A Person-Centric Investigation of Personality Types, Job Performance, and Attrition

Abstract

This study utilized a person-centered approach and latent profile analysis to investigate relationships among personality, attrition, and performance. Personality data from 4,763 Army recruits were used to create personality profiles or classes, which were then linked with supervisor's job performance ratings of discipline and effort as well as 24- and 48-month attrition. The latent profile analyses identified 5 personality profiles/classes, 3 of which (i.e., Resilient, Overcontrolled, Undercontrolled) have been commonly found in previous person-centered studies of personality. The results indicated that the Resilient class had significantly higher discipline ratings and significantly lower attrition than the Overcontrolled and Undercontrolled classes. Using the person-centered approach, the results showed that the classes developed using a relatively new personality measure and latent profile analysis predicted significant differences on important work outcomes such as performance ratings and attrition. Applied implications and future research directions are discussed.

Keywords: Personality, Performance, Five Factor Model, Latent Profile Analysis, Person-Centered Approach

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1. Introduction

Several theoretical conceptualizations of personality have been proposed, with the most widely studied and agreed upon taxonomy being the Five Factor Model (McCrae & Costa, 2008). The Five Factor Model (FFM) includes the following personality dimensions: Conscientiousness (e.g., achievement-oriented), Agreeableness (e.g., cooperative), Emotional Stability (e.g., even-tempered), Extraversion (attention-seeking), and Openness (e.g., tolerant). This model is the result of 1) a careful conceptual analysis of what most personality tests are trying to assess and 2) statistical analyses of personality test information gathered over many decades. There is now broad consensus among industrial and organizational (I-O) psychologists that personality dimensions included in the FFM predict a wide range of work-related behavior including job performance, training performance, and turnover (Barrick & Mount, 2005). More specifically, research indicates that a) personality differences play an important role in work behavior independent of the role played by cognitive ability; b) personality is more closely related to motivational aspects of work (e.g., effort expenditure) than to technical aspects of work (e.g., knowledge components); and c) personality is more likely to predict what a person will do, and ability measures are more likely to predict what a person can do. This study incorporates personality dimensions from FFM and the person-centered approach to help with understanding relationships among personality constructs, cognitive ability, and work outcomes such as attrition and job performance.

1.1 Person-Centered Approach

In contrast to the prevailing paradigm in I-O psychology that focuses on variables and relationships among variables, person-centric psychology focuses on the person and takes a

holistic and dynamic view of people (Foti, Thompson, & Allgood, 2011; Weiss & Rupp, 2011). Although variable-centered approaches focus on meaningful personality characteristics, these dimensions are typically treated as separate and isolated. In contrast, the person-centered approach considers personality as a whole, integrated system (Merz & Roesch, 2011).

Using a person-centered approach, several attempts have been made to organize groups of respondents based on personality traits into types or profiles. Three personality types (Resilients, Overcontrolled, and Undercontrolled) have been consistently identified in the research literature (e.g., Denissen, Asendorpf, & van Aken, 2008; Specht, Luhmann, & Geiser, 2014). *Resilients* have been characterized by below average Neuroticism, above average Conscientiousness, moderate Extraversion, and moderate Agreeableness. *Resilients* are often called well-adjusted because they tend to be adaptable, flexible, resourceful, and interpersonally successful. They tend to control their emotions and impulses appropriately, and they seem to handle adversity well. Those labeled as *Overcontrolled* tend to have above average Neuroticism, but below average Extraversion. They are often described as being uptight, difficult to deal with, self-conscious, and uncomfortable around strangers; in sum, they control their emotions too much. Those labeled as *Undercontrolled* tend to have above average Neuroticism, lower than average Conscientiousness, and above average Extraversion. They are often described as being impulsive and prone toward unsafe activities; in sum, they often have difficulty controlling their emotions and impulses.

