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Personality Remix: Integrating Variable-Centered and Person-Centered Approaches to Personality

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This study incorporates variable- and person-centered approaches to data analysis by exploring the existence of personality factorial profiles using mixture factor analysis (MFA). Using the Mini-IPIP, findings show that a 4-class MFA provides the best fit when compared to latent profile analyses (LPA) and a confirmatory factor analysis (CFA).

In the early 1990's personality experienced a rebirth in the field of Industrial/Organizational (I/O) psychology (Hough & Schneider, 1996). This renewal of interest in personality can be attributed in part to the development of a widely-accepted taxonomy of personality structure known as the Big Five (Digman, 1990; Funder, 2001; Hough & Schneider, 1996). Funder (2001) notes that despite criticism (e.g., Block, 1995), "the 'Big Five' organization of personality trait constructs seems almost ubiquitous in the current literature" (p. 200). Personality research traditionally adopted a variable-centered approach, which means that the variables and the relationships between variables are the focus of the research questions and analysis (Laursen & Hoff, 2006). However, many researchers have argued that it is important to consider personality from a person-centered perspective (e.g., Asendorpf, 2006). The person-centered approach focuses on differences between individuals when examining relationships between variables. This approach does not

assume that findings will generalize to all members of a population, but may differ for subgroups within the population. (Asendorpf, 2006; Pastor, Barron, Miller, & Davis, 2007). We believe that both approaches provide important information and examining issues from one perspective or the other inherently limits the findings. Fortunately, new methodological developments provide the advantage of looking at personality from both perspectives. This study incorporates both a variable-centered and person-centered approach by exploring the existence of personality factorial profiles through the use of mixture factor analysis (MFA).

Five Factor Model of Personality

The Five Factor Model (FFM) of personality consists of the following five factors: extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience (Barrick, Mount, & Judge, 2001; Costa & McCrae, 1992; Goldberg, 1990, 1992; Hough & Schneider, 1996). Different people define and label

these five factors in many ways, but Barrick et al. (2001) note there is general acceptance regarding the characteristics that define each factor. Extraversion is defined by a predisposition for positive emotions, sociability, gregariousness, warmth, dominance, ambition, and excitement-seeking. Agreeable individuals get along well with others, are cooperative, trusting, compliant, and sympathetic. Conscientious individuals are dependable, careful, persevering, planful, and strive for achievement. Emotional stability is characterized by low anxiety, and a lack of hostility, depression, or insecurity. Openness to experience is associated with originality, creativity, and unconventionality (Barrick et al., 2001; George & Jones, 2003).

Variable-Centered and Person-Centered Approaches to Data Analysis

Variable-centered and person-centered approaches differ in terms of focus and assumptions related to how findings generalize. The variable-centered approach focuses on examining relationships between variables. This approach assumes that the population is homogenous (i.e., that the relationships observed apply to all members of the population) and therefore the findings generalize to the entire population. Statistical techniques used in a variable-centered approach include correlations, regressions, and structural equations models. Conversely, the person-centered approach focuses on differences between individuals relative to the construct(s) of interest. This approach assumes a heterogeneous population (i.e., there are subgroups in the population) and therefore findings generalize to the relevant class or cluster within a population. Statistical techniques used to analyze data from a person-centered approach include cluster analysis, latent class analysis (LCA), and latent profile analysis (LPA; Block, 1971; Laursen &

Hoff, 2006; Lubke & Muthen, 2005; Pastor et al., 2007).

Most personality research has taken a variable-centered approach (Asendorpf & Denissen, 2006), focusing on the factorial structure of personality through the use of exploratory or confirmatory factor analysis (EFA or CFA; e.g., Donnellan, Oswald, Baird, & Lucas, 2006), or on relationships between personality factors and outcomes of interest (regression; e.g., Dean, Conte, & Blankenhorn, 2006). Findings emerging from the variable-centered approach include the development and validation of several measures of the Big Five personality characteristics [e.g., International Personality Item Pool (IPIP); Goldberg, 1999] and supporting predictive relationships with several criteria of interest (i.e., overall job performance, training performance, organizational citizenship behavior, and counterproductive work behavior; Barrick et al., 2001; Dean et al., 2006; Hattrup, O'Connell, & Wingate, 1998; Sackett & DeVore, 2002).

The productivity of the variable-centered approach cannot be denied yet this approach suffers some important limitations. To begin, the variable-centered approach ignores possible group heterogeneity and the feasible existence of subgroups of individuals with differing personality profiles thus ignoring a potent explanation of variation. In addition, CFA research conducted on several Big Five measures exhibits consistently poor model fit (e.g., Church & Burke, 1994; Donnellan et al., 2006; Lim & Ployhart, 2006; McCrae, Zonderman, Costa, Bond, & Paunonen, 1996). Donnellan et al. (2006) note that "it might not be possible to obtain reasonable fit from a CFA perspective on many or even most Big Five inventories" (p. 197). This poor model fit is primarily attributed to cross-loaders (items that load on multiple factors), but nonetheless, provides evidence

that there are flaws with focusing exclusively on a variable-centered approach.

In contrast to the variable-centered perspective, research using a person-centered approach occurs far less often (Asendorpf & Denissen, 2006). Typically, questions investigated from a person-centered perspective use cluster analysis as the traditional analytic technique (Ward, 1963) and recent studies have continued in this tradition to examine personality profiles (e.g., Asendorpf, 2006; Claes et al., 2006). Cluster analysis research consistently identifies three personality types/profiles: resilient, overcontrollers, and undercontrollers (Asendorpf & van Aken, 1999; Block & Block, 1980; Caspi, 1998; Hart, Hofmann, Edelstein & Keller, 1997; Robins, John, Caspi, Moffitt, & Stouthamer-Loeber, 1996). Resilient display below average neuroticism and average or above average on the other Big Five dimensions. Overcontrollers exhibit, in contrast to resilient, above average neuroticism, coupled with below average extraversion. Lastly, undercontrollers display both below average in conscientiousness and agreeableness (Asendorpf, 2006; Claes et al., 2006).

