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Mixture Modelling of the HEXACO Personality Inventory

Carolina Patryluk, *The University of Western Ontario*

Supervisor: Paul F. Tremblay, *The University of Western Ontario*
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ABSTRACT

Mixture models are used for identifying profiles or combinations of profiles and dimensions that explain observed variables. Given that these techniques can be misapplied (Lubke & Miller, 2014), much research is needed to understand their properties when applied to various data sets. The current study tests and compares the fit of mixture models to factor analytic models of personality trait facets based on the HEXACO Personality Inventory-Revised (Ashton & Lee, 2009a). This study also examines the relative amounts of variance in the facet variables that can be explained by underlying dimensions, latent profiles, and other sources. Ashton and Lee (2009b) concluded from a cluster analysis of the HEXACO traits that profiles did not explain much variance in the observed trait measures beyond the variance explained by the factors themselves. The present study builds on that research using a more sophisticated modeling approach, namely factor mixture modeling at the facet level.

Keywords:

Confirmatory Factor Analysis, Factor Mixture Models, Population Heterogeneity, Latent Profile Analysis, Personality, Sources of Variance

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CHAPTER 1: INTRODUCTION

There has been a growing interest in understanding the nature of unobserved population heterogeneity (Nylund, Asparouhov, & Muthén, 2007; Lubke, 2005; Masyn, 2013; Meyer & Morin, 2016). The term population heterogeneity refers to the fact that sometimes a population consists of a mixture of unknown subpopulations. For example, it is not uncommon to see bimodal distributions of test scores with subpopulations of poor and high performers. In a sense this overall bimodal distribution is a mixture to two normally distributed subpopulations. Mixture modelling techniques are useful for uncovering these unknown subpopulations consisting of only one variable or more typical cases consisting of multivariate sets of variables. However, these sophisticated methodologies require careful application and interpretations (Lubke & Miller, 2014). This study aims to improve our understanding of how to apply mixture models to investigate the structure of personality traits.

Researchers have already gained significant insights into the nature of personality trait structures, most notably in distinguishing between the variable-centered approach and the person-centered approach in personality research. The variable-centered approach, which relies on factor analytic procedures, describes the underlying factors or traits, such as the Big Five in the Five Factor Model (Costa & McCrae, 1992b) and the six factors in the HEXACO (Ashton & Lee, 2009a). The person-centered approach examines latent profiles (i.e., typologies) or classes of trait scores using conventional methods such as cluster analysis and newer mixture modeling approaches such as latent profile analysis.

In this chapter, I begin by providing a general description of key concepts in factor analysis that will be important for understanding mixture modeling. I then describe mixture modeling, specifically the two types of models referred to as latent profile analysis and factor mixture modeling. This description will provide the foundation for understanding the analytic approach used in this project, namely, the comparison of Confirmatory Factor Analysis (CFA), Latent Profile Analysis (LPA) and Factor Mixture Modeling (FMM) models of personality trait facets. I then review a sample of research in psychology in general, and personality trait research, that has used mixture modeling. In the two last sections of this chapter, I discuss an issue raised by Ashton and Lee (2009b) of whether profiles explain much variance in personality compared to dimensions and some of the ways to address this question and then summarize the objectives of the study.

1.1 Latent Variables and Factor Analysis

Unobserved variables are referred to as latent variables. Latent variables are measured indirectly by means of usually three or more observed variables, which are also called indicators. There is a degree of error associated with observed variables, as these indicators are a function of latent variables and unexplained left over variance. In a CFA, the factors or dimensions and the observed variables that define them (i.e., the indicators) in the model must be specified based on theory. A characteristic of this method is that the indicators typically load only on one factor, unlike exploratory factor analysis in which the indicators load on all factors. Hence CFA can also be referred to as a restricted measurement modelling approach.

CFA is an example of a variable-oriented approach, as the latent factor that is being measured is assumed to apply to the entire sample, or across all members of the population, to different degrees. Confirmatory factor analysis applies maximum likelihood to estimate the unknown parameters of a specific latent factor model. The number of factors and the relationship between them are specified prior to the analysis. This differs from exploratory factor analysis, in which there are no specifications before the analysis; all parameters emerge from the observed data (Gorsuch, 1983; Mueller & Hancock, 2015; Mulaik, 1972).

1.2 Mixture Modeling

It is common for researchers to contrast known subpopulations such as experimental and control groups or demographic categories. In contrast to this a priori conceptualization of distinct groups of people, unobserved heterogeneity refers to subpopulations existing in a univariate or multivariate distribution of responses that cannot be directly observed from the data (Lubke & Muthén, 2005). The primary difference between observed and unobserved heterogeneity is that the variable that causes the variability between subpopulations is unknown in the latter model (Wright & Hallquist, 2013). Mixture modeling can identify these subpopulations by identifying an underlying categorical latent structure. Participants are grouped into these profiles or classes based on the similarity of their responses, and each profile will have its own unique distributional properties such as unique means on the observed variables. In summary, distinct response sets help distinguish the unique subpopulations in the model (Peugh & Fan, 2013).

Latent variables in mixture modelling are not unlike clusters from a cluster analysis. However, there are limitations in using a cluster analysis, such as the sensitivity to measurement scales, the lack of direction in determining the correct number of clusters, and the inflexibility to assumptions of conditional independence, which is often not met (Morin et al., 2011; Ruscio & Ruscio, 2004). Meehl's work on taxonometrics (1992) specified why latent methods are more accessible than cluster analysis for typology assessment. Meehl (1992) explains three important points. (1) Cluster analyses will always yield clusters, regardless if the data has true clusters or not (Asendorpf et al., 2001; 2002). (2) Mixture model techniques are based on a mathematical approach. (3) Cluster analyses have proved to be not as powerful as researchers have hoped, as they are quite sensitive to small sample sizes (Meehl, 1992; Sava & Pova, 2011).

Mixture model techniques provide a suitable alternative. However, given that these techniques have only been made available recently through implementation in software packages such as Mplus and R, and that they can easily be misapplied (Lubke & Miller, 2014), much research is needed into the characteristics of samples and methodology that influence the validity of the results.

1.2.1 Latent Profile Analyses.

Latent Profile Analyses (LPA) identify latent categorical variables referred to as profiles, which are prototypical subgroups of people in a population. Participants are grouped into profiles based on response variability to observed variables, such that each subgroup will consist of distinct homogeneous responses. This approach is person-oriented as people are grouped by patterns of similar response sets. How the indicators interact with one another to create a distinct profile is of main interest here. Within the same subgroup of people, the traits interact similarly across members. However, between different subgroups of people, there are unique response sets.

Individuals can only belong to one latent profile, which means profiles do not overlap. Adding all the probabilities of belonging to each profile will add up to 1, just as the sum of all the profiles sizes is equal to the total population. All individuals who belong to the same profile have the same response probabilities. Individuals belonging to different profiles have different response probabilities. This structure holds for all models that are tested, as the fundamental purpose of this analysis is to detect heterogeneity by separating individuals into maximally different subgroups.

There are two particularly important sources of information in a latent profile analysis. First, each profile will have a specific set of means and standard deviations for the observed variables. Often the standard deviations are modeled to be identical across profiles. (A similar approach, Latent Class Analysis, uses observed variables that are dichotomous or ordinal and the subgroups in that case are referred to classes. In such analyses, thresholds, rather than means, are of interest.) The other important source of information in an LPA are the probabilities of membership in each profile. Each case (i.e. subject) will have an assigned probability score of belonging to each of the profiles in the model. Ideally, one of these probability scores will be large and the others will be small. Most LPA programs derive the most likely class that a person belongs to by selecting the highest probability.

To evaluate the strength of the association between the latent variable and the indicators, the pattern of responses across profiles must be examined. The understanding is that when there is no relationship between the latent variable and the indicators, the responses do not depend on the profile. Such a relationship is independent and the means of the observed variables will not vary across profiles. However, when the latent variable and the indicators have a dependent relationship, the means will change across profiles. Thus, large mean differences are observed for a LPA in which the profiles account for a large proportion of the variance in observed traits.

To summarize, profile membership is based on the observed response patterns of items. The local independence assumption states that given profile membership, observed variables within a profile are assumed to be independent, or in other words, have zero within-profile covariance. If the effect of the profile is factored out, there should be no significant relationships between the indicators (Lubke & Muthén, 2007). This is an important assumption in LPA and LCA, as the covariance between observed variables should be due to the latent profile. More information about how the profiles are selected is presented in the Method section.

Figure 1 illustrates an example of a LPA with a latent categorical variable *c* and four continuous observed variables, *y*1 to *y*4.

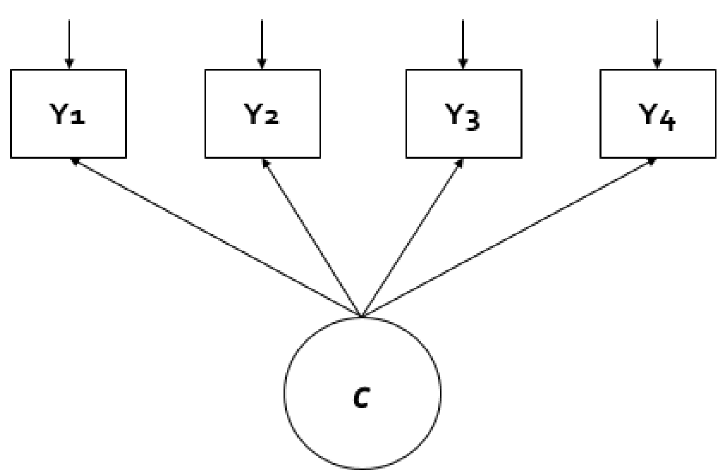

Figure 1. Illustration of Latent Profile Analysis

1.2.2 Factor Mixture Model

Factor Mixture Models (FMM) are a combination of LCA/LPA and CFA, such that both categorical and continuous latent variables can be accounted for in the model (Muthén & Muthén, 2015). As the effects of the profiles and factors are modelled simultaneously, subpopulations of similar people that still have some within group individual differences among them are identified. FMMs are known as hybrid models that relaxes the local independence assumption, meaning that once the categorical latent variable is accounted for, there remains some covariance among the observed variables that will be explained by the factors (Lubke & Muthén, 2005).

This method is more rigorous and flexible compared to methods in which only one type of latent variable can be assessed. Lubke and Muthén (2005) state that CFA and LPA can be identified as nested models in FMM. When the number of classes/profiles is set to one in a FMM, this solution is equivalent to a CFA. Since observed variables do not covary between profiles, any covariation in the indicators is due to the common factor. Alternatively, a FMM with zero factor variance within profiles is equivalent to a LPA. Due to the complex nature of FMM, many researchers have proposed specific guidelines and criteria that need to be met to apply these methods. One restriction is that FMM with more than 10 observed variables should not be conducted (Lubke, 2012).

In contrast to a LPA, fewer profiles are often required in a FMM, as some of the variance between the observed variables may be explained by the latent factor. The fit of this model may depend on the various covariance effects, the sample size and the nature of the parameters. Restrictions on parameters, or invariant models, refer to parameters that are not free to vary (Clark et al., 2013). Parameters that can be manipulated to be fixed at a given value or to vary across profiles are the factor means, the factor loadings, the factor covariance matrix and the means of the observed variables/indicators (referred to as intercepts). Often restrictions on parameters are relaxed to improve the fit of the model. In that case, more profiles may be needed. Thus, in addition to comparing the number of profiles in a FMM, invariant models and variant models should be compared to address best fit.

Lubke and Muthén (2005) described a stepwise approach for exploring unobserved heterogeneity within a FMM. Model comparisons should be carried out between solutions with different number of factors and profiles, and between models with fixed and varying parameters. Given the correct number of factors and profiles, as well as ideal parameter settings, improvements should be seen in the model fit indices. It is important to note that a model is penalized as the number of free parameters increases. Although a model with greater number of parameters, such as having three profiles rather than two, has more room to fit the data, the model will still be penalized for specifying more parameters. The idea is that a model has “to pay” for a better-fitting or complex model. The aim of modeling is to find a simple model that represents the data adequately.

An illustration of a FMM with two latent variables, both categorical (*c*) and dimensional (*f*), as well as four observed variables *y*1 to *y*4, is shown in Figure 2.

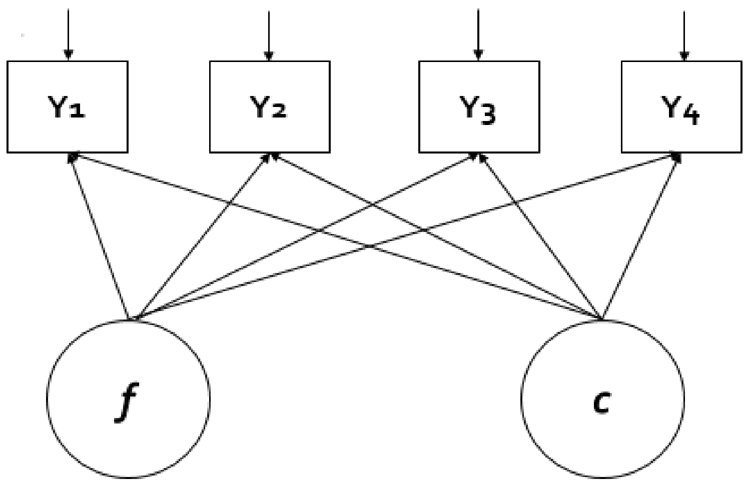

Figure 2. Illustration of Factor Mixture Model. F refers to factor and c refers to class.

1.3 Applications of Mixture Modelling in Psychology

LPA and LCA have been used in many areas of psychological research. These methods are especially useful in mental health research as the underlying causes or triggers of a disorder can be better understood. In a recent study that examined a sample of people suffering from eating disorders, Mikheeva and Tragesser (2016) observed six latent profiles of disordered eating and alcohol use in relation to personality features: Low risk, Negative temperament, Moderate risk, College drinking, Coping, and High urgency. Of interest was the High urgency profile, which had the highest risk for disordered eating and alcohol abuse. The findings suggest that members of this profile may by driven by impulsivity and coping motives.

Another area of study that has benefited from the use of mixture models is the research on depression. Subgroups of individuals who experience distinct forms of depression have been uncovered (Have et al., 2016; Sunderland, Carragher, Wong, & Andrews, 2013). The literature suggests that people have different disposing factors, whether genetic or physiological, and these factors may manifest themselves in different ways. This has been shown by the fact that some people respond better than others to specific antidepressant medications. Research and applications are already underway to develop genetic screeners for targeted pharmacological intervention for depression. Lee et al. (2012) sought to identify possible subgroups of elders that varied in depressive symptomatology. Using a LCA, the researchers discovered distinct subgroups of depressed elders and suggested that alternative diagnostic approaches are needed than what is currently available.

The research on personality disorders has also gained some insights on classifying heterogeneous subpopulations within a known population. Wright et al. (2013) assessed interpersonal inhibition in borderline personality disorder (BPD) by conducting a latent class analysis. Interpersonal impairment is known to be a significant feature of BPD, yet there is a lack of consensus across studies on the degree and manner to which interpersonal impairment effects BPD. Wright et al. (2013) observed six classes of unique interpersonal impairment. The profiles were labelled Intrusive, Vindictive, Avoidant, Non-assertive, and moderate and severe Exploitable interpersonal problems, and they demonstrated a unique set of clinical symptoms and features. Some of these differences were due to antisocial behaviors, self-injury, past suicide attempts.

The benefit of mixture models is in its ability to identify qualitatively different types of patterns of symptoms. This line of research has vast implications in clinical psychology. The structure of various constructs, such as psychological disorders, can be more accurately conceptualized and updated in the DSM-5. In better understanding the nature of these typologies, treatment models and interventions can be refined to alleviate the cause of the symptoms directly.

1.4 Applications of Mixture Modeling in Personality Trait Research

Mixture modelling techniques have also extended to personality trait research. Research in personality assessment focuses on the structure of personality and classification of personality traits. The factor analytic approach has played a major role in uncovering the basic personality dimensions. For example, the Five Factor Model proposes that there are five dimensions of personality that are relatively independent of one another: Neuroticism, Extraversion, Openness to Experience, Agreeableness and Conscientiousness (Costa & McCrae, 1992a, 1992b). There is great support for the replicability of the five-factor model of personality and numerous personality measures have operationalized these factors, most notably the NEO Personality Inventory - Revised (NEO-PI-R), which specifies six facets underlying each factor, so that there are 30 facets in total. Although the Five Factor Model has been empirically validated, an alternative six-factor model, known as the HEXACO (Ashton & Lee, 2007) has also received strong support.