Several studies have used a person-centered approach with the FFM to validate the three personality types (e.g., Asendorpf, Borkenau, Ostendorf, & Van Aken, 2001; Poncheri & Ward, 2008). In addition, numerous studies indicate that these personality types are associated with predictable outcomes. Research indicates that the Resilient type has been associated with a wide

variety of positive outcomes, whereas the Overcontrolled and Undercontrolled types have been associated with a wide variety of negative outcomes (Donnellan & Robins, 2010). In addition, Chapman and Goldberg (2011) that found that personality types showed associations with multiple health outcomes that were measured 40 years later. These investigations suggest that examining personality using a person-centered approach can help to enhance understanding of relationships among personality and work outcomes.

The present study used latent profile analysis (LPA), which identifies homogeneous groups based on a number of observed variables, such as the FFM personality dimensions. In particular, LPA (described further below) can be used to determine whether personality dimensions can help to organize respondents into groups with similar trait profiles. The identification of profile groups using LPA can reveal new multivariate relationships among observed variables that can contribute to greater understanding of the relationships among FFM personality dimensions and work outcomes. The present study extends previous work by using a person-centered approach to investigate relationships among personality dimensions using LPA in a large Army sample. This investigation will examine if the LPA provides evidence of multiple classes based on the personality data. In addition, this study will examine whether there are significant differences on performance and attrition among the personality classes.

2. Method

2.1 Participants and Measures

The sample for this study was obtained as part of the data collected from the Army Class Longitudinal project at the Army Research Institute (Knapp & Heffner, 2010). Predictor data were obtained in 2007 and early 2008 from 4,763 Soldiers who entered reception battalions. Predictor measures included the Armed Forces Qualification Test (AFQT, a general cognitive

ability measure) and the Tailored Adaptive Personality Assessment System (TAPAS, a Big Five measure). In terms of the gender breakdown, 3,902 (81.9%) were male, 825 (17.3%) were female, and 36 (0.7%) did not indicate their gender. The mean age of the sample was 27.91 (s.d. = 4.27).

The AFQT is a composite based on four subtests (Arithmetic Reasoning, Mathematics Knowledge, Word Knowledge, and Paragraph Comprehension) of the Armed Services Vocational Aptitude Battery (ASVAB). Applicants must meet a minimum score on the AFQT to enter the Army (Knapp, Heffner, & Owens, 2010). Scores on the AFQT range from 0 to 99. Previous research has indicated that AFQT scores correlate highly with other standardized aptitude tests (e.g., Orme, Brehm, & Ree, 2001). The AFQT's reliability from the current sample was not available, but previous large-scale studies indicate that the reliability is .90 or higher (Bock & Moore, 1986; Van Iddekinge, Ferris, & Heffner, 2009). The AFQT was used as a control variable to examine the influence of the personality types above the contribution of cognitive ability. For example, logistic regression analyses were conducted on the attrition outcomes while controlling for cognitive ability.

The TAPAS is a personality measure that was designed to promote resistance to faking (Stark, Chernyshenko, Drasgow, & White, 2012). The items were created by pairing statements that are similar on social desirability. The present study utilized 11 TAPAS dimensions that included 10 dimensions that can be aligned with Five Factor Model personality dimensions and a Physical Conditioning dimension that has been deemed important to assess in the military (Table 1). The TAPAS utilizes a multidimensional pairwise preference (MDPP) format, item response theory (IRT), and multidimensional Bayes model estimation (Stark, Chernyshenko, & Drasgow, 2010). The TAPAS dimensions are scored so that they range from -3 to +3. In developing the

TAPAS, Stark et al. (2010) noted that individual scale reliabilities are not traditionally used for IRT-scored measures. Nevertheless, marginal reliability, which is the IRT analog of traditional reliability measures, ranged from .66 to .75 in a subset of the TAPAS scales (Dragow, Stark, Chernyshenko, Nye, Hulin, & White, 2012).

Criterion measures included 1) attrition from the military at 24 and 48 months, and 2) behaviorally anchored performance rating scales that were completed by supervisors at the end of training in 2008. The performance ratings were assessed on 2 dimensions. *Effort* was a 3-item measure (internal consistency reliability of .89) assessing Soldiers' persistence and initiative demonstrated when completing study, practice, preparation, and participation activities during training. *Personal Discipline* was a 5-item measure (internal consistency reliability of .90) assessing Soldiers' willingness to follow directions and regulations and to behave in a manner consistent with the Army's Core Values (e.g., showing up on time; showing proper respect for superiors). The sample size for the performance ratings was 849. For the attrition criteria, data were available on over 2,000 Soldiers (the sample size ranged from 2,159 to 2,368) across the 2 time periods.