Despite consistent personality profile findings, the person-centered perspective, as with the variable-centered perspective, suffers some limitations. While this approach does not suffer from a failure to examine group heterogeneity it ignores variability that could be explained by variable variability. The methodological techniques used in these studies (i.e., cluster analysis) are somewhat more difficult to interpret than newer model-based techniques, such as LCA or LPA (Lubke & Muthen, 2005; Pastor et al., 2007). Although all of these techniques (i.e., cluster analysis, LCA, and LPA) explore unobserved heterogeneity within a population (Lubke & Muthen, 2005) model-based approaches as

Lubke and Muthen note “have the advantage that more rigorous methods can be applied for the comparison of alternative models” (p. 23).

Mixture Factor Analysis – Integrating Variable-Centered and Person-Centered Approaches

Asendorpf and Denissen (2006) argue that “Work in the mainstream variable-centered tradition has mostly ignored the issue of personality types, and little research has attempted to compare – let alone integrate – both perspectives in a broader theoretical framework” (p. 488). The development of latent variable hybrid models now makes it possible to incorporate both a variable-centered and person-centered approach when conducting analyses (Muthen, in press). Like other newly developed areas of research, confusion arises in the literature regarding the appropriate terms for these analyses. In this study we used mixture factor analysis (MFA) which is often confused with factor mixture analysis (FMA). The distinction according to Muthen between the two types of analyses concerns whether factorial invariance is held across classes or not. MFA holds the factorial structure invariant between classes, while FMA allows the factorial structure to vary between classes. MFA can be viewed as more rigid because it is more difficult to meet the standard of measurement invariance than to allow the factorial structure to vary (Muthen, in press).

The Current Study

The current study seeks to identify the existence of personality factorial profiles in a group of military trainees participating in foreign language training. The following research questions will be explored:

Research Question (RQ) 1: Will LPA provide evidence of multiple classes? If so,

will personality profiles found previously (i.e., resilient, overcontrollers, and undercontrollers) emerge in a group of military trainees?

RQ2: How does a variable-centered approach (i.e., CFA) compare to the person-centered approach (i.e., LPA; i.e., which approach provides better model fit)?

RQ3: Does MFA provide better model fit than the variable-centered or person-centered approach?

Method

Participants were 1,731 students partaking in foreign language training in a large military organization. In terms of their educational background, 25.4% had completed high school, 46.7% had completed some college, and 24.5% had earned a B.A. or B.S. degree. In terms of tenure in the military, 4.9% had been in the military for less than one year, 45.4% had been in the military between one and four years, 30.6% had been in the military between five and eight years, and 19.2% had been in the military for nine or more years.

Personality Measure

This study used a short version of Goldberg's (1999) IPIP 50-item measure of personality, called the Mini-IPIP (Donnellan et al., 2006). The IPIP contains items which assess each of the Big Five factors and was recently reduced from 10-items per factor to 4-items per factor on the Mini-IPIP (Donnellan et al., 2006). Respondents indicated the extent to which each item described themselves using the following response categories: 1 = *very inaccurate*, 2 = *moderately inaccurate*, 3 = *neither inaccurate nor accurate*, 4 = *moderately accurate*, and 5 = *very accurate*. Negatively

worded items were reverse-coded prior to conducting analyses.

Data Analysis

Latent Profile Analysis. LPA investigated RQ1 to determine the number and type of latent profiles in the data set. Figure 1 provides a conceptual LPA model. For each model tested, item means were allowed to vary across latent classes, but item variances were constrained to be equal. The first step of the LPA tested the hypothesis of a two class solution ($k = 2$). Each subsequent LPA analysis tested the hypothesis of a $k+1$ class solution until the best-fitting model was identified.

In order to identify the appropriate solution the Akaike information criterion (AIC; Akaike, 1974), Bayesian information criterion (BIC; Schwartz, 1978), and sample-size adjusted BIC (aBIC; Muthen & Muthen, 2005) were examined. Lower levels of the AIC, BIC, and aBIC indicate better fit. In addition, entropy was examined to evaluate classification. Entropy values closer to 1.00 provide evidence of better classification. The adjusted Lo-Mendell-Rubin likelihood ratio test (aLRT; Lo, Mendell, & Rubin, 2001) was examined to determine if there was a significant difference between a k -class solution and a $k-1$ class solution. Significant p -values from this test indicate support for the current class solution as opposed to a $k-1$ class solution (Lo et al., 2001).

Confirmatory Factor Analysis. RQ2 was examined using CFA (see Figure 2 for conceptual model). Although Muthen (in press) recommends comparing LPA with exploratory factor analytic (EFA) results, we opted to examine this issue from a CFA perspective because of the abundance of research supporting a five factor solution. Several fit indices were examined when assessing CFA model fit. First the chi-square statistic was examined. Significant

chi-square values are evidence of poor fit, while non-significant chi-square values are desirable. However, in addition to the chi-square statistic, which is sensitive to sample size and often found to be significant (Yu, 2002), several additional fit indices were examined [i.e., the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and the square root mean residual (SRMR)]. According to Hu and Bentler (1999), the CFI and TLI should be above 0.90, but values closer to 1.00 are better. Vandenberg & Lance (2000) and Millsap (2002) indicate that the RMSEA and SRMR should be below .08 for the model to be considered a good fit.

Mixture Factor Analysis. MFA was used to examine RQ3. This analysis combines a variable-centered and person-centered approach (see Figure 3 for a conceptual model). The same approach and fit statistics used to evaluate the fit of LPA models was used to evaluate the fit of MFA models (i.e., AIC, BIC, aBIC, aLRT, and entropy). The first step of the MFA tested the hypothesis of a two class solution ($k = 2$). Each subsequent MFA analysis tested the hypothesis of a $k+1$ class solution until the best-fitting model was identified.