The HEXACO model provides a viable alternative structure that consists of six factors. Three of these dimensions, Extraversion, Conscientiousness and Openness to Experience, are very closely matched to three factors from the Big Five model with the same labels. The remaining three factors, Honesty-Humility, Emotionality and Agreeableness, have some similarities to the Big-Five Factors Emotional Stability (on the opposite end of Neuroticism) and Agreeableness, but they also capture some additional variance that the Five Factor Model does not. The six dimensions of

HEXACO based on the 60-item scale consists of four underlying facets each, which represent consistent patterns of thoughts, feelings and behaviours. Thus, there are a total of 24 observed variables (facets) in this structure, as indicated in Table 1 which has been reproduced from Ashton and Lee (2009a). Ideally, the facets are clustered based on the similarities and differences in their function and fall under a specific factor. Although alternative versions of HEXACO include a 100-item and 200-item scale, the 60-item version was the focus in the current study.

A notable distinction between the Big Five model and HEXACO is the introduction of Honesty-Humility, which captures traits of Sincerity, Fairness, Greed Avoidance and Modesty. Another key difference between the Five Factor Model and the HEXACO model is that Emotionality excludes the 'Anger' facet that is associated with low Emotional Stability in the Big Five. Rather, the Anger characteristic is associated with Agreeableness in this model. Emotionality in the HEXACO-PI-R also includes the 'Sentimentality' facet that is associated with Agreeableness in the Five-Factor Model.

Evidence for the replicability of Honesty-Humility can be found in several studies. For example, De Raad and Szirmak (1994) called the sixth factor Integrity in their Hungarian study. Trustworthiness was observed in an Italian study conducted by Di Blas and Florzi (1999). A Korean study (Hahn, Lee & Ashton, 1999) also found this sixth factor and labelled it Truthfulness. There is clear evidence for the support of a sixth factor that encompasses certain features of personality that are not captured by the Five Factor Model. In addition, there is evidence to suggest that the HEXACO model predicts certain personality associations that are unexplained by a Five Factor Model, such as the relationship between personality factors and altruism (Ashton & Lee, 2007).

Honesty-Humility allows the improved prediction and understanding of personality constructs such as Social Adroitness, Self-Monitoring (Ashton and Lee, 2005) and Active Cooperation (Hilbig, Zettler, Leist, & Heydasch, 2013). There is also evidence that Honesty-Humility is a good predictor of the Dark Triad characteristics (Aghababaei et al., 2014; Lee & Ashton, 2005).

Although the validity of Honesty-Humility is supported in the literature, this dimension is substantially correlated with the Agreeableness dimension based on the Five Factor Model (Ashton & Lee, 2005). Ashton and Lee (2005) found that the correlation between these two dimensions in the HEXACO framework is limited. In the HEXACO framework, Honesty-Humility and Agreeableness are related to two distinct types of prosocial behaviours (Hilbig, Zettler, Leist, & Heydasch, 2013). Honesty-Humility measures how fair and genuine people are in their cooperation with others, where as Agreeableness deals with forgiveness and tolerance, even in the face of being exploited. Honesty-humility and Agreeableness encapsulates distinct types of cooperation; higher scores in Honesty-Humility are related to the tendency toward active cooperation and nonexploitation. Agreeableness deals with reactive cooperation and nonretaliation (Hilbig, Zettler, Leist, & Heydasch, 2013). Although these constructs are related, divergent validity is observed.

An alternative way to examine the structure of personality traits is to consider whether the facets or factors form different prototypical profiles. This approach is referred to as the person-oriented approach as the structure of personality within the individual is of interest. Generally, researchers have obtained three to five personality profiles (Sava and Popa, 2011). In the review conducted by Specht, Luhmann and

Geiser (2014), 14 of the 16 studies that examined personality profiles in the Five Factor Model used a cluster analysis. The other two studies used a Latent Class Analysis. This proclivity of using cluster analysis to assess personality structures was also noted in the body of literature that focuses on the six-factor model (Ashton and Lee, 2009b).

There are three personality types that tend to be detected across various studies: Resilient, Undercontrolled, and Overcontrolled (Donnellan & Robins, 2010; Raad et al., 2010). The Resilient personality type is characterized by having high Emotional Stability scores (Robins et al., 1996, Alessandri et al., 2013), and above average ratings in the other dimensions (see review conducted by Specht, Luhmann and Geiser in 2014). This type is often referred to being well-adjusted and having good interpersonal skills, (Asendorf et al., 2001; Robin et al., 1996), as indicated by the high competence in a wide range of domains. The Undercontrolled profile is associated with low Agreeableness and low Conscientiousness scores (Asendorf et al., 2001). People who are classified as Undercontrolled are impulsive, manipulative and express themselves openly, often inappropriately (Robins et al., 1996). Lastly, the Overcontrolled personality type has the least consensus in the literature of what characterizes the profile. Many researchers found that Overcontrolled is associated with low Emotional Stability and low Extraversion scores (Asendorf, 2002, Robins et al, 1996), and this is also supported by the review conducted by Specht, Luhmann and Geiser (2014). Some studies found low Openness to Experience scores, but it was not prevalent within the literature. People who are classified as Overcontrolled do not often express themselves externally and often restrict their needs and impulses. This profile can be summarized as being sensitive, shy, warm, cooperative and considerate.

Many studies support the replicability of a three-cluster solution across various types of samples (Caspi, 1998; Schnabel et al., 2002). Alessandri et al. (2013) found that three profiles were replicable across four different samples from Italy, United States, Spain, and Poland using cluster analyses. When the cluster assignment procedure was based on a sample from a different country, cluster membership remained stable. This speaks favorably to the reliability of profile membership across different cultures. Asendorf et al., (2001) found that the prototypes were consistent across ages, suggesting the stability of these profiles over time.

Ashton and Lee (2009b) conducted a cluster analysis to examine the replicability of profiles in the context of the six-factor model. The results showed that there is no clear clustering of individuals within the space of the HEXACO dimensions. Distinct personality types were not replicated in their study as the profiles did not explain much of the variance in observed scores beyond the factors. The study concluded that there is no evidence of clear personality profiles as most of the distinction between individuals exists at the factor level. Other researchers have also failed to replicate personality types in both the five-factor and six-factor models (Boehm et al., 2002; McCrae, Terracciano, Costa, & Ozer, 2006). Profiles that differ in level of intensity but have similar shapes have been noted in some studies (Morin & Marsh, 2015). These profiles appear parallel to one another, as they only differ in their elevation across observed variables (i.e. scoring high, medium and low on all traits). Morin and Marsh (2015) suggest that meaningful profiles must differ beyond their level of elevation, such that the profiles have distinct shapes across observed items.

Despite these findings, there is evidence for the replicability of distinct personality types in some of the literature using cluster analysis (Sava & Popa, 2011) and mixture models. In a recent study conducted by Western University colleagues (Daljeeta, Bremner, Giammarcoa, Meyer, & Paunonen, submitted), a LPA yielded a 5-profile solution on the HEXACO-PI-R. The same five profiles were observed in two independent samples that were collected at different points in time. The profiles had a unique response pattern across the observed variables. This suggests that there are a number personality trait profiles within the population, each with its set of means and variances. This study is of interest because one of the samples that was used will be the focus in the present study.

The Factor Mixture Model (FMM) assesses the effects the factors and profiles have on the covariance between observed items. As a FMM allows researchers to model both types of latent structures, it would be beneficial to examine the fit of these models on the HEXACO-PI-R (Ashton & Lee, 2009b; Ekehammar & Akrami, 2003; Meehl, 1992).

1.5 Objectives of the Study

To my knowledge, no studies that have applied mixture models to assess personality structures have used the faceta as the observed variables. The goal of this study is to examine the influence of both factors and profiles in the HEXACO framework. This will be achieved by examining the covariance between the facets rather than the factors.

This study aims to improve the knowledge of applying mixture models in the context of personality structures by comparing the fit indices between different latent variable models. FMMs on the four facets of each dimension of HEXACO-60 will be compared to CFAs and LPAs on the four facets. As the nature of the observed variables is on the facet level, rather than the factor level, FMMs can capture the effects of the latent factor and profiles. In addition to increasing the number of profiles, models in which intercepts are free to vary across profiles will be examined. The interpretations of the subpopulations obtained from the FMMs will be discussed, as well as the conditions that must be met to apply these procedures correctly.

This paper hypothesizes that the FMM will explain more of the covariance between the responses to the indicators than a LPA or a CFA, as FMM allows researchers to model data that has both latent variables. Little research has been conducted on how to quantify the sources of variance in observed items, thus a related objective of the current study is to better understand the sources of variance in FMMs. The sources of variance due to the factor and profiles will be deconstructed using repeated-measures ANOVA.

To summarize, the primary research questions that will be addressed are twofold:

1. In comparing the CFA, LPA and FMM, which method best models the facets of each dimension of HEXACO-60?
2. How much do the latent variables account for the proportion of variance in the facets?

CHAPTER 2: METHODS

2.1 Sample

An archival data set was used for this study. The sample was recruited from SONA (an online system that allows students to participate in research studies) by the department of Psychology at Western University in 2014 to 2015, as part of a larger data collection from student enrollment in introductory psychology courses. The sample consisted of 1149 undergraduate university students (60.7% female) whose ages ranged from 16 to 60 years old (M = 18.38, SD = 2.21). Participants completed the HEXACO-PI-R, 60-item scale as part of a large battery of measures, and received research credits.

2.2 Measure

The shortest version of the HEXACO-PI-R, the HEXACO-60 consists of 60 items that assess six traits with 10 items each. These traits are Honesty-Humility, Emotionality, Extraversion, Agreeableness, Conscientiousness, and Openness to Experience. Each trait subsumes four facets each consisting of two to three items, assessed on a 5-point Likert scale from Strongly Disagree (1) to Strongly Agree (5). The facet descriptions have been reproduced in abbreviated form from the hexaco.org website (Lee & Ashton, n.d.) in Table 1. Definitions for the six traits are also provided at the hexaco.org website. The Cronbach's alpha internal consistency reliability values for the facets based on the current sample are also presented in this table. (The reliability values for each dimension are presented in the Results' section along with other descriptive statistics.)

Table 1

Factor and Facet-Level Scales of HEXACO.

Honesty-Humility Domain		Cronbach's *a*
Sincerity	Genuineness in interpersonal relations.	.602
Fairness	Tendency to avoid fraud and corruption.	.737
Greed Avoidance	Tendency to be uninterested in possessing lavish wealth, luxury goods, and signs of high social status.	.485
Modesty	Tendency to be modest and unassuming.	.638
Emotionality Domain		**Cronbach's *a***
Fearfulness	Tendency to experience fear.	.631
Anxiety	Tendency to worry in a variety of contexts.	.627
Dependence	Need for emotional support from others.	.660
Sentimentality	Tendency to feel strong emotional bonds with others.	.619
Extraversion Domain		**Cronbach's *a***
Social Self-Esteem	Tendency to have positive self-regard, particularly in social contexts.	.637
Social Boldness	Comfort or confidence within a variety of social situations.	.734
Sociability	Tendency to enjoy conversation, social interaction, and parties.	.519
Liveliness	Typical enthusiasm and energy.	.622
Agreeableness Domain		**Cronbach's *a***
Forgivingness	Willingness to feel trust and liking toward those who may have caused one harm.	.698
Gentleness	Tendency to be mild and lenient in dealings with other people.	.619
Flexibility	Willingness to compromise and cooperate with others.	.543
Patience	Tendency to remain calm rather than to become angry.	.758
Conscientiousness Domain		**Cronbach's *a***

Organization	Tendency to seek order, particularly in one's physical surroundings.	.595
Diligence	Tendency to work hard.	.502
Perfectionism	Tendency to be thorough and concerned with details.	.625
Prudence	Tendency to deliberate carefully and to inhibit impulses.	.635
Openness to Experience Domain		Cronbach's *a*
Aesthetic Appreciation	Enjoyment of beauty in art and in nature.	.554
Inquisitiveness	Tendency to seek information about, and experience with, the natural and human world.	.446
Creativity	Preference for innovation and experiment.	.697
Unconventionality	Tendency to accept the unusual.	.450

2.3 Analytic Plan and Procedures

As indicated in the previous chapter, one of the objectives of the thesis is to compare the model fit of three types of models: CFA, LPA, and FMM. As listed in Table 2, this comparison was conducted on the facets of each the six HEXACO traits. For each set of analyses, model fit as well as sources of explained variance (using ANOVA) were conducted. In addition, preliminary descriptive statistics and factor analyses (CFA and ESEM) were conducted to confirm the overall facet structure of the HEXACO (i.e., the 24 facets belonging to their hypothesized factors). These analytic procedures are described in more detail below.

Table 2

Preliminary Analyses and Latent Variable Analysis on HEXACO-60

3.1	Data Inspection and Descriptive Statistics
3.2	Confirming the Factor Structure of the HEXACO-PI-R

3.3	Comparing CFA, LPA, and FMM of Honesty-Humility Facets
3.4	Comparing CFA, LPA, and FMM of Emotionality Facets
3.5	Comparing CFA, LPA, and FMM of Extraversion Facets
3.6	Comparing CFA, LPA, and FMM of Agreeableness Facets
3.7	Comparing CFA, LPA, and FMM of Conscientiousness Facets
3.8	Comparing CFA, LPA, and FMM of Openness to Experience Facets
3.9	Comparing Best Fit and Sources of Variance across Dimensions

2.3.1 Confirmatory Factor Analyses.

Although the focus of this study was to perform and contrast individual models on the four facets that underlie each of the six factors, an initial factor analysis of the six factors and their underlying 24 facets as observed variables was undertaken to confirm the hypothesized structure. All modeling analyses in this project were conducted in Mplus 7.4 (Muthén & Muthén, 2015) using Maximum Likelihood. Missing data (which was minimal and described in the Results section) was handled by the maximum likelihood procedure in Mplus. As will be seen in the Results section, it was decided after the fact to follow up the CFA analysis with an Exploratory Structural Equation Modeling procedure (ESEM) to improve fit. Specifically, ESEM (see Asparouhov & Muthén, 2009) was used primarily to see if a better fit would be obtained by not constraining the cross-loadings to zero as in a CFA.

The CFAs for each individual dimension of HEXACO (Honesty-Humility, Emotionality, Extraversion, Agreeableness, Conscientiousness and Openness to Experience) were simply one-factor models defined by their four facets (see Table 1).

2.3.2 Latent Profile Analyses.

LPAs were conducted on the four facets of each dimension of HEXACO using Mplus 7.4 (Muthén & Muthén, 2015). As the factor was not accounted for in this model, any covariance observed was due to the latent categorical variable. For all LPAs, the number of starts were increased from the default setting until each solution with *k*-profiles converged. The TYPE=MIXTURE alongside the Tech11 option was requested, which provided the Lo-Mendell-Rubin likelihood ratio test (LRT) of model fit and the adjusted Lo-Mendell-Rubin likelihood ratio test (aLRT) (Muthén & Muthén, 2015). For each LPA on the four given facets, the number of profiles were manipulated, starting at 1 profile until the *k*-profile model was rejected based on model fit indices. There are various ways to select the accurate number of subgroups that best fit the model, which include examining the information criteria, the LRT p-values and entropy (Hu & Bentler, 1995; 1999; Marsh et al., 2004).

