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Personality Style Clusters Using Unsupervised Machine Learning

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PERSONALITY STYLE CLUSTERS USING UNSUPERVISED MACHINE LEARNING

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ABSTRACT

This study replicates and then refutes portions of an article published in Nature by Gerlach, Farb, Revelle, & Nunes Amaral (2018) on personality clusters. The central claim of the current study is that the clusters were actually biases in the data, based on central tendency and social desirability biases. We find that with proper preprocessing of our data, that all personality clusters found in the Gerlach et al. (2018) study cease to exist as anything but random noise. The interpretation of these findings is that careless responding, response styles, and characteristics of Likert scale style data can lead to artificial clustering, leading to improper interpretation of the frequency of occurrence of certain arrangements of personality traits. The implications of these findings are that unsupervised machine learning approaches can be especially useful in personality research, but misuse of these approaches can lead to misleading results.

Keywords: personality, machine learning, unsupervised, hypothetico-deductive model, inductive reasoning, deductive reasoning, clustering, social desirability bias, central tendency bias.

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INTRODUCTION

History of the Lexical Hypothesis of Personality

Personality and related concepts have been discussed for millennia (Merenda, 1987). The modern interpretation of personality arose from assumptions about language being a good place to look for generalizable personality characteristics of human beings. The lexical hypothesis of personality states that personality characteristics of a society will have words in the language that represent fundamental personality characteristics (Cattell, 1943).

A quote from Francis Galton (1884) is recognized as a key starting point for the study of the lexical hypothesis of personality.

> I tried to gain an idea of the number of the more conspicuous aspects of the character by counting in an appropriate dictionary the words used to express them... I examined many pages of its index here and there as samples of the whole, and estimated that it contained fully one thousand words expressive of character, each of which has a separate shade of meaning, while each shares a large part of its meaning with some of the rest.

This quote gets to the heart of the primary premise of this study. The focus of this study is on what personality characteristics have in common and how those commonalties are represented. This means that when non-experts think of their own personality, they look for how their traits all form a cohesive whole, a distinctive pattern. Likewise, people feel that current research is deficient because it does not offer them personality as a cohesive whole, just an assortment of traits. This is where something like factor analysis or principal component analysis can come in to study a concept using multiple related items to measure the underlying construct.

Problems in Personality Research Prior to Big Five

The study of personality has had its difficulties. Criticisms by people like Walter Mischel essentially brought the field to a standstill (Mischel, 1968, 2004; Mischel et al., 2016; Mischel & Shoda, 1995). For example, one interpretation of Mischel is that personality is not a trait per se, but fundamentally is a set of adaptive strategies that individuals evolve to handle various situations. This decline of personality research may not have been the intent of Walter Mischel and his colleagues, what they were likely trying to do was show that personality was stable at a lower level of analysis, the situational level, instead of the global level. However, Stability at the situational level has been supported in studies of personality over the past few decades (Dunlop, 2015; Dunlop & Hanley, 2019; Heller et al., 2007; Robie et al., 2017; Shaffer & Postlethwaite, 2012; van Oers et al., 2005). Support for traditional personality approaches seemed to be diminishing and being replaced by other predictors of performance.

However, with the rise of the Five Factor Framework, studied by multiple research groups independently (Costa & Mccrae, 1992; Goldberg, 1990, 1992, 1993; R. R. McCrae & Costa, 1987; R. R. McCrae & John, 1992; Tupes & Christal, 1992), support for the global conception of personality began to increase. The Five Factor Framework allowed for the study of consistent, cross-culturally relevant personality traits. This was a major breakthrough in the field because, before this time, there were at least four key issues:

(1) Thousands upon thousands of personality traits were created but replication studies rarely supported their existence

(2) There was no overarching framework for researchers to work within

(3) Constructs that measured the same qualities were called different names

(4) Constructs that measured different qualities were called the same names

There is some dispute at the edges of the Big Five, such as maybe a sixth factor called Honesty-Humility being legitimate across cultures. Another issue is the proliferation of "facets" within the Big Five model (Johnson, 2014). Honesty-Humility is usually associated with the HEXACO model (Ashton et al., 2004; Ashton & Lee, 2009). However, the four key issues studied for most of the 1900s, have been mostly resolved by the Five Factor Framework.

Problems in Personality Research After Big Five

After the Big Five framework was largely accepted within the research community, researchers concluded that personality is legitimate to consider for predictive purposes (Dudley et al., 2006; Dunlop, 2015; Oh et al., 2011; Poropat, 2009; Shaffer & Postlethwaite, 2012). Now for the sake of most accurately predicting outcome variables, like job performance, researchers are deciding best practices for measuring personality for usage as a predictor of job performance. Some of the issues that have arisen to prominence in personality since the advent of the Five Factor Framework are:

(1) That personality might be most predictive at the facet or aspect levels (Credé et al., 2016; DeYoung et al., 2007, 2016; Dudley et al., 2006; Johnson, 2014; Paunonen & Ashton, 2013),

(2) The contextualization of personality (Baird & Lucas, 2011; Church et al., 2008; Dunlop, 2015; Dunlop & Hanley, 2019; Heller et al., 2007; Poropat, 2009; Robie et al., 2017; Shaffer & Postlethwaite, 2012; van Oers et al., 2005)

(3) Person-situation interactions, such as how situations can change expressed personality (Buss, 2009; Church et al., 2008; Fleeson, 2016; Fleeson & Noftle, 2009; Funder, 2006; funder et al., 2012; Funder, 2016; Furr & Funder, 2004; Geiser et al., 2015; Geukes et al., 2012; Griffo & Colvin, 2009; Hill & Lapsley, 2009; R. Hogan, 2009; Johnson, 2009; Judge & Zapata, 2014; Kuppens, 2009; Lucas & Donnellan, 2009; Michael Furr, 2009; Mischel, 2004; Mischel et al., 2016; Mischel & Shoda, 1995; Roberts & Caspi, 2001; Ross et al., 2011; Sherman et al., 2015; Shiner, 2009; Tett & Guterman, 2000; Tracy et al., 2009; van Oers et al., 2005; Webster, 2009)

(4) That personality does not fully converge between other-reports and self-reports (Coolidge et al., 1995; R. R. McCrae, 1993, 1994; R. R. McCrae & Costa, 1987; R. R. McCrae & Weiss, 2007; Oh et al., 2011).

The author of this paper believes there are two primary reasons for the differences between self-report and other ratings. One is that other ratings tend to be naturally contextualized since the observer only knows the person in specific contexts. The second is that the observer rating focuses specifically on behaviors of the person being observed. A person rating themselves considers their affect and cognitions, which are more distally related to the outcome variables being studied. Observer ratings are a mix of the observee's behavior and the observer's thoughts on the person as a whole. Observer's thoughts on the person can include biases, prejudices, and other characteristics unrelated to the actual trait being measured. This is in contrast to self-report ratings which are based on their thoughts, feelings, and perceptions of their behavior. The commonly mentioned quote about how we judge ourselves based on intentions and others based on behavior, perfectly sums up the differences between self-report and other-reports. Recognizing the role that the Fundamental Attribution Error plays in how people differentially answer self vs other reports is important for deciding whether the reports are actually tapping into the same construct.

The problem of facet or aspect level is obviously an issue of granularity. At its most basic level, researchers can look at three extremely specific categories of an individual: thoughts, feelings, and behaviors. If researchers know specifically what we are trying to predict, this level of granularity can be highly predictive. One level up is some combination within any of the three categories. A level up from that then is some combinations across categories. The Big Five personality traits show up at a level above basic combinations of the three categories, where combinations of categories are then combined to such a degree that researchers have a parsimonious amount of traits that can fit in working memory, meaning about five traits. The author of this study believes all psychological variables have to fit within the bounds of working memory, in order for them to be cohesive strategies to use in order to interact with the world.

Why Non-Experts Buy Into Pseudoscientific Personality Measures

There has been a great disparity between the personality measures studied in psychology by experts in the field and the personality measures that the average person buys into. Many people believe this is entirely the fault of non-experts. The author of this study believes that is only partly the case. Personality researchers have not fully studied the disparity between what non-experts of personality want from personality research and what personality researchers can provide from research studies. The author of this paper believes the disparity is primarily because of two reasons:

Inter-Personal Usage of Personality Information.

One reason for the disparity is that the measures studied by personality psychologists are created to be best understood and interpreted by people trained in the field, so they are optimized to not necessarily be easily interpretable by the average person. This is a problem related to lack of training by the people who are interested in personality but are not qualified to understand how to interpret results of personality tests correctly. This then leads to an inability to apply the results if the results cannot be correctly interpreted. Hence, the utility of valid personality test results, to the average person, is nullified or at the very least has a strong barrier to proper usage of results. A major factor to consider in this barrier to usage is that personality measures use statistics that non-experts are simply not trained in. Problems of inability to understand statistics is a growing problem in society that shows up in areas such as fake news (Best, 2001; Huff, 1993; Wheeler, 1976) and even in the implementation of artificial intelligence solutions for evaluative purposes, where bias and discrimination might arise (Cinnamon, 2017; O'Neil, 2016; Prates et al., 2019).

People want to know ways they disagree with each other on specific dimensions, which unfortunately typologies do artificially by washing away meaningful continuous data into vague dichotomies. This social comparison taps into people's desire to understand specific differences between them and others, what the author of this study considers to be the primary inter-personal usage of personality measures. An understanding of statistics would give them a better idea of the degree to which they differ and might come in conflict with others. It still does not offer people the clear black and white dichotomous choice they are looking for, and the researchers contend that legitimate measures should not cater to this notion either. This is the first of two reasons that personality tests are misunderstood and not accepted by non-experts.

Important Distinction for Intra-Personal Usage of Personality Information.

The researcher of this study also believe a distinction needs to be made. Researchers up until this point have called two separate phenomenon the same thing. Personality "types" is used as a term for the dichotomous choice between what actual researchers have accepted to truly be a continuum. Examples of personality types come from the commonly used Myers Briggs Typology Indicator (MBTI), such as

Introversion-Extroversion dichotomy. Research supports differing levels of introversion/extroversion, so dichotomizing the data is considered to be statistically illegitimate because the data researchers obtain is continuous and the people interpreting the data are cleaving it into two neat categories and washing away any nuance in the data. The only time categorizing continuous data is considered legitimate is if there meaningful categories in the real world, though even the results of that rule of thumb are mixed at best (Ofuya et al., 2014).

Intra-Personal Usage of Personality Information.

The other major reason for the disparity is that the field of personality psychology has not done a good enough job of producing measures that are meaningful to the individual consumer. If we take the Big Five personality traits as an example, researchers can tell an individual how they rate on any of the Big Five but researchers cannot tell them what all of their primary personality traits say about them as a whole. The primary intra-personal use of personality measures is for people to understand their own personality holistically. This is because they want to monitor whether they are acting consistently and the way that they think is best, given their goals and the situation. The researcher of this paper remembers when he took the MBTI out of curiosity for why people liked it so much, despite all its flaws. The research also remembers the feeling of accuracy when the results were spewed out saying that not only was he an INTJ but they even gave a fancy label of “The Mastermind”. The test tried to use this label to tell him how his personality meshed with other personality “styles”. While the Five Factor Framework might never offer people fanciful titles of “The Mastermind” or “The

Protector", there is no reason to assume that given large enough sample sizes and the right statistical techniques, that the cross-culturally legitimized big five personality traits could not be combined into personality styles for the sake of better prediction.

Some studies have been done on MBTI, and they found problems like artificial dichotomizations and other problems in terms of item creation, validity, etc. These results support the notion that MBTI has pseudoscientific qualities that delegitimize it (Boyle, 1995; R. McCrae & Costa, 1989; Pittenger, 1993; Sipps et al., 2016). Other personality measures popular among non-experts include measures such as Enneagram. Enneagram has similar problems with validity and item creation (Newgent et al., 2004). However, despite considering it a personality type indicator, it gives you something more resembling personality "styles" where the overarching result you get is the summation of all your results. This resembles a different level of analysis for the MBTI as well, where instead of personality type being the individual dichotomous choices, people who buy into MBTI are interested in what their personality says about them as a whole. Example being, MBTI gives 4 dichotomous choices: Intuitive/Sensing, Introversion/Extraversion, Feeling/Thinking, and Perception/Judging (Boyd & Brown, 2005; Higgs, 1996; Jafrani et al., 2017; Opt & Loffredo, 2003; Pittenger, 1993; Schell et al., 2012; Sliwa & Shade-Zeldow, 1994; Stilwell et al., 2000; Swanson et al., 2010; Yang et al., 2016). They call this personality typing or typology. They also call the grouping of all 4 results together personality typing/typology, but in reality, it is more similar to the overall results of Enneagram, which the researcher of this manuscript describes more as personality styles.

The latter grouping of personality into holistic styles can be done either based on dichotomous data (as in MBTI) or more scientifically legitimately, it can be done based off of continuous data, such as with the Big Five personality framework. The latter of which has been very rarely studied, most recently in articles such as Gerlach et al. (2018) published in Nature. The Gerlach et al. (2018) article describes a process of finding personality styles through gaussian mixture modeling (GMM), which is a specific clustering technique of the distribution-based clustering tradition (Cole & Bauer, 2016).

Personality Defined.

The starting point for this study can be found on the American Psychological Association website for the definition of personality (*Personality*, n.d.).

> Personality refers to individual differences in characteristic patterns of thinking, feeling, and behaving. The study of personality focuses on two broad areas:
>
> 1. One is understanding individual differences in particular personality characteristics, such as sociability or irritability.
>
> 2. The other is understanding how the various parts of a person come together as a whole.

We can see from this definition that personality research has always ideally cared about "understanding how the various parts of a person come together as a whole".

Personality researchers though have been focused on, rightfully so, trying to decide the specifics of what characteristics are cross-culturally relevant to all of humanity. Focusing on specifics like this was necessary, at first, to then go on and substantiate the study of personality holistically. Without validated component parts, creating a holistic representation of a person's personality would justifiably be considered illegitimate by researchers since we would need to know what our building blocks are before creating an amalgamation construct. This supports the researcher's assumption about the intra-personal usage of personality information for non-experts. This is the non-experts' more legitimately defensible complaint about the Five Factor Framework's deficiencies. Studying personality holistically is a domain that is entirely possible to study but the field has only just recently reached the point where it was viable and legitimate to focus on this type of personality research.

Other Instances of Combining Big Five.

There is already evidence that personality research is trending towards further study of personality holistically or at least in larger constructs than just the Big Five. Examples being stability and plasticity (Digman, 1997; Hirsh et al., 2009; Liu & Campbell, 2017), compound traits (Christiansen & Tett, 2013; Credé et al., 2016; J. Hogan et al., 1984; Hough & Oswald, 2000), and also a general personality factor (Christiansen & Tett, 2013; Musek, 2007; Rushton & Irwing, 2008; van der Linden et al., 2018; Viswesvaran et al., 2005). Personality "styles", where researchers find specific combinations of the Big Five and use them for predictive purposes, is just another variation of this.

Compound personality traits can also be considered an instance of studying personality more holistically than just the Big Five separately. Compound traits are linear combinations of big five personality traits that can be weighted in some way, if necessary (Credé et al., 2016). This can be seen specifically in research on customer service orientation (Christiansen & Tett, 2013; J. Hogan et al., 1984; Hough & Oswald, 2000). This is essentially saying that whether certain personality styles occur more frequently in the population or not, some combinations of traits at varying levels, can be most effective for certain types of outcome variables. This is basic criterion validity related support for the idea that personality styles can serve a legitimate function in modern organizations.

The traits that were formerly known as alpha and beta, are commonly called stability and plasticity now (DeYoung et al., 2002; Digman, 1997). Alpha is superordinate to conscientiousness, agreeableness, and neuroticism. Beta is considered to be superordinate to openness to new experience and extroversion. Alpha is now interpreted as stability factors of personality, hence named stability. Beta is known as the plasticity dimension, dealing with a person's cognitive flexibility, hence named plasticity. This is a different form of grouping personality traits to say that some things co-occur for specific reasons, whether that is because of similarity, some evolutionary purpose, some unknown reason, or some combination is currently largely unknown.

Finally, there is the general factor of personality which interprets the Big Five as having a single overarching personality factor. It is assumed that this personality factor is related to things like life satisfaction, well-being, self-esteem, and emotionality

(Musek, 2007). Some genetic research has supported this notion of a general personality factor. When studying twins, there is evidence that the socially desirable aspects of personality can be partially inherited (Rushton & Irwing, 2008). This also is essentially the factor that is equivalent to the Role Model cluster found within the Gerlach et al. (2018). Other prior research has shown that this general personality factor is likely the result of both testing artifacts and social desirability (de Vries, 2011; Linden et al., 2018; MacCann et al., 2017; Musek, 2007; Revelle & Wilt, 2013; Rushton & Irwing, 2008; van der Linden et al., 2010, 2018). This provides strong supporting evidence that at least one of the clusters found in Gerlach et al. (2018) was likely due to factors outside of the actual personality dimensions of interest.

Psychological Research Strategies

Traditionally, the hypothetico-deductive model has been the primary way that scientific inquiry supported relationships between variables. The author of this paper believes that researchers should reconsider the value of inductive reasoning because of the new era of big data and machine learning that we find ourselves in.

Inductive Reasoning, Exploratory Analyses, Prediction, and Data-Driven Research.

For this study to be considered legitimate, a justification needs to be made for the legitimacy of inductive reasoning, exploratory analyses, prediction over explanation, and overall data-driven research. This is not to say that the author of this study does not value deductive reasoning, explanatory analyses, explanation, or theory-driven research. The researcher is saying that in the coming era of big data and machine learning, concepts researchers previously dismissed, are becoming legitimized.

This would not be the first time that researchers have had to consider multiple sides of a debate and coming to some type of synthesis. When talking about the nature and nurture debate, research had to conclude that both were important and there were even found to be some interaction terms such as epigenetics. The same goes for quantitative vs qualitative research giving rise to mixed methods research where both quantitative and qualitative research traditions complement each other in the study of concepts of interest.

Prior Concerns with Inductive Reasoning for Psychological Research.

Inductive reasoning can be considered a bottom-up research strategy (Haig, 2013). This traditionally has not been widely accepted as a method of learning about psychological phenomenon. Partially this can be attributed to the problem researchers now face, of p-hacking, where researchers either ignore their prior hypotheses or thoughtlessly sift through data until they find something statistically significant (Head et al., 2015). P-hacking inflates Type 1 error rate and makes the research community cautious about any usage of exploration of the data to make an inductive argument about the population as a whole (Head et al., 2015). The author of this manuscript believes that intentional usage of this strategy can serve a functional role within scientific inquiry, so long as it is both (1) decided upon at the outset of the research study and also (2) explicitly mentioned when making inferences and discussing conclusions of the research studies.

Why Deductive Reasoning was Considered the Only Legitimate Research Strategy.

The prior notion of deductive reasoning being the only legitimate strategy for conducting psychological research partially stems from the problems of p-hacking discussed earlier but also partially from the sample sizes in the hundreds or potentially even just dozens, that researchers used to have to work with. It becomes far easier in those circumstances not only for p-hacking but for our very small samples to be unrepresentative of the phenomenon in the intended population as a whole. Biased, small sample sizes contribute to the dual crises that psychological research faces in modern times of the replication and generalizability crises (John et al., 2012; Neuroskeptic, 2012).

New Research Strategies for Psychological Research.

With the advent of big data and machine learning, psychological researchers have had to take a second look at inductive reasoning to see whether it is a viable strategy for understanding psychological phenomenon. Researchers now have sample sizes in the hundreds of thousands, if not millions, that is easily accessible. When our samples are such a considerable proportion of the population, it is nearly always necessarily more representative of the population. This legitimizes inductive reasoning style research for learning about psychological phenomenon.

Using unsupervised machine learning algorithms, such as cluster analysis, is usually scoffed at within traditional research circles in psychology. This likely arises from how traditionally researchers have had small sample sizes and in order to support research findings, we would have to use the hypothetico-deductive reasoning model, where we theorize about the relationships between variables and then study these relationships in very small samples. With the advent of Big Data, researchers sample sizes are closer approximations of the populations' researchers are interested in studying. Any inferences researchers make from these samples based on inductive reasoning are more likely to be legitimate instead of just bias in the data. This allows for distinct types of research within psychology, where before researchers were forced into one way of conducting research, based off of the resources available to us.

Importance of Data Cleaning Procedures for Legitimate Cluster Analytic Results.

Data cleaning is especially important when using unsupervised machine learning techniques such as cluster analysis. With supervised learning techniques, researchers will clearly know if they have garbage data because of Garbage In Garbage Out (GIGO). GIGO means that the garbage data will cause a suppressed relationship with any outcome variables of interest, to the point of potentially nullifying the relationship entirely. The only exception to this rule is when the garbage data is for some reason related to the outcome variables of interest. With cluster analysis though, the statistical techniques by definition find patterns in the data that are likely to be most interpretable. With data like personality where researchers can produce any number of combinations of the Big Five personality traits and interpret the combination however the researcher wants, it is impossible to tell from the final results that the data was not cleaned properly.

Exploratory and Confirmatory over Pseudo-Confirmatory Research.

An important notion that big data and machine learning has made possible is that research fits a model to one sample and then confirms that the model is not over or under fitted in a second sample (Cawley & Talbot, 2010). This can be done via actually collecting a new sample or splitting the original sample before fitting the model. The latter is a process known as cross-validation (Koul et al., 2018). The author of this study believes that exploratory research via unsupervised machine learning clustering algorithms and then the second step of conducting confirmatory research is a legitimate way of supporting a scientific argument. What has traditionally worked in psychological science has been to overfit a model to a particular sample and never do follow up research to see whether findings are actually replicable, hence the dual problems of the replication and generalizability crises (Cawley & Talbot, 2010; Head et al., 2015; Koul et al., 2018; Neuroskeptic, 2012).

Personality Research in an Era of Machine Learning and Big Data

With the rise of machine learning and big data, personality researchers face a convergence with researchers in business analytics, marketing, computer science and a variety of other fields, where everyone is starting to study personality and they are doing it in new and innovative ways (Berghel, 2018; Cinnamon, 2017; Oswald et al., 2020; Prates et al., 2019; Schneble et al., 2018; Sumpter, 2018). In most cases, it is ways in which personality is easier to use for prediction, but researchers are developing "black box" models where the explanatory power of our models is extremely low and bias in our data can have major consequences for individuals (Berghel, 2018; Best, 2001; Cinnamon, 2017; Huff, 1993; Navarro, 2019; O'Neil, 2016; Sumpter, 2018; Wheeler, 1976; Yarkoni & Westfall, 2017).

Psychologists interested in studying personality are at a point where studying personality using machine learning and big data is primarily done by non-psychologists (Berghel, 2018; Schneble et al., 2018; Sumpter, 2018). Personality psychologists are playing catch up in terms of studying their own area of expertise using machine learning (Gerlach et al., 2018). This is likely occurring because of the slow uptake of machine learning and big data-oriented graduate-level courses, meaning people who are not trained in machine learning techniques cannot use the techniques unless they learn them elsewhere. People like computer scientists, who study these techniques in graduate school have an advantage where they can work with the data without being subject matter experts in psychological variables, such as personality.

This study explores one way of studying potential personality styles, based on prior research. The belief is that personality styles, while they might be a beneficial level of analysis, are not best elucidated by studying them using cluster techniques. Prior research using the clustering technique used in this study likely found the clusters obtained because of noise in the data, aspects of the research design, and basic psychological biases such as central tendency bias and social desirability bias.

Hypotheses on Cluster Structure

Hypothesis 1: Following R equivalent code of the Gerlach study will show the same clusters as the prior study. This provides first pass support for the equivalence of data, allowing for the further study into controlling for social desirability and central tendency biases.

Hypothesis 2: Accurate preprocessing will get rid of the social desirability bias in the data sets, which will make the Role Model cluster disappear.