2.2 Analytic Approach

Latent profile analysis using Mplus Version 7 (Muthén & Muthén, 2012) was utilized to derive categorical latent variables that represent classes of individuals who share similar personality profiles (Lanza, Flaherty, & Collins, 2003). After assessing model assumptions, the determination of the optimal number of classes in LPA was conducted by specifying and testing multiple class solutions. This process requires the specification and testing of multiple class solutions (1-class, 2-class, etc.). From these models, the designation of the best-fitting model was determined. The Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMRT; Lo, Mendell,

& Rubin, 2001) was used to determine model fit. The LMRT provides an indication of statistically significant improvement in fit for a model with k latent classes/profiles as compared to a model with $k-1$ latent classes/profiles by approximating the differences between two log likelihood values (instead of using the χ^2 distribution). A significant LMRT test indicates that a more complex model (e.g., 3-class) provides better fit than a less complex model (e.g., 2-class).

A number of fit indicators based on information criteria were also employed, including the Akaike Information Criteria (AIC; Akaike, 1974), the Bayesian Information Criterion (BIC; Schwarz, 1978), and the sample size-adjusted BIC (sBIC; Sclove, 1987). These fit indicators are most often helpful when they decrease in overall value even though additional parameters are estimated when moving from a model with k latent classes/profiles as compared to a model with $k+1$ latent classes/profiles. In addition, entropy was used to measure how well classes or profiles can be distinguished, or the certainty that individuals were accurately classified given the specific class model (Ramaswamy, DeSarbo, Reibstein, & Robinson, 1993). Individuals in LPA are assigned a posterior probability for each class rather than outright assignment to one and only one class. Entropy is the aggregate of these posterior probabilities, with values greater than .70 considered noteworthy.

The interpretability of each class/profile was used to facilitate the determination of whether or not a specific class solution was consistent with past theory and empirical research. Two primary model parameters are useful in this regard in LPA: (1) conditional response means (CRM) and the (2) classification probabilities for the most likely latent class. The CRMs are analogous to factor loadings, and they refer to the mean for each observed variable *within* a latent profile. The CRMs are good indications of which observed variables within and between classes best identify the separate classes. For the classification probabilities for the most likely

latent class, higher values are preferred. Once classes were substantively interpreted, the proportion of cases within each class was used to identify the prevalence of class membership. Validity analyses were then conducted to examine if there were significant differences among classes on the attrition and performance criteria.

3. Results

Descriptive statistics and correlations were calculated among study variables (Table 2). Next, latent profile analyses with different class solutions were conducted using the TAPAS personality dimensions ($n = 4,763$) to narrow in on the best-fitting class solution. Table 3 shows the results for the class solutions. The best fitting and most substantively meaningful solution had 5 classes based on entropy, fit statistics, and meaningfulness of the conditional response means. In particular, the 5-class solution worked best based on these results: 1) Entropy was .72 for 5-class solution, but dropped below .70 when moving to 6- or 7-class solution; 2) the LMRT test went from significant with the 5-class solution to non-significant when moving to the 6-class solution; 3) although the 3-class solution had an entropy of .76, the LMRT was significant when moving to 4-class and 5-class solutions, indicating that the solutions with higher number of classes fit better than the 3-class solution; 4) the CRMs for the 5-class solution indicated meaningful and substantively different classes (3 of which overlapped with the personality types found in the literature); and 5) the classification probabilities for the most likely latent class were all above .70 and averaged .80 in the 5-class solution, indicating good classification. Table 4 shows the classification probabilities for the most likely latent class membership by latent class from the latent profile analyses. For a given row, the values not in bold indicate “misclassification.” In the diagonal (in bold) are the accuracy classification probabilities for each of the classes (higher and closer to 1 is better). The average for the diagonal entries is .79. To

further validate the distinctiveness of the latent classes, a discriminant function analysis (DFA) was performed on the 11 TAPAS dimensions as predictors of latent class membership (Keefer, Parker, & Wood, 2012). The DFA indicated that 93.9% of cases were correctly classified in the 5-class solution. Collectively, these results indicate evidence for multiple classes based on the personality data.