Information Criteria (IC) values are based on the loglikelihood of a fitted model. Usually the lowest value of IC indicates the best fitting model, but sometimes it is appropriate to choose a model that yields a similar value if it increased by a small increment. The IC values that were reported were Akaike's information criterion (AIC), the Bayesian information criterion (BIC) and the sample size adjusted BIC (aBIC). The BIC is known to be superior (Nylund, Asparouhov, & Muthén, 2007). The Likelihood Ratio Test (LRT) and adjusted Likelihood Ratio Test (aLRT) are inferential and provide *p*-values that compare the improvement of fit between neighboring models, where the estimated model is compared to the *k*-1 model (one less profile). A *p*-value less than .05 indicates that the null hypothesis has been rejected and estimated model with *k*-profiles is supported. Entropy, which ranges from 0 to 1, is based on the uncertainty of classification and measures the extent to which distinct profiles have been identified. Higher values of entropy indicate better fit and values greater than .80 suggest that profiles are discriminant (Muthén & Muthén, 2015). It is important to note that entropy alone is not sufficient in determining the correct number of profiles in a model (Nylund, Asparouhov, & Muthén, 2007). Interpretability of the model will also be considered when deciding on the number of correct profiles, such that models with profiles that are smaller than 5% will be rejected.

2.3.3 Factor Mixture Model.

FMMs were conducted on the four facets of each dimension of HEXACO using Mplus 7.4 (Muthén & Muthén, 2015). The number of starts were increased from the default setting until each solution with *k*-profiles converged. The TYPE=MIXTURE alongside the Tech11 option was requested. Both the dimension latent variable (i.e., factor) and the profile variables were included in these models. The suggestion on increasing the number of factors in the CFAs was relaxed, as only one factor was needed to explain the four observed variables in each model. The first model therefore consist of one dimensional and one categorical latent variables (starting with one profile). Additional models are tested in which the number of profiles are increased until the *k*-profile model was rejected based on model fit indices.

In addition to contrasting models with different *k*-profile solutions, models with fixed and varying parameters were examined. In the fixed models (or invariant FMM), the means of the observed variables (intercepts) were constrained to equality across profiles. This is the default setting in Mplus. The variant FMM allowed the intercepts to vary across profiles, in addition to fixing the factor means at zero in the overall model.

The factor means are fixed at zero to ensure that the variant models have sufficient degrees of freedom. To the extent that the variant model fits better than the non-variant model, it provides evidence for profiles in which the observed variables differ in their means.

The fit indices for selecting the best-fitting FMM models are the same as LPA (see Section 2.3.2).

Once the best FMM models were identified, a final step was to compare the information criterion fit indices (i.e., AIC, BIC, aBIC) across the CFA, the best-fitting LPA and the best-fitting FMM. The primary research objective was to assess if FMM, with invariant or variant intercepts, improved the model fit beyond the CFA and LPA for each dimension of HEXACO-PI-R.

2.4 Sources of Variance in Mixture Models

For each of the six sets of models (across the six HEXACO traits), ANOVA models were tested specifically to decompose the different sources of variances. In each of these models, the dependent variable is the score on a facet. There are four facets and these can be treated as a repeated-subjects factor because each respondent provides a score on each of the facet. The facet is therefore a within-subjects effect that indicates whether the sample of respondents as a whole obtain higher scores on one facet or another. The profile is a categorical variable that determines the most likely class/profile a respondent belongs to, which represents the between-subjects variable in the ANOVA design. This profile variable is obtained from the FMM in Mplus which saves each respondent's most likely profile. The factor score is also derived from FMM and indicates a respondent's position on the overall trait. In the ANOVA design it is entered as a covariate, not with the purpose of a traditional analysis of covariance, but as a continuous factor which may interact with the categorical predictors. The Type-III Sum of Square model was chosen as these values depict unique sources of variance in the model.

The sources of variance were calculated by obtaining the proportion of the Sum of Squares (SS), or by dividing unique SS-values by the total SS value. For each dimension of HEXACO-60, five proportions of variance were included in this study: the effects of the profile (level), the factor scores, the observed variables (facets), the interaction between the facets and profile (shape) and the interaction between the facets and factor scores (Tremblay, 2017).

CHAPTER 3: RESULTS

3.1 Data Inspection and Descriptive Statistics

On three items administered to assess careless responding, participants were instructed to choose a specific response (e.g., “Please respond ‘Strongly Disagree’ to this item”). It is important to note that these items were imbedded in the larger battery of measures administered to the sample and occurred following the HEXACO questionnaire. Participants who responded incorrectly to any of the three items were excluded from the sample. This exclusion criterion reduced the sample size from 1149 to 876 participants. Missing data ranged from 7 to 24 responses out of 876, representing less than 3% of missing responses per scale. In the modeling analyses using Mplus, missing data was handled using the full information maximum likelihood criterion (FIML), which means that parameters are estimated based on available data. The distributions of the HEXACO dimensions were compared to the normative statistics provided by Lee and Ashton (n.d.) in a sample of 1126 college students. As can be seen in Table 3, the means for this study are very similar to the means in the normative sample. (Tests of significance comparing these means were all statistically significant at alpha = .05, but this was due to very large sample sizes). All dimensions were normally distributed, with skewness values that ranged from – 0.40 to – 0.03 and kurtosis values that range from – 0.42 to 0.18.

Table 3

Descriptive Statistics for HEXACO Factors

	Study Sample M	Study Sample SD	Normative Sample M	Normative Sample SD	C. Alpha
Honesty-Humility	3.14	.66	3.23	.66	.75

Emotional Stability	3.43	.70	3.36	.70	.79
Extraversion	3.37	.64	3.51	.62	.79
Agreeableness	3.16	.66	3.10	.63	.78
Conscientiousness	3.69	.60	3.47	.61	.77
Openness to Exp.	3.18	.68	3.49	.67	.74

Note. C. Alpha - Cronbach's alpha values observed in the current study.

3.2 Factor Structure of the HEXACO-PI-R

A Confirmatory Factor Analysis (CFA) consisting of a six-factor correlated model was conducted on the 24 facets of the HEXACO-PI-R (see Figure 3). The fit indices were as follows: X^2 (237) = 1060.024, p < .001, RMSEA = .065 (90% CI of .061 – .069), SRMR = .063, CFI = .787 and TLI = .752. Although the RMSEA value suggests good fit, the CFI and TLI are below the recommended cut-off values of .90 to .95; however, it is not uncommon to have some fit indices fall short of the cut-off values in some models due to strong restrictions of zero cross-loadings.

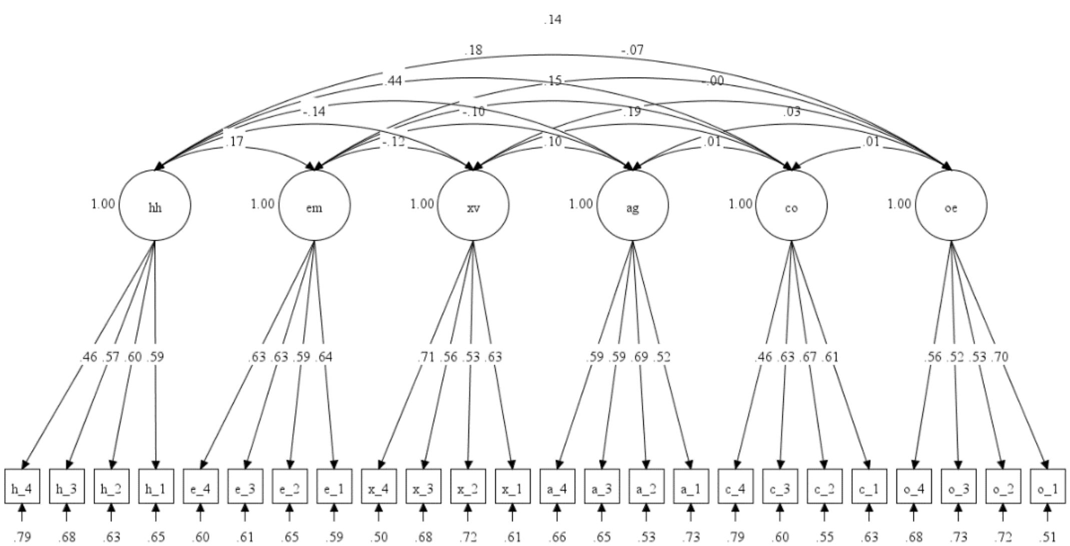

Figure 3. Full representation of CFA for the 24 Facets of HEXACO.
Note. The six dimensions of HEXACO are observed as latent variables (circles), where HH is Honesty-Humility, EM is Emotionality, XV is Extraversion, AG is Agreeableness, CO is Conscientiousness and OE is Openness to Experience. The facets are presented as observed variables (squares). For a full list of facets, see Table 1.

As a follow-up to the above CFA an Exploratory Structural Equation Model (ESEM) with a target rotation was conducted. Unlike a CFA which restricts the cross-loadings (i.e., loadings on secondary factors) at zero, the ESEM includes all loadings on all factors, but in addition, provides a targeted rotation that enables a less-restrictive test of a hypothesized factor structure. The fit indices were as follows: X^2 (147) = 378.449, $p < .001$, RMSEA = .042 (90% CI of .037 – .048), SRMR = .023, CFI = .943 and TLI = .894. The fit indices for this model improved overall, suggesting that a good fit can be reached by allowing non-zero cross-loadings. Although not discussed further, these cross-loadings are smaller than the loadings on the main factors.

3.3 Comparing CFA, LPA, and FMM of Honesty-Humility Facets

The main analyses of this project focus on individual HEXACO factors and their facets. As indicated in the Analytic Procedures section (2.3), a Confirmatory Factor Analysis (CFA), a Latent Profile Analysis (LPA) and a Factor Mixture Model (FMM) of the four Honesty-Humility facets were compared in terms of model fit. In addition, another way to evaluate the models is to determine how much variance in the observed variables (i.e., the facet scores) are accounted by the latent variables in the model (i.e., dimensional and categorical). One way of decomposing all the different sources of variance is to conduct a repeated-measures ANOVA on the facet scores with Facets as a within-subjects factor, Profiles as a between-subjects factor and the Honesty-Humility Factor score as a covariate. The purpose of this ANOVA is to determine how much variance in the facet scores can be attributed to the latent Honesty-Humility dimension (i.e., factor score) vs. the latent profiles.

Table 4 begins with the examination of a CFA, in which the Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC), the adjusted BIC (aBIC) values are included. Note that this is simply a 1-factor model with the four facets. These are fit indices that can be used to compare models, with lower values representing better fit. These values will be used to compare the fit of the CFA model to the LPA and FMM models. Although not presented in the table, the fit indices typically reported in CFA were as follows: $X^2(2) = 7.682$, $p = .02$, RMSEA = .058 (90% CI of .019 – .103), SRMR = .002, CFI = .985, and TLI = .955. The SRMR value fell below the recommended cut-off of .05 and the CFI and TFI values were above the recommended cut-off of .95, suggesting good fit. Although these fit indices are ideal, the more relevant fit indices for comparison with other models are the AIC, BIC, adjusted BIC.

The LPA analyses, listed by increasing number of profiles and their associated proportions of cases within profile, are presented in Table 4. In addition to the various Information Criteria values, the *p*-values associated with the Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test (VLMR-aLRT) and the entropy (E) are included. Indicated in bold is the model that was selected as having the best fit considering a combination of criteria (i.e., low values on information criteria, usually significant aLRT but not always, proportions of cases above 5% in each profile). As illustrated in Table 4, the 5-profile model was selected as the best fitting LPA model for Honesty-Humility.

The FMMs and their corresponding model fit indices are also presented in Table 4. It should be recalled that as described in the analytic procedures, these models combine the dimensional latent variable (i.e. factor) as well as the latent profile variable (i.e., a latent categorical variable that specifies which profile a respondent is most likely to be in). Models can constrain the intercepts (facet score means) to equality across the profiles or allow them to vary. An improvement of fit when the intercepts are free to vary is suggested by a substantial change in the fit indices. This indicates that the profiles do in fact vary after accounting for the latent dimension. In terms of labelling the FMMs in Table 4, the invariant FMMs (Invar) refers to a model in which the intercepts are forced to be invariant across profiles, while the variant FMMs are models in which intercepts are allowed to vary across profiles (Vary). The LPA and FMM solutions selected as best fitting is presented in bold.

Table 4

Mixture Model Solutions of Honesty Humility Facets

Model	q	AIC	BIC	aBIC	aLRT	E	Prop in Profile
CFA							
	12	9105.54	9162.61	9124.50	--	--	--
LPA							
1-Profile	8	9600.25	9638.44	9613.03	--	--	--
2-Profile	13	9309.06	9371.12	9329.84	.000	.536	.44, .56
3-Profile	18	9223.43	9309.37	9252.21	.000	.675	.17, .71, .12
4-Profile	23	9173.53	9283.34	9210.30	.006	.659	.15, .40, .34, .12
5-Profile	**28**	**9143.00**	**9276.68**	**9187.76**	**.031**	**.662**	**.14, .39, .28, .12, .07**
6-Profile	33	9124.93	9282.48	9177.68	.037	.702	.15, .11, .06, .35, .27, .07
FMM							
1-Profile	12	9231.81	9289.10	9251.00	--	--	--
2-Profile Invar	14	9235.52	9302.36	9257.90	.787	.367	.05, .95
2-Profile Vary	**17**	**9180.60**	**9261.77**	**9207.78**	**.000**	**.620**	**.44, .56**
3-Profile Invar	16	9239.52	9315.91	9265.09	.500	.600	.00, .20, .80
3-Profile Vary	22	9163.10	9268.13	9198.26	.004	.678	.21, .38, .41
4-Profile Invar	18	9236.63	9322.57	9265.40	.500	.686	.17, .14, .00, .69
4-Profile Vary	27	9147.18	9276.08	9190.34	.202	.634	.17, .25, .19, .39

Note. q is the number of estimated parameters in the model.

Table 5 contrasts the standardized loadings of the four Honesty-Humility facets on the latent dimension in the CFA with those in the FMM. As can be seen in this table, the loadings are somewhat smaller in the FMM model (except for Modesty) because part of the variance in the facet scores is now accounted for by the latent profile variable.

Table 5

Factor Loadings of CFA and Best-fitting FMM of Honesty-Humility Facets

Facets	CFA Factor Loadings*	FMM Factor Loadings*
H1: Sincerity	.619	.542
H2: Fairness	.595	.471
H3: Greed Avoid	.546	.511
H4: Modesty	.428	.459

Note. * All factor loadings were significant at $p < .001$

Figure 4 illustrates the best fitting LPA that was selected in Table 4 with a 5-profile solution. In contrast, Figure 5 illustrates the best fitting FMM selected in Table 4 with a 2-profile solution. However, based on the fit indices in Table 6, neither of these models are optimum for the facets of Honesty-Humility. The best fitting model for the facets of Honesty-Humility is the CFA as indicated by the smaller AIC, BIC, and aBIC values.