Hypothesis 3a: Accurate preprocessing will get rid of the central tendency bias in the data sets, which will make the Average cluster disappear.

Hypothesis 3b: Accurate preprocessing will get rid of the central tendency bias in the data sets, which will make the Self-Centered cluster disappear.

Hypothesis 3c: Accurate preprocessing will get rid of the central tendency bias in the data sets, which will make the Reserved cluster disappear.

Hypothesis 4: All cluster analytic results will be compared and no clusters will appear as anything but noise.

METHODS

Overview

This study was done with the intention of studying how personality clusters together in large samples. It was done in two phases. The first phase was meant to show equivalence to Gerlach et al. (2018). The second phase used significant preprocessing of data to show that all clusters found in first phase and in the Gerlach et al (2018) study were actually noise in the data. Data preprocessing is an underdiscussed part of data analysis, despite a lot of industry experts saying that the preprocessing of data takes up a sizable portion of their time.

Variables

The original five personality traits being used for cluster analysis are as follows:

1. Openness to New Experiences which deals with being openness to new art, emotion, adventure, unusual ideas, being imaginative, etc. An example question that was asked on the survey for openness to new experiences is “I have a vivid imagination”.

2. Conscientiousness is all about things like being reliable, dependable, self-disciplined, industriousness, etc. An example question that was asked on the survey for conscientiousness was “I pay attention to details”.

3. Extraversion is made up of constructs related to positive emotions, warm, assertiveness, excitement-seeking, etc. An example question that was asked on the survey for extraversion was “I am the life of the party”.

4. Agreeableness is composed of concepts related to altruism, compliance, trust, cooperation, etc. An example question that was asked on the survey for agreeableness was “I take time out for others”.

5. Neuroticism is a construct best represented by anxiety, depression, anger, impulsivity, vulnerability, etc. An example question that was asked on the survey for neuroticism was “I worry about things”.

Phase One: Equivalence Testing

For this study, we conducted analyses in two phases. Phase one we followed the Gerlach (2018) study’s methods to replicate the findings. This was intended as a method of showing data equivalence. Equivalence is necessary to show that no matter the personality data set, the problems that can arise from not preprocessing data correctly. The steps for phase one are found below.

Phase One: Factor Analysis with Oblique Rotations.

We did factor analysis to ensure that we found the same five factors that are expected to be found within a data set of Big Five personality traits. This also shows a first step in terms of equivalence of data with the Gerlach et al (2018) study. The data showed the five personality traits labeled openness to new experiences, conscientiousness, extraversion, agreeableness, and neuroticism, as expected of data that accurately elicits knowledge on cross-culturally relevant personality traits.

We used oblique rotations on our data because of prior research showing that the five factors are related to each other. Even if our data was not related, oblique rotations can allow for orthogonal relationships between our variables if necessary. Quartimin was used because it is both a well-established rotation method and also because the Gerlach et al. (2018) study also used that method. This is again a method of establishing equivalence in the studies for the first pass.

Phase One: Gaussian Mixture Modeling with Bayesian Information Criterion.

After factor analysis, we did Gaussian Mixture Modeling (GMM). This is a second step in terms of showing equivalence to the Gerlach et al. (2018) study. As expected, 5 to 15 clusters were found in each of the cluster analytic techniques. We used Bayesian Information Criterion (BIC) for Gaussian Mixture Modeling. BIC was used since it is stricter about punishing false positives than Akaike Information Criterion (AIC) (Burnham & Anderson, 2016). False positives were considered more of a problem because we had used multiple cluster analytic techniques and we wanted to be as sure as possible that the clusters we obtained were as representative of signal instead of noise as possible.

Phase One: Gaussian Mixture Model Benefits.

Some of the benefits of using GMM is that it can account for unequal sizes of clusters, which is important because there is no reason to expect the cluster sizes to be equivalent. GMM is also useful because it allows for covariance between the clusters. If we had just used k-means clustering, we would have not been able to let our clusters covary. The fact that GMM is probabilistic and k-means is non-probabilistic means GMM offers a significant advantage for making more nuanced predictions. It was expected that mixed membership will occur for some of our data, such that a point has a possibility of being a part of multiple clusters, given its location in five-dimensional space. When we allow mixed membership of our data, it is called soft clustering. We could have used hard clustering, where each point is definitively forced into one cluster or another. However, there is no supporting literature for personality styles working in that way.

Phase One: Gaussian Mixture Model Downsides.

There are some downsides to gaussian mixture modeling (GMM), that we considered to be acceptable. Most clustering techniques only find a local minimum, because of limitations on computational power. Local minimum instead of global minimum, is a primary limitation of GMM since it means our analyses will not naturally find the optimum number of clusters every time we run the analyses. This is considered acceptable because in the Gerlach et al (2018) study, they found more clusters than they ended up accepting as the most representative of the real world. They also used multiple data sets to try and confirm the clusters they found in the original set. Depending on several factors, including for example sample size and number of items per factor, some clusters which are considered to be noise were created. We expected more clusters than what was realistic not only because of the Gerlach et al. study but also because larger sample sizes intuitively means that even by random chance, there might be slight grouping of some data.

Phase One: Possible GMM Alternative.

Other clustering techniques were ruled out based on the type of data we had. K means clustering provides hard clustering outputs. K means can be considered a special case of gaussian mixture modeling, where we consider the covariance of each cluster to be 0. Covariance between clusters equaling 0 is not the form we expect to best represent the results. K means also requires you choose a certain number of clusters and randomly puts the cluster centers at the beginning. This leads to a problem of different clusters every time the k means algorithm is run.

Phase Two: Data Cleaning for Biases and Re-Analyzing Data

After phase 1 of the study supported the similarity of results between Gerlach et al. and this study, we needed to establish that even the clusters that arose for reasons other than chance, were not clusters that occurred because of any meaningful differences in the data. The clusters that arose were due entirely to the central tendency biases and social desirability biases. This can be found to a certain extent based on the fact that the follow up data sets used in Gerlach et al. only found 3 of 4 clusters in two of the three data sets, and it was not even the same 3 found in the two data sets that could not fully recreate the clusters of the original data set. This shows us that two clusters, at minimum, are unstable. Given that 3 clusters overall were considered to just be created because of the central tendency bias, this was expected. The Role Model cluster, expected to arise from the social desirability bias, was found in all 4 of Gerlach's data sets.

For phase two, we started off with data cleanup, also known in some fields as preprocessing, to reduce central tendency and social desirability biases. We then followed the previous steps from phase one to show that with proper data cleaning, the previous clusters that we thought were signal, were actually just specific types of noise in the data, that tends to occur in all personality data that is not properly preprocessed. The steps in order then are:

(1) Data cleaning/preprocessing

(2) factor analysis

(3) gaussian mixture modeling

(6) comparison of cluster analytic techniques to find common factors

(7) compare factors to Gerlach et al. (2018) study

RESULTS

Phase 1 Removal of Data

Samples usually have missing data in them and researchers have the option of imputing values, in which case using expectation maximization full information maximum likelihood missing data imputation is considered the most legitimate. Another option is data removal if missing data imputation would not be legitimate for reasons related to the analyses. Because of how cluster analysis works, removal of participants with missing data was considered to be the more legitimate option. Cluster analysis looks for patterns within the data, which missing data imputation would alter. In the first phase of this study, data cleaning is not being done, which means that patterns that are artifacts of garbage data would be reinforced if we used missing data imputation. This is obviously not something the researchers would consider a benefit in their study. During the second phase of the study, if missing data is imputed, clusters analysis will be sensitive to the imputed values and likely find clusters that are not actually more frequently occurring patterns than average in the data but instead arise from imputing missing values.

Phase 1 Descriptive Statistics Pre-Data Cleaning

The researchers conducted basic descriptive statistics on each of the item in the Openness to New Experiences scale before conducting further analyses. We can see an expected range of 1 to 5 for each item. There is no excessive skew or kurtosis to our potential Openness to New Experiences scale. The Cronbach's Alpha was also an acceptable value of α of .804.

Phase 1 Descriptive Statistics for Openness to New Experiences Items Pre-Data Cleaning									
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
OPN1	870778	1	5	3.70	1.099	-0.592	0.003	-0.334	0.005
OPN2	870778	1	5	3.93	1.094	-0.855	0.003	-0.038	0.005
OPN3	870778	1	5	4.04	1.038	-0.935	0.003	0.174	0.005
OPN4	870778	1	5	4.01	1.068	-0.941	0.003	0.198	0.005
OPN5	870778	1	5	3.82	0.932	-0.526	0.003	-0.044	0.005
OPN6	870778	1	5	4.10	1.083	-1.194	0.003	0.693	0.005
OPN7	870778	1	5	4.02	0.934	-0.860	0.003	0.418	0.005
OPN8	870778	1	5	3.22	1.221	-0.214	0.003	-0.928	0.005
OPN9	870778	1	5	4.17	0.968	-1.187	0.003	0.986	0.005
OPN10	870778	1	5	3.98	0.985	-0.754	0.003	-0.025	0.005
Valid N (listwise)	870778								

Table 1 Phase 1 Descriptive Statistics for Openness to New Experiences Items Pre-Data Cleaning

Phase 1 Reliability Statistics for Openness to New Experiences Items Pre-Data Cleaning	
Cronbach's Alpha	**N of Items**
0.804	10

Table 2 Phase 1 Reliability Statistics for Openness to New Experiences Items Pre-Data Cleaning

The researchers conducted basic descriptive statistics on each of the item in the Conscientiousness scale before conducting further analyses. We can see an expected range of 1 to 5 for each item. There is no excessive skew or kurtosis to our potential

Conscientiousness scale. The Cronbach's Alpha was also an acceptable value of α of .822.

Phase 1 Descriptive Statistics for Conscientiousness Items Pre-Data Cleaning									
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**	**Skewness**		**Kurtosis**	
	Statistic	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**
CSN1	870778	1	5	3.34	1.121	-0.348	0.003	-0.652	0.005
CSN2	870778	1	5	3.05	1.371	0.010	0.003	-1.265	0.005
CSN3	870778	1	5	4.00	0.994	-0.913	0.003	0.311	0.005
CSN4	870778	1	5	3.37	1.231	-0.313	0.003	-0.919	0.005
CSN5	870778	1	5	2.63	1.253	0.318	0.003	-0.932	0.005
CSN6	870778	1	5	3.16	1.398	-0.145	0.003	-1.300	0.005
CSN7	870778	1	5	3.73	1.077	-0.684	0.003	-0.129	0.005
CSN8	870778	1	5	3.52	1.118	-0.319	0.003	-0.647	0.005
CSN9	870778	1	5	3.22	1.246	-0.248	0.003	-0.973	0.005
CSN10	870778	1	5	3.63	0.996	-0.394	0.003	-0.290	0.005
Valid N (listwise)	870778								

Table 3 Phase 1 Descriptive Statistics for Conscientiousness Items Pre-Data Cleaning

Phase 1 Reliability Statistics for Conscientiousness Items Pre-Data Cleaning	
Cronbach's Alpha	**N of Items**
0.822	10

Table 4 Phase 1 Reliability Statistics for Conscientiousness Items Pre-Data Cleaning

The researchers conducted basic descriptive statistics on each of the item in the Extraversion scale before conducting further analyses. We can see an expected range of 1 to 5 for each item. There is no excessive skew or kurtosis to our potential Extraversion scale. The Cronbach's Alpha was also an acceptable value of α of .897.

Phase 1 Descriptive Statistics for Extraversion Items Pre-Data Cleaning									
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
EXT2	870778	1	5	3.21	1.305	-0.168	0.003	-1.079	0.005
EXT1	870778	1	5	2.65	1.249	0.163	0.003	-1.017	0.005
EXT3	870778	1	5	3.30	1.185	-0.220	0.003	-0.862	0.005
EXT4	870778	1	5	2.83	1.209	0.127	0.003	-0.911	0.005
EXT5	870778	1	5	3.30	1.237	-0.296	0.003	-0.917	0.005
EXT6	870778	1	5	3.59	1.206	-0.586	0.003	-0.621	0.005
EXT7	870778	1	5	2.78	1.379	0.183	0.003	-1.232	0.005
EXT8	870778	1	5	2.56	1.241	0.350	0.003	-0.924	0.005
EXT9	870778	1	5	2.98	1.324	-0.015	0.003	-1.174	0.005
EXT10	1013558	0	5	2.41	1.289	0.479	0.002	-0.873	0.005
Valid N (listwise)	1013558								

Table 5 Phase 1 Descriptive Statistics for Extraversion Items Pre-Data Cleaning

Phase 1 Reliability Statistics for Extraversion Items Pre-Data Cleaning	
Cronbach's Alpha	**N of Items**
0.897	10

Table 6 Phase 1 Reliability Statistics for Extraversion Items Pre-Data Cleaning

The researchers conducted basic descriptive statistics on each of the item in the Agreeableness scale before conducting further analyses. We can see an expected range of 1 to 5 for each item. There is no excessive skew or kurtosis to our potential Agreeableness scale. The Cronbach's Alpha was also an acceptable value of α of .833.

Phase 1 Descriptive Statistics for Agreeableness Items Pre-Data Cleaning									
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
AGR1	870778	1	5	3.76	1.313	-0.763	0.003	-0.662	0.005
AGR2	870778	1	5	3.88	1.069	-0.800	0.003	-0.037	0.005
AGR3	870778	1	5	3.74	1.260	-0.618	0.003	-0.809	0.005
AGR4	870778	1	5	3.97	1.062	-0.982	0.003	0.329	0.005
AGR5	870778	1	5	3.72	1.146	-0.721	0.003	-0.311	0.005
AGR6	870778	1	5	3.79	1.155	-0.766	0.003	-0.264	0.005
AGR7	870778	1	5	3.80	1.094	-0.748	0.003	-0.185	0.005
AGR8	870778	1	5	3.73	1.032	-0.650	0.003	-0.139	0.005
AGR9	870778	1	5	3.82	1.120	-0.842	0.003	-0.053	0.005
AGR10	870778	1	5	3.62	1.026	-0.436	0.003	-0.300	0.005
Valid N (listwise)	870778								

Table 7 Phase 1 Descriptive Statistics for Agreeableness Items Pre-Data Cleaning

Phase 1 Reliability Statistics for Agreeableness Items Pre-Data Cleaning	
Cronbach's Alpha	**N of Items**
0.833	10

Table 8 Phase 1 Reliability Statistics for Agreeableness Items Pre-Data Cleaning

The researchers conducted basic descriptive statistics on each of the item in the Neuroticism scale before conducting further analyses. We can see an expected range of 1 to 5 for each item. There is no excessive skew or kurtosis to our potential Neuroticism scale. The Cronbach's Alpha was also an acceptable value of α of .872.

Phase 1 Descriptive Statistics for Neuroticism Items Pre-Data Cleaning									
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
EST1	870778	1	5	3.31	1.316	-0.294	0.003	-1.077	0.005
EST2	870778	1	5	2.80	1.189	0.143	0.003	-0.917	0.005
EST3	870778	1	5	3.87	1.125	-0.888	0.003	-0.022	0.005
EST4	870778	1	5	3.31	1.225	-0.295	0.003	-0.877	0.005
EST5	870778	1	5	2.85	1.252	0.102	0.003	-1.062	0.005
EST6	870778	1	5	2.87	1.295	0.103	0.003	-1.128	0.005
EST7	870778	1	5	3.06	1.268	-0.031	0.003	-1.081	0.005
EST8	870778	1	5	2.70	1.323	0.266	0.003	-1.116	0.005
EST9	870778	1	5	3.10	1.272	-0.124	0.003	-1.098	0.005
EST10	870778	1	5	2.80	1.303	0.166	0.003	-1.114	0.005
Valid N (listwise)	870778								

Table 9 Phase 1 Descriptive Statistics for Neuroticism Items Pre-Data Cleaning

Phase 1 Reliability Statistics for Neuroticism Items Pre-Data Cleaning	
Cronbach's Alpha	**N of Items**
0.872	10

Table 10 Phase 1 Reliability Statistics for Neuroticism Items Pre-Data Cleaning

Since all the items for all the scales show reasonable levels of internal consistency, skew, kurtosis, and have the full range of values expected from our data. It is considered legitimate to create basic scale scores for each of the Big Five scales hypothesized. We see below the values for each. The skew and kurtosis are as expected. Some interesting aspects are how rare it is to find an extremely low agreeableness or openness to new experiences person in the sample. In terms of agreeableness, we actually have no one who answered 1s across all ten items in our scale. That is surprising consider this is a data set with hundreds of thousands of participants. Openness is expected to be high because this is a convenience sample instead of a random sample of the population. It is expected to be high because a participant usually needs a certain amount of openness to new experiences to go out and try to find personality tests to take online.

Phase 1 Descriptive Statistics for the Big Five Scales Pre-Data Cleaning									
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**	**Skewness**		**Kurtosis**	
	Statistic	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**
OPEN	870778	1.00	5.00	3.8986	0.62896	-0.441	0.003	-0.089	0.005
CONSCI	870778	1.00	5.00	3.3662	0.73605	-0.102	0.003	-0.417	0.005
EXTRA	870778	1.00	5.00	2.9620	0.90856	0.040	0.003	-0.700	0.005
AGREE	870778	1.10	5.00	3.7831	0.71495	-0.615	0.003	0.108	0.005
NEURO	870778	1.00	5.00	3.0685	0.85704	-0.082	0.003	-0.595	0.005
Valid N (listwise)	870778								

Table 11 Phase 1 Descriptive Statistics for the Big Five Scales Pre-Data Cleaning

Phase 1 Factor Analysis Pre-Data Cleaning

The five factors are easily extracted, and we see a noticeable drop-off after the conscientiousness factor. This leads the researchers to conclude that the total variance explained table further supports a five-factor solution. Having only 40% of variance explained by the five-factor solution is a cause for concern and should provide some caution when interpreting the results of this cluster analysis.

Based on an outdated rule of thumb on eigenvalues greater than one being factors, the researchers decided to explore an 8-factor solution to be thorough. This was done with the expectation that the other factors were a mixture of errors in the data based on the negatively scored items and also the fact that data cleaning has not been done yet. There was no added benefit from using an 8-factor solution. The data became less interpretable. There was some evidence that some of the agreeableness and extraversion items were overly related to each other, which was leading to some of the problems with finding interpretable factors. See supplementary materials at the end of the manuscript for 8-factor solution output tables and figures.

Phase 1 Total Variance Explained Using Factor Analysis Pre-Data Cleaning									
	Initial Eigenvalues			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**		
Factor	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
EXTRA	7.625	15.251	15.251	7.062	14.123	14.123	5.148	10.297	10.297
NEURO	4.953	9.906	25.156	4.390	8.781	22.904	4.614	9.228	19.525
AGREE	3.974	7.947	33.103	3.342	6.685	29.589	3.739	7.478	27.003
OPEN	3.652	7.304	40.408	3.022	6.043	35.632	3.383	6.765	33.768
CONSC	2.861	5.722	46.129	2.348	4.696	40.328	3.280	6.560	40.328
6	1.492	2.983	49.113						
7	1.343	2.686	51.799						
8	1.031	2.062	53.861						

Table 12 Phase 1 Total Variance Explained Using Factor Analysis Pre-Data Cleaning

Below we see the 5-factor rotated factor matrix. This matrix shows that each item aligns with the factor it is supposed to align with. This further supports the expected five factor solution. Note that this was done with a Quartimax rotation since we can expect from prior research literature on oblique vs orthogonal rotations that oblique rotations are more legitimate when studying personality data. A few of the factor loadings are in the <0.40 range and should be cautiously interpreted. Some of the items with low loadings are negatively scored and the items potentially confused participants. Other items seem like they would fit better with the data using ideal point response format instead of dominance modeling of the data. That is unfortunately outside of the scope of this project.

Phase 1 Big Five Rotated Factor Matrix Pre-Data Cleaning for 5-Factor Solution					
	Factor				
	EXTRA	NEURO	AGREE	OPEN	CONSC
EXT4	0.737	-0.116	0.037	0.029	0.003
EXT7	0.726	-0.077	0.199	0.082	0.068
EXT5	0.723	-0.086	0.143	0.025	0.014
EXT1	0.703	0.004	0.121	-0.020	0.036
EXT2	0.695	-0.040	0.065	-0.010	0.018
EXT10	0.683	-0.161	0.054	0.031	0.009
EXT3	0.646	-0.255	0.244	0.095	-0.026
EXT9	0.631	-0.051	-0.029	-0.048	0.126
EXT8	0.590	-0.032	-0.045	-0.070	0.047
EXT6	0.551	-0.062	0.128	0.027	0.257
EST8	0.000	0.754	-0.043	-0.164	-0.019
EST7	-0.038	0.738	0.021	-0.063	-0.092
EST6	0.018	0.734	-0.030	-0.156	-0.014
EST9	-0.119	0.695	0.101	-0.001	-0.081
EST1	-0.027	0.695	-0.168	-0.036	-0.051
EST10	-0.247	0.606	-0.028	-0.187	0.081
EST3	-0.144	0.604	0.183	0.041	-0.007
EST2	-0.103	0.544	-0.002	0.050	-0.032
EST5	-0.046	0.508	-0.005	-0.076	-0.110
EST4	-0.136	0.368	0.028	-0.097	0.075
AGR4	0.036	0.078	0.793	0.034	0.032
AGR9	0.093	0.130	0.705	0.049	0.065
AGR5	0.141	0.001	0.646	0.004	0.031
AGR7	0.307	-0.080	0.606	0.013	0.057
AGR6	-0.009	0.172	0.597	0.021	-0.049
AGR8	0.147	-0.005	0.552	0.094	0.032

AGR2	0.353	-0.049	0.532	-0.001	0.099
AGR1	0.022	-0.033	0.478	0.028	0.082
AGR3	0.318	-0.122	0.391	0.118	0.096
AGR10	-0.114	-0.216	0.390	0.189	-0.051
OPN10	0.029	-0.088	0.019	0.638	0.081
OPN5	0.074	-0.074	0.047	0.624	-0.081
OPN2	0.054	0.023	0.103	0.617	-0.061
OPN1	-0.013	-0.163	-0.002	0.615	-0.054
OPN8	0.046	-0.347	0.023	0.577	-0.001
OPN3	-0.054	-0.100	-0.041	0.571	-0.117
OPN4	-0.048	0.083	0.029	0.557	0.020
OPN6	0.044	-0.209	0.123	0.484	0.051
OPN7	0.030	-0.014	0.046	0.446	0.240
OPN9	-0.034	0.027	0.091	0.398	0.239
CSN6	0.185	-0.009	0.035	0.017	0.674
CSN5	0.214	-0.075	-0.023	0.134	0.591
CSN9	0.040	-0.033	-0.037	0.043	0.576
CSN1	0.014	-0.183	0.014	0.004	0.568
CSN4	0.041	0.117	0.092	-0.088	0.549
CSN2	0.029	0.060	-0.108	-0.028	0.542
CSN7	-0.015	-0.088	0.098	-0.069	0.516
CSN8	0.074	-0.031	0.094	-0.027	0.512
CSN10	0.073	-0.143	-0.012	0.168	0.471
CSN3	-0.127	0.130	0.169	0.041	0.389
Extraction Method: Maximum Likelihood. Rotation Method: Quartimax with Kaiser Normalization.					
a. Rotation converged in 5 iterations.					

Table 13 Phase 1 Big Five Rotated Factor Matrix Pre-Data Cleaning for 5-Factor Solution

The below scree plot shows the ideal number of factors. It could be argued based on the Scree Plot that five or seven factors are legitimate. Since all available evidence both from this study and prior studies show a five-factor solution to be the more well-substantiated, that is the one the authors of this manuscript are pursuing further. Another reason the five factor is most legitimate is because the last 2 potential factors do not make any actual sense when trying to interpret. This Scree Plot can be considered to provide further support for our hypothesized 5-factor structure.