The overall sample means and the CRMs (shown in Table 5) were used to substantively interpret the classes. To help with interpretation of the CRMs, Table 5 also shows the standardized value for each CRM that takes into account the overall mean and the standard deviation of each dimension. The classes can be highlighted by focusing on standardized values that were above an absolute value of .25. Class 1 (24% of the sample) had low Neuroticism, high Conscientiousness, and high Agreeableness, and thus was labeled *Resilient*. Class 2 (20% of the sample) had high Neuroticism, low Extraversion, low Openness, and low Agreeableness, and this class was labeled *Overcontrolled*. Class 3 (7% of the sample) had high Agreeableness, high Extraversion, low Conscientiousness, and low Openness, and this class was labeled *Amiable*. Class 4 (26% of the sample) had low Conscientiousness, high Extraversion, high Neuroticism, and low Agreeableness, and this class was labeled *Undercontrolled*. Class 5 (33% of the sample) had high Conscientiousness, high Openness, and low Agreeableness, and this class was labeled *Conscientious/Disagreeable*. Given that there were multiple scales for each FFM dimension (except for Agreeableness), mean z-scores for each personality type were calculated for each FFM dimension. These mean z-scores are shown in Figure 1.

After the classes were identified, validity analyses were conducted to examine if there were significant differences among classes on the attrition and performance criteria. In the validity analyses, ANOVAs and post-hoc comparisons with Bonferroni adjustments were used to

examine differences among the five classes on the performance dimensions. As shown in Table 6, significant differences were found across classes for the Discipline ratings but not for the Effort ratings. Specifically, Discipline ratings were significantly ($p < .05$) higher for Class 1 compared to Class 2 ($d = .30$), Class 3 ($d = .14$), and Class 4 ($d = .27$). Discipline ratings were also significantly ($p < .05$) higher for Class 5 compared to Class 4 ($d = .46$). Further, an ANCOVA indicated that the Class variable remained significant ($p < .01$) when predicting Discipline ratings even after controlling for cognitive ability and gender.

Chi-squared analyses were used to examine the attrition outcomes. These analyses indicated that Class 2 (*Overcontrolled*) had significantly higher 24-month attrition than Class 1 (*Resilients*), and Class 4 (*Undercontrolled*) had significantly higher 24-month and 48-month attrition than Class 1 (*Resilients*). Because organizational decision makers often discuss retention rates, the attrition data were converted to retention rates by subtracting attrition rates from 1. Class 1 (*Resilients*) had the highest retention rate among the classes across both time periods. Specifically, the retention rate for the *Resilient* class 1 was 77% at 24 months and 64% at 48 months. In contrast, Class 4 (*Undercontrolled*) had the lowest retention rate across both time periods. Specifically, the retention rate for the *Undercontrolled* class was 68% at 24 months and 53% at 48 months.

Further, logistic regression analyses were conducted on the attrition outcomes while controlling for gender and cognitive ability. The predictors were the dummy coded class variables. The results indicated that, after controlling for gender and cognitive ability, the class variable explained significant variance in attrition at 24 months. Specifically, there was significantly higher attrition at 24 months in Class 4 than Class 5 (Odds Ratio = 1.46, $p = .013$), in Class 4 than Class 1 (Odds Ratio = 1.59, $p = .004$), and in Class 2 than Class 1 (Odds Ratio =

1.26, $p = .032$). For attrition measured at 48 months, the results indicated that, after controlling for gender and cognitive ability, the class variable explained significant variance in attrition at 48 months. Specifically, significantly higher attrition was found at 48 months in Class 2 than Class 1 (Odds Ratio = 1.44, $p = .006$), in Class 3 than Class 1 (Odds Ratio = 1.54, $p = .023$), and in Class 4 than Class 1 (Odds Ratio = 1.59, $p = .002$). Practically, an odds ratio of 1.44 indicates that the likelihood of attrition at 48 months for individuals in Class 2 (*Overcontrolled*) is about 44% higher than for individuals in Class 1 (*Resilients*).

