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Implementing ODA from Within Stata: *A Priori* Hypothesis, Three-Category Class Variable, Four-Level (Integer) Attribute

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This paper describes how to test a directional (confirmatory) hypothesis for a design relating a three-category class ("dependent") variable and a four-level categorical ordinal attribute ("Likert-type independent variable") vis-à-vis the new Stata package for implementing ODA.

Recent papers[1-20] introduce the new Stata package called **oda**[21] for implementing ODA from within the Stata environment. Because this package is a wrapper for the MegaODA software system[22-24], the MegaODA.exe file must be loaded on the computer for the **oda** package to work (MegaODA software is available at https://odajournal.com/resources/). To download the **oda** package, at the Stata command line type: "ssc install oda" (without the quotation marks). This paper demonstrates use of the **oda** package to evaluate a one-tailed hypothesis for a design involving a three-category class variable and a four-category ordinal (integer) attribute.

Methods

Data

Consider Thompson and Yarnold's data[25] on the relationship of categorized ratings of a patient's perceived waiting time to see a doctor (1=longer than expected; 2=as long as expected; 3=shorter than expected)—called *time* and treated as a class variable, and satisfaction (1=poor; 2=fair; 3=good; 4=excellent)—called *satis* and treated as an ordered attribute.

Analytic Process

The directional ("confirmatory") alternative hypothesis is that longer perceived waiting times (lower *time* scores) can be discriminated by greater patient dissatisfaction with care received (lower *satis* scores), and the null hypothesis is that this is not true. The exact *p* is estimated by a 25,000-iteration permutation test. For the entire sample, **oda** is implemented with the following syntax (see the help file for **oda** for a complete description of syntax options):

```
oda time satis , pathoda("C:\ ODA\")
store("C:\ ODA") iter(25000) dir(< 1 2 3)
```

This syntax is explained as follows: "time" is the *class* variable and "satis" is the

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attribute; "C:\ODA\" is the directory path where the MegaODA.exe file exists on the computer, and where other files generated in analysis are stored; and 25,000 iterations (repetitions) are used to obtain a permutation *p*-value. The directional hypothesis is lower *wait* ratings predict lower *satis* ratings, and the null hypothesis is this is not true. Data for each observation was entered in free format on a separate line in space-delimited text (ASCII) characters.[26,27]

The **oda** package produces an extract of the total output produced by the ODA software (the complete output is stored in the specified directory with the extension ".out").

```
ODA model:
----------
IF SATIS <= 2.5 THEN TIME = 1
IF 2.5 < SATIS <= 3.5 THEN TIME = 2
IF 3.5 < SATIS THEN TIME = 3

Summary for Class TIME  Attribute SATIS
---------------------------------------

Performance Index          Train
-----------------         ------
Overall Accuracy           51.08%
PAC TIME=1                 36.21%
PAC TIME=2                 44.59%
PAC TIME=3                 70.78%
Effect Strength PAC        25.79%
PV TIME=1                  68.28%
PV TIME=2                  46.94%
PV TIME=3                  49.14%
Effect Strength PV         32.18%
Effect Strength Total      28.99%

Monte Carlo summary (Fisher randomization):
-------------------------------------------
Iterations:  25000
Estimated p: 0.000000
```

The effect strength for sensitivity (ESS) is labelled in the output as the "Effect Strength PAC" (Percentage Accurate Classification). As seen, ESS for the *a priori* hypothesis is 25.79%, which barely exceeds the minimal criterion (ESS$\leq$0.25) to be classified as a moderate effect[26] and has permutation *p*<0.0001.

In summary, ODA identified a model having moderate strength which supported the *a priori* hypothesis that longer perceived patient waiting times predicted decreasing patient satisfaction ratings.

We believe ODA should be considered the preferred statistical approach over other methods because it avoids statistical assumptions required of conventional models, is insensitive to skewed data or outliers, and has the ability to handle any variable metric including categorical, Likert-type integer, and real number measurement scales.[26] In contrast to alternative methods, only ODA can identify the optimal (maximum-accuracy) assignments (categorical attributes) or cutpoints (ordered attributes) that exist for the attribute, which in turn facilitates the use of measures of predictive accuracy.

Furthermore, ODA can evaluate model reproducibility by multiple methods, allowing assessment of potential cross-generalizability of the model applied to classify an independent random sample.[26]

For these reasons we recommend that researchers employ ODA and CTA frameworks to evaluate the statistical hypotheses which are explored in their laboratory and field research endeavors.[28-46]

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Author Notes

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