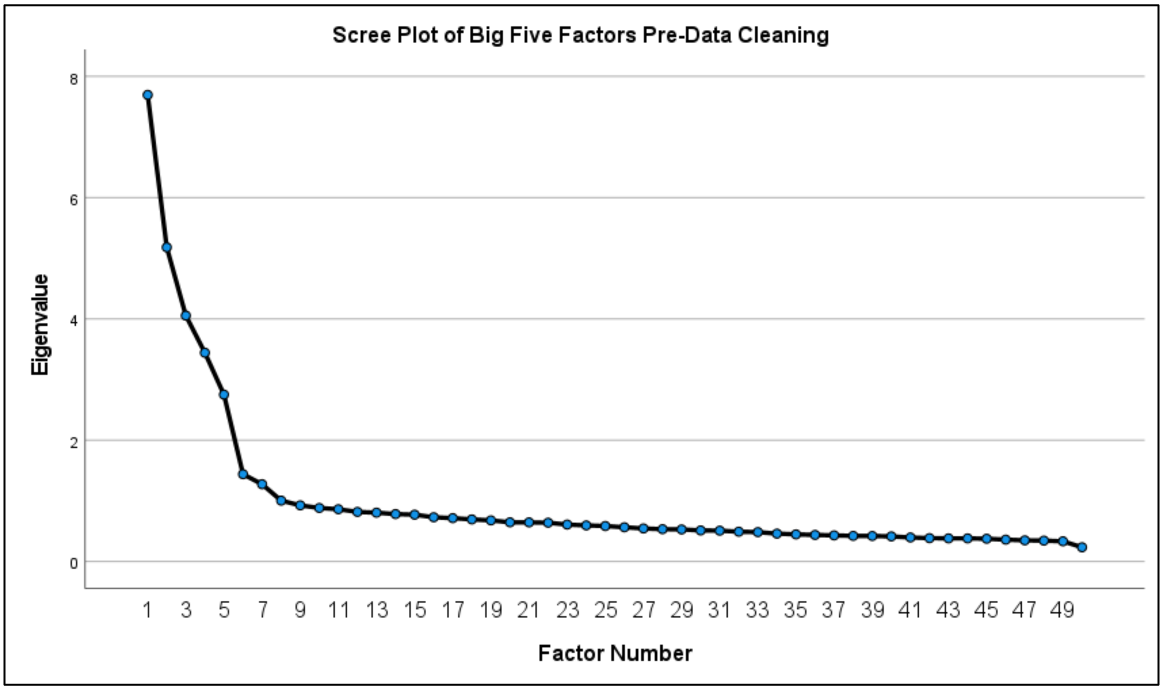


Figure 1 Phase 1 Screen Plot of Big Five Factors Pre-Data Cleaning

Phase 1 Cluster Analysis Pre-Data Cleaning

Now that we have a factor structure consistent with the research literature, it is time to start conducting cluster analysis. Some other cluster analyses, aside from gaussian mixture modeling, was done in order to compare results. K-means cluster, known as quick cluster in SPSS, was done initially. The results for that analysis are below. Note that from here, we will be talking about both refined and unrefined scale scores. Unrefined is simply scales that were created by adding up the items and dividing by the number of items. Refined were scale scores created through initial factor analytic results. We will also be looking at the unrefined scale scores after being transformed into z scores for interpretabilities sake in both the original units and in standardized units.

As a reminder, 3 is the exact middle of the scale with a range of 1 to 5. We see the formation of four barely distinct clusters. Cluster 1 looks remarkably similar to the cluster labeled “Role Model” in the Gerlach et al. study. My sample is far higher in openness to new experience on average and lower in extraversion than the samples Gerlach et al. looked at. All clusters seem to be differentiated based on neuroticism and extraversion. Cluster 2 is about average on extraversion and neuroticism. Cluster 3 is high on extraversion and neuroticism. Cluster 1 is high on extraversion and low on neuroticism. Cluster 4 is low on extraversion and high on neuroticism.

Because of the four clusters relative lack of variability on all other variables, we can conclude that extraversion and neuroticism are the salient variables for this cluster analysis technique. Cluster 1 because of its characteristics similar to a cluster in Gerlach et al. was labeled the Role Model cluster. Cluster 2 was labeled neurotic extroverts. Cluster 3 was labeled neurotic introverts. If we ignore the overall higher levels of openness to new experience in this sample, cluster 1 looks remarkably similar to the role model cluster found in Gerlach et al.

Phase 1 K-Means Final Cluster Centers for Unrefined Scale Scores: Restricted to 4 Clusters				
	Cluster			
	Role Model (1)	AvgEN	HighEN	Reserved (4)
OPEN	4.11	3.79	3.97	3.75
CONSCI	3.82	3.52	3.07	3.11
EXTRA	3.80	2.44	3.59	2.09
AGREE	4.20	3.43	3.99	3.56
NEURO	2.25	2.52	3.55	3.88

Table 14 Phase 1 K-Means Final Cluster Centers for Unrefined Z Scale Scores Restricted to 4 Clusters

A different picture emerges when looking at standardized scores. For ease of understanding, 0 is the midpoint and 1 in either direction is a standard deviation above or below. Cluster 2 seems to be primarily differentiated based on its extremely low openness scores. In fact, this looks remarkability similar to the self-centered cluster, if not for the lower extraversion scores. Cluster 1 still looks like the Role Model cluster. Cluster 3 also looks similar to self-centered cluster aside from its high openness. Cluster 4 does not look similar to any of the clusters from prior cluster analytic studies on personality data.

Phase 1 K-Means Final Cluster Centers for Unrefined Z Scale Scores: Restricted to 4 Clusters				
	Cluster			
	Role Model (1)	Self-Centered (2)	Self-Centered (3)	4
ZOPEN	.31812	-1.21671	.42014	.50584
ZCONSCI	.65879	-.14813	-.02071	-.62630
ZEXTRA	.67347	-.43488	-.69101	.10283
ZAGREE	.58323	-.20801	-1.31296	.42558

ZNEURO	-.77823	.28142	-.12836	.74367

Table 15 Phase 1 K-Means Final Cluster Centers for Unrefined Z Scale Scores Restricted to 4 Clusters

For our refined clusters, we are looking at z scores as well. No clusters here look similar to clusters in the Gerlach (2018)study. We have 2 extreme scores in our 4-cluster solution. One agreeableness score that is more than one standard deviation below the median. We also have openness score that is over a standard deviation below the median in cluster 4. Cluster 3 at least somewhat shows the pattern of the Role Model cluster from Gerlach (2018). Though the scores are nowhere near extreme enough in either a positive direction for openness, conscientiousness, extraversion, and agreeableness or negative direction for neuroticism.

Phase 1 K-Means Final Cluster Centers for Phase 1 Refined Scale Scores: Restricted to 4 Clusters				
	Cluster			
	1	2	Role Model (3)	4
ROPEN	.43507	.48348	.22811	-1.12180
RCONSCI	.04106	-.31118	.30548	-.03963
REXTRA	-.30992	-.06401	.45514	-.24288
RAGREE	-1.36000	.40110	.46801	-.03093
RNEURO	-.22590	.82194	-.76326	.13712

Table 16 Phase 1 K-Means Final Cluster Centers for Refined Scale Scores Restricted to 4 Clusters

Two-step clustering shows five clusters to be the most legitimate cluster solution for our refined scales. Though we can see that the cluster analytic technique is not particularly confident in this solution. Since the first phase is not the primary focus of this study, the majority of the figures related to the two-step cluster solutions can be found in the supplementary section of this manuscript.

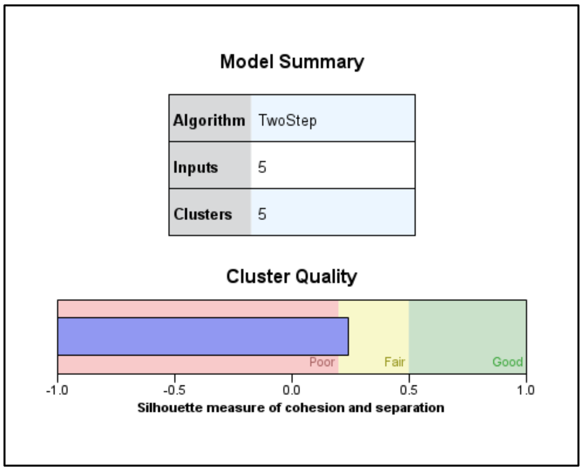


Figure 2 Phase 1 Model summary for the refined scales two-step cluster analytic solution, fixed to 4 clusters.

The unrefined scales show that a two-cluster solution is considered the most legitimate. We can see that this cluster analytic technique says two clusters fits the data fairly well, better than any of our other combinations of cluster numbers and scale scores. This does not make sense given prior research on cluster analysis of personality data.

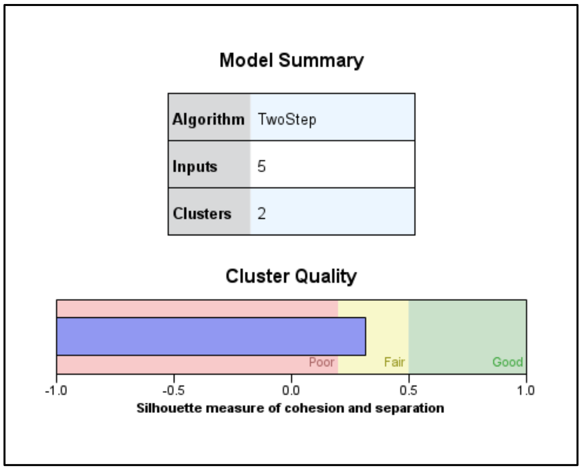


Figure 3 Phase 1 Model summary for the refined scales two-step cluster analytic solution, fixed to 4 clusters.

Our k-means cluster analysis looking at the two clusters specified in two-step cluster analysis shows a cluster similar to the Role Model Cluster from prior research. The second cluster is indecipherable.

Phase 1 Final Cluster Centers for K-means: Restricted to 2 Clusters		
	Cluster	
	Role Model (1)	2
OPEN	4.04	3.77
CONSCI	3.55	3.19
EXTRA	3.63	2.33
AGREE	4.06	3.52
NEURO	2.66	3.46

Table 17 Phase 1 Final Cluster Centers for Unrefined Scale Scores Restricted to 2 Clusters

K-means clustering using the 5 clusters discussed in two-step clustering shows cluster 5 having similarity to the role model cluster found in prior research. The openness to new experience score is lower than needed to fully justify considering it a match with the Role Model cluster in prior research.

Phase 1 K-Means Final Cluster Centers: Restricted to 5 Clusters					
	Cluster				
	1	2	3	4	Role Model (5)
ROPEN	.44455	-1.23456	.24139	.44428	.17816
RCONSCI	.06276	-.06274	-.34231	-.12251	.41899
REXTRA	-.30887	-.24996	.92689	-.90059	.43467
RAGREE	-1.48411	-.12073	.18506	.47104	.45494
RNEURO	-.25723	.08684	.69253	.43504	-.90063

Table 18 Phase 1 K-Means Final Cluster Centers for Refined Scale Scores Restricted to 5 Clusters

We see below using two step cluster analysis that 4 clusters are considered barely acceptable for our unrefined scale scores. Note we checked four clusters since four clusters was the number of clusters found in the study we are replicating.

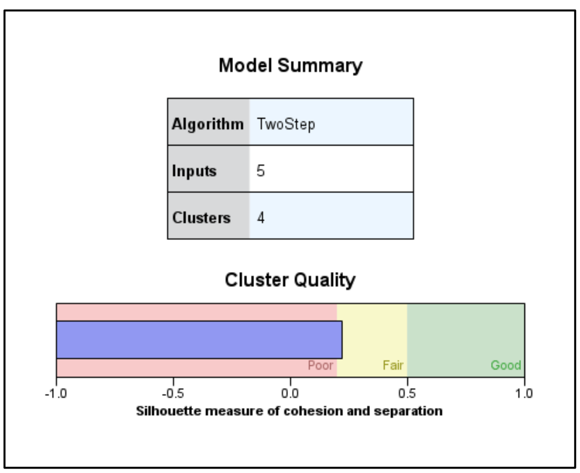


Figure 4 Cluster Sizes for the refined scales two-step cluster analytic solution, fixed to 4 clusters.

When restricting our clusters to four for our refined scale, we see a similar level of cluster quality that is just barely considered fair by the algorithm's standards for our refined clusters. As a reminder, the number of clusters for this cluster analytic technique was chosen based on prior research.

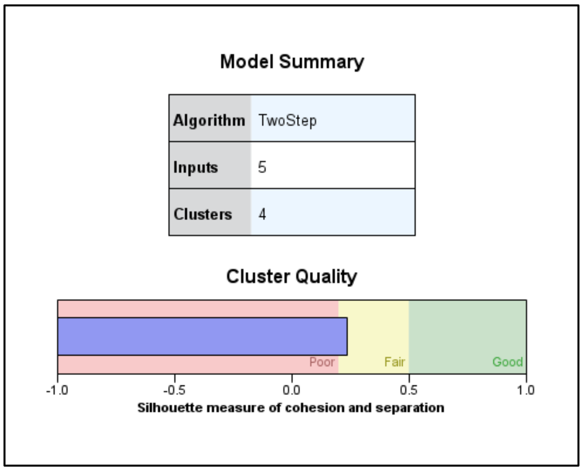


Figure 5 Model summary for the refined scales two-step cluster analytic solution, fixed to 4 clusters.

Phase 1: Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales.

Our refined scales, during phase one of the study, showed 1 discernable factor that overlaps with prior research. The below analysis used Gaussian Mixture Modeling with the number of clusters restricted to 4. The Role Model cluster found in prior research seems to somewhat show up in this data set in cluster 2. Though the conscientiousness score is a bit lower than what we would ideally find to justify saying this is a direct equivalent to prior research.

Refined Scale Means

	1	Role Model (2)	3	4
REXTRA	-0.06599573	0.92304293	-0.1095324	-0.411517906
RNEURO	-0.1062096	-0.10144892	0.01968589	0.107443171
RAGREE	-0.73386769	0.59675156	-0.40114786	0.426550589
RCONSCI	-0.11938095	0.07064504	0.02888024	0.006602814
ROPEN	0.74523208	0.19762454	-0.75655251	0.062870231

Table 19 Phase 1 Gaussian Mixture Model Cluster Means for Refined Scales Restricted to 4 Clusters

Gaussian Mixture Modeling on Refined Scales.

Our refined scales, during phase one of the study, showed 1 discernable factor that overlaps with prior research. The below analysis used Gaussian Mixture Modeling with the number of clusters not restricted. The Role Model cluster found in prior research seems to somewhat show up in this data set. Though the openness to new experiences score is a bit lower than would be expected for an actual Role Model Cluster.

Refined Scale Means					
	1	**2**	**3**	**4**	**5**
REXTRA	0.27083043	0.1060442	0.46995832	-1.12590595	0.18067
RNEURO	0.17913802	-0.1145856	-0.89509442	-0.08269537	-0.0294
RAGREE	0.06919578	-0.8701047	0.36160906	-0.65885917	-0.8773
RCONSCI	0.05853343	-0.1699235	0.05349096	-0.04644959	-0.1019
ROPEN	-0.39420325	1.053173	0.29924678	0.28556497	-0.7675

Refined Scale Means				
	6	**7**	**Role Model (8)**	**9**
REXTRA	-0.764807	-0.75529554	0.8622997	0.1763624
RNEURO	0.2704158	-0.03692057	-0.2424241	0.7850811
RAGREE	0.1648134	0.93950211	1.0326675	0.6636649

RCONSCI	-0.5594625	0.66314491	0.7227086	-0.2005471
ROPEN	-0.1666558	-0.09059795	0.1489898	0.709642

Table 20 Phase 1 Gaussian Mixture Model Cluster Means for Refined Scales

Gaussian Mixture Modeling Restricted to 4 Clusters on Standardized Unrefined Scales.

Our standardized unrefined scales, during phase one of the study, showed 1 discernable factor that overlaps with prior research. The below analysis used Gaussian Mixture Modeling with the number of clusters restricted to 4. We see cluster 4 somewhat resembles the Role Model cluster from prior research.

Standardized Unrefined Scale Means				
	1	**2**	**3**	**Role Model (4)**
ZEXTRA	-0.11647005	-0.03477673	-1.01049447	0.3902596
ZNEURO	-0.0516685	-0.12095867	0.82296425	-0.1510226
ZAGREE	-0.8255152	0.90809934	0.02177133	0.116422
ZCONSCI	-0.00591693	-0.21730575	-0.20226624	0.1648385
ZOPEN	-0.49353472	-0.55232139	0.07855746	0.5619129

Table 21 Phase 1 Gaussian Mixture Model Cluster Means for Unrefined Standardized Scales Restricted to 4 Clusters

Gaussian Mixture Modeling on Standardized Unrefined Scales.

Our standardized unrefined scales, during phase one of the study, showed 1 discernable factor that overlaps with prior research. The below analysis used Gaussian Mixture Modeling with the number of clusters restricted to 4. We see that cluster 1 resembles the Role Model cluster from prior research. Conscientiousness is a bit low in cluster 1 but all the other variables show the correct pattern. The Role Model cluster is the one that is expected to be the most noticeable in the data, particularly unrefined scales like this one, because its likely related to socially desirable responding.

Standardized Unrefined Scale Means					
	Role Model (1)	**2**	**3**	**4**	**5**
ZEXTRA	0.9007323	0.5419193	-0.36285196	-1.37689457	-0.1407
ZNEURO	-0.1420462	0.1175844	0.01285482	0.14721179	-0.0331
ZAGREE	0.7351396	-0.132433	0.30003191	-0.49822	-0.6748
ZCONSCI	0.2180332	-0.3140634	-0.33698551	-0.06801415	-0.1098
ZOPEN	1.2239164	0.3181589	0.22586188	-1.02597025	-0.6526

Standardized Unrefined Scale Means				
	6	**7**	**8**	**9**
ZEXTRA	0.02505254	0.25663106	1.18228791	-0.59318484
ZNEURO	-0.13742001	-0.7888052	-0.18466138	0.89158846
ZAGREE	1.09867529	-0.0043976	-0.17089191	-0.23464621
ZCONSCI	-0.13497423	0.91132402	-0.00319498	0.00917688
ZOPEN	-0.59684594	0.6182238	0.37311961	0.17877855

Table 22 Phase 1 Gaussian Mixture Model Cluster Means for Unrefined Standardized Scales

Gaussian Mixture Modeling Restricted to 4 Clusters on Unrefined Scales.

Our unrefined scales, during phase one of the study, showed 1 discernable factor that overlaps with prior research. The below analysis used Gaussian Mixture Modeling with the number of clusters restricted to 4. The neuroticism score was a bit higher than the middle of the Likert scale but its low enough that it is on the lower end of the sample distribution of scores. We see that cluster 4 resembles the Role Model cluster from prior research.

Unrefined Scale Means				
	1	**2**	**3**	**Role Model (4)**
EXTRA	3.775568	2.323946	2.802814	3.172833
NEURO	3.08472	3.320821	3.070092	2.689761
AGREE	4.14917	4.092652	3.740127	3.663122
CONSCI	3.301173	3.29618	3.30148	3.694986
OPEN	4.274495	4.032802	3.270287	3.963398

Table 23 Phase 1 Gaussian Mixture Model Cluster Means for Unrefined Scales Restricted to 4 Clusters

Gaussian Mixture Modeling on Unrefined Scales.

Our unrefined scales, during phase one of the study, showed 1 discernable factor that overlaps with prior research. The below analysis used Gaussian Mixture Modeling with the number of clusters unrestricted.

Gaussian Mixture Model Clusters: Unrefined Scale Means					
	1	**2**	**3**	**4**	**5**

EXTRA	2.45798	3.997438	3.018457	2.684617	1.74762
NEURO	3.084117	2.969607	2.923901	3.84407	3.12874
AGREE	4.18291	4.28638	4.654102	3.829302	3.62603
CONSCI	3.310281	3.261794	3.272319	3.156896	3.30267
OPEN	3.998905	4.280159	3.387924	3.562092	3.16059

Gaussian Mixture Model Clusters: Unrefined Scale Means				
	Role Model (6)	**7**	**8**	**9**
EXTRA	3.255872	3.12914	3.229806	2.956626
NEURO	2.529183	2.803964	2.851914	4.004092
AGREE	3.847468	3.600673	3.44383	3.942545
CONSCI	4.105172	3.420825	3.216131	3.20901
OPEN	4.458086	3.755278	3.244599	4.377275

Table 24 Phase 1 Gaussian Mixture Model Cluster Means for Unrefined Scales

Overall, our cluster analytic techniques rarely showed similar clusters to prior research. The one instance where similarities existed revolved around the cluster likely related to socially desirable responding, the Role Model cluster. The other clusters in prior research had too many traits that overlapped with the response midpoint. Because the primary trait that differentiated these three other clusters were low openness to new experiences, the fact that our sample had higher than average openness to new experiences makes it unlikely to replicate these prior clusters. Phase 2 of the study will hopefully make the socially desirable cluster disappear through rigorous outlier analysis.

Phase 2 Outlier Analysis

We were especially cautious and intentional about outlier analysis for this study. Because of the nature of cluster analysis, it is extremely easy for outlier analysis to create artificial clusters since outlier analysis is all about removing data that is dissimilar to the rest of the data set. The way we are defining univariate outlier analysis is based off of best practices in the field of organizational research methods. Univariate outlier analysis can be described as removing "data values that are unusually large or small compared to the other values of the same constructs" (Aguinis et al., 2013, p. 275).

The definition that accurately represents multivariate outlier analysis is described as removing "data points with large residual values" (Leys et al., 2019). Since we do not have potential moderators to look at, making a distinction between interesting outliers and error outliers was unnecessary (Aguinis et al., 2013; Leys et al., 2019). Since this is cluster analysis instead of some form of predictor and outcome variables relationship, we do not have any reason or way of looking at influential outliers since we have no y variable.

Univariate Outlier Results.

Originally, we were going to look at time spent on the entire survey, but the data on overall time spent on the survey has to be inaccurate because there are cases where the entire survey takes less time than individual survey responses. Our prior plan about reasonable cutoff scores can be found in the rest of the paragraph. For elapsed time for the entire survey, we looked to remove extremely high or extremely low scores. For the extreme low end, we used a cutoff score based on reasonable reading times for a human being (300 seconds). For the extreme high end, we decided that participants completing the survey within a day (86400 seconds) was reasonable considering it was only a bit over 50 questions. Too much distraction and it was unlikely the results would have been accurate for the participants.

We also looked for whether any participants spent an unreasonably long or brief time on each individual question. This was looked at both on an individual participant level and also at the group level since it is possible that participants spent more time thinking about their responses to specific questions. Taking 2 seconds or less (2,000 milliseconds) on a question was considered to mean the participant did not spend enough time answering the question. Taking 5 minutes or more (300,000 milliseconds) was considered to be the upper limit on an individual question.

Before fully removing the participants using the above-mentioned criteria, we created a histogram to visualize the problem with the data. We still had 823.400 participants after removing some data that was clearly not possible and was making the histogram unreadable. An example of impossible data was a participant taking 2,147,483,647 milliseconds to complete a question. This is equivalent to taking 24.86 days for a participant to decide how strongly they agree with the question “I am the life of the party”. Response time was calculated by taking the time when the button for the question was clicked minus the time of the most recent other button click.

