR, Scheetz MH (2010). Evaluation of a potential clinical interaction between ceftriaxone and calcium. *Antimicrobial Agents and Chemotherapy*, *54*, 1534-1540.

[5]Yarnold PR, Bryant FB (2013). Analysis involving categorical attributes having many categories. *Optimal Data Analysis*, *2*, 69-70.

[6]Belknap S, Georgopoulos CH, Lagman J, Weitzman SA, Qualkenbush L, Yarnold PR, Edwards BJ, McKoy JM, Trifilio SM, West DP (In Press). Reporting of serious adverse events during cancer clinical trials to the Institutional Review Board: An evaluation by the *R*esearch on *A*dverse *D*rug Events *A*nd *R*eports (RADAR) project. *The Journal of Clinical Pharmacology*.

[7]Blackman T, Wistow, J, Byrne D (2013). Using Qualitative Comparative Analysis to understand complex policy problems. *Evaluation*, *19*, 126-140.

[8]Yarnold PR, Soltysik RC (2005). *Optimal data analysis: Guidebook with software for Windows*. Washington, D.C.: APA Books.

[9]Yarnold PR, Soltysik RC (2010). Optimal data analysis: A general statistical analysis paradigm. *Optimal Data Analysis*, *1*, 10-22.

[10]Yarnold PR (2013). Standards for reporting UniODA findings expanded to include ESP and all possible aggregated confusion tables. *Optimal Data Analysis*, *2*, 106-119.

[11]Soltysik RC, Yarnold PR (2010). Automated CTA software: Fundamental concepts and control commands. *Optimal Data Analysis*, *1*, 144-160.

[12]Yarnold PR (2013). Initial use of hierarchically optimal classification tree analysis in medical research. *Optimal Data Analysis*, 2, 7-18.

[13]Yarnold PR, Soltysik RC (2013). Ipsative transformations are *essential* in the analysis of serial data. *Optimal Data Analysis*, 2, 94-97.

[14]Yarnold PR (2013). Ascertaining an individual patient's *symptom dominance hierarchy*: Analysis of raw longitudinal data induces Simpson's Paradox. *Optimal Data Analysis*, 2, 159-171.

[15]Yarnold PR, Soltysik RC (2013). Confirmatory analysis for an ordered series of a dichotomous attribute: Airborne radiation and congenital hypothyroidism of California newborns. *Optimal Data Analysis*, 2, 222-227.

[16]Exploratory analysis for an ordered series of a dichotomous attribute: Airborne radiation and congenital hypothyroidism of California newborns. *Optimal Data Analysis*, 2, 228-231.

[17]Yarnold PR (2013). Comparing responses to dichotomous attributes in single-case designs. *Optimal Data Analysis*, *2*, 154-156.

## Author Notes

*ODA* Blog: odajournal.com