4. Discussion

Using a person-centered approach, this study utilized latent profile analysis to identify five classes based on personality dimensions assessed in a large military sample. The results from the present study showed that the classes developed based on the TAPAS can predict significant differences across classes on important work outcomes such as performance ratings and attrition. The findings in the present study are the first to use LPA to examine work outcomes in a such large sample, the first to investigate these relationships in a military sample, and the first to examine such outcomes where there are multiple work outcome measures from different sources (attrition, performance ratings).

Three of the classes identified in the present study (i.e., *Resilients*, *Overcontrolled*, *Undercontrolled*) have been commonly found in previous person-centered studies of personality (Donnellan & Robins, 2010; Honkaniemi, Feldt, Metsäpelto, & Tolvanen, 2013). Across many previous research studies, the *Resilient* class has been associated with a variety of positive outcomes, whereas the *Overcontrolled* and *Undercontrolled* classes have been associated with negative outcomes. Consistent with previous research, the validity analyses in the present study indicated that the *Resilient* class had significantly higher discipline ratings and significantly

lower attrition compared to other classes. Specifically, the results indicated that individuals classified as *Overcontrolled* and *Undercontrolled* do not adapt as well to military life as *Resilients* as evidenced by their lower performance ratings on discipline and their relatively higher attrition.

4.1 Limitations and Suggestions for Future Research

In terms of limitations of this study, this research was conducted in a military sample, which potentially limits the generalizability and indicates that similar research should be conducted in other types of samples. As noted by Herzberg and Roth (2006), the personality types found in specific samples do not precisely match those found in previous samples (due at least partly to differences in samples, personality measures used, and methods to derive the personality types), and this was the case in the present study. For example, *Resilients* had below average Extraversion, even though previous research has typically found that Extraversion is above average in *Resilients*. Nevertheless, the 3 personality types found in the present study had the most central features of the personality types found in previous research.

Another potential limitation is that this research focused on the FFM dimensions instead of the 11 TAPAS personality facets. Although the facet data would have provided a more fine-grained examination of personality types, focusing on the FFM dimensions enabled this research to be more comparable to many other LPA analyses that formed personality types based on the FFM dimensions (e.g., Asendorpf & Van Aken, 1999; Denissen, Asendorpf, & van Aken, 2008). Given these considerations, we focused on the FFM dimensions rather than the more specific TAPAS facets.

4.2 Conclusion

In summary, this paper utilized a person-centered approach and LPA to develop personality classes that were validated with attrition and job performance ratings. Based on the personality data, the LPA indicated 5 classes that were consistent with previous research that used person-centric approaches. Validity analyses indicated that the personality classes identified predicted significant differences in attrition and job performance ratings.

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Table 1. TAPAS facets, descriptions, and corresponding Big 5 personality factors

Facet Name	Description	Big 5 Factor
Dominance	High scoring individuals are domineering, “take charge” and are often referred to by their peers as "natural leaders."	Extraversion
Attention Seeking/ Excitable	High scoring individuals tend to engage in behaviors that attract social attention; they are loud, loquacious, entertaining, and even boastful.	
Cooperation/Trust	High scoring individuals are trusting, cordial, non-critical, and easy to get along with.	Agreeableness
Achievement	High scoring individuals are seen as hard working, ambitious, confident, and resourceful.	Conscientiousness
Order	High scoring individuals tend to organize tasks and activities and desire to maintain neat and clean surroundings.	
Non-Delinquent	High scoring individuals tend to comply with rules, customs, norms, and expectations, and they tend not to challenge authority.	
Even Tempered	High scoring individuals tend to be calm and stable. They don't often exhibit anger, hostility, or aggression.	Emotional Stability
Well-Being/ Optimistic	High scoring individuals have a positive outlook on life and tend to experience joy and a sense of well-being.	
Intellectual Efficiency	High scoring individuals are able to process information quickly and would be described by others as knowledgeable, astute, and intellectual.	Openness To Experience
Tolerance	High scoring individuals scoring are interested in other cultures and opinions that may differ from their own. They are willing to adapt to novel environments and situations.	
Physical Conditioning	High scoring individuals routinely participate in vigorous sports or exercise and enjoy physical work.	Other

Adapted from Table 3.1 of Stark, Chernyshenko, & Drasgow (2010).