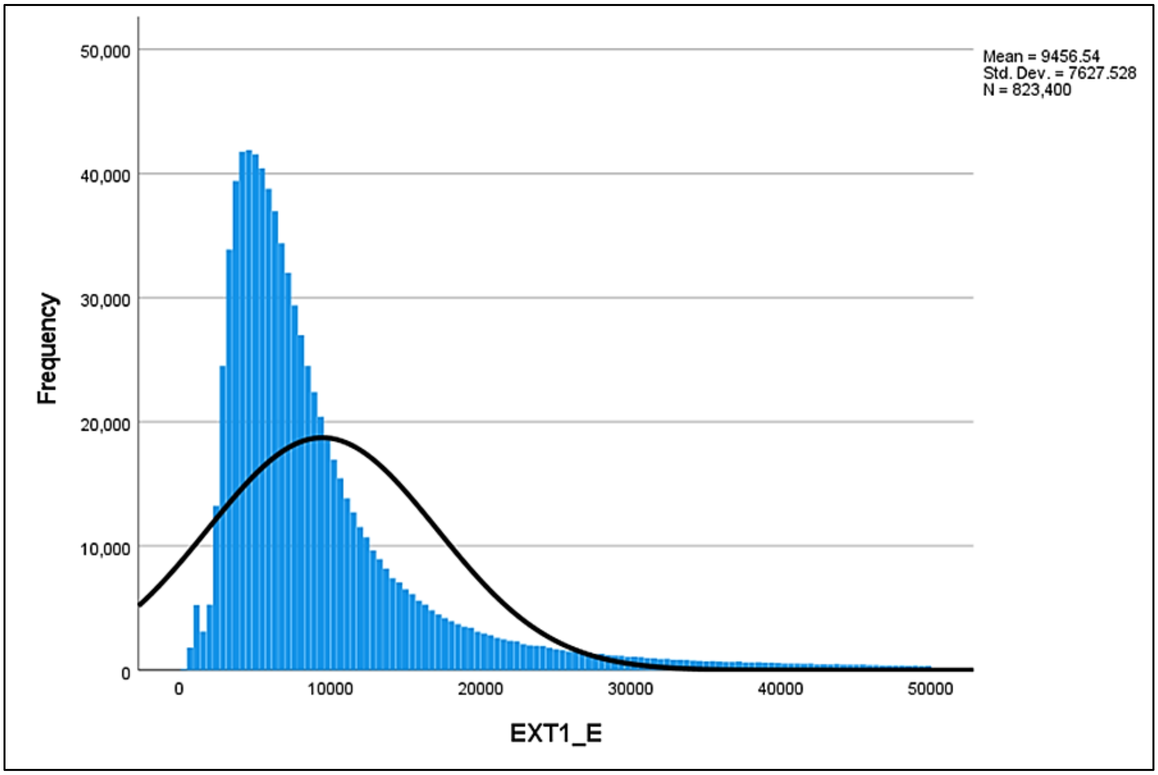


Figure 6 Histogram of Response Time in Milliseconds for the Extraversion Question: "I am the life of the party".

Multivariate Outlier Results.

We can predict that our cluster solution will be more representative of the data once outliers are removed. Multivariate outliers are known to negatively affect fit indices (Kline, 2010). This means that the cluster quality indices that we are looking at will show higher quality clusters. This will be used as one indicator of how beneficial outlier analysis was to the process of selecting clusters.

For Mahalanobis Distance we decided a value of 3 was better to use than 3.29. This means that our outliers are the 5% most extreme scores instead of the top 1% most extreme scores. It was important that our sample was broadly representative of the population as a whole and because this survey could easily be taken by anyone, with any amount of distractions, it was better to remove more data instead of not enough. This is especially the case since we removed the absolute minimum data possible in phase 1 of this study.

Our cutoff rule for Mahalanobis distance is < 0.001 (Hair et al., 2009). Any Cook's distance below 3 was considered to be normal data. With studentized deleted residuals, a score of 3 or above was considered non-normal data. Because of the initial univariate outlier analysis being so thorough since we had data on how long participants spent on each question and on the survey as a whole, very few participants were removed from the analysis during the multivariate outlier analysis stage.

Unsupervised machine learning, like any other analyses conducted on data, is based on the quality of the data provided. Unsupervised machine learning, like what was used here and in the Gerlach et al. (2018) study shows that if data is not properly cleaned, you have the well-known problem of "Garbage In, Garbage Out" (GIGO). This is even more of a problem in unsupervised machine learning than other forms of machine learning because you do not have direct control over the structure of the results via a statistical model and since it intentionally gives you the most interpretable results, you can end up making faulty inferences. We see that greater than 90% of data was removed during outlier analysis following simple rules related to time spent on page and missing data. This is even more serious of an issue because the data that was within the data set was already screened based on a question at the end of the survey asking participants whether the data was accurate enough to use for research purposes.

Phase 2 Descriptive Statistics Post-Data Cleaning

The researchers conducted basic descriptive statistics on each of the item in the Extraversion scale before conducting further analyses. We can see an expected range of 1 to 5 for each item. There is no excessive kurtosis to our potential Openness to New Experiences scale. We do see a couple of items, OPN6 and OPN9 which have higher than normal skewness. The Cronbach's Alpha was also an acceptable value of α of .775.

Phase 2 Descriptive Statistics for
Openness to New Experiences Items Post-Data Cleaning

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
OPN1	81334	1	5	3.50	1.109	-.392	.009	-.517	.017
OPN2	81334	1	5	3.86	1.097	-.717	.009	-.292	.017
OPN3	81334	1	5	3.99	1.014	-.802	.009	-.032	.017
OPN4	81334	1	5	3.97	1.065	-.833	.009	-.017	.017
OPN5	81334	1	5	3.77	.899	-.334	.009	-.292	.017
OPN6	81334	1	5	4.16	1.031	-1.217	.009	.815	.017
OPN7	81334	1	5	3.92	.947	-.673	.009	-.006	.017
OPN8	81334	1	5	2.94	1.209	-.018	.009	-.946	.017
OPN9	81334	1	5	4.14	.959	-1.051	.009	.614	.017
OPN10	81334	1	5	3.92	.965	-.569	.009	-.370	.017
Valid N (listwise)	81334								

Table 25 Phase 2 Descriptive Statistics for Openness to New Experiences Items Post-Data Cleaning

Phase 2 Reliability Statistics for
Openness to New Experiences Items Post-Data Cleaning

Cronbach's Alpha	N of Items
.775	10

Table 26 Phase 2 Reliability Statistics for Openness to New Expierences Items Post-Data Cleaning

The researchers conducted basic descriptive statistics on each of the item in the Extraversion scale before conducting further analyses. We can see an expected range of 1 to 5 for each item. There is no excessive skew or kurtosis to our potential Conscientiousness scale. The Cronbach's Alpha was also an acceptable value of α of .805.

Phase 2 Descriptive Statistics for Conscientiousness Items Post-Data Cleaning									
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
CSN1	81334	1	5	3.29	1.090	-.294	.009	-.602	.017
CSN2	81334	1	5	3.20	1.376	-.128	.009	-1.252	.017
CSN3	81334	1	5	4.00	.982	-.842	.009	.133	.017
CSN4	81334	1	5	3.55	1.184	-.452	.009	-.734	.017
CSN5	81334	1	5	2.73	1.238	.213	.009	-.938	.017
CSN6	81334	1	5	3.31	1.382	-.282	.009	-1.214	.017
CSN7	81334	1	5	3.74	1.079	-.657	.009	-.173	.017
CSN8	81334	1	5	3.61	1.115	-.344	.009	-.689	.017
CSN9	81334	1	5	3.18	1.237	-.203	.009	-.958	.017
CSN10	81334	1	5	3.66	.982	-.400	.009	-.268	.017
Valid N (listwise)	81334								

Table 27 Phase 2 Descriptive Statistics for Conscientiousness Items Post-Data Cleaning

Phase 2 Reliability Statistics for Conscientiousness Items Post-Data Cleaning	
Cronbach's Alpha	**N of Items**
.805	10

Table 28 Phase 2 Reliability Statistics for Conscientiousness Items Post-Data Cleaning

The researchers conducted basic descriptive statistics on each of the item in the Extraversion scale before conducting further analyses. We can see an expected range of

1 to 5 for each item. There is no excessive skew or kurtosis to our potential Extraversion scale. The Cronbach's Alpha was also an acceptable value of α of .880.

Phase 2 Descriptive Statistics for Extraversion Items Post-Data Cleaning									
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
EXT2	81334	1	5	3.14	1.297	-.108	.009	-1.066	.017
EXT1	81334	1	5	2.62	1.207	.150	.009	-.908	.017
EXT3	81334	1	5	3.33	1.165	-.207	.009	-.827	.017
EXT4	81334	1	5	2.86	1.166	.110	.009	-.794	.017
EXT5	81334	1	5	3.31	1.212	-.287	.009	-.850	.017
EXT6	81334	1	5	3.55	1.193	-.505	.009	-.681	.017
EXT7	81334	1	5	2.77	1.358	.182	.009	-1.184	.017
EXT8	81334	1	5	2.53	1.230	.366	.009	-.878	.017
EXT9	81334	1	5	2.91	1.311	.053	.009	-1.136	.017
EXT10	81334	1	5	2.45	1.264	.447	.009	-.913	.017
Valid N (listwise)	81334								

Table 29 Phase 2 Descriptive Statistics for Extraversion Items Post-Data Cleaning

Phase 2 Reliability Statistics for Extraversion Items Post-Data Cleaning	
Cronbach's Alpha	**N of Items**
.880	10

Table 30 Phase 2 Reliability Statistics for Extraversion Items Post-Data Cleaning

The researchers conducted basic descriptive statistics on each of the item in the Extraversion scale before conducting further analyses. We can see an expected range of 1 to 5 for each item. There is no excessive skew or kurtosis to our potential Agreeableness scale. The Cronbach's Alpha was also an acceptable value of α of .814.

Phase 2 Descriptive Statistics for Agreeableness Items Post-Data Cleaning							
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis

	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
AGR1	81334	1	5	3.68	1.339	-.648	.009	-.853	.017
AGR2	81334	1	5	3.83	1.081	-.694	.009	-.258	.017
AGR3	81334	1	5	3.96	1.184	-.875	.009	-.344	.017
AGR4	81334	1	5	4.00	1.015	-.929	.009	.286	.017
AGR5	81334	1	5	3.69	1.131	-.633	.009	-.399	.017
AGR6	81334	1	5	3.85	1.111	-.780	.009	-.163	.017
AGR7	81334	1	5	3.81	1.076	-.686	.009	-.286	.017
AGR8	81334	1	5	3.71	1.023	-.574	.009	-.228	.017
AGR9	81334	1	5	3.86	1.075	-.844	.009	.054	.017
AGR10	81334	1	5	3.69	1.000	-.444	.009	-.269	.017
Valid N (listwise)	81334								

Table 31 Phase 2 Descriptive Statistics for Agreeableness Items Post-Data Cleaning

Phase 2 Reliability Statistics for <u>Agreeableness</u> Items Post-Data Cleaning	
Cronbach's Alpha	**N of Items**
.814	10

Table 32 Phase 2 Reliability Statistics for Agreeableness Items Post-Data Cleaning

The researchers conducted basic descriptive statistics on each of the item in the Extraversion scale before conducting further analyses. We can see an expected range of 1 to 5 for each item. There is no excessive skew or kurtosis to our potential Neuroticism scale. The Cronbach's Alpha was also an acceptable value of α of .897.

Phase 2 Descriptive Statistics for <u>Neuroticism</u> Items Post-Data Cleaning									
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**	**Skewness**		**Kurtosis**	
	Statistic	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**
EST2	81334	1	5	3.14	1.305	-.128	.009	-1.114	.017
EST1	81334	1	5	2.71	1.172	.211	.009	-.853	.017
EST3	81334	1	5	3.77	1.116	-.717	.009	-.285	.017
EST4	81334	1	5	3.19	1.191	-.170	.009	-.839	.017
EST5	81334	1	5	2.84	1.244	.115	.009	-1.029	.017
EST6	81334	1	5	2.75	1.268	.198	.009	-1.045	.017

EST7	81334	1	5	2.90	1.258	.098	.009	-1.033	.017
EST8	81334	1	5	2.53	1.293	.401	.009	-.988	.017
EST9	81334	1	5	2.94	1.267	.018	.009	-1.095	.017
EST10	81334	1	5	2.62	1.247	.289	.009	-.959	.017
Valid N (listwise)	81334								

Table 33 Phase 2 Descriptive Statistics for Neuroticism Items Post-Data Cleaning

Phase 2 Reliability Statistics for Neuroticism Items Post-Data Cleaning	
Cronbach's Alpha	**N of Items**
.859	10

Table 34 Phase 2 Reliability Statistics for Neuroticism Items Post-Data Cleaning

Since all the items for all the scales show reasonable levels of internal consistency, skew, kurtosis, and have the full range of values expected from our data. It is considered legitimate to create basic scale scores for each of the Big Five scales hypothesized. We see below the values for each. The skew and kurtosis are as expected. Some interesting aspects are how rare it is to find an extremely low agreeableness or openness to new experiences person in the sample. In terms of agreeableness, we actually have no one who answered 1s across all ten items in our scale. That is surprising consider this is a data set with hundreds of thousands of participants. Openness is expected to be high because this is a convenience sample instead of a random sample of the population. It is expected to be high because a participant usually needs a certain amount of openness to new experiences to go out and try to find personality tests to take online. The fact that it is so high that the lowest score is 2.10 is very surprising though in a sample of over 80,000 participants.

Phase 2 Descriptive Statistics for the Big Five Scales Post-Data Cleaning									
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
OPEN	81334	2.10	5.00	3.8172	.59378	-.224	.009	-.513	.017
CONSCI	81334	1.00	5.00	3.4270	.70739	-.151	.009	-.389	.017
EXTRA	81334	1.00	5.00	2.9467	.86056	.022	.009	-.619	.017
AGREE	81334	1.10	5.00	3.8081	.67686	-.584	.009	.161	.017
NEURO	81334	1.00	5.00	2.9379	.82102	.024	.009	-.578	.017
Valid N (listwise)	81334	2.10	5.00	3.8172	.59378	-.224	.009	-.513	.017

Table 35 Phase 2 Descriptive Statistics for the Big Five Scales Post-Data Cleaning

Phase 2 Factor Analysis Post-Data Cleaning

The five factors are easily extracted, and we see a noticeable drop-off after the conscientiousness factor. This leads the researchers to conclude that the total variance explained table further supports a five-factor solution. Having only 40% of variance explained by the five-factor solution is a cause for concern and should provide some caution when interpreting the results of this cluster analysis.

Based on an outdated rule of thumb on eigenvalues greater than one being factors, the researchers decided to explore an 8-factor solution to be thorough. This was done with the expectation that the other factors were a mixture of errors in the data based on the negatively scored items and also the fact that data cleaning has not been done yet. There was no added benefit from using an 8-factor solution. The data became less interpretable. There was some evidence that some of the agreeableness and extraversion items were overly related to each other, which was leading to some of the problems with finding interpretable factors. See supplementary materials at the end of the manuscript for 8-factor solution output tables and figures.

Phase 2 Total Variance Explained Using Factor Analysis Post-Data Cleaning									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
EXTRA	7.400	14.800	14.800	6.806	13.611	13.611	4.679	9.357	9.357
NEURO	4.606	9.211	24.012	4.015	8.030	21.641	4.312	8.625	17.982
AGREE	3.643	7.285	31.297	3.006	6.011	27.653	3.470	6.939	24.922
OPEN	3.311	6.621	37.918	2.638	5.275	32.928	3.148	6.297	31.218
CONSC	2.632	5.264	43.182	2.071	4.141	37.070	2.926	5.851	37.070
6	1.503	3.006	46.188						
7	1.284	2.568	48.756						
8	1.109	2.218	50.974						

Table 36 Phase 2 Total Variance Explained Using Factor Analysis Post-Data Cleaning

Below we see the 5-factor rotated factor matrix. This matrix shows that each item aligns with the factor it is supposed to align with. This further supports the expected five factor solution. Note that this was done with a Quartimax rotation since we can expect from prior research literature on oblique vs orthogonal rotations that oblique rotations are more legitimate when studying personality data. A few of the factor loadings are in the <0.40 range and should be cautiously interpreted. Some of the items with low loadings are negatively scored and the items potentially confused participants. Other items seem like they would fit better with the data using ideal point response format instead of dominance modeling of the data. That is unfortunately outside of the scope of this project.

Big Five Rotated Factor Matrix Post-Data Cleaning for 5-Factor Solution					
	Factor				
	EXTRA	NEURO	AGREE	CONSC	OPEN
EXT7	.709	-.095	.155	.025	.038
EXT5	.708	-.083	.208	.091	.070
EXT4	.691	-.103	.035	.040	.007

EXT2	.671	.021	.122	-.032	.047
EXT1	.651	-.035	.059	-.007	.033
EXT10	.647	-.141	.073	.044	.024
EXT3	.621	-.271	.243	.108	-.029
EXT9	.584	-.051	-.033	-.053	.118
EXT8	.549	-.002	-.049	-.059	.040
EXT6	.527	-.058	.140	.027	.262
EST8	.006	.736	-.055	-.162	-.024
EST6	-.032	.719	-.007	-.063	-.091
EST7	.022	.711	-.050	-.163	-.021
EST9	-.023	.675	-.174	-.064	-.047
EST1	-.112	.671	.074	-.037	-.087
EST10	-.229	.572	-.035	-.184	.066
EST3	-.126	.568	.167	.022	-.026
EST2	-.077	.528	.003	.036	-.043
EST5	-.033	.509	-.023	-.096	-.115
EST4	-.119	.340	.006	-.085	.043
AGR4	.036	.057	.773	.056	.029
AGR9	.086	.114	.683	.058	.073
AGR5	.143	-.007	.622	.017	.039
AGR7	.315	-.092	.605	.022	.049
AGR6	.003	.156	.566	.041	-.048
AGR2	.348	-.071	.530	.004	.082
AGR8	.145	-.036	.513	.087	.043
AGR1	.008	-.057	.389	.039	.109
AGR10	.292	-.142	.379	.129	.085
AGR3	-.095	-.205	.369	.208	-.077
CSN6	-.015	-.146	.012	.615	-.046
CSN5	.092	-.073	.064	.611	-.086
CSN1	.029	-.098	.015	.594	.087
CSN9	.048	-.015	.092	.576	-.063
CSN4	.037	-.328	.045	.570	-.001
CSN2	-.040	-.091	-.034	.560	-.116
CSN7	-.043	.047	.040	.492	.042
CSN8	.046	-.191	.134	.482	.036
CSN10	.036	-.031	.058	.399	.235
CSN3	-.032	-.007	.094	.390	.243

OPN10	.188	-.031	.033	.029	.628
OPN1	.051	-.056	-.022	.042	.553
OPN5	.200	-.084	-.004	.134	.552
OPN2	.011	-.173	.005	.012	.546
OPN8	.016	.050	-.106	-.057	.514
OPN3	.058	.105	.081	-.073	.506
OPN4	-.008	-.077	.084	-.070	.473
OPN6	.093	-.026	.097	.002	.473
OPN7	.068	-.161	-.001	.170	.441
OPN9	-.127	.115	.167	.019	.354
Extraction Method: Maximum Likelihood. Rotation Method: Quartimax with Kaiser Normalization.					
a. Rotation converged in 5 iterations.					

Table 37 Phase 2 Big Five Rotated Factor Matrix Post-Data Cleaning for 5-Factor Solution

The below screen plot shows the ideal number of factors. It could be argued based on the Scree Plot that 5 or 7 factors are legitimate. Since all available evidence both from this study and prior studies show a five-factor solution to be the more well-substantiated. This is including the fact that the last 2 potential factors do not make any actual sense when trying to interpret. This Scree Plot can be considered to provide further support for our hypothesized 5-factor structure.

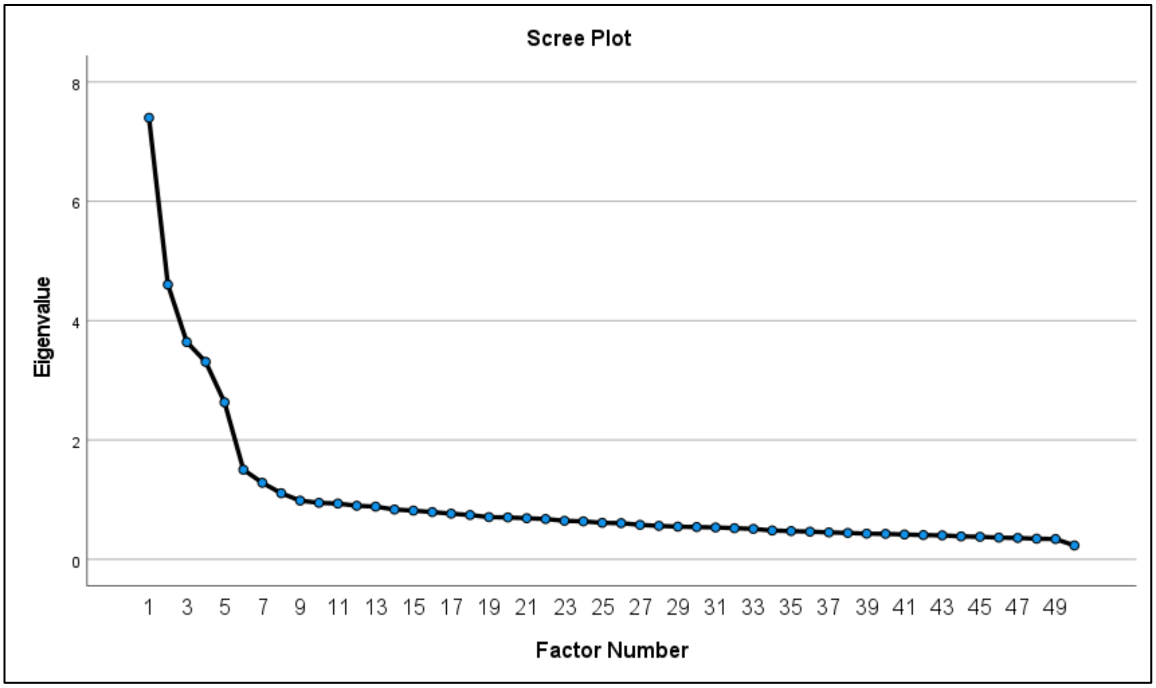


Figure 7 Screen Plot of Big Five Factors Pre-Data Cleaning

Phase 2 Cluster Analysis Post-Data Cleaning

Three cluster analytic techniques were used for this study. K-means clustering, two-step clustering, and gaussian mixture modeling. The first two were recommended by committee members as a comparison with the primary cluster analytic technique for this study, Gaussian mixture modeling.

Phase 2 K-Means Cluster Analysis Restricted to 4 Clusters on Unrefined Scales.

Our k-means cluster analysis on unrefined scales, with a 4-factor restriction, shows the Role Model cluster found in prior studies prominently. No other clusters are similar enough to prior research for them to be considered equivalent.

Final Cluster Centers for Unrefined Scores Post-Data Cleaning				
	Cluster			
	1	2	Role Model (3)	4
OPEN	3.73	3.63	4.05	3.87
CONSCI	3.60	3.10	3.90	3.12
EXTRA	2.43	2.11	3.72	3.53
AGREE	3.55	3.49	4.24	3.97
NEURO	2.45	3.74	2.18	3.40

Table 38 Phase 2 Final Cluster Centers for Unrefined Scale Scores Restricted to 4 Clusters

Phase 2 K-Means Cluster Analysis Restricted to 4 Clusters on Standardized Unrefined Scales.

Our k-means cluster analysis on standardized unrefined scales, with a 4-factor restriction, shows the Role Model cluster found in prior studies prominently. No other clusters are similar enough to prior research for them to be considered equivalent.

Final Cluster Centers for Unrefined Standardized Post-Data Cleaning				
	Cluster			
	1	2	3	Role Model (4)
Zscore(OPEN)	.52706	.41532	-1.14233	.32724
Zscore(CONSCI)	-.72500	-.08117	-.17583	.76317
Zscore(EXTRA)	.36317	-.76407	-.47510	.57944

Zscore(AGREE)	.39776	-1.26120	-.19632	.60727
Zscore(NEURO)	.61456	-.05291	.38522	-.77806

Table 39 Phase 2 Final Cluster Centers for Unrefined Standardized Scale Scores Restricted to 4 Clusters

Phase 2 Two-Step Cluster Analysis on Unrefined Scales.