Software. The analyses conducted in this study were performed in Mplus (Muthen & Muthen, 2006).

Results

Latent Profile Analysis

Fit statistics were examined for 2-, 3-, and 4-class LPA solutions (see Table 1). Although the AIC, BIC, and aBIC were the lowest for the 4-class solution, the entropy and aLRT indicated that the 3-class solution was the appropriate solution. The entropy for the 3-class solution was the highest (0.774) when compared to the 2-class (0.754) and the 4-class solution (0.764),

indicating that the 3-class solution provided the best classification. In addition, the aLRT indicated that the 2-class solution should be accepted over a one-class solution ($p = 0.000$) and that a 3-class solution should be accepted over a 2-class solution ($p = 0.0120$). However, the aLRT indicated that a 4-class solution should not be accepted in favor of a 3-class solution ($p = 0.1120$). Therefore, a 3-class solution provides the best fitting LPA model.

There were 722 participants (43.4%) assigned to the largest class (Class 3), 591 participants (35.7%) assigned to the second largest class (Class 1), and 350 participants (21.0%) assigned to the smallest class (Class 2; see Figure 4). For the most part, participants assigned to Class 3 have relatively high standing on all of the items measuring the Big Five constructs than participants assigned to the other classes. Participants assigned to Class 1 have mean responses that are lower than participants in the other two classes for all items, except extraversion items. This class has below average standing on extraversion items when compared with participants in Class 3 and higher than average standing than participants in the smallest class (Class 2). Participants assigned to Class 2 have the lowest mean response on extraversion items, but mean responses that are higher than participants assigned to Class 1.

Confirmatory Factor Analysis

A five-factor, uncorrelated error CFA was conducted. The AIC, BIC, and aBIC indicate that the CFA provided a better fit than the 2-, 3-, and 4-class LPA models (see Table 1). However, the chi-square statistic for this model was significant, which is an indication of poor fit [$\chi^2 = 1035 (160)$, $p = 0.00$]. This statistics is sensitive to sample size and is often significant, but other fit statistics also indicated relatively poor fit

[CFI = 0.881; TLI = 0.858; RMSEA = 0.057; SRMR = 0.050].

Mixture Factor Analysis

Fit statistics were examined for 2-, 3-, 4-, and 5-class MFA solutions (see Table 1). Stable loglikelihood values indicated that the global maxima were reached for the 2-, 3-, and 4-class solutions, but a stable solution was not found for the 5-class solution. The AIC, BIC, and aBIC were the lowest for the 4-class solution and the aLRT indicated that the 4-class solution was the appropriate solution. The entropy for the 2-class solution was the highest (0.930) when compared to the 3-class (0.860) and the 4-class solution (0.836). The aLRT indicated that the 2-class solution should be accepted over a one-class solution ($p = 0.0056$), that a 3-class solution should be accepted over a 2-class solution ($p = 0.0105$), and that a 4-class solution should be accepted over a 3-class solution ($p = 0.0141$). Failure to find a stable solution for the 5-class solution provides further evidence that a 4-class solution provides the best fitting MFA model.

There were 1267 participants (76.2%) assigned to the largest class (Class 4), 319 participants (19.2%) assigned to the second largest class (Class 1), 52 participants (3.1%) assigned to the third largest class (Class 2), and 25 participants (1.5%) assigned to the smallest class (Class 3; see Figure 5). Participants assigned to the largest class, Class 4, have relatively high standing on the Big Five factors when compared to participants assigned to the other classes. This group is extraverted, agreeable, conscientious, emotionally stable, and open to experience. Participants assigned to the second largest class, Class 1, have lower mean responses across all Big Five constructs when compared with Class 4, and are lower in emotional stability than participants assigned to Class 4. Participants

assigned to Class 2 have the lowest standing on extraversion and agreeableness, but relatively high standing on conscientiousness, emotional stability, and openness to experience. Finally, participants assigned to the smallest class, Class 3, have the highest standing on extraversion, agreeableness, conscientiousness, and openness to experience, but have low emotional stability when compared with the other classes.

Discussion

This study compared person-centered and variable-centered approaches when examining personality data for a group of military trainees. RQ1 examined whether LPA would provide evidence of multiple classes, thereby justifying the need for a person-centered approach. LPA findings supported a 3-class solution, and therefore provided evidence that a person-centered approach is meaningful in this context. In order to compare the person-centered approach with a variable-centered approach, RQ2 explored the fit of a five-factor CFA model. Results provided evidence of a strong alternative model. The AIC, BIC, and aBIC suggest that the CFA provides a better fit than the LPA. However, the overall fit of the CFA was relatively poor, indicating that the variable-centered approach is providing an incomplete picture. Fortunately, MFA provides researchers with the ability to incorporate both variable- and person-centered approaches. Findings from this study show that the MFA 4-class solution produced the best fitting model when compared with the CFA and LPA models.

Interpreting the classes. Some notable differences emerge when comparing the results for the MFA with the results of the LPA and profiles found in the previous literature. Neither the LPA nor the MFA produced profiles identical to that found in

the previous literature, although there is some evidence of an overcontroller group (i.e., low emotional stability, low extraversion; Claes et al., 2006) in both the LPA and MFA results.

The LPA produced three classes with visually similar profiles. One class (Class 3) has a high standing on all Big Five factors, while another class (Class 1) has a similar profile pattern as Class 3, but more average standing on the Big Five factors. Interestingly, the smallest class (Class 2) was defined by low standing on extraversion, one of the characteristics of overcontrollers (see Figure 4). Using suggested labels from Howard and Howard (2001), we label this group the introverts.