Table 2

Descriptive statistics and correlations among study variables

	Mean	Std. Dev.	n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Achievement	0.17	0.64	4763	--																
2. Non-Delinquency	0.09	0.65	4763	.17**	--															
3. Dominance	-0.15	0.61	4763	.14**	.02	--														
4. Even-Tempered	-0.46	0.77	4763	.06**	.12**	-.05**	--													
5. Attention-Seeking/Excitable	-0.14	0.79	4763	-.11**	-.37**	.13**	-.12**	--												
6. Intellectual Efficiency	-0.19	0.64	4763	.16**	.03*	.15**	.14**	-.05**	--											
7. Order	-0.04	0.64	4763	.19**	.14**	.07**	-.02	-.07**	.07**	--										
8. Physical Conditioning	0.11	0.71	4763	.19**	-.09**	.06**	-.01	.10**	.02	.05**	--									
9. Tolerance	-0.42	0.67	4763	.06**	.06**	.10**	.08**	-.03*	.15**	.06**	.01	--								
10. Trust	-0.30	0.86	4763	.01	.19**	-.13**	.12**	-.05**	-.07**	.02	-.13**	-.01	--							
11. Well-Being	-0.07	0.6	4763	.06**	.03*	.07**	.22**	-.04*	.18**	.00	.06**	.09**	.09**	--						
12. AFQT	57.24	19.51	4672	.05**	.06**	.05**	.11**	-.06**	.36**	-.03*	-.02	.02	-.02	.17**	--					
13. Gender	0.17	0.38	4727	.08**	.15**	.09**	-.06**	-.01	-.06**	.12**	-.11**	-.02	.05**	-.04**	-.07**	--				
14. Effort	3.53	0.73	859	.09**	.06	-.04	.08*	-.10**	.04	.02	.10**	.03	.01	.02	.19**	-.01	--			
15. Discipline	3.77	0.71	859	.05	.16**	-.09**	.14**	-.17**	.02	.03	.02	.06	.08*	.04	.21**	-.01	.79**	--		
16. Attrition 24-month	0.26	0.44	2368	-.06**	-.02	-.05*	-.02	.04*	.02	.01	-.10**	.02	-.03	-.02	-.06**	.09**	-.26**	-.25**	--	
17. Attrition 48-month	0.41	0.49	2159	-.06**	-.04	.01	-.02	.06**	.02	.02	-.10**	.01	-.03	-.01	-.11**	.09**	-.32**	-.30**	.76**	--

Note. For gender, females coded 0, males coded 1. For attrition, 0 = separated from Army, 1 = still in Army. * $p < .05$; ** $p < .01$. Class is not included in correlation matrix as it is a categorical variable.

Table 3

Model fit indices for the latent profile analysis solutions (n = 4,763)

Solution	LMRT (<i>p</i>)	AIC	BIC	sBIC	Entropy	%'s for Classes	No. Parameters
2 class	1399.56 (< .001)	107356.20	107576.14	107468.10	.85	67,33	34
3 class	933.02 (< .001)	106438.00	106735.56	106589.39	.76	17,32,51	46
4 class	609.61 (< .001)	105846.39	106221.57	106037.26	.70	20,32,35,13	58
5 class	410.60 (< .001)	105455.75	105908.56	105686.12	.72	13,20,7,26,33	70
6 class	236.19 (.08)	105241.23	105771.66	105511.10	.69	14,13,19,13,7,33	82
7 class	175.89 (.08)	105087.62	105695.67	105396.97	.65	18,20,17,14,13,12,7	94

Note. LMRT = Lo-Mendell-Rubin Test, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, sBIC = sample size-adjusted Bayesian Information Criterion.