The number of clusters found using the two-step cluster technique on unrefined scales is 3 and the results are fair but trending towards poor cluster cohesion. Results show that cluster 2 resembles the Role Model cluster.

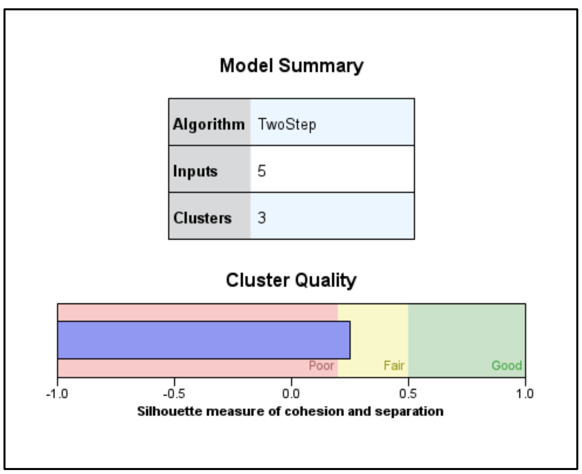


Figure 8 Model summary for the phase 2 refined scales two-step cluster analytic solution, fixed to 4 clusters.

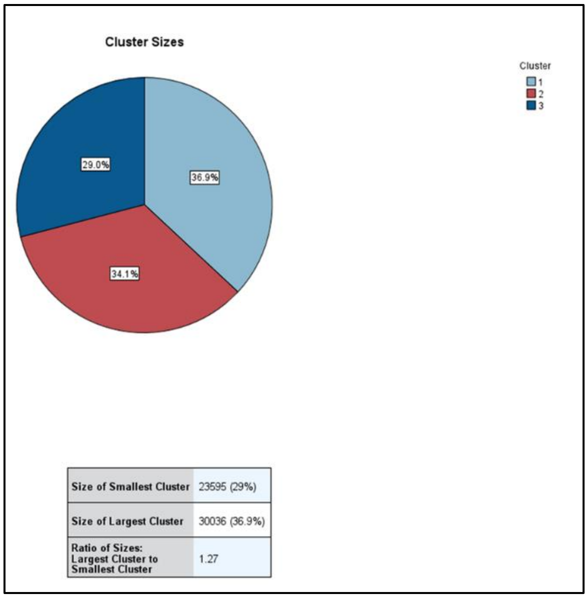


Figure 9 Cluster Sizes for the phase 2 refined scales two-step cluster analytic solution, fixed to 4 clusters.

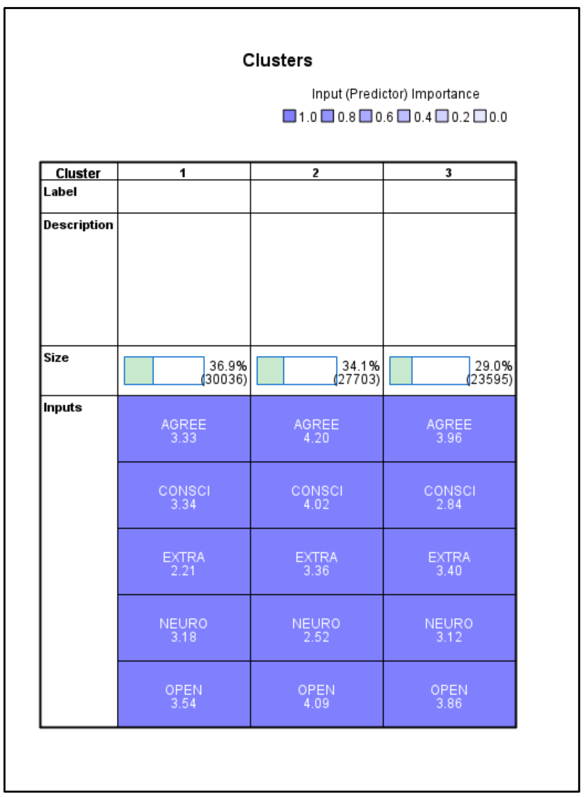


Figure 10 Detailed clusters for the phase 2 refined scales two-step cluster analytic solution, fixed to 4 clusters.

Phase 2 Two-Step Cluster Analysis Restricted to 4 Clusters on Unrefined Scales.

We fit a four-cluster solution, as found by the original Gerlach et al. (2018) study for our unrefined scales and the results are fair but trending towards poor cluster cohesion. Results show that cluster 3 resembles the Role Model cluster.

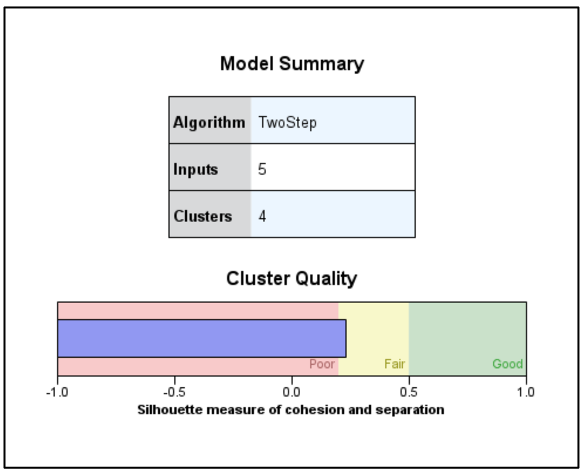
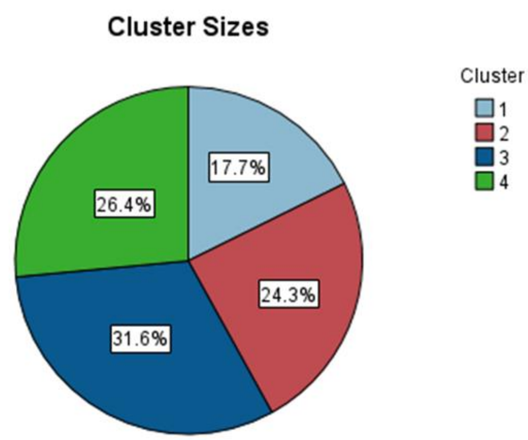


Figure 11 Model summary for the phase 2 refined scales two-step cluster analytic solution, fixed to 4 clusters.



Size of Smallest Cluster	14357 (17.7%)
Size of Largest Cluster	25693 (31.6%)
Ratio of Sizes: Largest Cluster to Smallest Cluster	1.79

Figure 12 Cluster Sizes for the phase 2 refined scales two-step cluster analytic solution, fixed to 4 clusters.

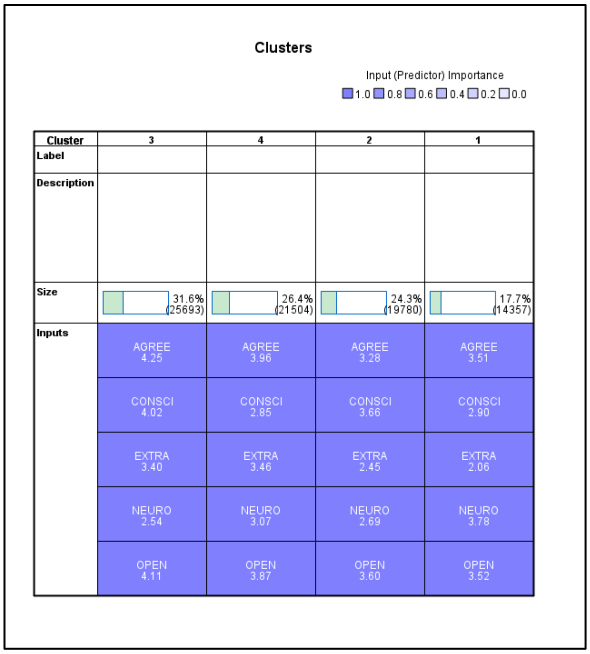


Figure 13 Detailed clusters for the phase 2 refined scales two-step cluster analytic solution, fixed to 4 clusters.

Phase 2 K-Means Cluster Analysis on Unrefined Scales.

Our k-means clustering on unrefined scales restricted to 3 clusters, based on the recommendation of the two-step clustering technique, show 1 decipherable cluster that resemble prior cluster analytic findings on personality data. We have again found a cluster resembling the Role Model cluster.

Phase 2 Final Cluster Centers for Unrefined Standardized Scores Post-Data Cleaning

	Cluster		
	1	2	Role Model (3)
Zscore(OPEN)	-.64905	.40560	.29613
Zscore(CONSCI)	-.13736	-.71424	.71679
Zscore(EXTRA)	-.75432	.26032	.51672
Zscore(AGREE)	-.75632	.26834	.51209

Zscore(NEURO)	.23117	.63146	-.73984

Table 40 Phase 2 Final Cluster Centers for Unrefined Standardized Scale Scores Restricted to 3 Clusters

Phase 2 K-Means Cluster Analysis Restricted to 4 Clusters on Refined Scales.

Our k-means clustering on unrefined scales restricted to 4 clusters, based on the recommendation of the two-step clustering technique, show 1 decipherable cluster that resemble prior cluster analytic findings on personality data. Results show that cluster 4 resembles the Role Model cluster.

Phase 2 Final Cluster Centers for Refined Scale Scores Restricted to 4 Clusters				
	Cluster			
	1	2	3	Role Model (4)
ROPEN	.38838	-1.01669	.46684	.24840
RCONSCI	-.03564	-.01650	-.39691	.38989
REXTRA	-.36899	-.36509	.14907	.41953
RAGREE	-1.31195	.03659	.36161	.45538
RNEURO	-.22882	.14445	.84932	-.74300

Table 41 Phase 2 Final Cluster Centers for Refined Scale Scores Restricted to 4 Clusters

Two-Step Cluster Analysis on Unrefined Scales.

We used two-step cluster analysis, without restricting number of clusters for our refined scales and the results are fair but trending towards poor cluster cohesion. Results show that cluster 1 resembles the Role Model cluster.

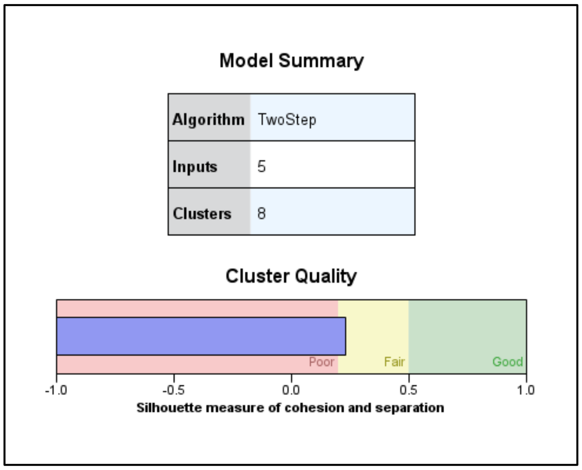
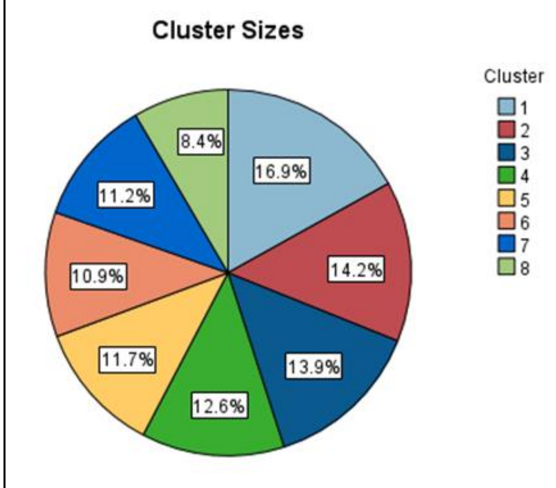


Figure 14 Model summary for the Phase 2 refined scales two-step cluster analytic solution, fixed to 4 clusters.



Size of Smallest Cluster	6867 (8.4%)
Size of Largest Cluster	13785 (16.9%)
Ratio of Sizes: Largest Cluster to Smallest Cluster	2.01

Figure 15 Cluster Sizes for the Phase 2 refined scales two-step cluster analytic solution, fixed to 4 clusters.

Input (Predictor) Importance
1.0 0.8 0.6 0.4 0.2 0.0

Cluster	1	2	3	4	5	7	6	8
Label								
Description								
Size	16.9% (13785)	14.2% (11524)	13.9% (11328)	12.6% (10279)	11.7% (9514)	11.2% (9148)	10.9% (8889)	8.4% (6867)
Inputs	RAGREE 0.69	RAGREE -0.37	RAGREE 0.48	RAGREE -0.83	RAGREE 0.31	RAGREE 0.37	RAGREE 0.27	RAGREE -1.58
	RCONSCI 0.49	RCONSCI -0.21	RCONSCI -1.12	RCONSCI -0.11	RCONSCI 0.80	RCONSCI 0.11	RCONSCI 0.13	RCONSCI -0.04
	REXTRA 0.68	REXTRA -0.28	REXTRA -0.23	REXTRA 0.86	REXTRA -0.80	REXTRA -0.84	REXTRA 0.90	REXTRA -0.76
	RNEURO -0.65	RNEURO 0.02	RNEURO 0.47	RNEURO -0.38	RNEURO 0.67	RNEURO -0.97	RNEURO 1.12	RNEURO -0.01
	ROPEN 0.23	ROPEN -1.28	ROPEN 0.32	ROPEN 0.17	ROPEN 0.18	ROPEN -0.00	ROPEN -0.01	ROPEN 0.66

Figure 16 Detailed clusters for the Phase 2 refined scales two-step cluster analytic solution, fixed to 4 clusters.

We fit a four-cluster solution, as found by the original Gerlach et al. (2018) study for our refined scales and the results are fair but trending towards poor cluster cohesion. Results show that cluster 3 resembles the Role Model cluster.

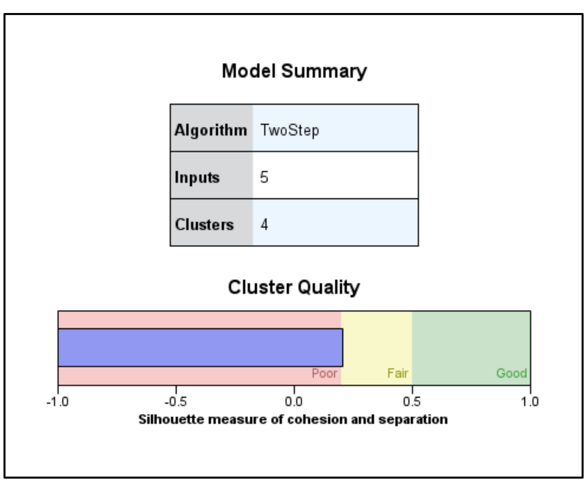


Figure 17 Model summary for the Phase 2 refined scales two-step cluster analytic solution, fixed to 4 clusters.

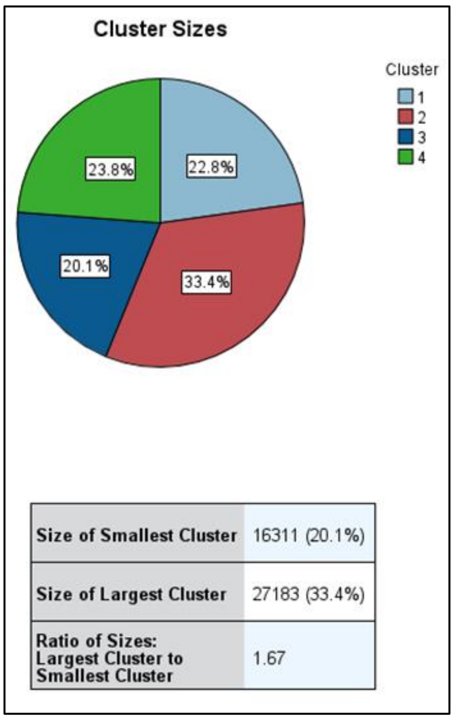


Figure 18 Cluster Sizes for the Phase 2 refined scales two-step cluster analytic solution, fixed to 4 clusters.

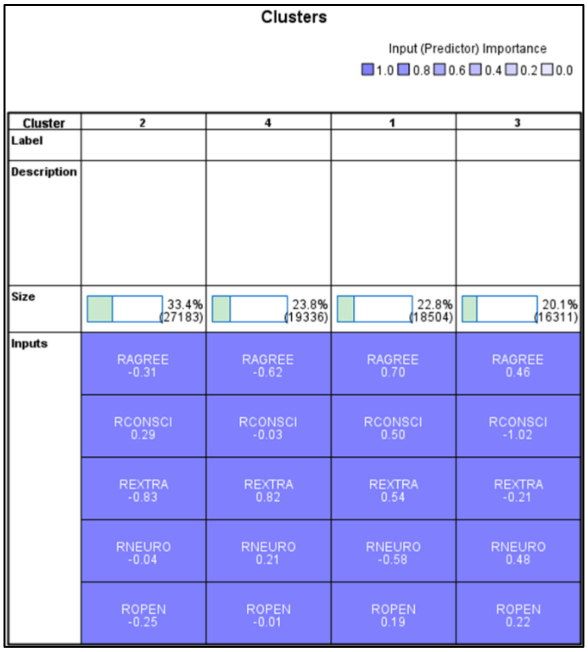


Figure 19 Detailed clusters for the phase 2 refined scales two-step cluster analytic solution, fixed to 4 clusters.

Phase 2 Gaussian Mixture Modeling on Refined Scales.

For our phase 2 Gaussian Mixture Modeling on refined scales, we tried not restricting the number of clusters and found that 9 clusters arose. Cluster 7 resembles the Role Model cluster.

Refined Scale Means					
	1	**2**	**3**	**4**	**5**
REXTRA	-1.08527341	0.12292325	-0.1891393	0.38551059	0.0026
RNEURO	0.16125005	-0.95021595	1.1188058	0.060152	-0.10904
RAGREE	0.26818718	0.03093757	-0.4142598	1.09637141	-0.98972
RCONSCI	-0.12450178	0.64977076	-0.7049184	0.02808734	-0.10956
ROPEN	0.07098107	-0.12135597	-0.2147527	0.21770574	0.319141

Refined Scale Means				
	6	**Role Model (7)**	**8**	**9**
REXTRA	-0.202220916	0.5211298	0.20387	0.2364659
RNEURO	-0.001371422	-0.6734878	0.6742479	0.1949753
RAGREE	-0.515471148	0.4765237	0.3075927	0.1038984
RCONSCI	-0.07297058	0.1247168	-0.1710787	0.1291375
ROPEN	-1.390782006	0.422987	0.7899101	-0.5165883

Table 42 Phase 2 Gaussian Mixture Model Cluster Means for Refined Scales

Phase 2 Gaussian Mixture Modeling Restricted to 4 Clusters on Standardized Unrefined Scales.

For our phase 2 Gaussian Mixture Modeling, we restricted the number of clusters to 4 for our standardized unrefined scales. The Role Model cluster arose in cluster 2 in this analysis.

Standardized Unrefined Scale Means				
	1	**Role Model (2)**	**3**	**4**
ZEXTRA	0.4906222	0.6668102	0.04056247	-0.8715719
ZNEURO	-0.16552153	-0.1651332	0.71061206	-0.1573322
ZAGREE	-0.22535257	0.1554335	0.41283611	-0.1996382
ZCONSCI	-0.86062998	0.5732667	0.53832352	-0.1661998
ZOPEN	-0.01871543	0.1819406	-0.78594133	0.3105828

Table 43 Phase 2 Gaussian Mixture Model Cluster Means for Unrefined Standardized Scales Restricted to 4 Clusters

Phase 2 Gaussian Mixture Modeling Restricted to 4 Clusters on Unrefined Scales.

For our phase 2 Gaussian Mixture Modeling, we restricted the number of clusters to 4 for our unrefined scales. The Role Model cluster is found in cluster 4 in this analysis.

Unrefined Scale Means				
	1	**2**	**3**	**Role Model (4)**
EXTRA	2.698443	2.781884	3.07334	3.301755
NEURO	3.141408	3.00448	3.08728	2.312278
AGREE	3.113649	4.074933	4.028101	3.858605
CONSCI	3.2893	3.299151	3.345311	3.955823
OPEN	3.586243	3.357265	4.216292	4.114348

Table 44 Phase 2 Gaussian Mixture Model Cluster Means for Unrefined Scales Restricted to 4 Clusters

Phase 2 Gaussian Mixture Modeling on Unrefined Scales.

For our phase 2 Gaussian Mixture Modeling, we did not restrict the number of clusters for our unrefined scales. Interestingly enough, 3 of out 9 clusters resemble the Role Model cluster in this analysis. This will be discussed further in the discussion section of this manuscript.

Unrefined Scale Means					
	1	**2**	**Role Model (3)**	**4**	**5**
EXTRA	2.009685	3.741588	3.083323	2.896259	2.88503
NEURO	3.154567	2.968144	2.430443	2.965958	3.16862
AGREE	3.503802	3.80738	3.73764	4.428171	3.26737
CONSCI	3.213958	3.368415	3.945598	3.260506	3.31017
OPEN	3.274475	4.197576	4.033148	3.135232	3.61378

Unrefined Scale Means				
	Role Model (6)	**Role Model (7)**	**8**	**9**
EXTRA	3.041629	3.896273	2.727394	3.291563
NEURO	2.127755	2.081368	3.541017	2.939365
AGREE	4.08577	4.251232	4.05372	4.209891
CONSCI	3.38962	4.103751	3.245594	3.52049
OPEN	3.776306	4.540833	3.907664	4.693709

Table 45 Phase 2 Gaussian Mixture Model Cluster Means for Unrefined Scales

Phase 2 Gaussian Mixture Modeling on Standardized Unrefined Scales.

For our phase 2 Gaussian Mixture Modeling, we did not restrict the number of clusters for our standardized unrefined scales. We did not find any clusters that represented the Role Model cluster. Gaussian Mixture Modeling, as opposed to two-step and k-means cluster analysis, was less likely to find the cluster associated with social desirability across multiple scales. This phenomenon was especially true in phase 2 of our study.

Standardized Unrefined Scale Means					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.5902339	-0.48142233	-0.1563125	0.04725129	0.449431054
ZNEURO	-0.3524451	-0.23423099	0.5432932	-0.08267764	0.002509809
ZAGREE	-0.119895	0.10108043	0.2921288	0.14906059	1.224380799
ZCONSCI	0.2064615	-0.72628309	0.2517877	0.46639011	1.098985583
ZOPEN	0.8118384	-0.09703248	-0.7920568	-0.09570594	-0.12605019

Standardized Unrefined Scale Means				
	6	**7**	**8**	**9**
ZEXTRA	-0.2032035	-0.8471228	1.23373439	-0.2632903
ZNEURO	1.2503584	-0.439655	-0.253811	-0.2818676
ZAGREE	-0.273719	-0.3689803	0.07802691	-1.3886311

ZCONSCI	0.3241854	-0.2260351	-0.57032371	-0.8047934
ZOPEN	-0.2383304	0.8294625	-0.07503884	0.2545284

Table 46 Phase 2 Gaussian Mixture Model Cluster Means for Unrefined Scales Restricted to 4 Clusters

Phase 2 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales.

For our phase 2 Gaussian Mixture Modeling, we restricted the number of clusters to 4 for our refined scales. Notice that this is one of the rare instances where there is no discernible Role Model Cluster. The researchers suspect that because this is a standardized scale that has extracted out factor solutions, it has managed to control for the amount of socially desirable responding to a certain extent.