The MFA produced four classes, although the size of the classes differed substantially from the size of the LPA classes, with one large class, one moderately sized class, and two small classes. The largest class produced by the MFA (Class 4) had a similar profile pattern but a slightly more moderate standing on all Big Five factors when compared with the high class from the LPA (Class 3). The second largest class produced by the MFA (Class 1) showed a similar pattern and but slightly more moderate standing on the factors when compared with Class 4 from the MFA. However, this group showed slightly lower levels of emotional stability. This class is labeled responsives (mid-range score on emotional stability), which are described by Howard and Howard (2001) as those who are occasionally bothered by stressful circumstances. Of the two small classes that were identified in the MFA, one class (Class 3) had high standing on all Big Five factors, but lower standing on emotional stability. This class is labeled reactives (tense, alert, anxious; Howard & Howard, 2001) and appears to have split from the class with the highest standing on the factors (i.e., Class 4). In addition, Class 2 also appears to have

split from Class 4 and includes individuals who have a low standing on extraversion and agreeableness, but a high standing on the other three factors. We label this class the introverted challengers, meaning that they are quiet, yet questioning and competitive (Howard & Howard, 2001).

Limitations and Future Research

There are several important limitations associated with this study. The first is related to the military nature of the sample. These participants may have important differences with other groups, calling into question the generalizability of the findings. Future research should explore these research questions using a non-military sample.

Another limitation is the lack of covariates used in the LPA and MFA analyses. Muthen (2004) recommends including relevant covariates as omitting important covariates may lead to errors in the way classes are defined. Future research should examine covariates to see if class membership can be predicted. Future research should also examine the extent to which membership in a class is predictive of outcomes of interest.

Conclusions

This study demonstrates the value of examining issues from both a person-centered and a variable-centered perspective. The development of latent variable hybrids and other sophisticated modeling techniques gives researchers the ability to develop a more accurate and complete picture of human behavior and constructs of interest. Researchers are encouraged to explore these techniques for their potential to develop new lines of research into organizational and employee topics.

References

- Akaike, H. (1974). A new look at statistical model identification. *IEEE Transactions on Automatic Control*, *AU-19*, 719-722.
- Asendorpf, J. B. (2006). Typeness of personality profiles: A continuous person-centred approach to personality data. *European Journal of Personality*, *20*, 83-106.
- Asendorpf, J. B., & Denissen, J. J. A. (2006). Predictive personality types versus personality dimensions from early childhood to adulthood: Implications for the distinction between core and surface traits. *Merrill-Palmer Quarterly*, *52*, 486-513.
- Asendorpf, J. B., & van Aken, M. A. G. (1999). Resilient, overcontrolled, and undercontrolled personality prototypes in childhood: Replicability, predictive power, and the trait-type issue. *Journal of Personality and Social Psychology*, *77*, 815-832.
- Barrick, M. R., Mount, M. K., & Judge, T. A. (2001). Personality and performance at the beginning of the new millennium: What do we know and where do we go next? *International Journal of Selection and Assessment*, *9*, 9-30.
- Block, J. (1971). *Lives through time*. Berkeley, CA: Bancroft Books.
- Block, J. (1995). A contrarian view of the five-factor approach to personality description. *Psychological Bulletin*, *117*, 187-215.
- Block, J. H., & Block, J. (1980). The role of ego-control and ego-resiliency in the organization of behavior. In W. A. Collins (Ed.), *Minnesota symposium on child psychology* (Vol. 13, pp. 39-101). Hillsdale, NJ: Erlbaum.
- Caspi, A. (1998). Personality development across the life course. In N. Eisenberg (Ed.), *Handbook of child psychology: Social, emotional, and personality development* (Vol. 3, 5th ed., pp. 311-388). New York: Wiley.
- Church, A. T., & Burke, P. J. (1994). Exploratory and confirmatory tests of the Big Five and Tellegen's three and four-dimensional models. *Journal of Personality and Social Psychology*, *66*, 93-114.
- Claes, L., Vandereycken, W., Luyten, P., Soenens, B., Pieters, G., & Vertommen, H. (2006). Personality prototypes in eating disorders based on the Big Five model. *Journal of Personality Disorders*, *20*, 401-416.
- Costa, P. T., Jr., & McCrae, R. R. (1992). *NEO-PI-R professional manual*. Odessa, FL: Psychological Assessment Resources.
- Dean, M. A., Conte, J. M., & Blankenhorn, T. R. (2006). Examination of the predictive validity of the Big Five dimensions across training performance criteria. *Personality and Individual Differences*, *41*, 1229-1239.
- Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. *Annual Review of Psychology*, *41*, 417-440.
- Donnellan, M. B., Oswald, F. L., Baird, B. M., & Lucas, R. E. (2006). The mini-IPIP scales: Tiny-yet-effective measures of the big five factors of personality. *Psychological Assessment*, *18*, 192-203.
- Funder, D. C. (2001). Personality. *Annual Review of Psychology*, *52*, 197-221.
- George, J. M., & Jones, G. R. (2003). Psychological dimensions of organizational behavior. In B. M. Staw (Ed.), *Psychological dimensions of*