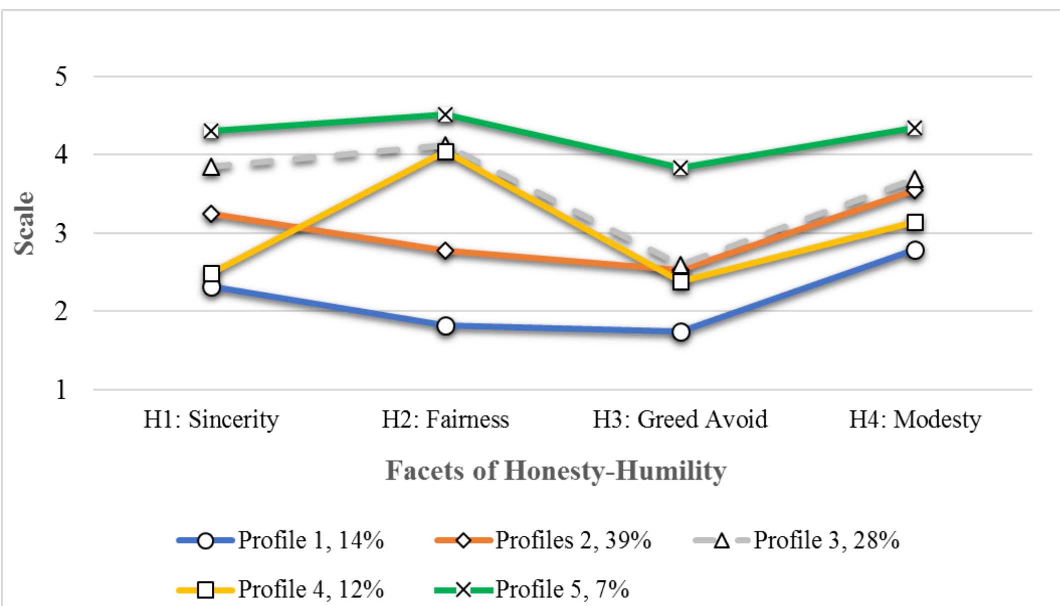

Figure 4. 5-Profile LPA Solution for Honesty-Humility Facets

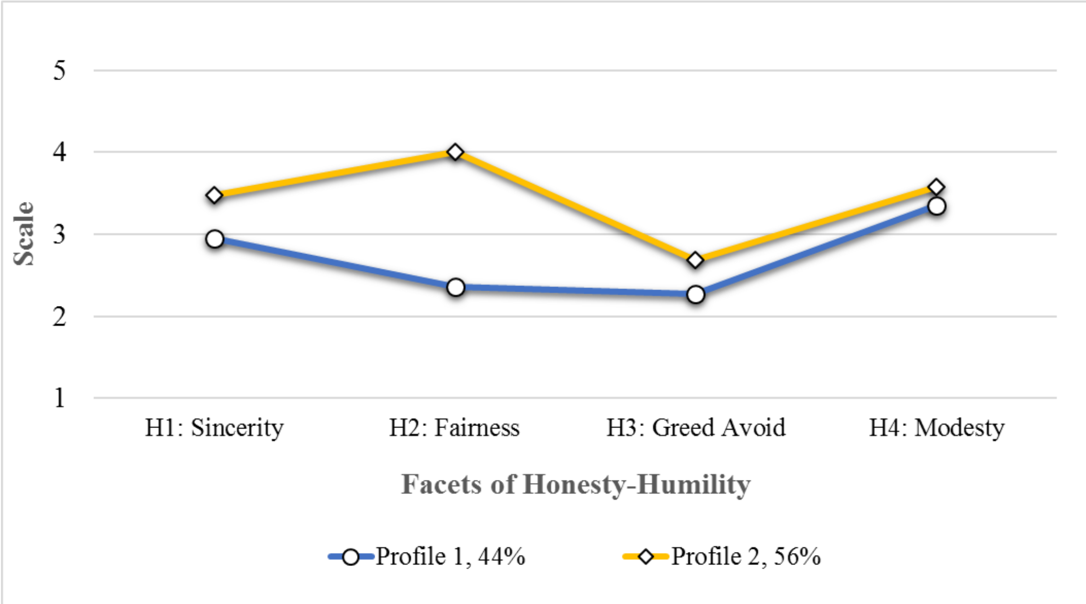

Figure 5. 2-Profile FMM Solution for Honesty-Humility Facets

The ANOVA table is presented in Table 6. Recall that this is essentially a split-plot design (Profile as the between-subjects factor and Facets as the within subjects factor) with the addition of a continuous predictor (covariate) consisting of the Factor score. This ANOVA model corresponds to the best FMM model with a categorical variable representing the two profiles. Of particular relevance are the Sums of Squares which allow us to calculate the proportion of variance explained by taking a specific SS and dividing by the total SS. It should also be noted that the Facet by Factor score interaction and the three-way interaction (Facet by Factor Score by Profile) have been omitted because there is no reason to hypothesize that these would account for much variance. The tests of significance for each effect in the ANOVA model are less relevant but are still reported (and based on the Greenhouse-Geisser correction to adjust for the violation of sphericity when assessing within-subjects effects). Post hoc analyses (Bonferroni) comparing the facet scores across profiles are presented in Appendix A rather than in the main text. This is because the profiles produced from LPA and FMM impose a criterion of maximizing their mean differences on the variables. It was therefore expected that most of these post hoc tests would be significant.

To assess sources of variance explained by each effect, the Sum of Squares (SS) for the effect divided by the total SS, provides proportions of variance accounted for. Given that the Type-III SS ANOVA model was used, these SS values represent unique portions of variances accounted for by the source in question. There are five sources of variance that are of interest. The factor scores which represent the unique amount of variance that factor explains in the facets in 28.54%. The Profile is a categorical variable that places respondents in their most likely class. In this case, there are only two profiles, and this variable accounts for 5.97 % of the variance. This source of variance is also referred to as level or elevation because it models the equivalent of a main effect where participants in one profile tend to get higher scores on all facets. A third source that is less important is Facet which accounts for 13.18 %. This source refers to the fact that some facets have higher mean scores than others. For example, Greed avoidance has a lower mean score than the other facets. The most interesting source from the perspective of mixture modeling is the Facet by Profile interaction, also referred to as Shape, which in this example accounted for 10.50% of the variance. This is the source that shows the qualitatively different forms of the profiles that remain after controlling for the other sources. Finally, another interaction is the Facets by Factor scores which accounts for 2.65 % of the variance. This is a less important source that simply suggests that some facets are weighted more heavily in the derivation of the factor scores.

Table 6

Source of Variance of Honesty-Humility Variables

Source		Type-III SS	df	MS	F	Var.
Between	Profile (level)	202.92	1	292.92	5462.20**	5.97
	Factor Scores	969.64	1	969.64	26100.99**	28.54
	Error	31.80	856	.037		
Within	H Facets	447.97	2.68	166.90	295.30**	13.18
	H Facets x Profile (shape)	356.83	2.68	132.94	235.22**	10.50
	H Facets x Factor Scores	89.96	2.68	33.52	59.30**	2.65
	Error	1298.55	2297.60	.57		
Total		3397.67				

Note. ** indicates significant at p<.001. Var. = Unique Proportion of Variance

3.4 Comparing CFA, LPA, and FMM of Emotionality Facets

The structure of the models conducted for the Emotionality facets were the same as in the previous section on the Honesty-Humility models. In this section, a CFA, LPAs and FMMs of the four Emotionality facets were compared in terms of model fit. The same ANOVA design as in the previous section was used.

Table 7 compares the fit indices of the CFA, LPAs, and FMMs. For the CFA, the Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC), and the adjusted BIC (aBIC) values were included. The additional fit indices for the CFA were as follows: X^2 (2) = 10.958, p = .004, RMSEA = .072 (90% CI of .034 – .116), SRMR = .002, CFI = .985 and TLI = .955. The RMSEA value was reasonable, falling below .08 and the SRMR value fell below the recommended cut-off of .05. The CFI and TFI values were above the recommended cut-off of .95, suggesting good fit.

The FMM solution that was selected as optimum is presented in bold. Compared to other FMM solutions, the 3-profile solution with varying intercepts was observed to have the smallest IC values associated with a significant aLRT p-value and was selected as the best fitting model.

Table 7

Mixture Model Solutions of Emotionality Facets

Model	q	AIC	BIC	aBIC	aLRT (p)	E	Prop in Profile
CFA							
	12	8926.11	8983.31	8945.20	--	--	--
LPA							
1-Profile	8	9563.08	9601.29	9575.88	--	--	--
2-Profile	13	9068.53	9130.61	9089.32	.000	.646	.42, .58
3-Profile	18	8956.40	9042.35	8985.19	.655	.655	.13, .51, .36
4-Profile	**23**	**8897.60**	**9007.43**	**8934.39**	**.006**	**.686**	**.11, .39, .12, .38**
5-Profile	28	8872.63	9006.34	8917.42	.195	.686	.11, .04, .41, .12, .32
FMM							
1-Profile	12	8980.98	9038.28	9000.17	--	--	--
2-Profile Invar	14	8975.33	9042.18	8997.72	.113	.433	.22, .78
2-Profile Vary	17	8880.21	8961.39	8907.40	.000	.738	.24, .76
3-Profile Invar	16	8971.20	9047.60	8996.79	.264	.591	.10, .56, .34
3-Profile Vary	**22**	**8839.55**	**8944.61**	**8874.74**	**.002**	**.776**	**.06, .31, .63**
4-Profile Invar	18	8970.35	9056.31	8999.14	.086	.674	.17, .02, .53,.28
4-Profile Vary	27	8825.18	8954.11	8868.37	.272	.744	.07, .57, .31, .05

Note. q is the number of estimated parameters in the model.

Table 8 contrasts the standardized loadings of the four Emotionality facets on the latent dimension in the CFA with those in the FMM with the three profiles. As can be seen in this table, the loadings are somewhat smaller in the FMM model (apart from Dependence) because part of the variance in the facet scores is now accounted for by the latent profile variable.

Table 8

Factor Loadings of CFA and Best-fitting FMM of Emotionality Facets

Facets	CFA Factor Loadings*	FMM Factor Loadings*
E1: Fearfulness	.627	.557
E2: Anxiety	.552	.438
E3: Dependence	.642	.683

E4: Sentimentality	.645	.584

Note. * All factor loadings and intercepts were significant at $p < .001$

Figure 6 illustrates the best fitting LPA that was selected in Table 7 with a 4-profile solution. In contrast, Figure 7 portrays the best fitting FMM selected in Table 7 with a 3-profile solution. Based on fit indices and interpretability, the best fitting model for the facets of Emotionality is the FMM with the 3-profile solutions that allow intercepts to vary across profiles.

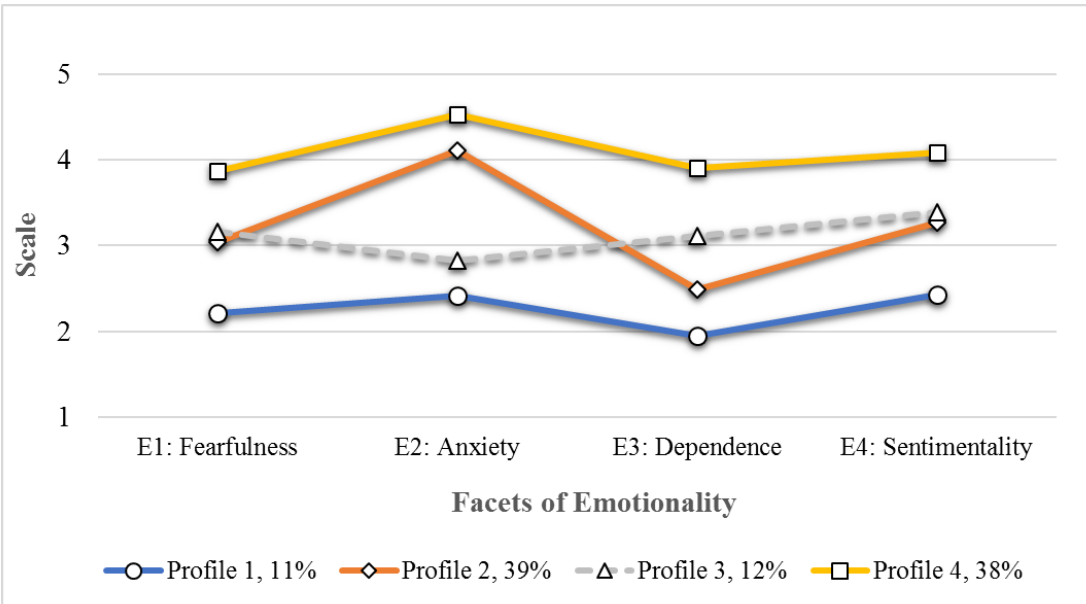

Figure 6. 4-Profile LPA Solution for Emotionality Facets

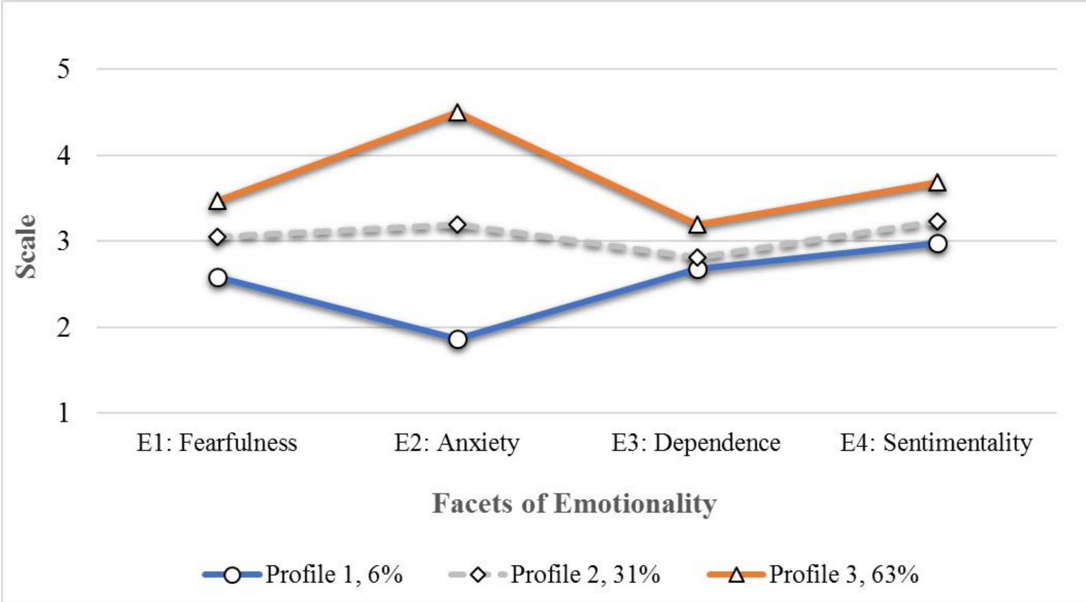

Figure 7. 3-Profile FMM Solution for Emotionality Facets

The ANOVA table is presented in Table 9 for the FMM with three profiles. Post hoc analyses (Bonferroni) are presented in Appendix A. The different sources of variance are also highlighted in Table 9, with the greatest proportion attributed to the Factor Scores.

Table 9

Source of Variance of Emotionality Variables

Source		Type-III SS	df	MS	F	Var.
Between	Profile (level)	385.97	2	192.99	6407.02**	12.81
	Factor Scores	1040.65	1	1040.65	34548.70**	34.53
	Error	26.03	864	.03		
Within	E facets	26.50	2.49	10.58	22.53**	0.88
	E facets x Profile (shape)	287.86	4.98	57.84	122.36**	9.55
	E facets x Factor Scores	229.98	2.49	92.42	195.50**	7.63
	Error	1016.35	2150.03	.47		
Total		3013.34				

Note. ** indicates significant at p<.001. Var. = Unique Proportion of Variance

3.5 Comparing CFA, LPA, and FMM of Extraversion Facets

The structure of the models conducted for the Extraversion facets is the same as in the previous section on the Honesty-Humility models. In this section, a CFA, LPAs and FMMs of the four Emotionality facets were compared in terms of model fit. The same ANOVA design as in the previous section was used.

Table 10 compares the fit indices of the CFA, LPAs, and FMMs. For the CFA, the Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC), and the adjusted BIC (aBIC) values were included. The additional fit indices for the CFA were as follows: X^2 (2) = 31.967, p = .001, RMSEA = .131 (90% CI of .094 – .173), SRMR = .032, CFI = .95 and TLI = .851. The RMSEA was too large, however the SRMR value fell below the recommended cut-off of .05. The CFI met the cut-off of .95, while the TLI was a bit small. It should be noted that some of these fit indices, especially, RMSEA, and been shown to be biased when the degrees of freedom are small such as for the present models (Kenny, Kaniskan, & McCoach, 2014).

The FMM solution that was selected as optimum is presented in bold. Compared to other FMM solutions, the 2-profile solution with varying intercepts was observed to have the smallest IC values associated with a significant aLRT p-value.

Table 10

Mixture Model Solutions of Extraversion Facets

Model	q	AIC	BIC	aBIC	aLRT (p)	E	Prop in Profile
CFA							
	12	8452.23	8509.44	8471.33	--	--	--
				LPA			
1-Profile	8	9072.84	9111.05	9085.64	--	--	--
2-Profile	13	8610.10	8672.18	8630.89	.000	.678	.33, .67
3-Profile	18	**8511.59**	**8597.55**	**8540.38**	**.005**	**.643**	**.11, .34, .55**
4-Profile	23	8486.48	8596.31	8523.27	.368	.624	.10, .42, .12, .36

5-Profile	**28**	8459.47	8593.18	8504.25	.177	.628	.08, .36, .21, .06, .29
6-Profile	33	8443.09	8600.67	8495.87	.694	.651	.03, .10, .07, .35, 26, .18
FMM							
1-Profile	12	8507.28	8564.59	8526.48	--	--	--
2-Profile Invar	14	8492.32	8559.17	8514.71	.011	.652	.09, .91
2-Profile Vary	17	**8467.40**	**8548.58**	**8494.60**	**.000**	**.567**	**.32, .68**
3-Profile Invar	16	8493.92	8570.33	8519.52	.288	.549	.35, .03, .62
3-Profile Vary	**22**	8445.04	8550.09	8480.23	.028	.668	.07, .22, .71
4-Profile Invar	18	8497.05	8583.01	8525.84	.703	.566	.11, .03, .58, .29
4-Profile Vary	27	8404.77	8533.70	8447.96	.000	.679	.09, .14, .59, .17

Note. *q* is the number of estimated parameters in the model.