Phase 2 Gaussian Mixture Modeling Refined Scale Means				
	1	**2**	**3**	**4**
REXTRA	-0.1213988	0.1130903	0.28585969	-0.2556162
RNEURO	-0.01827475	0.2404665	-0.75212272	0.1659847
RAGREE	-0.71115272	0.5237179	0.3331804	-0.3459607
RCONSCI	-0.0932917	-0.1261439	0.57342978	-0.1096663
ROPEN	0.60640077	0.2114376	-0.03927327	-0.9046356

Table 47 Phase 2 Gaussian Mixture Model Cluster Means for Refined Scales Restricted to 4 Clusters

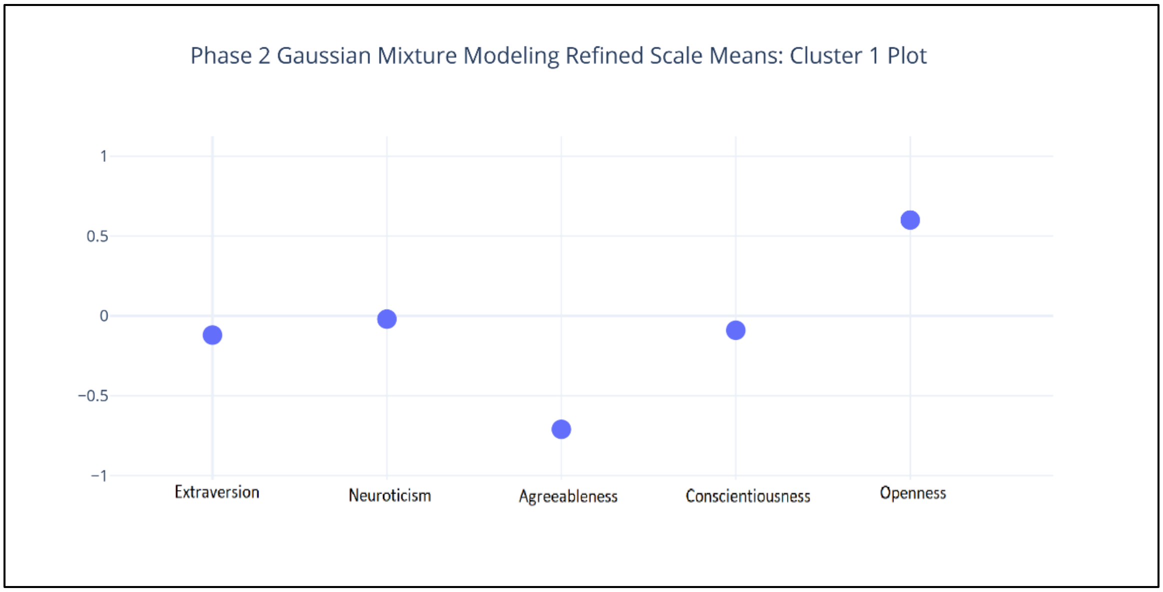


Figure 20 Phase 2 Gaussian Mixture Modeling Refined Scale Means Cluster 1 Plot

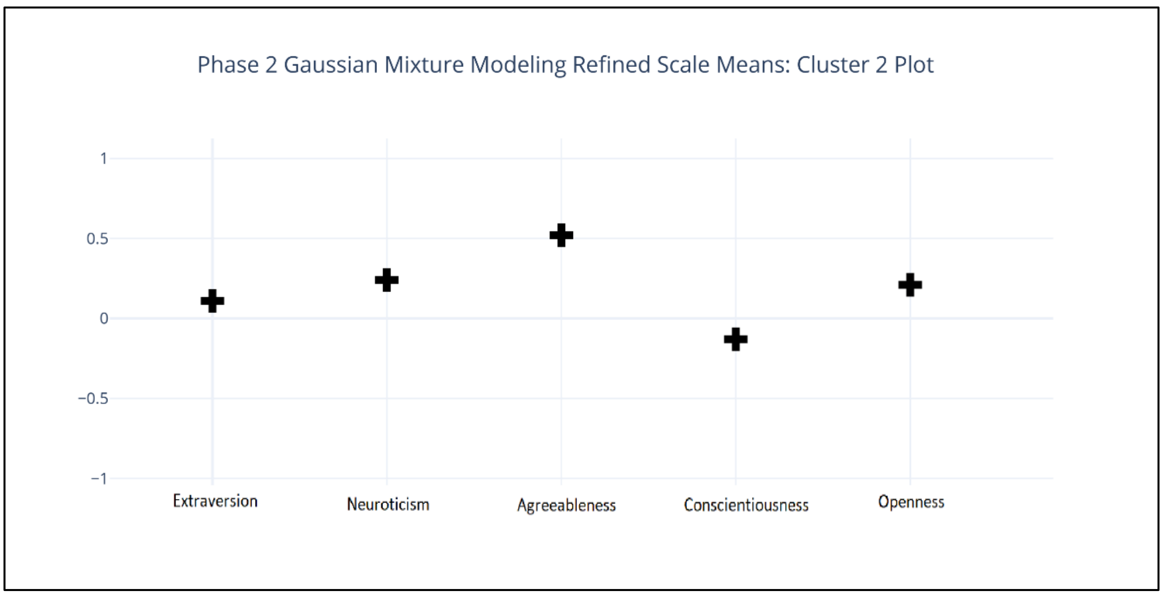


Figure 21 Phase 2 Gaussian Mixture Modeling Refined Scale Means Cluster 1 Plot

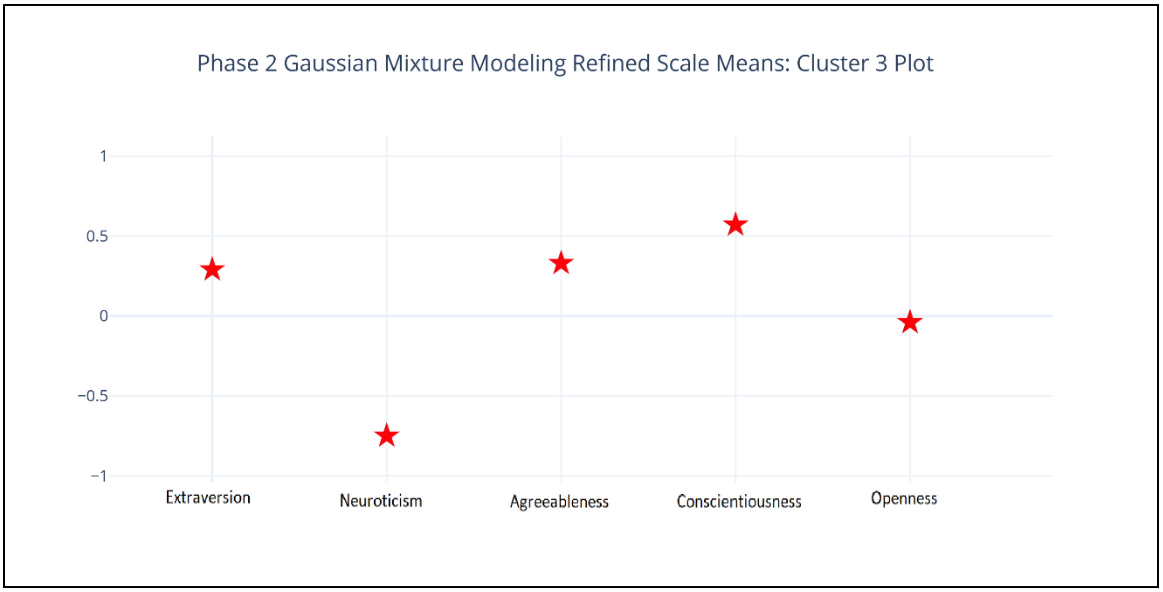


Figure 22 Phase 2 Gaussian Mixture Modeling Refined Scale Means Cluster 1 Plot

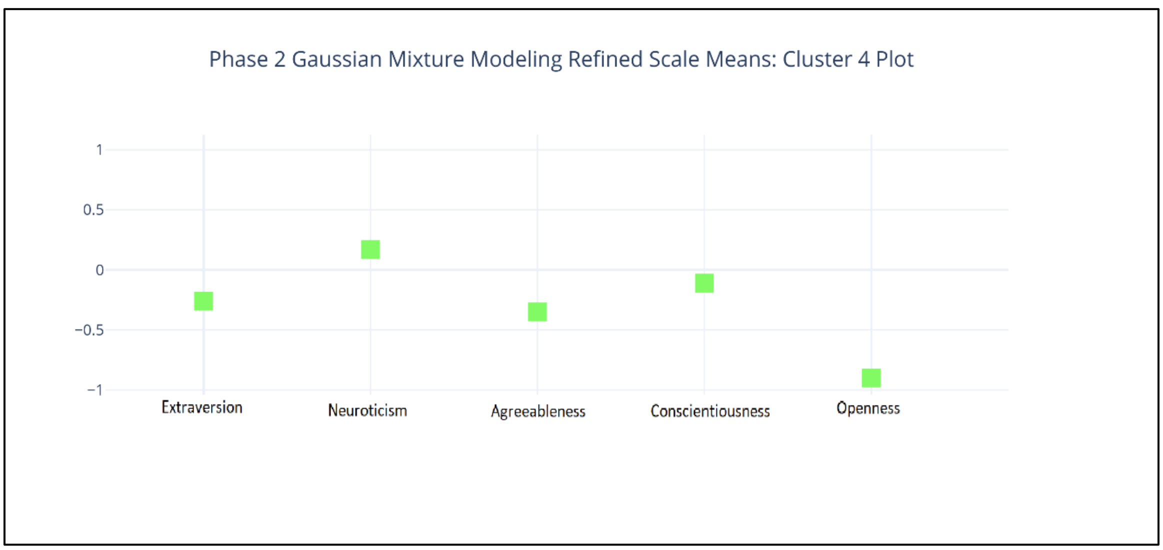


Figure 23 Phase 2 Gaussian Mixture Modeling Refined Scale Means Cluster 1 Plot

DISCUSSION

Summary Findings

The exploration of personality styles is a growing field of research that will likely provide a serious contribution to the prediction of human behavior in the future. The researchers learned that characteristics of the data, especially range restriction, a Likert scale with few anchor points, and amount of time spent on questions, can significantly alter the results of cluster analytic procedures. The researchers also believe this study shows that perhaps other ways of studying personality styles will be more fruitful in the future for predictive purposes. While certain clusters, such as the Role Model cluster, were more resilient across samples than others, the overall purpose of looking at personality styles in this way seems of limited use. Even the Role Model cluster seems to disappear if enough data cleaning procedures and advanced enough cluster analytic techniques are used. The final results for our various hypotheses can be found below.

Hypothesis 1: *Following R equivalent code of the Gerlach study will show the same clusters as the prior study. This provides first pass support for the equivalence of data, allowing for the further study into controlling for social desirability and central tendency biases.*

Hypothesis 1 Results: Hypothesis 1 was **supported**. Because Gerlach et al. (2018) made seemingly arbitrary distinctions in terms of showing equivalence with prior research, essentially everything could be supported as being equivalent.

Hypothesis 2: *Accurate preprocessing will get rid of the social desirability bias in the data sets, which will make the Role Model cluster disappear.*

Hypothesis 2 Results: The researcher considers this hypothesis to be **partially supported** since the Role Model cluster was not substantiated in our more advanced data analytic techniques after strict data cleaning procedures were used.

Hypothesis 3a: *Accurate preprocessing will get rid of the central tendency bias in the data sets, which will make the Average cluster disappear.*

Hypothesis 3a Results: Upon further review and comparison with prior literature, the Average cluster is not a legitimate cluster and is not supported in enough of our analyses to say it is anything but a statistical abnormality in prior data sets. The researcher considers this hypothesis to be **supported** since the cluster was not substantiated in our research.

Hypothesis 3b: *Accurate preprocessing will get rid of the central tendency bias in the data sets, which will make the Self-Centred cluster disappear.*

Hypothesis 3b Results: Upon further review and comparison with prior literature, the Self-Centred cluster is not a legitimate cluster and is not supported in enough of our analyses to say it is anything but a statistical abnormality in prior data sets. The researcher considers this hypothesis to be **supported** since the cluster was not substantiated in our research.

Hypothesis 3c: *Accurate preprocessing will get rid of the central tendency bias in the data sets, which will make the Reserved cluster disappear.*

Hypothesis 3c Results: Upon further review and comparison with prior literature, the Reserved cluster is not a legitimate cluster and is not supported in enough of our analyses to say it is anything but a statistical abnormality in prior data sets. The researcher considers this hypothesis to be **supported** since the cluster was not substantiated in our research.

Hypothesis 4: *All cluster analytic results will be compared, and no clusters will appear as anything but noise.*

Hypothesis 4 Results: This hypothesis was **partially supported**. The Role Model cluster turned up in quite a few of our analyses. However, the more we cleaned up our data and the more advanced cluster analytic techniques we used, the less likely we were to find the Role Model cluster.

Implications for Theory, Research, and Practice

The most important takeaway from this research is that a few relatively minor quantitative decisions can have a rather profound impact on the inferences made. We see two minor quantitative decisions in the Gerlach et al. (2018) study that had profound impacts on the inferences made, which were likely incorrect. One is that it is hard to see the legitimacy of saying that the results from Gerlach et al. (2018) truly overlapped with prior research. For example, the Reserved cluster had neuroticism results that were so different from the five prior studies on the ARC typology, that even with error bars including 3 standard errors of the mean, Gerlach's results do not overlap at all with any prior neuroticism mean scores. Another example, the Average cluster, was not found in any prior research. The self-centred cluster, only fully overlaps with all five prior research studies for two personality traits, agreeableness and conscientiousness. Interestingly enough, the only cluster that may have some legitimacy, the Role Model cluster, overlaps entirely with all five prior research studies within 3 standard errors of the mean. The Role Model cluster was the one found most frequently in the multitude of analysis done in this study as well.

A second quantitative decision that is likely erroneous is the Gerlach et al. (2018) study said they found legitimate clusters. They did not really find legitimate clusters, if by legitimate we mean differing significantly from 0 and from each other. 16 of 20 personality traits across the four personality clusters had traits that overlapped with 0 within 3 standard errors of the mean. If the error bars are supposed to represent where the true mean is likely going to be found, we would want to see the majority of the error bars in a cluster not overlapping with 0 unless the cluster is supposed to be an Average cluster. In Gerlach et al. (2018) we technically do have an average cluster but it is hard to see how the Average cluster is any more average than the Self-centered cluster considering both clusters have error bars that overlap with 0 for literally all 5 of their traits. The Role Model cluster, once again, shows its potential legitimacy since 3 of the 5 personality traits have error bars that differ significantly from 0.

Cluster Analysis Interpretation.

The results of our phase 2 GMM means table for unrefined scales show 3 of 9 clusters resembling the Role Model cluster. The researchers suspect these findings are due to relatively minor differences in responding on a 5-point Likert scale. It was suspected prior to analysis that if the Role Model cluster was at least somewhat caused by socially desirable responding, then it would be most noticeable in the untransformed scales. This was suspected because participants cannot know how much others will respond in a socially desirable way and therefore cannot respond in an even more socially desirable way in order to respond above the mean scores for the distribution. The participants only midpoint to go off of would be the middle of the Likert scale for the questions they are answering. Likewise, in the extracted factors, we were less likely to find social desirability clusters. This was expected because the extracted factors are less susceptible to socially desirable responding on an individual level. Extracted factors are another way that participants cannot know in advance how other participants respond, and hence cannot know for sure whether they are truly responding higher or lower on average for the socially desirable or undesirable traits.

Data Categorization.

The perils of using categorical data for cluster analysis can be clearly seen in this study. Categorization of data can occur in 3 places but only one is legitimate in most instances. Categorization can occur in the methods/data collection phase, which occurred in this study. This is where we provide categories on the actual survey when the data is actually theorized to be continuous. What this means is that even if we wanted to go back afterwards and look at the data continuously, we could not since we did not collect it in a continuous manner. This is the worst form of categorization since there is no fix to a study once the data is collected. This is a problem with conventional Likert scales of 5 to 7 anchor points. This study used 5 anchor points and from reviewing the data, it looks like very minor changes in answering can significantly alter which cluster a participant is categorized in. When the questions have a problem of range restriction and few options to differentiate between levels of the variable, it becomes difficult to use cluster analytic techniques in any justifiable way.

The second way to categorize data is in the data analysis phase. Categorization in the data analysis phase means we are analyzing our data in a categorical way. Take for example MBTI and Enneagram. These personality questionnaires in some situations collect continuous data (with terrible psychometric legitimacy) yet go on to interpret it in categorical ways in the case of Enneagram and outright dichotomous ways in the case of MBTI. This, even putting aside the psychometric problems with the surveys, is illegitimate because we have theoretical reasons to believe personality is continuous.

The third way to categorize data is in the interpretation and communication phase. This type of categorization is the only one that I, the author, consider to be legitimate usage of categorization for continuous data. This is where the analysis conducted is on continuous data, so that you do not find spurious correlations. However, in the data visualization and data communication stages of the research process researchers can wash away some nuance so that non-experts can buy-in and understand the research. Machine learning, because of its complexity, makes this step necessary even for experts in a subject.

With something like personality styles being extreme forms of moderation, it is hard even for an expert to wrap their heads around a personality style such as 99th percentile openness to new experience, 56th percentile conscientiousness, 79th percentile extraversion, 21st percentile agreeableness, and 11th percentile neuroticism. One percentile ranking would be easily interpretable in comparison with others to someone trained in statistics. While five combined, where each potentially moderates the other four depending on the context, might as well be gibberish. It is far easier to understand something more like the best performers of this job have high extraversion and openness, moderate conscientiousness, and low agreeableness and neuroticism than specifically talking about percentile ranking. Going forward, if personality researchers want personality styles to matter to researchers, they need to have as continuous of data as possible up until the data communication and visualization phase of the research process. If personality researchers want personality styles to matter to non-experts, there is a lower bar that needs to be met in that any categorical data is likely more easily understandable.

Missing Data Imputation Limitation

Our research study had some limitations, one of which is we did not use missing data imputation. The researchers could not find enough prior research literature to conclude that missing data imputation is actually reasonable for cluster analysis. It is entirely possible that missing data imputation in some circumstances artificially creates clusters. This study did not explore further to validate whether artificial clusters would be created due to missing data imputation. We believed that our sample sizes were large enough that removal of data to avoid this problem would be an acceptable solution, given the limitations of this study.

Likert Scale Format Limitation

Another limitation to this study, is that if personality styles do exist, the Likert scale format is a really terrible way to utilize for creating clusters. We see range restriction problems occurring even in sample sizes of hundreds of thousands of participants, which creates some major problems when working over a small scale such as this 1 through 5 Likert scale format. When doing cluster analysis on scales with so few options being chosen by participants, even very slight variations in choice on the participants part can have major repercussions for which cluster they most likely belong to.

Alternative Forms of Personality Style Limitation

A third limitation of this study, and with this way of studying personality styles in general, is what is the purpose of studying these clusters? Numerous research studies have found clusters with poor convergent validity with prior research findings and poor discriminant validity between clusters within a study. Personality styles research using cluster analytic techniques on Likert scales, faces the limitation of minimal actual applicability. It is not being utilized for predictive purposes, researchers have found few ways to work around the limitations of Likert scale format when used for cluster analytic purposes, and we have not come up with good ways to remove social desirability from data sets being used for cluster analysis. There are better ways of going about creating combinations of personality traits, which will be discussed further in the future research section of this manuscript.

Future Personality Styles Research: Exploration of Alternatives to Cluster Analysis

A potential future direction of research is that personality styles should still be used, even if few or no styles occur more often than others. We have to ask ourselves what the point of personality styles is? Whether some styles occur more frequently than others is not the most important research question to be asking. What matters for most researchers and practitioners is whether there is any incremental validity from looking at personality traits in combination. This is a question of extreme moderation where each personality trait has the potential to moderate all four of the others. This means that certain combinations might be especially highly related to an outcome variable compared to looking at any single trait or what would be expected when combining them. We are essentially asking if looking at personality traits together provides anything extra to our understanding and ability to predict important outcome variables.

Future Personality Styles Research: Compound Traits

A more viable alternative for looking at personality styles would be further study of compound traits. In compound traits, we are creating amalgamations of either superordinate constructs or facets of those superordinate constructs, in order to predict outcome variables most accurately or equally as accurately while asking for less from the research participants. The research literature has supported that these compound traits have the reliability and validity necessary for us to consider compound traits in place of narrow traits (Credé et al., 2016). Compound traits have the benefit of creating a higher-level construct that is applicable in a specific circumstance, and hence likely has high applicability because of its potential predictive validity.

Future Participant Characteristics Research: Response Time

One important and unexpected finding from this study was that non-experts have a very radically different understanding of what participant responses are considered valid for research usage. Participants were specifically asked whether their responses could be used for research purposes. The author of this study interpreted that to mean they spend at least 2 seconds per question and up to 5 minutes on a question. Since these questions are supposed to be knowledge elicitation techniques, a couple seconds was not considered too much to ask from participants. Only one-tenth of respondents fulfilled these minimum criteria for inclusion in the phase 2 portion of the study. This leads the author to believe that either participants do not understanding what behavior on their part is legitimate for research purposes or that Likert scale style questions are not functioning as a knowledge elicitation technique of past behavior but instead participants are using a gut feeling after quickly skimming a question. We know from prior research on how inaccurate gut feelings are for making decisions (Kahneman, 2013) but further research likely needs to be done to find out how accurate, or even how similar, gut feelings are compared to spending time thinking over responses for personality data.

Future Participant Characteristics Research: Online Questionnaires

It is entirely possible that new lines of research on questionnaire & participant characteristics can be pursued now that we have online questionnaires. For example, is there more than one type of fast responder who takes under 2 seconds to read and respond to each question? The researchers of this study can think of at least four groups of fast responders. The first and most obvious are the careless responders who are just pressing buttons. The second are those who focus on impression management and might read a question and immediately answer in a socially desirable way. A third would be individuals who understand parts of their personality so well that they can rapidly respond without thinking through the answer, this would likely be related to identity centrality. The fourth would be those whose referent group are so strongly different compared to themselves on the trait that they immediately think of themselves in the opposite way. An example of the fourth type of fast responder would be an introvert who is friends with a lot of extreme extroverts might quickly mark down the lowest score for an extroversion question because of the salience of the referent group.

APPENDICES

Openness to New Experience Items

Item
I have a rich vocabulary
I have difficulty understanding abstract ideas
I have a vivid imagination
I am not interested in abstract ideas
I have excellent ideas
I do not have a good imagination
I am quick to understand things
I use difficult words
I spend time reflecting on things
I am full of ideas

Note: Bolded are reverse scored because they are negatively worded

(Johnson, 2014)

Conscientiousness Items

Item
I am always prepared
I leave my belongings around
I pay attention to details
I make a mess of things
I get chores done right away
I often forget to put things back in their proper place
I like order
I shirk my duties
I follow a schedule
I am exacting in my work

Note: Bolded are reverse scored because they are negatively worded

(Johnson, 2014)

Extraversion Items

Item
I am the life of the party
I don’t talk a lot
I feel comfortable around people
I keep in the background
I start conversations
I have little to say
I talk to a lot of different people at parties
I don’t like to draw attention to myself
I don’t mind being the center of attention
I am quiet around strangers

Note: Bolded are reverse scored because they are negatively worded

(Johnson, 2014)

Agreeableness Items

Item
I feel little concern for others
I am interested in people
I insult people
I sympathize with others' feelings
I am not interested in other people's problems
I have a soft heart
I am not really interested in others
I take time out for others
I feel others' emotions
I make people feel at ease

Note: Bolded are reverse scored because they are negatively worded

(Johnson, 2014)

Neuroticism Items

Item
I get stressed out easily
I am relaxed most of the time
I worry about things
I seldom feel blue
I am easily disturbed
I get upset easily
I change my mood a lot
I have frequent mood swings
I get irritated easily
I often feel blue

Note: Bolded are reverse scored because they are negatively worded

(Johnson, 2014)

Likert Scale Points

<u>Indicate how much the following statements describe you:</u>

1 = Disagree	3 = Neutral	5 = Agree

The 5-point Likert scale was used based on research showing people struggle to make distinctions between too many Likert scale points and it is thought that having fewer point on the scale might make it easier for people to make meaningful decisions instead of carelessly deciding between two points (Jamieson, 2004). The decision to use an odd or even number Likert scale is thought to be up for debate. The research is undecided on the issue.