- organizational behavior* (Vol. 3rd, pp. 3-23). Upper Saddle River, NJ: Prentice Hall.
- Goldberg, L. R. (1990). An alternative “description of personality”: The Big-Five Factor structure. *Journal of Personality and Social Psychology*, *59*, 1216-1229.
- Goldberg, L. R. (1992). The development of marker variables for the Big-Five Factor structure. *Psychological Assessment*, *4*, 26-42.
- Goldberg, L. R. (1999). A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models. In I. Mervielde, I. Deary, F. De Fruyt, & Ostendorf (Eds.), *Personality Psychology in Europe*, Vol. 7 (pp. 7-28). Tilburg, The Netherlands: Tilburg University Press.
- Hart, D., Hofmann, V., Edelstein, W., & Keller, M. (1997). The relation of childhood personality types to adolescent behavior and development: A longitudinal study of Icelandic children. *Developmental Psychology*, *33*, 195-205.
- Hattrup, K., O'Connell, M. S., & Wingate, P. H. (1998). Prediction of multidimensional criteria: Distinguishing task and contextual performance. *Human Performance*, *11*, 305-319.
- Hough, L. M., & Schneider, R. J. (1996). Personality traits, taxonomies, and applications in organizations. In K. R. Murphy (Ed.), *Individual differences and behavior in organizations* (pp. 31-88). San Francisco: Jossey-Bass.
- Howard, P. J., & Howard, J. M. (2001). *The owner's manual for personality at work: How the Big Five personality traits affect performance, communication, teamwork, leadership, and sales*. Atlanta, GA: Bard Press.
- Hu, L., & Bentler, P.M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equations Modeling*, *6*, 1-55.
- Laursen, B., & Hoff, E. (2006). Person-centered and variable-centered approaches to longitudinal data. *Merrill-Palmer Quarterly*, *52*, 377-389.
- Lim, B. C., & Ployhart, R. E. (2006). Assessing the convergent and discriminant of Goldberg's International Personality Item Pool: A multitrait-multimethod examination. *Organizational Research Methods*, *9*, 29-54.
- Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*, 767-778.
- Lubke, G. H., & Muthen, B. (2005). Investigating population heterogeneity with factor mixture models. *Psychological Methods*, *10*, 21-39.
- McCrae, R. R., Zonderman, A. B., Costa, P. T., Bond, M. H., & Paunonen, S. V. (1996). Evaluating the replicability of factors in the revised NEO personality inventory: Confirmatory factor analysis versus Procrustes rotation. *Journal of Personality and Social Psychology*, *70*, 552-566.
- Millsap, R.E. (2002). Structural equation modeling: A user's guide. In F. Drasgow & N. Schmitt (Eds.), *Measuring and analyzing behavior in organizations: Advances in measurement and data analysis* (pp. 257-301). San Francisco: Jossey-Bass.
- Muthen, B. (2004). Latent variable analysis: Growth mixture modeling and related

- techniques for longitudinal data. In D. Kaplan (Ed.), *Handbook of quantitative methodology for the social sciences* (pp. 345-368). Newbury Park, CA: Sage Publications.
- Muthen, B. (in press). Latent variable hybrids: Overview of old and new models. In Hancock, G. R., & Samuelsen, K. M. (Eds.). *Advances in latent variable mixture models*. Charlotte, NC: Information Age Publishing, Inc.
- Muthen, L. K., & Muthen, B. O. (2005). *Mplus user's guide*. Los Angeles, CA: Muthen & Muthen.
- Muthen, L. K., & Muthen, B. O. (2006). *Mplus (Version 4.2) [Computer software]*. Los Angeles, CA: Muthen & Muthen.
- Pastor, D. A., Barron, K. E., Miller, B. J., & Davis, S. L. (2007). A latent profile analysis of college students' achievement goal orientation. *Contemporary Educational Psychology, 32*, 8-47.
- Robins, R. W., John, O. P., Caspi, A., Moffitt, T. E., & Stouthamer-Loeber, M. (1996). Resilient, overcontrolled, and undercontrolled boys: Three replicable personality types. *Journal of Personality and Social Psychology, 70*, 157-171.
- Sackett, P. R., & DeVore, C. J. (2002). Counterproductive behaviors at work. In N. Anderson et al. (Eds.) *Handbook of Industrial, Work, & Organizational Psychology, Volume 1: Personnel Psychology*. Thousand Oaks, CA: Sage.
- Schwartz, G. (1978). Estimating the dimensions of a model. *The Annals of Statistics, 6*, 461-464.
- Vandenberg, R.J., & Lance, C.E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods, 3*, 4-69.
- Ward, J. H. (1963). Hierarchical grouping to optimize an objective function. *Journal of the American Statistical Association, 58*, 236-244.
- Yu, C.Y. (2002). *Evaluating cutoff criteria of model fit indices for latent variable models with binary and continuous outcomes*. Doctoral dissertation, University of California, Los Angeles.

Table 1

Model fit results for CFA, LPA, and MFA

	N^1	Loglikelihood H0 Value	# parameters	AIC	BIC	aBIC	Entropy	aLRT
CFA	1663	-40910.434	50	81920.869	82191.688	82032.845	--	--
LPA – 2c	1663	-42833.332	61	85788.664	86119.063	85925.275	0.754	$p = 0.0000$
LPA – 3c	1663	-42395.564	82	84955.128	85399.271	85138.769	0.774	$p = 0.0120$
LPA – 4c	1663	-42093.507	103	84393.013	84950.900	84623.684	0.764	$p = 0.1120$
MFA – 2c	1663	-40867.393	76	81886.786	82298.431	82056.990	0.930	$p = 0.0056$
MFA – 3c	1663	-40793.089	82	81750.178	82194.322	81933.820	0.860	$p = 0.0105$
MFA – 4c	1663	-40748.417	88	81672.835	82149.476	81869.913	0.836	$p = 0.0141$
MFA – 5c	1663	-40730.205 ²	94	81648.409	82157.549	81858.925	0.811	$p = 0.3240$

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; aBIC = sample-size adjusted BIC; aLRT = Adjusted Lo-Mendell-Rubin

likelihood ratio test.

¹Listwise deletion reduced sample size from 1731 to 1663.

²A stable solution was not reached.