Table 11 contrasts the standardized loadings of the four Extraversion facets on the latent dimension in the CFA with those in the FMM with the two profiles. The loadings for Social Boldness and Liveliness are smaller in the FMM model, but are larger for Social Self-Esteem and Sociability.

Table 11

Factor Loadings of CFA and Best-fitting FMM of Extraversion Facets

Facets	CFA Factor Loadings*	FMM Factor Loadings*
X1: Social Self-Esteem	.591	.605
X2: Social Boldness	.522	.511
X3: Sociability	.599	.684
X4: Liveliness	.724	.663

Note. * All factor loadings and intercepts were significant at $p < .001$

Figure 8 illustrates the best fitting LPA that was selected in Table 10 with a 3-profile solution. In contrast, Figure 9 portrays the best fitting FMM selected in Table 10 with a 2-profile solution. However, based on the fit indices in Table 10, neither of these models are optimum for the facets of Extraversion. The best fitting model for the facets of Honesty-Humility is the CFA.

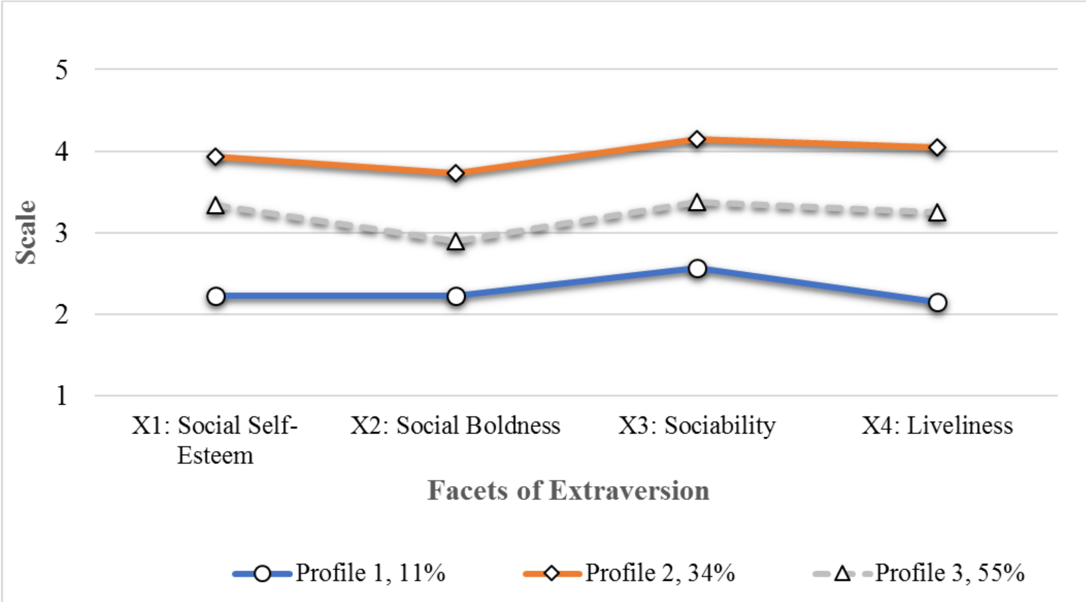

Figure 8. 3-Profile LPA Solution for Extraversion Facets

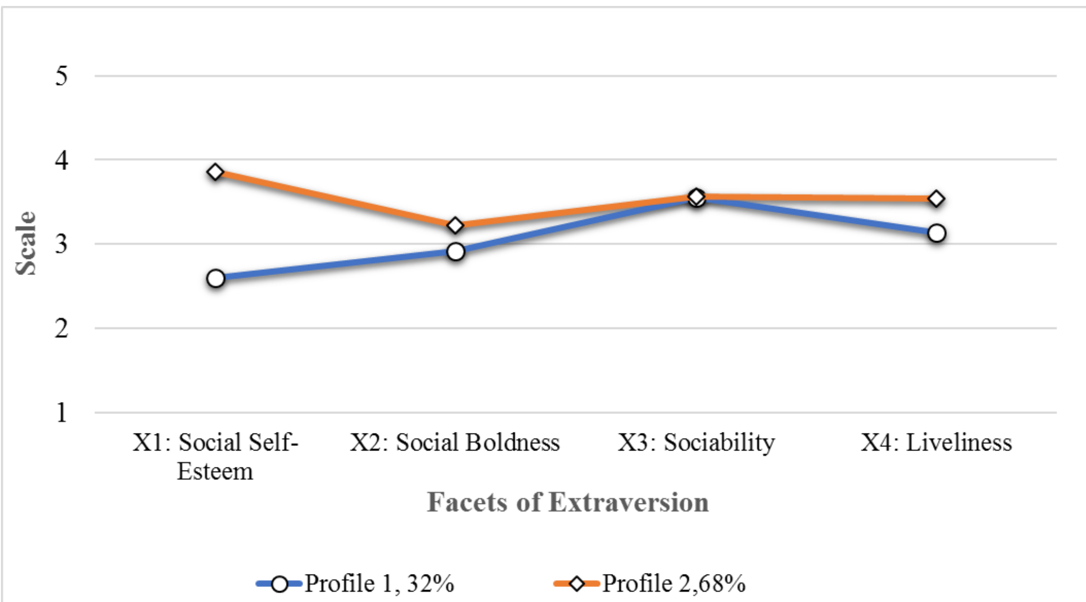

Figure 9. 2-Profile FMM Solution for Extraversion Facets

The ANOVA table is presented in Table 12 for the FMM with two profiles. Post hoc analyses (Bonferroni) are presented in Appendix A. The different sources of variance are also highlighted in Table 12, with the greatest proportion attributed to the Factor Scores.

Table 12

Source of Variance of Extraversion Variables

Source		Type-III SS	df	MS	F	Var.
Between	Profile (level)	86.03	1	86.03	2070.61**	3.15
	Factor Scores	1174.67	1	1174.67	28272.56**	42.95
	Error	35.98	866	.042		
Within	X Facets	120.12	2.57	46.74	104.32**	4.39
	X Facets x Profile (shape)	250.55	2.57	97.49	217.58**	9.16
	X Facets x Factor Scores	70.23	2.57	27.33	60.99**	2.57
	Error	997.21	866	1.15		
Total		2734.79				

Note. ** indicates significant at p<.001. Var. = Unique Proportion of Variance

3.6 Comparing CFA, LPA, and FMM of Agreeableness Facets

The structure of the models conducted for the Agreeableness facets is the same as in the previous section on the Honesty-Humility models. In this section, a CFA, LPAs and FMMs of the four Agreeableness facets were compared in terms of model fit The same ANOVA design as in the previous section was used.

Table 13 compares the fit indices of the CFA, LPAs, and FMMs. For the CFA, the Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC), and the adjusted BIC (aBIC) values were included. The additional fit indices for the CFA were as follows: X^2 (2) = 8.708, *p* = .013, RMSEA = .063 (90% CI of .024 – .108), SRMR = .017, CFI = .987 and TLI = .962. The RMSEA value was reasonable, falling below .08 and the SRMR value fell below the recommended cut-off of .05. The CFI and TFI values were above the recommended cut-off of .95, suggesting good fit.

The FMM solution that was selected as optimum is presented in bold. Compared to other FMM solutions, the 3-profile solution with varying intercepts was observed to have the smallest IC values associated with a significant aLRT p-value.

Table 13

Mixture Model Solutions of Agreeableness Facets

Model	q	AIC	BIC	aBIC	aLRT (p)	E	Prop in Profile
CFA							
	12	8600.20	8657.26	8619.15	--	--	--
LPA							
1-Profile	8	9246.20	9284.40	9259.00	--	--	--
2-Profile	13	8791.58	8853.66	8812.38	.000	.706	.28, .72
3-Profile	18	8697.03	8782.99	8725.82	.006	.655	.18, .62, .20
4-Profile	23	8624.30	8734.13	8661.09	.064	.665	.15, .26, .25, .34
5-Profile	**28**	**8593.90**	**8727.61**	**8638.68**	**.004**	**.697**	**.10, .13, .33, .13, .30**
6-Profile	33	8571.10	8728.69	8623.89	.064	.737	.11, .05, .33, .13, .11, .28
FMM							
1-Profile	12	8723.35	8780.65	8742.54	--	--	--
2-Profile Invar	14	8711.83	8778.68	8734.22	.054	.540	.19, .81
2-Profile Vary	17	8623.69	8704.87	8650.88	.000	.731	.33, .67
3-Profile Invar	16	8702.38	8778.78	8727.97	.019	.638	.17, .62, .21
3-Profile Vary	**22**	**8595.61**	**8700.67**	**8630.80**	**.000**	**.733**	**.22, .29, .49**
4-Profile Invar	18	8703.24	8789.19	8732.03	.422	.636	.19, .53, .17,.11
4-Profile Vary	27	8585.82	8714.76	8629.01	.405	.711	.05, .45, .29, .22

Note. q is the number of estimated parameters in the model.

Table 14 contrasts the standardized loadings of the four Agreeableness facets on the latent dimension in the CFA with those in the FMM with the three profiles. As can be seen in this table, the loadings are somewhat smaller in the FMM model (except for Gentleness) because part of the variance in the facet scores is now accounted for by the latent profile variable.

Table 14

Factor Loadings of CFA and Best-fitting FMM of Agreeableness Facets

Facets	CFA Factor Loadings*	FMM Factor Loadings*
A1: Forgiveness	.498	.405
A2: Gentleness	.670	.693

A3: Flexibility	.610	.485
A4: Patience	.609	.317

Note. * All factor loadings and intercepts were significant at $p < .001$

Figure 10 illustrates the best fitting LPA that was selected in Table 13 with a 5-profile solution. In contrast, Figure 11 portrays the best fitting FMM selected in Table 13 with a 3-profile solution. Based on fit indices and interpretability, the best fitting model for the facets of Agreeableness is the FMM with the 3-profile solutions that allow intercepts to vary across profiles.

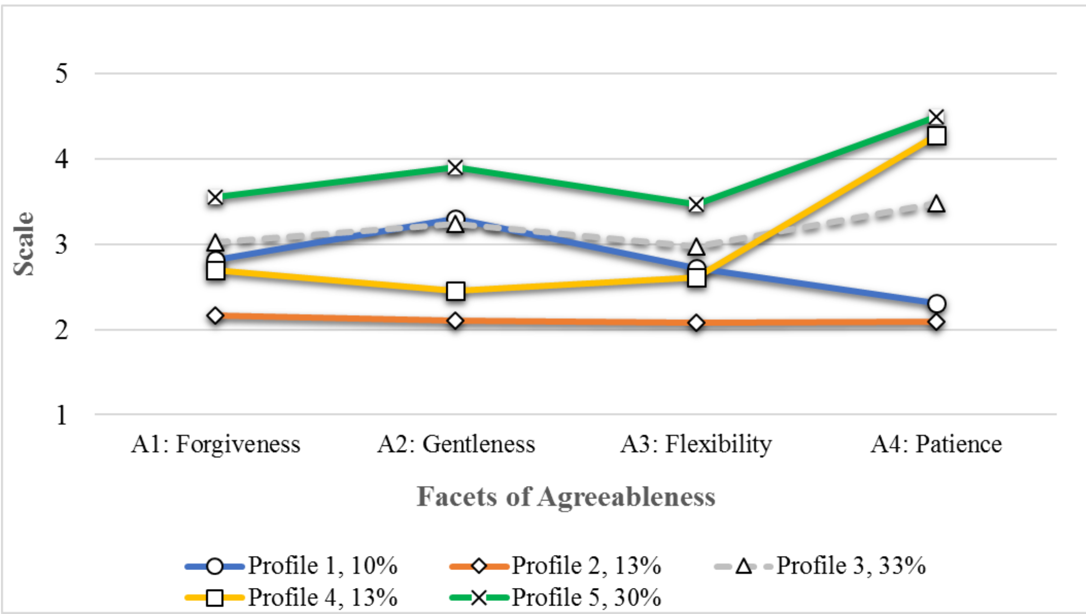

Figure 10. 5-Profile LPA Solution for Agreeableness Facets

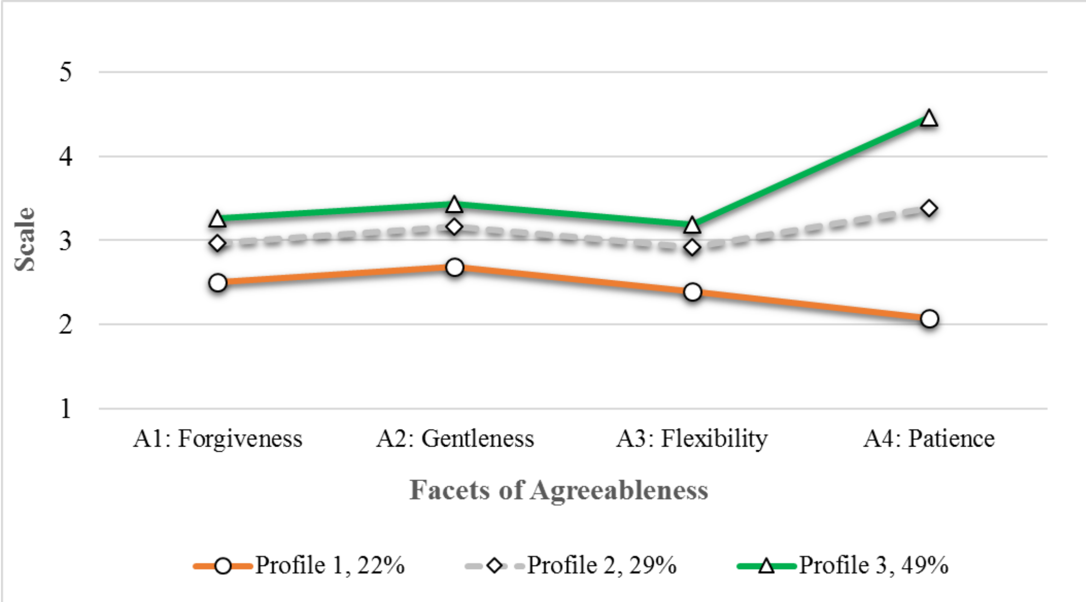

Figure 11. 3-Profile FMM Solution for Agreeableness Facets

The ANOVA table is presented in Table 15 for the FMM with three profiles. Post hoc analyses (Bonferroni) are presented in Appendix A. The different sources of variance are also highlighted in Table 15, with the greatest proportion attributed to the Factor Scores.

Table 15

Source of Variance of Agreeableness Variables

Source		Type-III SS	df	MS	F	Var.
Between	Profile (level)	580.34	2.00	290.17	2400.56**	20.12
	Factor Scores	660.22	1.00	660.22	5462.01**	22.89
	Error	103.23	854.00	0.12		
Within	A Facets	85.27	2.20	38.78	75.76**	2.96
	A Facets x Profile (shape)	318.17	4.40	72.36	141.34**	11.03
	A Facets x Factor Scores	175.60	2.20	79.87	156.02**	6.09
	Error	961.18	1877.56	0.51		
Total		2884.01				

Note. ** indicates significant at p<.001. Var. = Unique Proportion of Variance

3.7 Comparing CFA, LPA, and FMM of Conscientiousness Facets

The structure of the models conducted for the Conscientiousness facets is the same as in the previous section on the Honesty-Humility models. In this section, a CFA, LPAs and FMMs of the four Conscientiousness facets were compared in terms of model fit. The same ANOVA design as in the previous section was used.