Table 4

Classification probabilities for the most likely latent class membership (column) by latent class (row)

	1	2	3	4	5
1	0.72	0.19	0.01	0.05	0.03
2	0.10	0.85	0.00	0.03	0.03
3	0.03	0.01	0.70	0.05	0.21
4	0.09	0.09	0.02	0.80	0.00
5	0.02	0.03	0.04	0.00	0.90

Note. 1 = Resilient class; 2 = Overcontrolled class; 3 = Amiable class; 4 = Undercontrolled class; 5 = Conscientious/Disagreeable class.

Table 5

Overall sample means, conditional response means (CRMs), and z-scores for 5-class solution (n = 4,763)

Class Name				Resilient		Overcontrolled		Amiable		Undercontrolled		Conscientious/ Disagreeable	
Sample Size				642		950		350		1,232		1,589	
% of Sample				14%		20%		7%		26%		33%	
TAPAS Dimension	Five Factor Model Domain	Overall Mean	S.D.	Class 1 (CRM)	Class 1 (z)	Class 2 (CRM)	Class 2 (z)	Class 3 (CRM)	Class 3 (z)	Class 4 (CRM)	Class 4 (z)	Class 5 (CRM)	Class 5 (z)
Achievement	Conscientiousness	0.17	0.64	0.23	0.10	-0.17	-0.53	0.00	-0.27	0.00	-0.26	0.45	0.44
Non-Delinquency	Conscientiousness	0.09	0.65	0.44	0.54	-0.10	-0.29	-0.29	-0.58	-0.41	-0.77	0.25	0.24
Order	Conscientiousness	-0.04	0.64	-0.01	0.04	-0.25	-0.32	-0.14	-0.15	-0.14	-0.16	0.14	0.28
Dominance	Extraversion	-0.15	0.61	-0.29	-0.24	-0.44	-0.48	-0.23	-0.13	0.08	0.37	0.08	0.37
Attention-Seeking/Excitable	Extraversion	-0.14	0.79	-0.48	-0.44	-0.36	-0.28	0.65	1.00	1.02	1.47	-0.42	-0.35
Intellectual Efficiency	Openness	-0.19	0.64	-0.23	-0.06	-0.44	-0.39	-0.35	-0.24	-0.24	-0.08	0.07	0.40
Tolerance	Openness	-0.42	0.67	-0.41	0.01	-0.62	-0.30	-0.55	-0.19	-0.48	-0.08	-0.25	0.25
Physical Conditioning	Non-FFM	0.12	0.71	-0.04	-0.23	-0.05	-0.23	0.07	-0.07	0.33	0.30	0.27	0.21
Cooperation/Trust	Agreeableness	-0.30	0.86	0.74	1.21	-0.83	-0.61	0.69	1.16	-0.83	-0.62	-0.80	-0.58
Well-Being/Optimism	Emotional Stability	-0.07	0.60	0.03	0.17	-0.29	-0.37	-0.11	-0.06	-0.15	-0.13	0.04	0.18
Even-Tempered	Emotional Stability	-0.46	0.77	-0.23	0.29	-0.61	-0.19	-0.64	-0.23	-0.86	-0.52	-0.33	0.17

Table 6

Comparison of classes on performance ratings (n = 859)

Outcome	<i>F</i>	<i>df</i>	$p\eta^2$	<i>M (SD)</i>				
				Class 1	Class 2	Class 3	Class 4	Class 5
Discipline Rating	7.66**	4, 854	.04	3.91 ^a (.62)	3.70 ^{b,c} (.81)	3.61 ^{b,c} (.78)	3.52 ^c (.77)	3.83 ^{a,b} (.64)
Effort Rating	2.15	4, 854	.01	3.57(.69)	3.47(.74)	3.40(.83)	3.42(.76)	3.59(.73)

Note. $p\eta^2$ = partial eta-squared from omnibus ANOVA. Means in the same row that do not share a subscript are significantly ($p < .05$) different from each other.

Class 1 = Resilient (n = 241); Class 2 = Overcontrolled (n = 170); Class 3 = Amiable (n = 70); Class 4 = Undercontrolled (n = 107); Class 5 = Conscientious/Disagreeable (n = 271).

* $p < .05$; ** $p < .01$.

Figure 1. Personality Classes by Average Five Factor Model Z-Score