Figure 1. LPA Conceptual Model

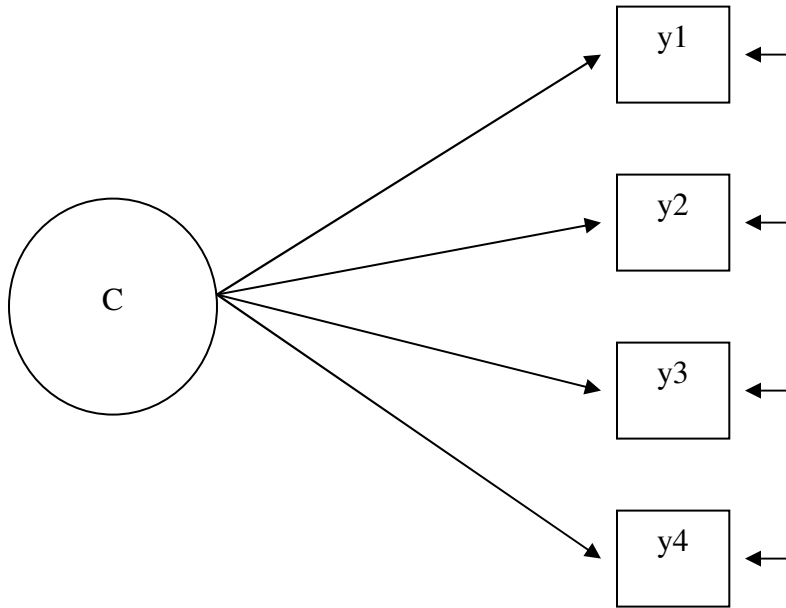


Figure 2. CFA Conceptual Model

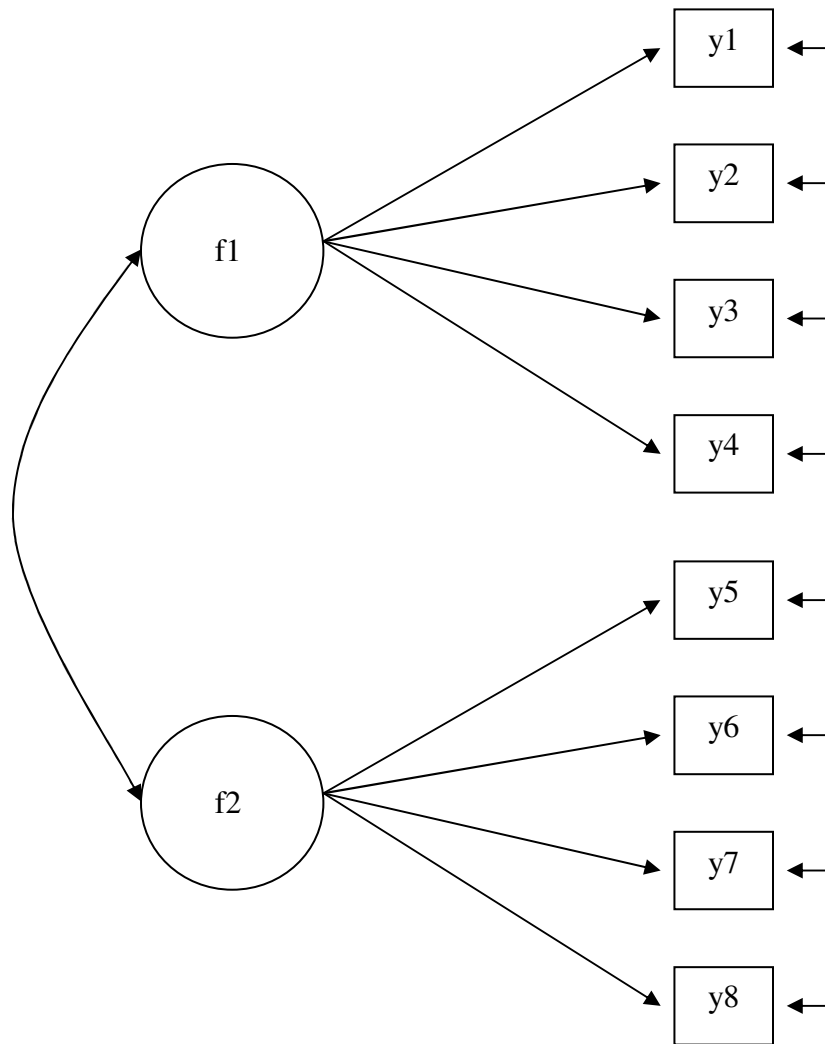


Figure 3. MFA Conceptual Model

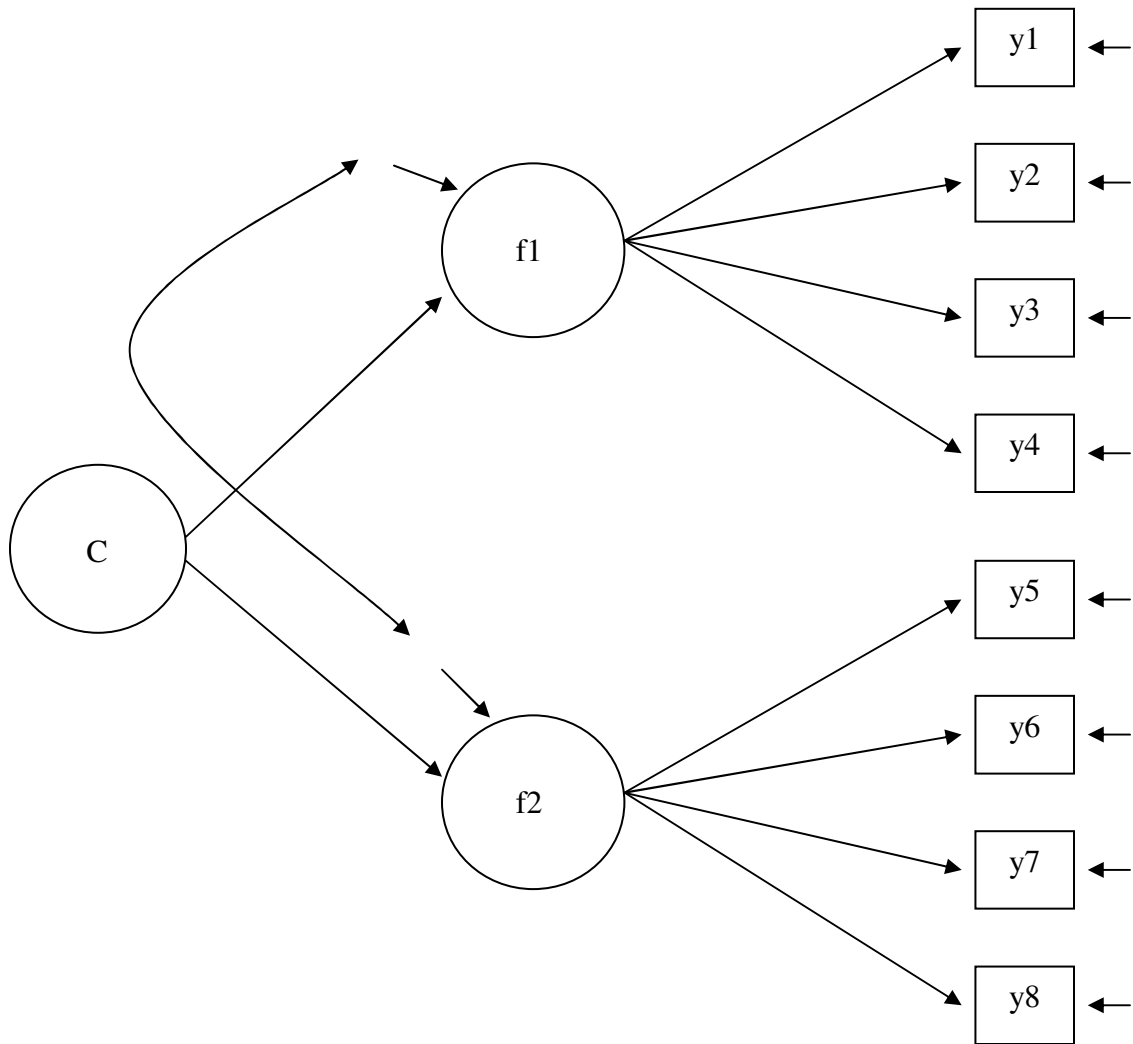


Figure 4. 3-Class LPA Profiles

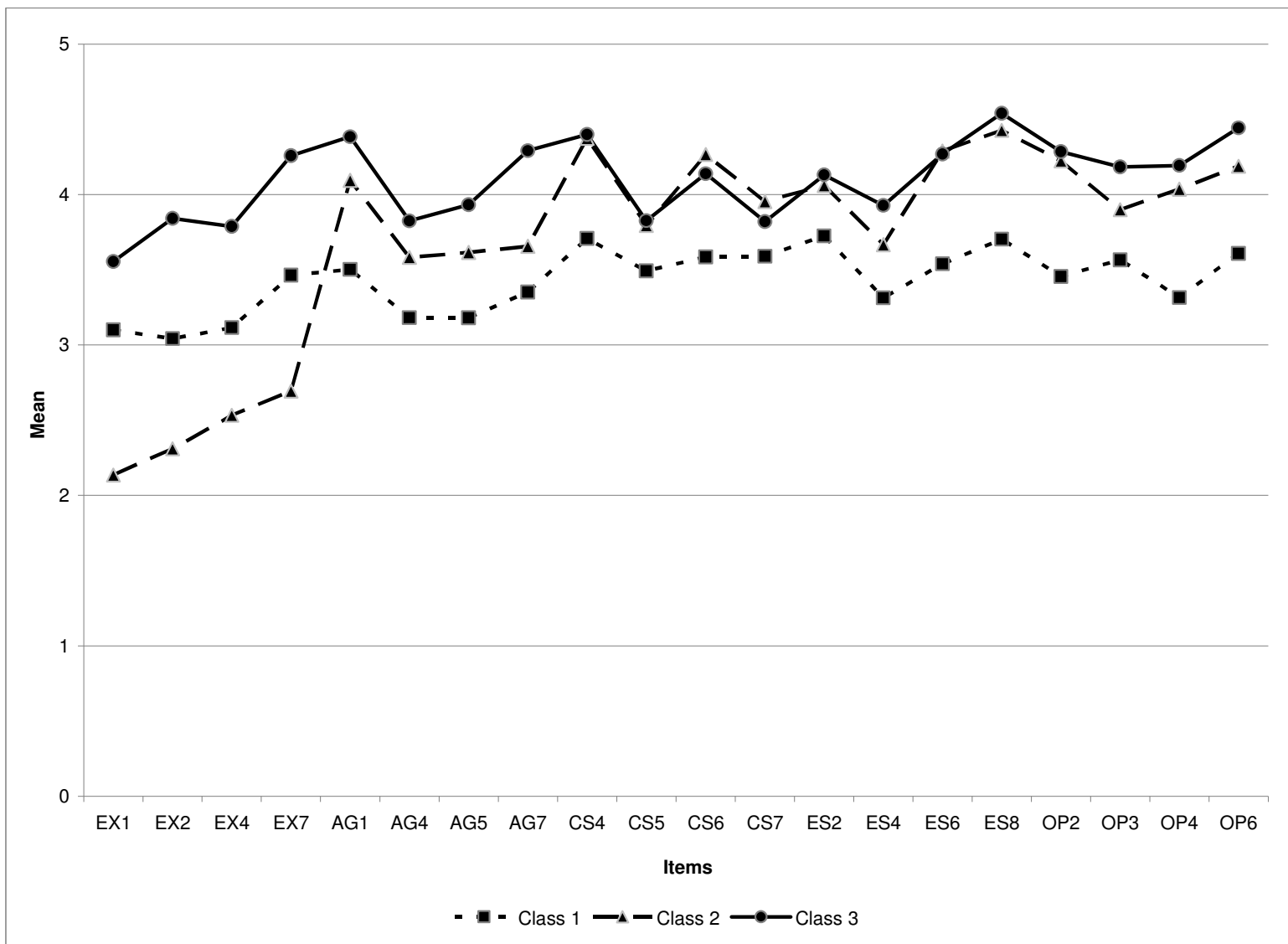
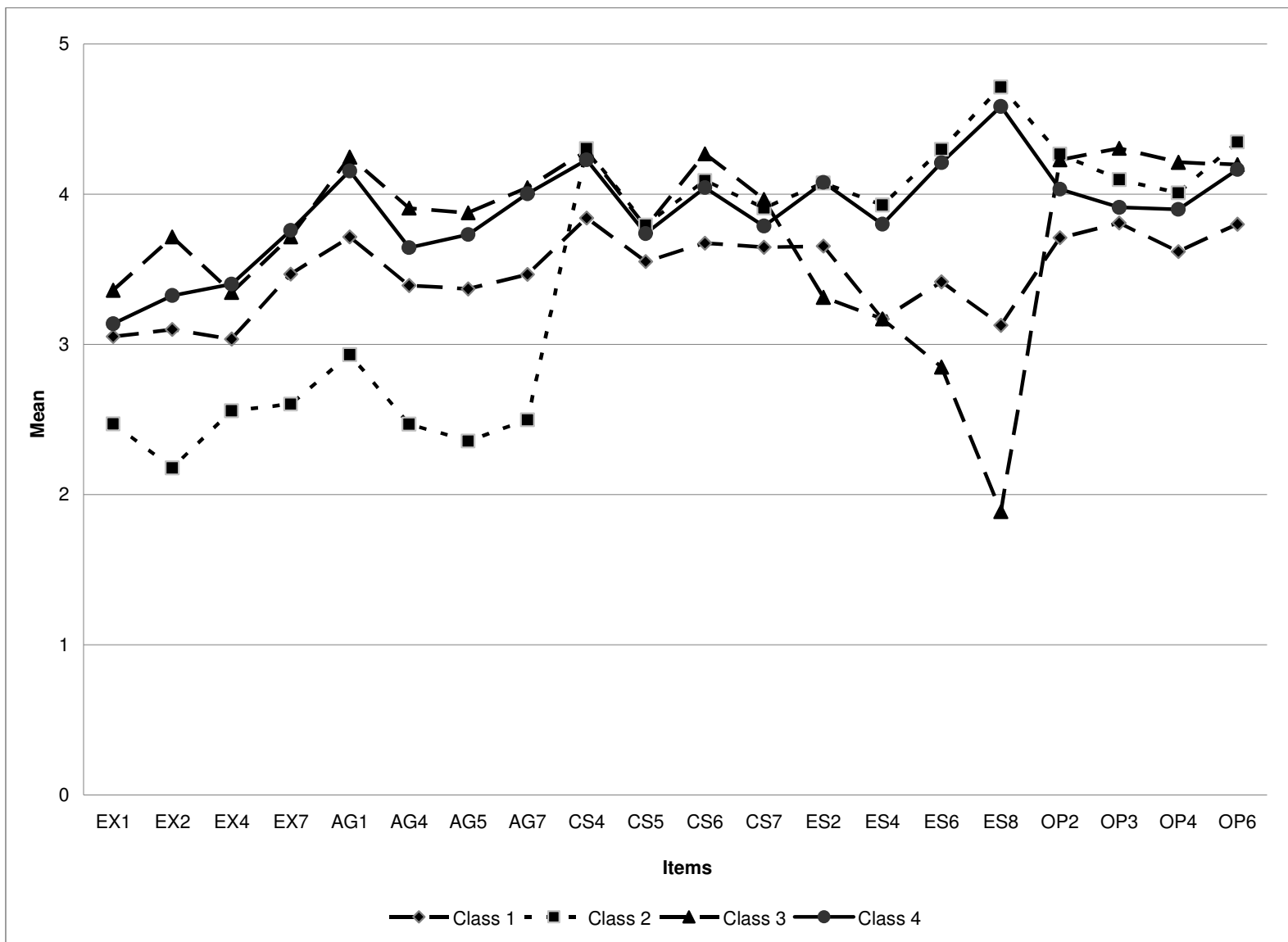


Figure 5. 4-Class MFA Profiles



ABOUT SWA CONSULTING INC.

SWA Consulting Inc. (formerly Surface, Ward, and Associates) provides analytics and evidence-based solutions for clients using the principles and methods of industrial/organizational (I/O) psychology. Since 1997, SWA has advised and assisted corporate, non-profit and governmental clients on:

- Training and development
- Performance measurement and management
- Organizational effectiveness
- Test development and validation
- Program/training evaluation
- Work/job analysis
- Needs assessment
- Selection system design
- Study and analysis related to human capital issues
- Metric development and data collection
- Advanced data analysis

One specific practice area is analytics, research, and consulting on foreign language and culture in work contexts. In this area, SWA has conducted numerous projects, including language assessment validation and psychometric research; evaluations of language training, training tools, and job aids; language and culture focused needs assessments and job analysis; and advanced analysis of language research data.

Based in Raleigh, NC, and led by Drs. Eric A. Surface and Stephen J. Ward, SWA now employs close to twenty I/O professionals at the masters and PhD levels. SWA professionals are committed to providing clients the best data and analysis with which to make solid data-driven decisions. Taking a scientist-practitioner perspective, SWA professionals conduct model-based, evidence-driven research and consulting to provide the best answers and solutions to enhance our clients' mission and business objectives. SWA has competencies in measurement, data collection, analytics, data modeling, systematic reviews, validation, and evaluation.

For more information about SWA, our projects, and our capabilities, please visit our website (www.swa-consulting.com) or contact Dr. Eric A. Surface (esurface@swa-consulting.com) or Dr. Stephen J. Ward (sward@swa-consulting.com).