Table 16 compares the fit indices of the CFA, LPAs, and FMMs. For the CFA, the Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC), and the adjusted BIC (aBIC) values were included. The additional fit indices for the CFA were as follows: X^2 (2) = 13.028, p = .002, RMSEA = .08 (90% CI of .042 – .123), SRMR = .022, CFI = .98 and TLI = .939. The RMSEA and SRMR have reasonable values. The CFI values was above the recommended cut-off of .95, suggesting good fit.

The FMM solution that was selected as optimum is presented in bold. Compared to other FMM solutions, the 2-profile solution with varying intercepts was observed to have the best fit. Although the 3-profile solution with varying intercepts has smaller IC values and a significant aLRT p-value, the proportion of one of its profiles fell below 5%.

Table 16

Mixture Model Solutions of Conscientiousness Facets

Model	q	AIC	BIC	aBIC	aLRT (p)	E	Prop in Profile
CFA							
	12	8107.62	8164.83	8126.72	--	--	--
LPA							
1-Profile	8	8682.10	8720.30	8694.89	--	--	--
2-Profile	13	8219.14	8281.22	8239.93	.000	.658	.37, .63
3-Profile	**18**	**8113.75**	**8199.70**	**8142.54**	**.000**	**.689**	**.07, .49, .44**
4-Profile	23	8061.99	8171.83	8098.78	.089	.684	.08, .33, .45, .14
5-Profile	28	8036.25	8169.96	8081.04	.225	.683	.25, .10, .09, .44, .13

6-Profile	33	8010.12	8167.70	8062.90	.312	.751	.05, .11, .08, .36, .06, .33
FMM							
1-Profile	12	8149.30	8206.61	8168.50	--	--	--
2-Profile Invar	14	8129.83	8196.68	8152.22	.022	.635	.11, .89
2-Profile Vary	**17**	**8070.26**	**8151.44**	**8097.45**	**.001**	**.721**	**.20, .80**
3-Profile Invar	16	8115.11	8191.52	8140.71	.076	.656	.47, .05, .47
3-Profile Vary	22	8045.72	8150.78	8080.91	.028	.760	.04, .30, .67
4-Profile Invar	18	8119.11	8205.07	8147.90	.501	.727	.47, .05, .00, .47
4-Profile Vary	27	8008.44	8137.37	8051.63	.056	.743	.07, .68, .15, .10

Note. *q* is the number of estimated parameters in the model.

Table 17 contrasts the standardized loadings of the four Conscientiousness facets on the latent dimension in the CFA with those in the FMM with the two profiles. As can be seen in this table, the loadings are somewhat smaller in the FMM model (except for Prudence) because part of the variance in the facet scores is now accounted for by the latent profile variable.

Table 17

Factor Loadings of CFA and Best-fitting FMM of Conscientiousness Facets

Facets	CFA Factor Loadings*	FMM Factor Loadings*
C1: Organization	.614	.610
C2: Diligence	.646	.547
C3: Perfectionism	.645	.552
C4: Prudence	.490	.510

Note. * All factor loadings and intercepts were significant at $p < .001$

Figure 12 illustrates the best fitting LPA that was selected in Table 16 with a 3-profile solution. In contrast, Figure 13 portrays the best fitting FMM selected in Table 16 with a 2-profile solution. Based on fit indices and interpretability, the best fitting model for the facets of Conscientiousness is the FMM with the 2-profile solutions that allow intercepts to vary across profiles.

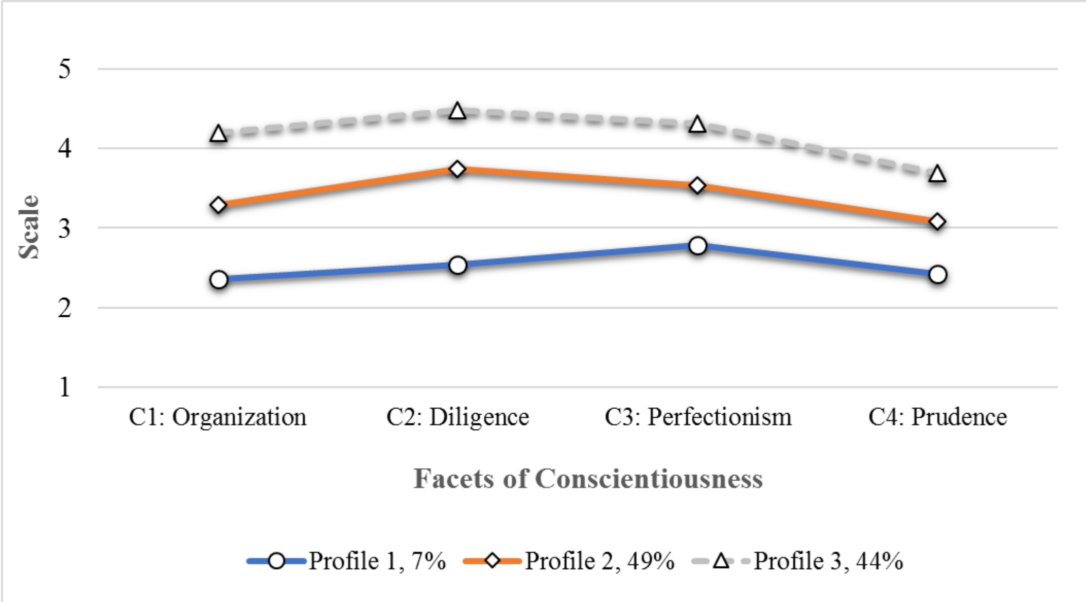

Figure 12. 3-Profile LPA Solution for Conscientiousness Facets

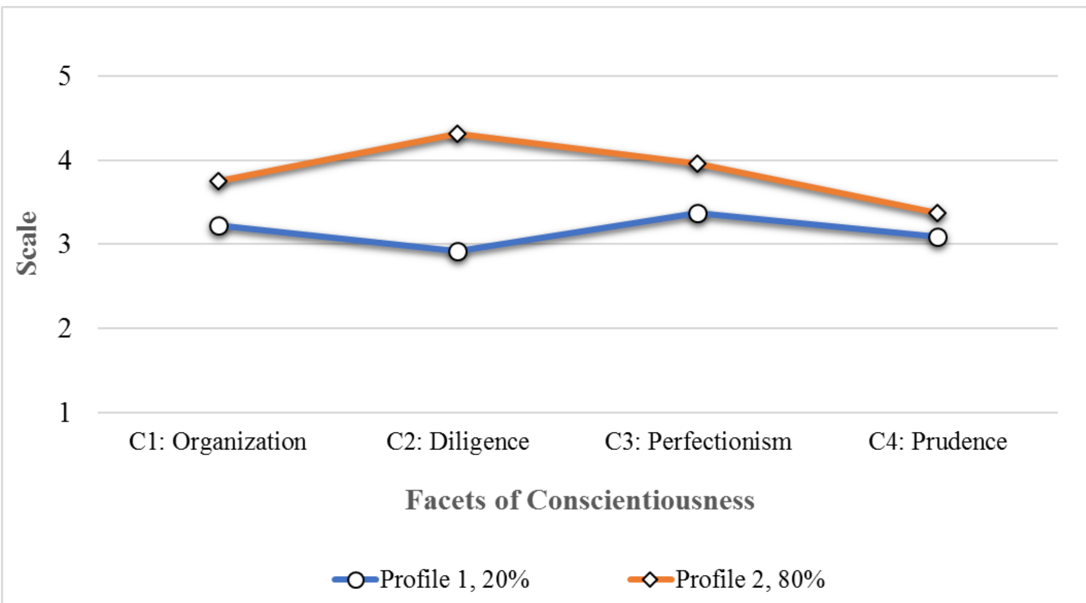

Figure 13. 2-Profile FMM Solution for Conscientiousness Facets

The ANOVA table is presented in Table 18 for the FMM with two profiles. Post hoc analyses (Bonferroni) are presented in Appendix A. The different sources of variance are also highlighted in Table 18, with the greatest proportion attributed to the Factor Scores.

Table 18

Source of Variance of Conscientiousness Variables

Source		Type-III SS	df	MS	F	Var.
Between	Profile (level)	149.28	1.00	149.28	6687.73**	6.35
	Factor Scores	913.16	1.00	913.16	40911.03**	38.82
	Error	19.33	866.00	0.02		
Within	C Facets	53.63	2.70	19.90	47.38**	2.28
	C Facets x Profile (shape)	153.64	2.70	57.01	135.73**	6.53
	C Facets x Factor Scores	82.77	2.70	30.71	73.12**	3.52
	Error	980.30	2334.07	0.42		
Total		2352.11				

Note. ** indicates significant at p<.001. Var. = Unique Proportion of Variance

3.8 Comparing CFA, LPA, and FMM of Openness to Experience Facets

The structure of the models conducted for the Openness to Experience facets is the same as in the previous section on the Honesty-Humility models. In this section, a CFA, LPAs and FMMs of the four Openness to Experience facets were compared in terms of model fit. The same ANOVA design as in the previous section was used.

Table 19 compares the fit indices of the CFA, LPAs, and FMMs. For the CFA, the Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC), and the adjusted BIC (aBIC) values were included. The additional fit indices for the CFA were as follows: X^2 (2) = 10.361, p = .006, RMSEA = .07 (90% CI of .034 – .115), SRMR = .02, CFI = .982 and TLI = .945. The RMSEA and SRMR values were reasonable, falling below the recommended cut-offs. The CFI was above the recommended cut-off of .95, suggesting good fit.

The FMM solution that was selected as optimum is presented in bold. Compared to other FMM solutions, the 3-profile solution with varying intercepts was observed to have the smallest IC values associated with a significant aLRT p-value.

Table 19

Mixture Model Solutions of Openness to Experience Facets

Model	q	AIC	BIC	aBIC	aLRT (p)	E	Prop in Profile
CFA							
	12	8880.37	8937.34	8899.23	--	--	--
LPA							
1-Profile	8	9524.16	9562.36	9536.95	--	--	--
2-Profile	13	9103.55	9165.63	9124.35	.000	.643	.48, .52
3-Profile	**18**	**9043.76**	**9129.72**	**9072.56**	**.033**	**.597**	**.28, .47, .24**
4-Profile	23	8999.62	9109.46	9036.41	.131	.643	.23, .32, .25, .20
5-Profile	28	8990.32	9124.03	9035.10	.478	.668	.20, .29, .24, .08, .20
6-Profile	33	8981.81	9139.39	9034.59	.452	.675	.05, .17, .24, .22, .19, .13
FMM							
1-Profile	12	9068.03	9125.33	9087.22	--	--	--
2-Profile Invar	14	9057.60	9124.46	9080.00	.645	.502	.44, .56
2-Profile Vary	17	9001.74	9082.92	9028.93	.000	.647	.46, .54
3-Profile Invar	16	9036.30	9112.71	9061.89	.003	.745	.42, .24, .34
3-Profile Vary	**22**	**8963.94**	**9069.00**	**8999.13**	**.000**	**.755**	**.24, .39, .37**
4-Profile Invar	18	9036.51	9122.46	9065.30	.489	.684	.30, .24, .28, .19
4-Profile Vary	27	8963.85	9092.79	9007.04	.221	.673	.24, .39, .14, .22

Note. q is the number of estimated parameters in the model.

Table 20 contrasts the standardized loadings of the four Openness to Experience facets on the latent dimension in the CFA with those in the FMM with the three profiles. Except for Unconventionality, the loadings are somewhat smaller in the FMM model because part of the variance in the facet scores is now accounted for by the latent profile variable.

Table 20

Factor Loadings of CFA and Best-fitting FMM of Openness to Experience Facets

Facets	CFA Factor Loadings*	FMM Factor Loadings*
O1: Aesthetic Appreciation	.641	.517

O2: Inquisitiveness	.757	.404
O3: Creativity	.717	.366
O4: Unconventionality	.352	.664

Note. * All factor loadings and intercepts were significant at $p < .001$

Figure 14 illustrates the best fitting LPA that was selected in Table 19 with a 5-profile solution. In contrast, Figure 15 portrays the best fitting FMM selected in Table 19 with a 2-profile solution. However, based on the fit indices in Table 19, neither of these models are optimum for the facets of Openness to Experience. The best fitting model for the facets of Openness to Experience is the CFA.

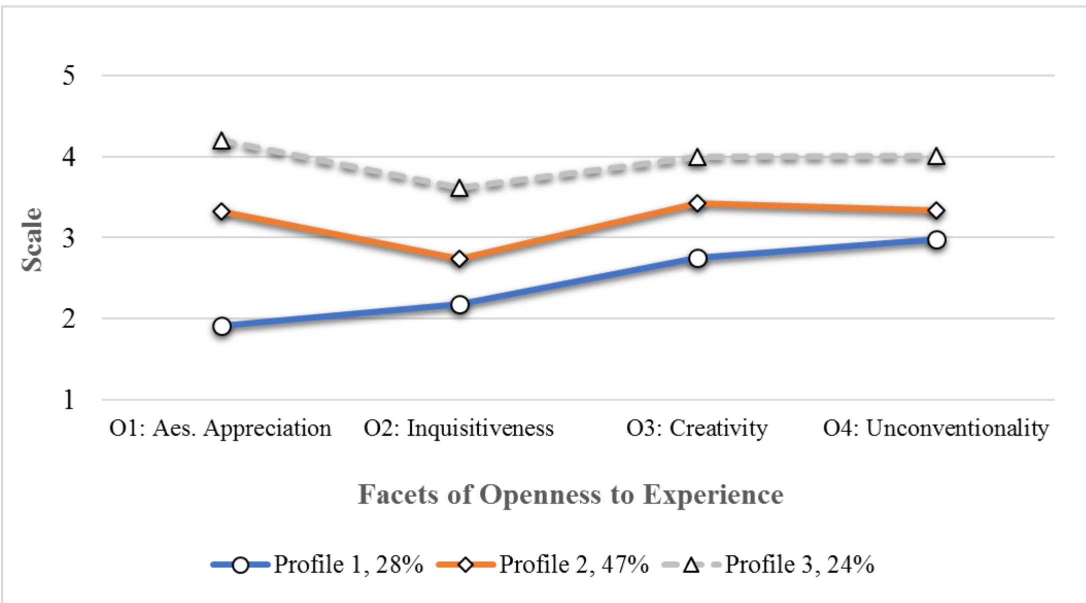

Figure 14. 3-Profile LPA Solution for Openness to Experience Facets

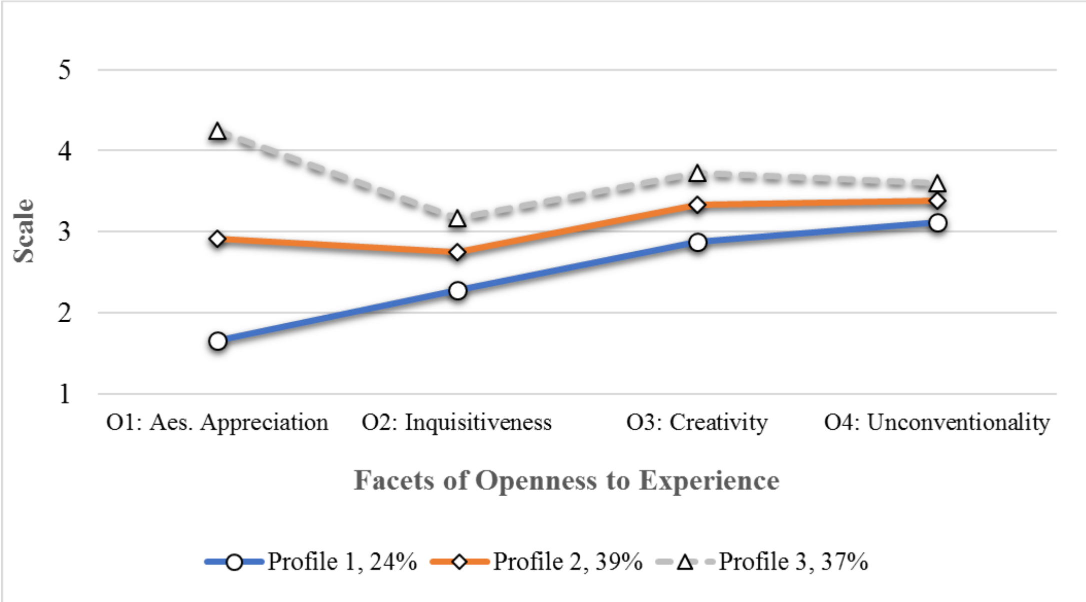

Figure 15. 3-Profile FMM Solution for Openness to Experience Facets

The ANOVA table is presented in Table 21 for the FMM with three profiles. Post hoc analyses (Bonferroni) are presented in Appendix A. The different sources of variance are also highlighted in Table 21, with the greatest proportion attributed to the Factor Scores.