Not having specific names for each anchor point might have contributed to the central tendency bias. The assumptions that people make about what comes in between disagree and neutral might be something along the lines of "Somewhat Disagree" or "Slightly Disagree" and there is not enough research on whether those are considered the same in people's minds. On top of that, the scaling options do not have "Strongly Agree" or "Strongly Disagree" which provides pretty hard caps on the strongest of opinions on these items, which again might lead to more of a central tendency bias.

Supplementary Tables

Big Five Rotated Factor Matrix Pre-Data Cleaning for 8-Factor Solution								
	Factor							
	1	2	3	4	5	6	7	8
EXT4	0.751	-0.092	0.033	0.030	-0.010	-0.016	0.119	-0.037
EXT7	0.724	-0.072	0.198	0.085	0.051	0.019	-0.075	-0.009
EXT2	0.720	0.034	0.117	-0.022	0.019	0.009	0.097	-0.078
EXT5	0.715	-0.092	0.144	0.029	0.007	-0.005	-0.113	0.046
EXT10	0.691	-0.146	0.054	0.034	-0.012	0.010	0.089	-0.004
EXT1	0.686	-0.048	0.063	-0.006	0.031	-0.036	-0.146	0.047
EXT3	0.641	-0.260	0.244	0.101	-0.031	-0.033	-0.132	0.029
EXT9	0.625	-0.064	-0.026	-0.044	0.101	0.055	-0.094	0.051
EXT8	0.593	-0.026	-0.046	-0.068	0.042	-0.002	0.069	0.018
EXT6	0.576	-0.031	0.125	0.030	0.215	0.105	0.185	-0.095
EST1	-0.115	0.748	0.097	-0.012	-0.054	-0.026	0.006	-0.172
EST8	-0.051	0.726	0.023	-0.078	-0.060	-0.033	-0.085	0.029
EST6	-0.019	0.717	-0.030	-0.168	0.001	-0.003	-0.001	0.523
EST7	-0.003	0.688	-0.017	-0.161	0.016	-0.025	-0.032	0.460
EST9	-0.040	0.680	-0.163	-0.051	-0.040	0.009	-0.096	0.034
EST3	-0.143	0.645	0.180	0.032	0.016	-0.015	-0.021	-0.169
EST10	-0.086	0.604	-0.006	0.043	-0.036	0.020	0.245	-0.145
EST2	-0.254	0.581	-0.016	-0.193	0.060	0.091	0.081	0.149
EST5	-0.058	0.503	-0.009	-0.087	-0.067	-0.064	-0.131	-0.016
EST4	-0.130	0.371	0.033	-0.102	0.062	0.046	0.210	0.023
AGR4	0.032	0.066	0.792	0.038	0.041	-0.011	-0.066	0.015
AGR9	0.084	0.108	0.705	0.053	0.084	-0.024	-0.101	0.066
AGR5	0.151	0.013	0.654	0.004	0.019	0.008	0.171	-0.024
AGR7	0.319	-0.065	0.610	0.016	0.054	-0.013	0.162	-0.035
AGR6	-0.021	0.159	0.593	0.021	0.000	-0.089	-0.145	0.015
AGR8	0.142	-0.014	0.554	0.097	0.029	0.001	-0.106	0.015
AGR2	0.354	-0.052	0.535	0.003	0.080	0.035	-0.008	0.009
AGR1	0.037	-0.013	0.485	0.029	0.036	0.095	0.167	-0.085
AGR3	0.308	-0.141	0.390	0.127	0.106	-0.016	-0.195	0.056

AGR10	-0.107	-0.203	0.383	0.195	-0.019	-0.094	0.124	-0.007
CSN6	0.028	-0.082	0.020	0.637	0.040	0.067	-0.086	-0.017
CSN5	-0.007	-0.152	-0.007	0.633	-0.047	-0.066	0.229	0.056
CSN1	0.066	-0.077	0.043	0.624	-0.062	-0.072	-0.054	0.067
CSN4	0.050	0.038	0.100	0.611	-0.067	-0.018	-0.114	-0.052
CSN9	0.055	-0.331	0.018	0.590	-0.006	-0.041	0.174	0.003
CSN2	-0.053	-0.093	-0.049	0.586	-0.079	-0.129	0.199	0.074
CSN7	-0.048	0.095	0.030	0.553	-0.015	0.057	-0.060	-0.054
CSN8	0.056	-0.185	0.120	0.485	0.026	0.023	0.110	-0.074
CSN10	0.030	-0.017	0.049	0.447	0.184	0.130	-0.138	-0.024
CSN3	-0.036	0.020	0.092	0.401	0.209	0.084	-0.100	0.001
OPN10	0.188	-0.025	0.016	0.032	0.732	0.072	-0.126	-0.007
OPN3	0.039	0.102	0.074	-0.080	0.649	-0.015	-0.052	0.006
OPN6	0.080	-0.034	0.072	-0.016	0.627	-0.073	0.086	-0.016
OPN5	0.214	-0.093	-0.035	0.151	0.596	0.127	-0.189	-0.001
OPN2	0.004	-0.091	0.100	-0.061	0.483	0.147	0.300	0.004
OPN4	0.034	-0.190	0.022	0.016	0.482	0.247	0.268	0.019
OPN7	0.077	-0.168	0.002	0.178	0.348	0.306	-0.073	0.055
OPN9	-0.122	0.117	0.172	0.045	0.340	0.170	0.008	-0.009
OPN8	0.043	0.049	-0.077	-0.021	0.299	0.733	0.022	0.013
OPN1	0.056	-0.039	-0.006	0.055	0.338	0.720	0.041	-0.039
Extraction Method: Maximum Likelihood. Rotation Method: Quartimax with Kaiser Normalization.								
a. Rotation converged in 6 iterations.								

Table 48 Big Five Rotated Factor Matrix Pre-Data Cleaning for 8-Factor Solution

Refined Scale: Cluster 1 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	1.02876488	0.034346	-0.01107884	-0.087668704	-0.062
RNEURO	0.034346	1.03690368	-0.02233989	0.048482483	0.02678
RAGREE	-0.01107884	-0.02233989	0.98381028	-0.14654097	-0.0248
RCONSCI	-0.0876687	0.04848248	-0.14654097	0.993793662	0.00081
ROPEN	-0.0620458	0.02678294	-0.02479088	0.000807188	0.30393

Table 49 Phase 1 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales: Cluster 1 Variance

Refined Scale: Cluster 2 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.30065328	0.055456633	-0.03267482	-0.03367571	0.02489
RNEURO	0.05545663	0.90886147	-0.03684202	-0.1207654	-0.0057
RAGREE	-0.03267482	-0.03684202	0.23175921	0.0274467	0.02546
RCONSCI	-0.03367571	-0.1207654	0.0274467	0.85537022	-0.0045
ROPEN	0.02488686	-0.00567991	0.02546134	-0.0045495	0.4978

Table 50 Phase 1 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales: Cluster 2 Variance

Refined Scale: Cluster 3 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.850709558	-0.0073861	0.008644627	-0.0177262	0.01705618
RNEURO	-0.0073861	0.824360525	0.044588525	0.02746033	-0.0442539
RAGREE	0.008644627	0.044588525	0.823653161	0.04028749	-0.0786135
RCONSCI	-0.01772616	0.027460326	0.040287492	0.77403718	0.11298099
ROPEN	0.017056176	-0.04425388	-0.0786135	0.11298099	0.71018335

Table 51 Phase 1 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales: Cluster 3 Variance

Refined Scale: Cluster 4 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.52594279	-0.01657874	-0.1005245	0.04384186	-0.0609977
RNEURO	-0.01657874	0.819106	-0.02208183	-0.0855671	0.06843986
RAGREE	-0.1005245	-0.02208183	0.34619032	0.02626507	0.07666298
RCONSCI	0.04384186	-0.08556706	0.02626507	0.75947255	-0.0212732
ROPEN	-0.06099771	0.06843986	0.07666298	-0.0212732	0.60594669

Table 52 Phase 1 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 1 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.58077534	0.064487268	0.020326998	-0.08564041	0.030646529
RNEURO	0.06448727	0.666984791	0.004911209	-0.04120794	0.081580674

RAGREE	0.020327	0.004911209	0.337530033	-0.03748404	-0.06795792
RCONSCI	-0.0856404	-0.04120794	-0.03748404	0.646096014	-0.00640139
ROPEN	0.03064653	0.081580674	-0.06795792	-0.0064014	0.546798722

Table 53 Phase 1 Gaussian Mixture Modeling on Refined Scales: Cluster 1 Variance

Refined Scale: Cluster 2 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.95997975	0.07049602	0.04637607	-0.19034616	-0.09481788
RNEURO	0.07049602	1.0445303	0.00481052	0.03966071	0.03587087
RAGREE	0.04637607	0.00481052	0.96873778	-0.15708444	-0.02362703
RCONSCI	-0.19034616	0.03966071	-0.15708444	1.04695558	0.01866551
ROPEN	-0.09481788	0.03587087	-0.02362703	0.01866551	0.1576281

Table 54 Phase 1 Gaussian Mixture Modeling on Refined Scales: Cluster 2 Variance

Refined Scale: Cluster 3 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.53325488	0.002672	-0.03066898	-0.04189000	0.01183224
RNEURO	0.002672	0.30678935	0.005187	0.00152772	-0.00290303
RAGREE	-0.03066898	0.005187	0.29958241	-0.09381768	0.0188031
RCONSCI	-0.04189	0.00152772	-0.09381768	0.787896	0.0186761
ROPEN	0.011832238	-0.0029030	0.018803099	0.018676045	0.374414869

Table 55 Phase 1 Gaussian Mixture Modeling on Refined Scales: Cluster 3 Variance

Refined Scale: Cluster 4 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.235664553	0.05055054	-0.0736709	-0.00990021	-0.0005351
RNEURO	0.050550537	0.95874678	-0.0837899	0.071093488	0.019922968
RAGREE	-0.07367086	-0.0837899	0.96142628	-0.09831621	0.058698435
RCONSCI	-0.00990021	0.07109349	-0.0983162	0.905488181	-0.01834189
ROPEN	-0.0005351	0.01992297	0.05869843	-0.01834189	0.516270549

Table 56 Phase 1 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 5 Variance

	1	2	3	4	5
REXTRA	0.916344518	-0.00780295	-0.1274275	0.01413427	0.25728363
RNEURO	-0.00780295	0.931305416	0.06113567	0.07820832	-0.061469
RAGREE	-0.1274275	0.061135666	0.83556811	-0.06516294	-0.2002319
RCONSCI	0.014134272	0.078208319	-0.0651629	0.91303996	0.16115831
ROPEN	0.257283632	-0.06146845	-0.2002319	0.16115831	0.955972

Table 57 Phase 1 Gaussian Mixture Modeling on Refined Scales: Cluster 5 Variance

Refined Scale: Cluster 6 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.335642499	-0.02581157	-0.1387709	0.03536829	0.004615222
RNEURO	-0.02581158	0.6882947	-0.0173319	-0.07633	-0.01527128
RAGREE	-0.13877088	-0.01733189	0.4612633	-0.1062321	0.082969018
RCONSCI	0.035368292	-0.07632446	-0.1062321	0.48300135	-0.09245424
ROPEN	0.004615222	-0.01527128	0.08296902	-0.0924542	0.734914378

Table 58 Phase 1 Gaussian Mixture Modeling on Refined Scales: Cluster 6 Variance

Refined Scale: Cluster 7 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.366412019	-0.0106388	-0.028535	0.001087384	-0.02397204
RNEURO	-0.01063884	0.82232012	-0.06001056	0.027754473	-0.08656862
RAGREE	-0.028535	-0.0600106	0.146963001	-0.00695904	0.038759732
RCONSCI	0.001087384	0.02775447	-0.00695904	0.452048461	-0.00263564
ROPEN	-0.02397204	-0.0865686	0.038759732	-0.00263564	0.762999663

Table 59 Phase 1 Gaussian Mixture Modeling on Refined Scales: Cluster 7 Variance

Refined Scale: Cluster 8 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.341549358	0.05857535	-0.0618815	-0.00167913	0.03644827
RNEURO	0.05857535	0.84956198	-0.04207159	-0.03118438	-0.07916
RAGREE	-0.0618815	-0.0420716	0.06295046	-0.01577906	-0.0115619
RCONSCI	-0.00167913	-0.0311844	-0.01577906	0.472452155	0.02301069
ROPEN	0.036448267	-0.07916	-0.01156194	0.023010691	0.53639282

Table 60 Phase 1 Gaussian Mixture Modeling on Refined Scales: Cluster 8 Variance

Refined Scale: Cluster 9 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.82704691	-0.026026	-0.05684568	-0.13887984	-0.03454035
RNEURO	-0.02602604	0.41819262	-0.01203692	0.05793874	0.030928444
RAGREE	-0.05684568	-0.0120369	0.192649332	-0.08261497	0.007365142
RCONSCI	-0.13887984	0.05793874	-0.08261497	0.84579687	0.012594215
ROPEN	-0.03454035	0.03092844	0.007365142	0.01259422	0.265066053

Table 61 Phase 1 Gaussian Mixture Modeling on Refined Scales: Cluster 9 Variance

Standardized Unrefined Scale: Cluster 1 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.90921794	-0.13580996	0.13736362	0.02499701	0.2558442
ZNEURO	-0.13580996	0.8672972	-0.15162354	-0.1327171	-0.0345633
ZAGREE	0.13736362	-0.15162354	0.87992514	0.15210365	-0.046475
ZCONSCI	0.02499701	-0.1327171	0.15210365	0.89807394	0.15148701
ZOPEN	0.2558442	-0.03456333	-0.04647501	0.15148701	0.96585453

Table 62 Phase 1 Gaussian Mixture Modeling Restricted to 4 Clusters on Standardized Unrefined Scales: Cluster 1 Variance

Standardized Unrefined Scale: Cluster 2 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	1.10949126	-0.09488263	0.058231394	-0.10600944	0.33244955
ZNEURO	-0.09488263	1.171925688	-0.00320813	-0.17087074	-0.0217101
ZAGREE	0.05823139	-0.00320813	0.270686831	0.02625739	0.04450801
ZCONSCI	-0.10600944	-0.17087074	0.026257385	1.20405096	-0.135608
ZOPEN	0.33244955	-0.02171013	0.044508011	-0.13560802	1.24980794

Table 63 Phase 1 Gaussian Mixture Modeling Restricted to 4 Clusters on Standardized Unrefined Scales: Cluster 2 Variance

Standardized Unrefined Scale: Cluster 3 Variance					
	1	**2**	**3**	**4**	**5**

ZEXTRA	0.29869116	-0.0454775	0.04027253	0.03641465	0.02530801
ZNEURO	-0.0454775	0.46726692	0.04622754	-0.0958095	0.01585548
ZAGREE	0.04027253	0.04622754	0.74610793	0.06189664	0.1605233
ZCONSCI	0.03641465	-0.0958095	0.06189664	0.9961568	0.13614351
ZOPEN	0.02530801	0.01585548	0.1605233	0.13614351	0.68042817

Table 64 Phase 1 Gaussian Mixture Modeling Restricted to 4 Clusters on Standardized Unrefined Scales: Cluster 3 Variance

Standardized Unrefined Scale: Cluster 4 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.75320895	-0.0994301	0.16786102	0.05031208	0.14890369
ZNEURO	-0.0994301	0.93375073	-0.0738165	-0.3049187	-0.0717681
ZAGREE	0.16786102	-0.0738165	0.64438314	0.0926993	0.14627348
ZCONSCI	0.05031208	-0.3049187	0.0926993	0.91208256	0.13375363
ZOPEN	0.14890369	-0.0717681	0.14627348	0.13375363	0.37838059

Table 65 Phase 1 Gaussian Mixture Modeling Restricted to 4 Clusters on Standardized Unrefined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 1 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.50370321	-0.20398506	0.08044531	0.10301229	0.04548614
ZNEURO	-0.20398506	1.05906867	-0.01276097	-0.14823722	-0.054141
ZAGREE	0.08044531	-0.01276097	0.3520947	0.0217651	0.01170375
ZCONSCI	0.10301229	-0.14823722	0.0217651	0.96914796	0.05446312
ZOPEN	0.04548614	-0.05414095	0.01170375	0.05446312	0.09181941

Table 66 Phase 1 Gaussian Mixture Modeling on Standardized Unrefined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 2 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.4614398	0.10433637	0.33178486	-0.16706111	0.17265415
ZNEURO	0.1043364	0.73938306	0.09529211	-0.23729542	0.08106175
ZAGREE	0.3317849	0.09529211	0.72036308	-0.18417825	0.1068376

ZCONSCI	-0.1670611	-0.23729542	-0.18417825	0.72968005	-0.0962451
ZOPEN	0.1726541	0.08106175	0.1068376	-0.09624508	0.34660719

Table 67 Phase 1 Gaussian Mixture Modeling on Standardized Unrefined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 3 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.475678676	-0.052773	-0.00550459	0.10847862	-0.0650691
ZNEURO	-0.052773	0.84879581	0.103129225	-0.2776549	0.04700894
ZAGREE	-0.00550459	0.10312923	0.42870543	-0.02379116	0.13034107
ZCONSCI	0.108478617	-0.2776549	-0.02379116	0.77979187	-0.038055
ZOPEN	-0.06506908	0.04700894	0.130341069	-0.03805504	0.43793383

Table 68 Phase 1 Gaussian Mixture Modeling on Standardized Unrefined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 4 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.18496821	-0.08048424	0.02829823	0.02075072	0.06303424
ZNEURO	-0.0804842	1.08207955	-0.1957418	-0.21242462	-0.02142202
ZAGREE	0.02829823	-0.19574183	1.3153531	0.14972503	-0.23394077
ZCONSCI	0.02075072	-0.21242462	0.14972503	1.14877951	0.10017012
ZOPEN	0.06303424	-0.02142202	-0.233941	0.10017012	1.13558888

Table 69 Phase 1 Gaussian Mixture Modeling on Standardized Unrefined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 5 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.64028227	-0.11484205	-0.0261891	0.01036411	-0.03991315
ZNEURO	-0.1148421	0.854235981	-0.0624136	-0.1308354	-0.0046538
ZAGREE	-0.0261891	-0.06241361	0.9251172	0.16075434	-0.08566533
ZCONSCI	0.01036411	-0.1308354	0.16075434	0.86654788	0.059607592
ZOPEN	-0.0399132	-0.0046538	-0.0856653	0.05960759	0.823977913

Table 70 Phase 1 Gaussian Mixture Modeling on Standardized Unrefined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 6 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.96198634	-0.14602521	0.02257528	-0.03124473	0.095493081
ZNEURO	-0.1460252	1.222078249	0.00165581	-0.16721077	-0.00923329
ZAGREE	0.02257528	0.001655806	0.17232329	0.01764472	0.053196407
ZCONSCI	-0.0312447	-0.16721077	0.01764472	1.23163331	0.007657878
ZOPEN	0.09549308	-0.00923329	0.05319641	0.007657878	1.124506483

Table 71 Phase 1 Gaussian Mixture Modeling on Standardized Unrefined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 7 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.76242637	-0.2332773	0.1575084	0.08328244	0.03697363
ZNEURO	-0.23327726	0.53629784	-0.2048677	-0.148936	-0.08950648
ZAGREE	0.1575084	-0.2048677	0.72110281	0.14818738	0.08284691
ZCONSCI	0.08328244	-0.148936	0.14818738	0.40431566	0.13206889
ZOPEN	0.03697363	-0.0895065	0.08284691	0.13206889	0.32630289

Table 72 Phase 1 Gaussian Mixture Modeling on Standardized Unrefined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 8 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.26289832	-0.0377615	0.07253582	-0.0424306	0.0422334
ZNEURO	-0.03776146	0.88066343	-0.1404796	0.07355453	-0.02129205
ZAGREE	0.07253582	-0.1404796	0.78999545	0.0543627	-0.10347667
ZCONSCI	-0.0424306	0.07355453	0.0543627	0.9716493	0.11918769
ZOPEN	0.0422334	-0.0212921	-0.1034767	0.11918769	0.43423208

Table 73 Phase 1 Gaussian Mixture Modeling on Standardized Unrefined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 9 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.468070357	-0.1102875	-0.0679641	0.05889814	-0.00774885

ZNEURO	-0.11028751	0.34617911	0.0873296	-0.1011354	0.037237665
ZAGREE	-0.06796412	0.0873296	0.78893005	0.13923107	0.116788389
ZCONSCI	0.058898142	-0.1011354	0.13923107	0.8831775	0.192432247
ZOPEN	-0.00774885	0.03723767	0.11678839	0.19243225	0.501362895

Table 74 Phase 1 Gaussian Mixture Modeling on Standardized Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 1 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.342016347	-0.08141823	0.047717094	-0.003570978	0.05502202
NEURO	-0.08141823	0.690623783	-0.00622847	-0.062606808	-0.0261071
AGREE	0.047717094	-0.00622847	0.231794994	-0.01362613	0.02311468
CONSCI	-0.00357098	-0.06260681	-0.01362613	0.529986253	0.0481828
OPEN	0.055022017	-0.02610706	0.02311468	0.048182803	0.17228305

Table 75 Phase 1 Gaussian Mixture Modeling Restricted to 4 Clusters on Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 2 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.34095986	-0.07504384	0.030323035	0.013475302	0.02806988
NEURO	-0.07504384	0.68801689	-0.01775383	-0.115779826	-0.0106132
AGREE	0.03032303	-0.01775383	0.240735384	0.006680675	0.02496237
CONSCI	0.0134753	-0.11577983	0.006680675	0.546949999	0.0548254
OPEN	0.02806988	-0.01061319	0.024962369	0.054825395	0.24292208

Table 76 Phase 1 Gaussian Mixture Modeling Restricted to 4 Clusters on Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 3 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.83182286	-0.12067265	0.04983337	-0.011945	0.166107405
NEURO	-0.1206727	0.758556439	-0.0592249	-0.0990806	0.006173754
AGREE	0.04983337	-0.05922493	0.48667035	0.04006567	-0.11352168
CONSCI	-0.011945	-0.09908058	0.04006567	0.56483128	0.029100724
OPEN	0.1661074	0.006173754	-0.1135217	0.02910072	0.51741348

Table 77 Phase 1 Gaussian Mixture Modeling Restricted to 4 Clusters on Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 4 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.588506	-0.2687355	0.229336	0.1824369	0.1562911
NEURO	-0.2687355	0.5685172	-0.2571483	-0.2529901	-0.1717141
AGREE	0.229336	-0.2571483	0.3711166	0.1854706	0.1395298
CONSCI	0.1824369	-0.2529901	0.1854706	0.3674696	0.187632
OPEN	0.1562911	-0.1717141	0.1395298	0.187632	0.2825866

Table 78 Phase 1 Gaussian Mixture Modeling Restricted to 4 Clusters on Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 1 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.346962957	-0.10150012	0.006293171	-0.02085159	0.001953849
NEURO	-0.10150012	0.580174251	0.038707011	0.03596223	-0.00764645
AGREE	0.006293171	0.038707011	0.140963388	0.03986961	0.044661125
CONSCI	-0.02085159	0.035962226	0.039869613	0.47401429	0.01927755
OPEN	0.001953849	-0.00764645	0.044661125	0.01927755	0.224656345

Table 79 Phase 1 Gaussian Mixture Modeling on Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 2 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.24015798	-0.05413377	0.031367503	-0.00136518	0.0516701
NEURO	-0.05413377	0.64819534	0.009334175	-0.02893096	-0.04702684
AGREE	0.0313675	0.009334175	0.147444743	0.03357605	0.0345714
CONSCI	-0.00136518	-0.02893096	0.033576048	0.51585115	0.02706057
OPEN	0.0516701	-0.04702684	0.0345714	0.02706057	0.16625394

Table 80 Phase 1 Gaussian Mixture Modeling on Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 3 Variance