Table 21

Source of Variance of Openness to Experience Variables

Source		Type-III SS	df	MS	F	Var.
Between	Profile (level)	549.52	2.00	274.76	1551.21**	16.92
	Factor Scores	645.42	1.00	645.42	3643.82**	19.88
	Error	150.20	848.00	0.18		
Within	O Facets	216.22	2.22	97.58	154.95**	6.66
	O Facets x Profile (shape)	410.10	4.43	92.54	146.94**	12.63
	O Facets x Factor Scores	92.58	2.22	41.78	66.34**	2.85
	Error	1183.32	1879.07	0.63		
Total		3247.36				

Note. ** indicates significant at p<.001. Var. = Unique Proportion of Variance

3.9 Comparing Best Fit and Sources of Variance across Dimensions

In summary when comparing CFA, LPA and FMMs, the best-fitting models for Emotionality, Agreeableness and Conscientiousness were the FMM, suggesting that these structures are best described in terms of a combination of both the latent factor and profile. The CFA were the optimum models for Honesty-Humility, Extraversion and Openness to Experience, which supports the notion that most of the covariance observed in the facets are due to the factor. Note that there are no tests of significance to determine whether one modeling approach is better than the other. These comparisons are based entirely on comparing AIC, BIC, and aBIC values. It should also be noted that these indices adjust for parsimony (i.e., number of parameters).

To compare the sources of variance from each dimension of HEXACO, the values have been reproduced in Table 22.

Table 22

Proportions of Variance Explained in Each Set of HEXACO Analyses

	H	E	X	A	C	O
Profile (level)	5.97	12.81	3.15	20.12	6.35	16.92
Factor Scores	28.54	34.53	42.95	22.89	38.82	19.88
Facets	13.18	0.88	4.39	2.96	2.28	6.66
Facets by Profile (shape)	10.5	9.55	9.16	11.03	6.53	12.63
Facets by Factor Scores	2.65	7.63	2.57	6.09	3.52	2.85
No. Profiles in FMM	2	3	2	3	2	3

The implications of these findings will be discussed in greater detail in the Discussion section.

CHAPTER 4: DISCUSSION

The preliminary CFA and ESEM of the 24 facets confirmed the factor structure of the HEXACO-PR-R. This is as expected, as the six-factor model proposed by Ashton and Lee (2009a) has been validated extensively in the literature. The facets also demonstrate reasonable fit with their associated factor, as demonstrated by the fit indices and factor loadings in the CFA conducted on the 24 facets and the CFAs on the four facets of each dimension. It was expected that the CFA for each dimension would do well as the facets are highly correlated.

For each of the six dimensions of HEXACO, separate sets of models were tested beginning with a Confirmatory Factor Analysis to establish unidimensionality and essentially a baseline model. Next, Latent Profile Analyses were conducted to assess the correct number of profiles explaining the facets, given that no latent factor is modelled. At last, Factor Mixture Models that combined the effects of the factor and the profiles were run. Although there are several types of FMMs that could be investigated, I focused on models in which the intercepts were constrained to equality across the profiles vs. models in which the intercepts were free to vary. Essentially models with intercepts that vary show differences in means of the observed variables, which translates into different profiles, controlling for the factor.

The ANOVAs for each set of analyses were conducted on the best fitting FMM. In some cases, these FMMs consisted of two or three latent profiles. As explained previously, the ANOVAs included five sources of explained variance. These consisted of the factor scores, the profiles, the facets, the profile by facet interaction (shape) and the facet by factor score interaction. The last source is not that meaningful and could have alternatively been left out of the model (like two other interactions that were left out). These sources of variance are described in detail below.

4.1 Factor Scores

Upon examining the sources of variance, it became clear that the proportion of variance of the factor scores are the largest source of variance across the dimensions. When comparing CFA, LPA and FMM for the facets of Honesty-Humility, Extraversion and Openness to Experience, the best models are the CFA. The FMM is somewhat comparable and there was the least support for the LPA in Extraversion and Openness to Experience. This indicates that different profiles of these dimensions do not provide much information on the structure of this dimension and can be described as more of a variable-centered model, with the factors providing the greatest variance in scores. In fact, the proportion of variance due to the Factor was the highest among the five sources of variance, with values of 29% for Honesty-Humility, 43% for Extraversion and 20% for Openness to Experience.

In contrast, the best fitting models for the facets of Emotionality, Agreeableness and Conscientiousness are the FMM that allow intercepts to vary with varying number of profiles. In these latter models, there is evidence that both the factor and profiles contribute to explaining variance in the observed facet scores. The LPA with four profiles and the LPA with five profiles have slightly better fit indices than the CFA for Emotionality and Agreeableness, but the CFA is a better model than the LPA with three profiles for Conscientiousness. The proportion of variance due to the Factor is still highest among the three dimensions at 35% for Emotionality, 23% for Agreeableness and 39% for Conscientiousness, although the proportion of variance due to the profile is substantial at 13%, 20% and 6%, respectively.

The variance of the factor scores in the ANOVA models is not unlike the variance accounted for by a factor in a factor analysis, regardless of the fact that the ANOVA model uses unique sums of squares (Type III). Although not described in this study, ANOVA models were also ran using a hierarchical approach giving priority to the factor (Type I) in order to uncover all the explainable variance, whether unique or not. The differences between the sources of variance were trivial, and this suggests that there is very little overlapping variance between the latent factor and profile variables. The variance explained by the factor is related to the factor loadings, such that higher factor loadings indicate that the factor is stronger, which will result in higher factor scores. For example, the factor loadings of Extraversion are highest compared to the other dimensions, and Extraversion also has the highest proportion of variance due to the factor scores. In contrast, Openness to Experience has the lowest factor loadings, particularly in Creativity, suggesting that there is a smaller factor effect. To summarize, the variance of the factor scores describes the variability in individual total scores. It is not surprising that this source of variance has the largest effects in comparison to the other latent variables, as the factors of HEXACO are valid and reliable instruments in the literature.

4.2 Profile

The profile on the one hand is a categorical variable that places a respondent in their most likely subpopulation, but it also refers to the mean level score across the observed variables, in this case the four facets. This is also described as the level effect by Morin and Marsh (2015) to refer to profiles that can be summarized as high, medium and low across all indicators. Therefore, these are the overall elevation differences observed for each line in the FMM graphs. In themselves, they are not that interesting because they simply capture leftover variance in elevation once the factor score is accounted for. This is not unlike the presence of a main effect in combination with an interaction. Although we should focus on the interaction, there is still some information about elevation in the main effect.

The dimensions with the greatest differences between the profiles, or the greatest level effects, will have highest proportions of variance explained in their facets by these profiles. This is most notably the case when there are large differences in elevation among the profiles. Across the six set of models, the profile effects were highest in the Agreeableness and Openness to Experience dimensions.

One might expect that once factor scores are taken into account, as in the case for FMM, there would be no unique variance remaining due to the profile or elevation, but it seems not to disappear entirely. However, it can be seen to some extent, when comparing the LPA and FMM graphs that the effect of the profile decreases somewhat in the FMM models. For example, this is evident in the Extraversion models where the two profiles in the FMM models are very tight together and show no more elevation except for one facet.

This remaining source of variance can be explained in an alternative way. Specifically, in FMM, both the factors and the profiles can contribute to the covariance between two facet scores. Figures 16 and 17 below explain this concept. Both figures represent a scatterplot of one observed variable against the other (i.e., Greed Avoidance by Modesty). In Figure 16, we can see a clear linear trend that is due partly to the profile but also to a person's position within a profile. This figure represents the FMM case where both the profile and the factor score contribute to the covariance between two observed variables. In Figure 17, there is also a positive linear relationship but it is due entirely to the profile. Once the profile is partialled out, there would remain no covariance between the two variables. In LPA this would satisfy the assumption of local independence (i.e., only profiles explains covariance between the observed variables).

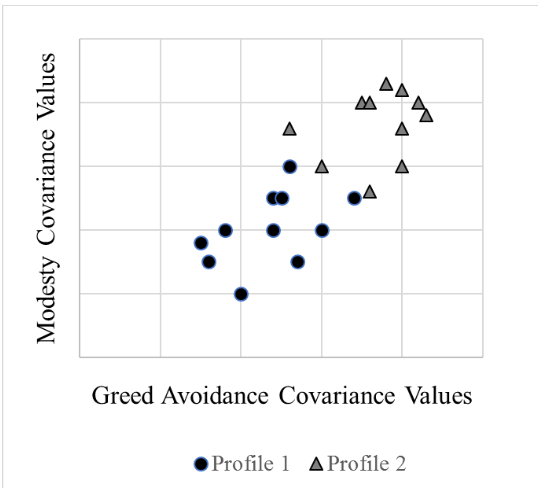

Figure 16. A scatterplot of the covariance values between two facets of Honesty-Humility is displayed when the local independence assumption cannot be assumed, as variation in these scores is due to the profiles

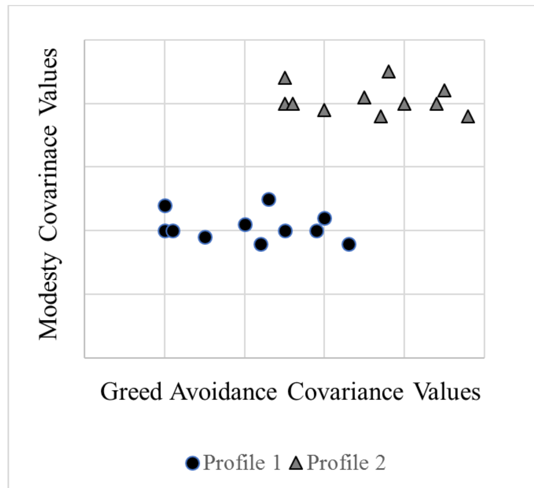

Figure 17. A scatterplot of the covariance values between two facets of Honesty-Humility is displayed when the local independence assumption is not violated, as the covariance between observed variables is only due to distinct profiles.

4.3 Facets

The source of variance attributable to facets is the "repeated measures" effect, and it simply indicates that the sample has higher mean scores on some facets than others. Honesty-Humility has the greatest differences between its facets, such that the average score of Modesty is higher compared to the other facets of this dimension. In contrast, the average differences between the facets of Emotionality were small. It should be noted that the source of variance attributable to the facets is not that informative. In fact, some researchers (see Meyer & Morin, 2016) standardize the observed variable scores (i.e., the facets in this case), eliminating the facet source of variance. Standardization sometimes helps interpret the profile graphs more easily and would be especially important if the observed variables are measured on different scales. In my case, I wanted to evaluate the magnitude of the facets and therefore did not standardize the scores.

4.4 Facets by Factor Scores

As described previously the interaction between the facets and factor scores is not particularly meaningful except for noting that it reflects the fact that some facets are weighted more heavily than others in the calculation of the factor scores. This is observable in the CFA and FMM loadings. More specifically this source of variance seems to be higher when there is a larger discrepancy in the factor loadings. Across the six dimensions, factor loadings for the facets are all relatively similar and small differences in the range of these loadings account for this source of variance.

4.5 Facets by Profile Interaction: Shape

In a sense, the interaction between the facets and the profiles is the primary source of interest to researchers who investigate profiles. The aim in profile analysis is to uncover qualitatively different profiles, rather than profiles that only differ in elevation (Morin & Marsh, 2015). One important question in my study is to determine how much variance is explained by the facet by profile interaction (the shape element of profile analysis) controlling for factor scores. This study essentially addressed the point raised by Ashton and Lee (2009b) when they questioned whether profiles would explain much variance controlling for factor score.

Profiles with distinct shapes between them (i.e., non-parallel profiles) will have greater values for this variance effect. This is observed in Openness to Experience, where the distance between the profiles decreases across the profiles, such that Aesthetic Appreciation is distinct between the profiles, yet Unconventionality is very similar across the three profiles. In contrast, the dimension of Consciousness has a low value for this variance, suggesting that the shapes of the profiles are not as pronounced as the profiles from other dimensions. Although the differences in the profiles are a bit larger for Diligence than for the other facets of Conscientiousness, the lines do not depart dramatically from parallelism, and the amount of variance explained by the shape is the smallest (6.53%) compared with the other traits. It seems that when averaging across the six sets of models, the Shape component accounts for roughly 10 % of the variance after controlling for other sources of variance, but that amount can vary substantially. It should be noted that this value could be higher or lower in other types of unexplored models.

A brief comment is warranted on the shape in the other five traits. For the Honesty-Humility trait, it is the Fairness facet that stands out at contributing to the shape pattern. In the HEXACO, Fairness is defined as the tendency to avoid fraud and corruption. People with low scores in this facet are more likely to cheat or steal, whereas those with high scores are unwilling to exploit others for personal gain. It is not evident why high vs. low Honesty-Humility individuals should differ more on this facet than on the other three (Sincerity, Greed-Avoidance, Modesty). One speculation is that Fairness might differentiate to some extent law-abiding individuals which may not necessarily be as high on the other three facets of Sincerity, Greed-Avoidance and Modesty.

For the Emotionality Trait, it is the Anxiety facet that contributes to the shape effect. The other three facets are Fear, Dependence, and Sentimentality. Although it may seem surprising that anxiety and fear did not behave identically, it may be the case that anxiety addresses a unique affect disposition that differs from fear.

For the Extraversion trait, it was Social Self Esteem that was responsible for the shape effect. In the HEXACO, Social Self-Esteem is conceptualized as the tendency to have positive self-regard in social contexts. People with low scores in this facet are more likely to sense personal worthlessness and see themselves as unpopular, whereas those with high scores see themselves as having favourable qualities and are generally satisfied with themselves. It seems reasonable that Social Self-Esteem may have contributed to these results because it focuses specifically on the self, whereas the other three facets of Social Boldness, Sociability, and Liveliness are more behavioural.

For the Agreeableness dimension, the facet Patience is responsible for the shape effect. In the HEXACO, Patience is the tendency to remain calm rather than to become angry. People who score higher tend to have higher thresholds for feeling or expressing anger, whereas individuals with low scores tend to lose their tempers quickly. The other three facets are Forgiveness, Gentleness, and Flexibility. It is certainly possible for people who are seen as agreeable to show some differences in patience.

Similar findings are observed for the Conscientiousness profile, in which Diligence is the facet that is driving the shape effect. Diligence is the tendency to work hard, such that high scores indicate strong work ethic.

For the Openness to Experience trait, it was the facet of Aesthetic Appreciation that contributed to the shape effect. In the HEXACO, Aesthetic Appreciation is the tendency to enjoy beauty in art and nature. People who score high on this facet tend to have a strong appreciation for art and nature, whereas those with low scores find it difficult to become absorbed in art forms and natural wonders. The other facets are Inquisitiveness, Creativity, and Unconventionality. These results suggest that it is possible for people who have relatively similar scores in Openness to Experience to show some heterogeneity in Aesthetic Appreciation.

In summary, it was possible to identify one facet that was responsible for the shape effect. One may wonder whether the facet that stands out from the others would also stand out in the CFAs. It does seem that across the six sets of analyses to the exception of Openness to Experience, the facets that were identified as contributing to the shape effect also had lower loadings on their factor, most notably in the FMMs. Thus, it seems that the shape effect is not entirely unrelated to the composition of the factor. Future research will be needed to understand this connection more clearly.

4.6 Implications and Limitations

The main purpose of this study was to contribute to knowledge of the application of mixture modelling to the structure of personality traits. The rise in interest in potential trait profiles was met by a caution in Ashton and Lee (2009b). They suggested that once we control for factor scores, there is little evidence that qualitative profiles would explain much additional unique variance in behaviour. In my study, I addressed Ashton and Lee’s point by using a combination of state-of-the-art methodology in mixture modeling and more traditional but effective analysis of variance models to evaluate the merits of latent profiles in terms of model fit and variance explained. To my knowledge no studies so far have merged latent profiles and latent dimensions into factor mixture models to compare the various sources of variance in facet expression. Although Morin and Marsh (2015) proposed how to compare various mixture and factor analytic models and related these to analysis of variance, this study is the first to apply these ideas to personality trait data. Within personality research, the question of the latent dimensional vs. categorical variables is of interest, as these complex constructs are often used in applied settings (Meyer & Morin, 2016). It is important to acknowledge that this study focused on a limited and simple scenario of modeling only four facets underlying a well established factor structure. More specifically, it was expected that the very simple CFA models with one-factor and four facets as the observed variables would fit well and explain a large portion of the variance, given that these factors have been well established. These analyses were replicated across the six dimensions to explore variations in model fit and variance explained.

An interesting question was whether an alternative model that focuses on profiles could explain the relations among the facets equally well, and in general it did not. More specifically the CFAs had the best model fit in most cases based on the AIC, BIC, and ABIC indices. In some cases the FMMs matched the fit of the CFAs, and although these may seem less parsimonious, their level of complexity is accounted for by the fit indices. It can be argued that both CFAs and FMMs provide equally valid models.

This is context specific in the sense that the observed variables were known to be highly correlated and explainable by an underlying factor. Other contexts could generate stronger profiles and weaker factors. For example, researchers who model the Big Five or the six factors in the HEXACO would likely not incorporate an underlying dimensional factor to explain relations between the six factors because these factors are fairly independent. The context in my study was ideal for Factor Mixture Modelling because it was reasonable to expect a strong underlying factor but perhaps also the influence of qualitatively different profiles of responses across the four facets.

In addition to the caution raised by Ashton and Lee (2009b), another challenge for the application of mixture models is that although there is evidence that distinct profiles of personality are obtainable (and to some degree, replicable), some researchers have merely observed level or elevation differences across personality profiles. More specifically this refers to patterns where the profiles can be described as essentially scoring high, medium, and low on a set of observed variables. Morin and Marsh (2015) drew attention to this and suggested that an important prerequisite to interpret the meaningfulness of profiles is that they differ beyond elevation and that differences in their shapes are observable.

There are two noteworthy limitations of this study. The first is that the data set used was based on the short version of the HEXACO. As such the facets are assessed with only two to three items each, and this small number places a limit on the reliability of the observed scores. Using the longer form of HEXACO (such as the 100 item or 200 item forms) would improve the reliability of the facets and perhaps decrease the unexplained proportion of variance due to error.

The second limitation is the simplicity of the sets of variables that were used in each model. More specifically these consisted of well defined facets with strong underlying factors. At the same time, it is a good idea to start with simple cases when complex methods are fairly new.

Despite these limitations, this study provides a methodological contribution to the understanding of Factor Mixture Models. Other than the Morin and Marsh study in 2015, this is the only study that has deconstructed the sources of variance in a FMM. In addition, this study examined the effects of allowing intercepts to vary across profiles. Other studies may focus on the effects of having different parameters be unrestricted across profiles, such as the factor loadings. Future studies that contrast models that focus on different parameters would likely be informative. Learning more about FMM will also require other sets of observed variables that may have different patterns of correlations and covariances. Improving the understanding of how to apply these procedures to better account for the sources of unobserved heterogeneity is of great value to vast areas of research.

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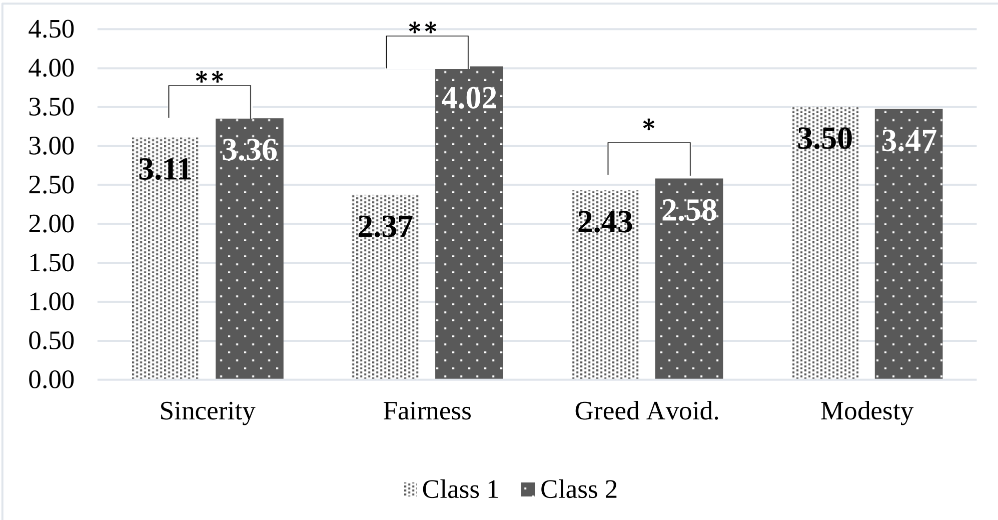
APPENDICES

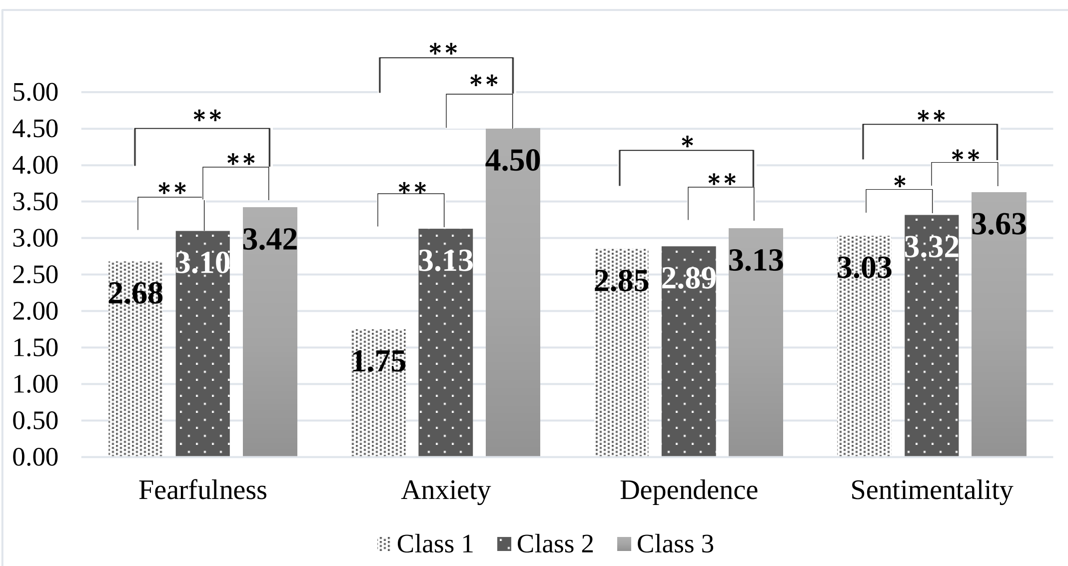
Appendix A: Bonferroni Pairwise Comparisons for ANOVA Tests

Pairwise Comparisons between Profile by Facet Scores in Honesty-Humility



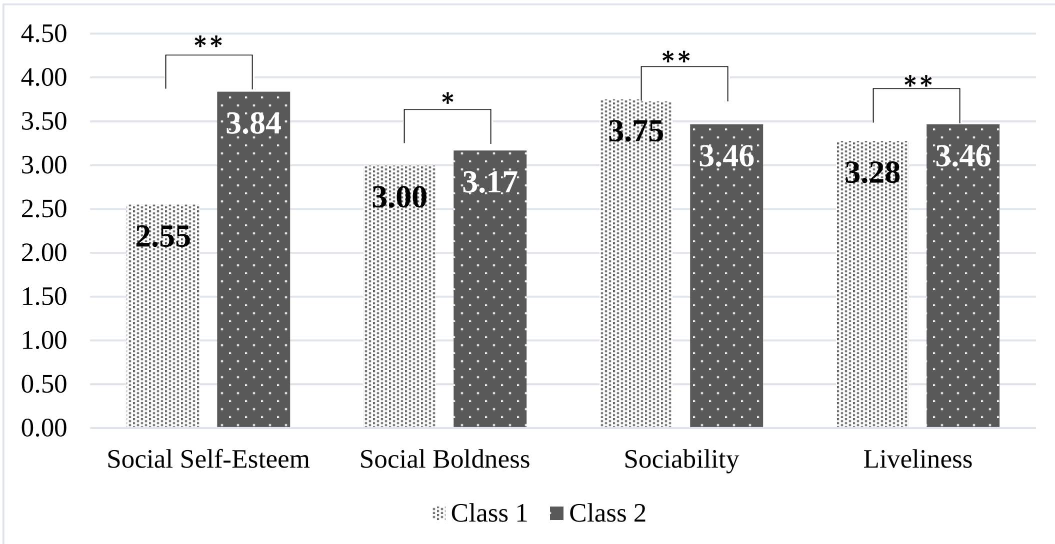
Note. * indicates significance at p<.05; ** indicates significant at p<.001.

Pairwise Comparisons between Profile by Facet Scores in Emotionality



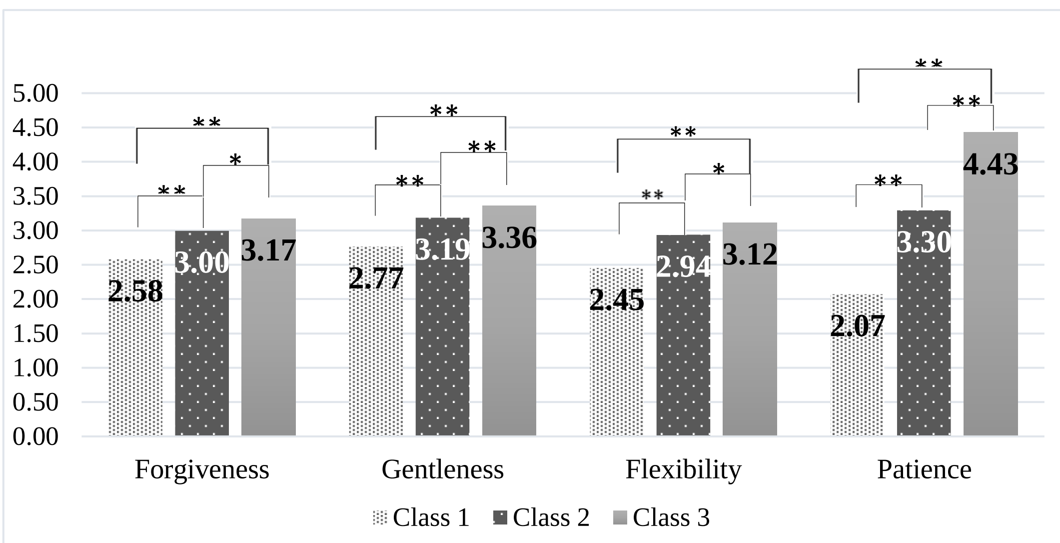
Note. * indicates significance at p<.05; ** indicates significant at p<.001.

Pairwise Comparisons between Profile by Facet Scores in Extraversion



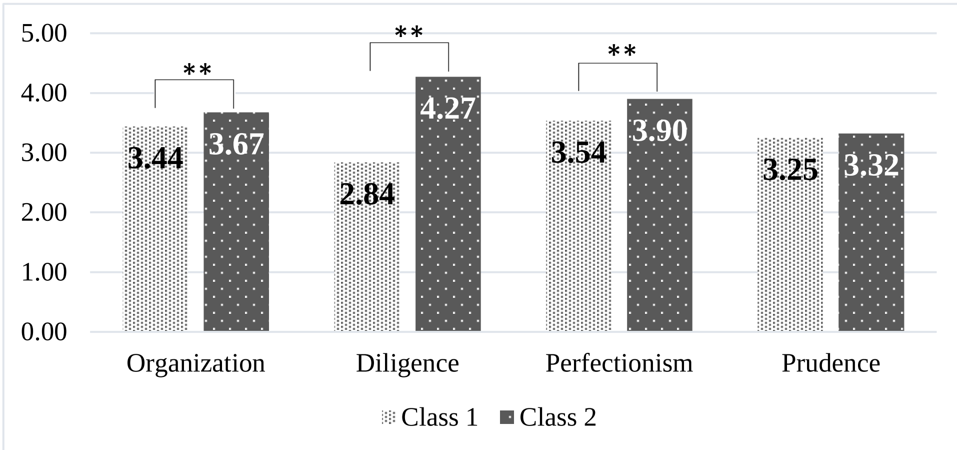
Note. ** indicates significant at p<.001; * indicates significance at p<.05.

Pairwise Comparisons between Profile by Facet Scores in Agreeableness



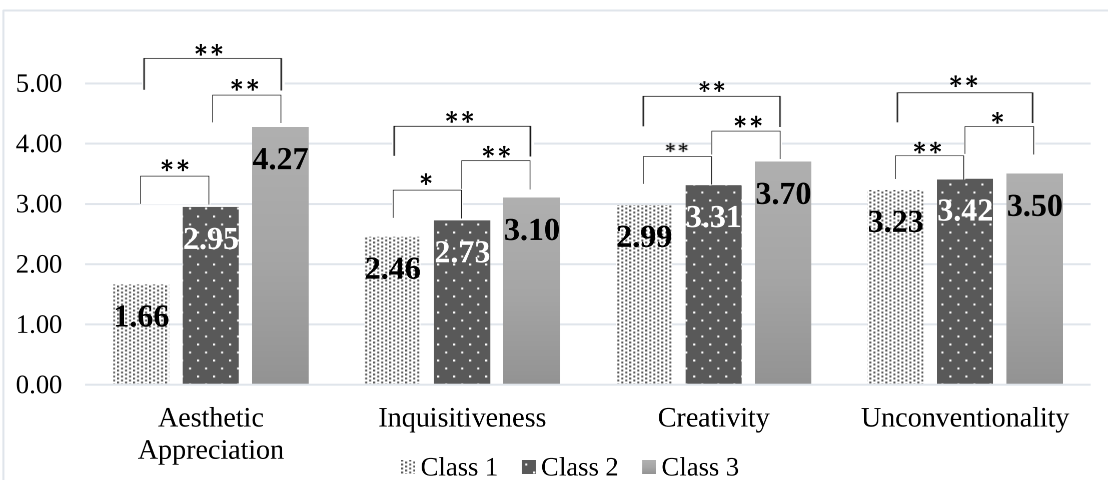
Note. * indicates significance at p<.05; ** indicates significant at p<.001.

Pairwise Comparisons between Profile by Facet Scores in Conscientiousness



Note. * indicates significance at p<.05; ** indicates significant at p<.001.

Pairwise Comparisons between Profile by Facet Scores in Openness to Experience



Note. * indicates significance at p<.05; ** indicates significant at p<.001.

CURRICULUM VITAE

Name:	Carolina Patryluk
Post-secondary Education and Degrees:	York University Toronto, Ontario, Canada 2009-2014 - BA (Hons)
	Western University London, Ontario, Canada 2015-2017 - MSc
Honours and Awards:	York University cum laude & Dean's Honour Roll list 2014
	Ralph S. Devereux Award in Psychology 2016
Related Work Experience:	Research Assistant & Statistical Advisor York University 2011-2013
	Research Assistant Pearson Clinical Assessment 2013-2015
	Teaching Assistant Western University 2016-2017
	Graduate Student Assistant (GSA) Western University 2016-2017
	Research Assistant & Statistical Advisor Fanshawe College 2016-2017
Conferences:	*Examining the efficacy of CBT for delusions: A meta-analysis approach.* OPU Thesis Conference. Toronto 2013
	WISC-V Canadian. OPA, Toronto 2014

Comparing BASC2-Parent Rating Scales among Canadian and American children with ADHD. APA, Toronto
2015

Mixture Modelling of The HEXACO Personality Inventory, APA. Toronto
2017

Examining Risk Factors for University Students using LPA, CACUSS, Ottawa.
2017