	1	2	3	4	5
REXTRA	0.8263009	-0.11414698	0.01279238	- 0.059369706	0.10734504
RNEURO	-0.11415	0.855584483	0.005936756	-0.08215203	-0.0040697
RAGREE	0.01279238	0.005936756	0.05154005	0.001752512	0.023531242
RCONSCI	-0.0593697	-0.08215203	0.001752512	0.65060466	-0.05922847
ROPEN	0.10734504	-0.0040697	0.023531242	-0.05922847	0.586565602

Table 81 Phase 1 Gaussian Mixture Modeling on Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 4 Variance					
	1	2	3	4	5
EXTRA	0.54408538	-0.0868024	-0.0100415	0.08500425	0.04296355
NEURO	-0.0868024	0.22700866	0.02653815	-0.0863156	-0.0530342
AGREE	-0.0100415	0.02653815	0.21452158	-0.0717592	-0.0469203
CONSCI	0.08500425	-0.0863156	-0.0717592	0.47211074	0.05877342
OPEN	0.04296355	-0.0530342	-0.0469203	0.05877342	0.28775238

Table 82 Phase 1 Gaussian Mixture Modeling on Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 5 Variance					
	1	2	3	4	5
EXTRA	0.15856994	-0.0706019	0.02250918	0.01566491	0.04937226
NEURO	-0.0706019	0.77530503	-0.1351728	-0.1207319	-0.0381414
AGREE	0.02250918	-0.1351728	0.44872232	0.05450429	-0.1295673
CONSCI	0.01566491	-0.1207319	0.05450429	0.60115647	0.0536385
OPEN	0.04937226	-0.0381414	-0.1295673	0.0536385	0.59743151

Table 83 Phase 1 Gaussian Mixture Modeling on Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 6 Variance					
	1	2	3	4	5
EXTRA	0.67569385	-0.1548963	0.11802642	0.06284123	0.08457927
NEURO	-0.1548963	0.51437221	-0.131138	-0.0903387	-0.0587607
AGREE	0.11802642	-0.131138	0.33518818	0.07250779	0.06456684
CONSCI	0.06284123	-0.0903387	0.07250779	0.21449545	0.03902142
OPEN	0.08457927	-0.0587607	0.06456684	0.03902142	0.10900762

Table 84 Phase 1 Gaussian Mixture Modeling on Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 7 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.49725882	-0.18251868	0.13518921	0.09543998	0.12850316
NEURO	-0.18251868	0.4886614	-0.16624565	-0.1971592	-0.06574222
AGREE	0.13518921	-0.16624565	0.28010247	0.11729911	0.06045247
CONSCI	0.09543998	-0.1971592	0.11729911	0.35523431	0.02845036
OPEN	0.12850316	-0.06574222	0.06045247	0.02845036	0.24428712

Table 85 Phase 1 Gaussian Mixture Modeling on Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 8 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.67815789	-0.02836303	0.09907075	-0.061856	0.15334789
NEURO	-0.02836303	0.6768494	-0.06929838	-0.0470086	-0.01479309
AGREE	0.09907075	-0.06929838	0.45385634	0.03877651	-0.06205212
CONSCI	-0.06185603	-0.04700857	0.03877651	0.55692805	0.00561224
OPEN	0.15334789	-0.01479309	-0.06205212	0.00561224	0.54716864

Table 86 Phase 1 Gaussian Mixture Modeling on Unrefined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 9 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.771744147	-0.07923501	0.006683785	0.01987933	0.045465075
NEURO	-0.07923501	0.219945867	0.017373699	-0.0534094	-0.00656106
AGREE	0.006683785	0.017373699	0.296211814	-0.0409052	0.040585046
CONSCI	0.019879327	-0.05340938	-0.04090517	0.57966636	0.029594783
OPEN	0.045465075	-0.00656106	0.040585046	0.02959478	0.112248694

Table 87 Phase 1 Gaussian Mixture Modeling on Unrefined Scales: Cluster 4 Variance

Refined Scale: Cluster 1 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.98769041	0.04080453	-0.04068007	-0.07215951	-0.06199
RNEURO	0.04080453	0.93810365	0.06622175	0.05621415	0.029833

RAGREE	-0.04068007	0.06622175	0.93968721	-0.10873024	-0.03909
RCONSCI	-0.07215951	0.05621415	-0.10873024	0.90982497	-0.0225
ROPEN	-0.06199117	0.02983345	-0.03908585	-0.02250246	0.414275

Table 88 Phase 2 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 2 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.88887788	0.01402874	-0.052856688	-0.0302507	-0.0405
RNEURO	0.01402874	0.79857659	-0.029334132	0.085086454	0.014882
RAGREE	-0.05285669	-0.02933413	0.297197707	0.000876621	0.044847
RCONSCI	-0.0302507	0.08508645	0.000876621	0.800990691	-0.03153
ROPEN	-0.04050409	0.01488156	0.044847236	-0.031533335	0.577098

Table 89 Phase 2 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 3 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.609896	-0.01326	-0.02197	0.029112	0.113633
RNEURO	-0.01326	0.325459	-0.05849	-0.01426	-0.08482
RAGREE	-0.02197	-0.05849	0.395631	0.096148	0.042931
RCONSCI	0.029112	-0.01426	0.096148	0.387035	0.09996
ROPEN	0.113633	-0.08482	0.042931	0.09996	0.580545

Table 90 Phase 2 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 4 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.791969	0.001963	-0.03362	-0.03948	-0.0511
RNEURO	0.001963	0.801865	0.068611	0.00685	0.017645
RAGREE	-0.03362	0.068611	0.798605	0.015039	-0.06601
RCONSCI	-0.03948	0.00685	0.015039	0.750235	0.02322

ROPEN	-0.0511	0.017645	-0.06601	0.02322	0.441998

Table 91 Phase 2 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 1 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.254343835	0.01146693	-0.0398931	-0.00754535	-0.02250317
RNEURO	0.011466932	0.80887072	0.01540052	0.101226335	-0.11175175
RAGREE	-0.03989308	0.01540052	0.44535579	-0.03455113	-0.03017763
RCONSCI	-0.00754535	0.10122634	-0.03455113	0.844268052	0.008244829
ROPEN	-0.02250317	-0.11175175	-0.03017763	0.008244829	0.703979325

Table 92 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 2 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.695009867	-0.00243338	-0.07772801	0.037307395	0.02243258
RNEURO	-0.00243338	0.229136399	-0.02968312	0.004533746	-0.05088107
RAGREE	-0.07772801	-0.02968312	0.4941614	0.06323415	-0.10277891
RCONSCI	0.037307395	0.004533746	0.06323415	0.329192745	0.084193
ROPEN	0.022432584	-0.05088107	-0.10277891	0.084193	0.61225884

Table 93 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 3 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.7361731	0.05395256	0.2212472	-0.06961065	0.02214596
RNEURO	0.05395256	0.2598438	0.05761516	0.01153169	0.05373788
RAGREE	0.2212472	0.05761516	0.77186511	-0.08272182	-0.14663089
RCONSCI	-0.06961065	0.01153169	-0.0827218	0.49840977	0.02326631
ROPEN	0.02214596	0.05373788	-0.146631	0.02326631	0.79827766

Table 94 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 4 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.759507949	0.14951653	-0.09652395	-0.10924321	-0.00192336
RNEURO	0.14951653	0.80079162	-0.06585535	0.072584201	0.043363561
RAGREE	-0.09652395	-0.0658554	0.071342249	0.001361293	-0.00913385
RCONSCI	-0.10924321	0.0725842	0.001361293	0.892659146	-0.05856814
ROPEN	-0.00192336	0.04336356	-0.00913385	-0.05856814	0.613004333

Table 95 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 5 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	1.00616704	0.09248008	0.06582259	-0.14833174	-0.0905241
RNEURO	0.09248008	0.8713027	0.05802825	0.15346373	0.01151915
RAGREE	0.06582259	0.05802825	0.84080272	-0.16341849	-0.1345312
RCONSCI	-0.14833174	0.15346373	-0.16341849	0.92608493	-0.016997
ROPEN	-0.0905241	0.01151915	-0.13453122	-0.01699648	0.61616993

Table 96 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 6 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.83806738	0.07694405	-0.03975094	-0.11071013	-0.0386815
RNEURO	0.07694405	0.77618371	0.03896633	0.10486152	-0.01629915
RAGREE	-0.03975094	0.03896633	0.83989493	0.1030955	-0.08248024
RCONSCI	-0.11071013	0.10486152	0.1030955	0.77904302	0.01171965
ROPEN	-0.0386815	-0.0162992	-0.08248024	0.01171965	0.25161597

Table 97 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 7 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.48341647	-0.0370569	-0.01104381	0.02473137	0.02002756
RNEURO	-0.0370569	0.36467336	-0.05479992	0.01039822	-0.0333295
RAGREE	-0.0110438	-0.0547999	0.21669809	0.13814554	0.01033031

RCONSCI	0.02473137	0.01039822	0.13814554	0.7409934	0.04211247
ROPEN	0.02002756	-0.0333295	0.01033031	0.04211247	0.35424314

Table 98 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 8 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.78998319	-0.0492215	-0.17714329	0.026185933	-0.06840275
RNEURO	-0.0492215	0.51859365	0.08306219	0.03887166	0.020618805
RAGREE	-0.1771433	0.08306219	0.32566331	-0.09982222	0.021128543
RCONSCI	0.02618593	0.03887166	-0.09982222	0.823001579	-0.00467758
ROPEN	-0.0684028	0.02061881	0.02112854	-0.00467758	0.279598543

Table 99 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Refined Scale: Cluster 9 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.47090806	0.04567316	0.00900887	-0.01377027	0.02159921
RNEURO	0.04567316	0.54994845	0.033389797	0.094790425	0.03224963
RAGREE	0.00900887	0.0333898	0.283396035	0.005783078	-0.02001042
RCONSCI	-0.0137703	0.09479042	0.005783078	0.551144495	0.0660671
ROPEN	0.02159921	0.03224963	-0.02001042	0.0660671	0.35373179

Table 100 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 1 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.59653889	0.02043024	0.08162172	-0.03252093	-0.03909935
ZNEURO	0.02043024	1.07176152	-0.021451	-0.00812785	-0.17183066
ZAGREE	0.08162172	-0.02145059	1.03786541	0.27009257	-0.13525497
ZCONSCI	-0.032521	-0.00812785	0.27009257	1.010800417	-0.00280219

ZOPEN	-0.0390994	-0.17183066	-0.135255	-0.0028022	1.059902821

Table 101 Phase 2 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 2 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.43394969	0.02973591	0.06685862	0.06116582	-0.0206394
ZNEURO	0.02973591	0.98845683	-0.02999565	0.06627695	-0.07342975
ZAGREE	0.06685862	-0.02999565	1.03118339	0.12592201	-0.14916226
ZCONSCI	0.06116582	0.06627695	0.12592201	0.40027407	-0.03211042
ZOPEN	-0.0206394	-0.07342975	-0.14916226	-0.03211042	0.94365143

Table 102 Phase 2 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 3 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.7490469	0.18124533	0.25128251	0.1310113	-0.1768002
ZNEURO	0.1812453	0.51919145	0.09504085	0.172436	-0.1644008
ZAGREE	0.2512825	0.09504085	0.75077581	0.1673197	-0.1176738
ZCONSCI	0.1310113	0.17243603	0.16731966	0.4513204	-0.1442901
ZOPEN	-0.1768002	-0.1644008	-0.1176738	-0.1442901	0.5076959

Table 103 Phase 2 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 4 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.58375216	0.06512392	0.09437432	0.1095153	0.005862601
ZNEURO	0.06512392	0.88263663	0.02137103	0.1431474	-0.13548711
ZAGREE	0.09437432	0.02137103	0.90138516	0.2181642	-0.14488673

ZCONSCI	0.10951528	0.1431474	0.21816424	0.8211067	0.013460182
ZOPEN	0.0058626	-0.1354871	-0.1448867	0.0134602	0.810846937

Table 104 Phase 2 Gaussian Mixture Modeling Restricted to 4 Clusters on Refined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 1 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.648205949	-0.10464914	0.029796528	0.006881678	0.11861911
NEURO	-0.10464914	0.57414712	-0.00853214	-0.098571281	-0.01334816
AGREE	0.029796528	-0.00853214	0.154243863	0.016877206	0.01002101
CONSCI	0.006881678	-0.09857128	0.016877206	0.44617074	0.08196741
OPEN	0.118619109	-0.01334816	0.010021006	0.081967411	0.40500885

Table 105 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 2 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.76120898	-0.09115235	0.043027645	-0.011027536	0.155279203
NEURO	-0.09115235	0.70160059	-0.03057403	-0.100942861	0.031489417
AGREE	0.04302765	-0.03057403	0.214504824	0.007595906	-0.01437938
CONSCI	-0.01102754	-0.10094286	0.007595906	0.524067327	-0.00794846
OPEN	0.1552792	0.03148942	-0.01437938	-0.007948455	0.467301459

Table 106 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 3 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.74366203	-0.1150512	0.047956361	-0.01590974	0.07347437
NEURO	-0.1150512	0.62079797	-0.01949042	-0.03414487	-0.0276004
AGREE	0.04795636	-0.0194904	0.226184568	0.002594135	0.04269994
CONSCI	-0.0159097	-0.0341449	0.002594135	0.467912546	0.04147024
OPEN	0.07347437	-0.0276004	0.042699944	0.041470237	0.16840399

Table 107 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 4 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.53665898	-0.0948748	0.11626511	0.06506085	0.11320029
NEURO	-0.0948748	0.35458185	-0.09802092	-0.10634384	-0.1040543
AGREE	0.11626511	-0.0980209	0.25824509	0.08072881	0.06467099
CONSCI	0.06506085	-0.1063438	0.08072881	0.24166061	0.09863695
OPEN	0.11320029	-0.1040543	0.06467099	0.09863695	0.22842876

Table 108 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 1 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.252962311	-0.06605848	0.01052457	0.002270078	0.04345146
NEURO	-0.06605848	0.66328785	-0.0263161	-0.126065285	-0.0132094
AGREE	0.01052457	-0.02631611	0.31101503	0.036803463	-0.01387187
CONSCI	0.002270078	-0.12606529	0.03680346	0.493040601	0.03182144
OPEN	0.043451458	-0.0132094	-0.013872	0.031821435	0.45992042

Table 109 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 1 Variance

Unrefined Scale: Cluster 2 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.31147838	-0.02316806	0.06854262	-0.029966992	0.043715067
NEURO	-0.02316806	0.566012603	-0.0159811	0.005748571	0.001969647
AGREE	0.06854262	-0.01598117	0.29213129	-0.021904974	-0.02518556
CONSCI	-0.02996699	0.005748571	-0.021905	0.455430257	0.035432359
OPEN	0.04371507	0.001969647	-0.025186	0.035432359	0.132818001

Table 110 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 2 Variance

Unrefined Scale: Cluster 3 Variance					
	1	**2**	**3**	**4**	**5**
REXTRA	0.470120446	-0.049304	0.0029608	0.03129985	0.003504586
RNEURO	-0.04930357	0.35639157	-0.0543348	-0.1084068	-0.08361122

RAGREE	0.0029608	-0.0543348	0.26218828	0.07099728	0.017879648
RCONSCI	0.031299854	-0.1084068	0.07099728	0.22623787	0.071231811
ROPEN	0.003504586	-0.0836112	0.01787965	0.07123181	0.180836069

Table 111 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 3 Variance

Unrefined Scale: Cluster 4 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.78484517	-0.02853123	0.013886149	-0.07193433	0.13902173
NEURO	-0.02853123	0.727615432	-0.00785982	-0.0588445	0.07247009
AGREE	0.01388615	-0.00785982	0.103629674	0.003644138	0.02221502
CONSCI	-0.07193433	-0.0588445	0.003644138	0.596223847	-0.04612798
OPEN	0.13902173	0.072470094	0.022215023	-0.04612798	0.49104933

Table 112 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Unrefined Scale: Cluster 5 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.48091633	-0.06573231	0.030216922	-0.11666932	-0.07542522
NEURO	-0.06573231	0.512731657	-0.00872027	-0.04455439	0.051991176
AGREE	0.03021692	-0.00872027	0.194034802	0.01475504	0.008866114
CONSCI	-0.11666932	-0.04455439	0.014755042	0.41266117	0.039075083
OPEN	-0.07542522	0.051991176	0.008866114	0.03907508	0.312110516

Table 113 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 5 Variance

Unrefined Scale: Cluster 6 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.612049332	-0.06424435	0.021085151	0.096117611	-0.00028287
NEURO	-0.06424435	0.220042846	-0.03218697	-0.06648603	0.004931912
AGREE	0.021085151	-0.03218697	0.175391672	0.000427707	0.055385986
CONSCI	0.096117611	-0.06648603	0.000427707	0.409183681	-0.07561152
OPEN	-0.00028287	0.004931912	0.055385986	-0.07561152	0.234432818

Table 114 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 6 Variance

Unrefined Scale: Cluster 7 Variance

	1	2	3	4	5
EXTRA	0.27370587	-0.08684201	0.046359996	0.0762631	0.041894072
NEURO	-0.08684201	0.30337794	-0.03813015	-0.07904284	-0.05079246
AGREE	0.04636	-0.03813014	0.144931929	0.03948616	0.007709528
CONSCI	0.0762631	-0.07904284	0.039486165	0.23148497	0.057152364
OPEN	0.04189407	-0.05079246	0.007709528	0.05715236	0.079691786

Table 115 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 7 Variance

Unrefined Scale: Cluster 8 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.510843899	-0.07346411	-0.0007896	0.023462813	-0.03929049
NEURO	-0.07346411	0.319462503	-0.00014341	-0.06759432	0.019511305
AGREE	-0.0007896	-0.00014341	0.176942307	0.009126202	0.046458158
CONSCI	0.023462813	-0.06759432	0.009126202	0.462434297	-0.00015953
OPEN	-0.03929049	0.019511305	0.046458158	-0.00015953	0.194909276

Table 116 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 8 Variance

Unrefined Scale: Cluster 9 Variance					
	1	**2**	**3**	**4**	**5**
EXTRA	0.65995157	-0.04868629	0.064089557	-0.10663152	0.032818823
NEURO	-0.04868629	0.677854808	0.006168348	-0.06123115	-0.02624818
AGREE	0.06408956	0.006168348	0.177851185	-0.01237073	0.006697405
CONSCI	-0.10663152	-0.06123115	-0.01237073	0.50042924	0.020854603
OPEN	0.03281882	-0.02624818	0.006697405	0.0208546	0.036594304

Table 117 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 9 Variance

Standardized Unrefined Scale: Cluster 1 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.37891783	0.04607632	0.04023552	0.13975739	0.01705573
ZNEURO	0.04607632	0.88544161	0.05667994	0.01098603	-0.03841854
ZAGREE	0.04023552	0.05667994	0.79856906	-0.04559978	-0.09926937
ZCONSCI	0.13975739	0.01098603	-0.04559978	0.50416008	0.07107134
ZOPEN	0.01705573	-0.0384185	-0.09926937	0.07107134	0.46835008

Table 118 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 1 Variance

Standardized Unrefined Scale: Cluster 2 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.87612055	0.12315193	-0.03116961	- 0.135042201	-0.07159648
ZNEURO	0.12315193	0.96266154	-0.16327049	-0.0698259	-0.13468232
ZAGREE	-0.0311696	-0.163271	0.79581779	0.201410216	-0.00182095
ZCONSCI	-0.1350422	-0.069826	0.201410216	1.008506809	-0.00034053
ZOPEN	-0.071597	-0.1346823	-0.00182095	-0.00034053	0.942089805

Table 119 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 2 Variance

Standardized Unrefined Scale: Cluster 3 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.8366529	0.3244354	0.2750949	0.2150198	-0.2437982
ZNEURO	0.3244354	0.541566	0.2658609	0.2810073	-0.2199847
ZAGREE	0.2750949	0.2658609	0.6880461	0.2216002	-0.1832588
ZCONSCI	0.2150198	0.2810073	0.2216002	0.569839	-0.2092945
ZOPEN	-0.2437982	-0.2199847	-0.1832588	-0.2092945	0.4419243

Table 120 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 3 Variance

Standardized Unrefined Scale: Cluster 4 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.67001825	0.04403181	0.03953589	0.08593422	-0.2641408
ZNEURO	0.04403181	0.65670952	0.03920575	0.12234731	0.12270442
ZAGREE	0.03953589	0.03920575	0.69395884	-0.080843	-0.0943034
ZCONSCI	0.08593422	0.12234731	-0.080843	0.33883712	-0.011559
ZOPEN	-0.2641408	0.12270442	-0.09430335	-0.01155895	0.69315977

Table 121 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 4 Variance

Standardized Unrefined Scale: Cluster 5 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.64728322	0.058990463	0.048881603	0.03392288	-0.0879591
ZNEURO	0.05899046	1.020219593	0.001330574	0.10473375	-0.1680563

ZAGREE	0.0488816	0.001330574	0.308457623	0.01591185	-0.0475701
ZCONSCI	0.03392288	0.104733753	0.015911852	0.16301416	-0.0627482
ZOPEN	-0.0879591	-0.1680563	-0.04757013	-0.06274824	1.00470089

Table 122 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 5 Variance

Standardized Unrefined Scale: Cluster 6 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.95921062	0.08468281	0.022941955	0.055738317	-0.1142941
ZNEURO	0.08468281	0.2090437	0.034235719	0.094535833	-0.0970179
ZAGREE	0.02294195	0.03423572	0.681766436	0.005110367	-0.065773
ZCONSCI	0.05573832	0.09453583	0.005110367	0.554910442	-0.0923737
ZOPEN	-0.1142941	-0.09701789	-0.06577298	-0.09237371	0.89539055

Table 123 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 6 Variance

Standardized Unrefined Scale: Cluster 7 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.617905225	-0.00916202	0.09154601	0.05543378	0.05226913
ZNEURO	-0.00916202	0.673701303	0.03744948	0.05906813	-0.18613733
ZAGREE	0.091546011	0.037449475	0.54052701	0.1508074	-0.10292019
ZCONSCI	0.055433778	0.05906813	0.1508074	0.64070978	0.01308115
ZOPEN	0.052269129	-0.18613734	-0.10292019	0.01308115	0.43888787

Table 124 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 7 Variance

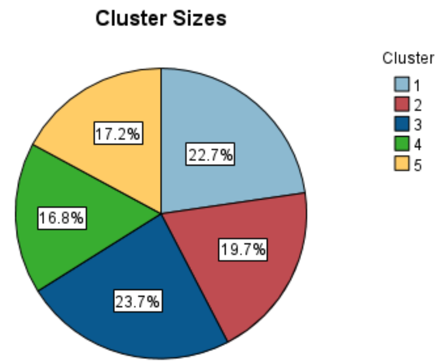
Standardized Unrefined Scale: Cluster 8 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	0.176016821	0.001208221	0.05122048	0.03050229	0.01979642
ZNEURO	0.001208221	1.149652629	-0.10663176	-0.10326802	-0.15646315
ZAGREE	0.051220479	-0.10663176	1.03153311	0.21526481	-0.08837008
ZCONSCI	0.030502287	-0.10326802	0.21526481	1.18946095	0.05143474
ZOPEN	0.019796423	-0.15646315	-0.08837008	0.05143474	1.06387123

Table 125 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 8 Variance

Standardized Unrefined Scale: Cluster 9 Variance					
	1	**2**	**3**	**4**	**5**
ZEXTRA	1.00737334	0.017987241	0.050774142	-0.0974866	-0.09178992
ZNEURO	0.01798724	1.064089176	-0.00909939	0.103980491	-0.11207854
ZAGREE	0.05077414	-0.00909939	0.191853297	0.064640212	-0.07713749
ZCONSCI	-0.0974866	0.103980491	0.064640212	1.161858878	-0.00928387
ZOPEN	-0.091799	-0.11207854	-0.07713749	-0.00928387	1.058336102

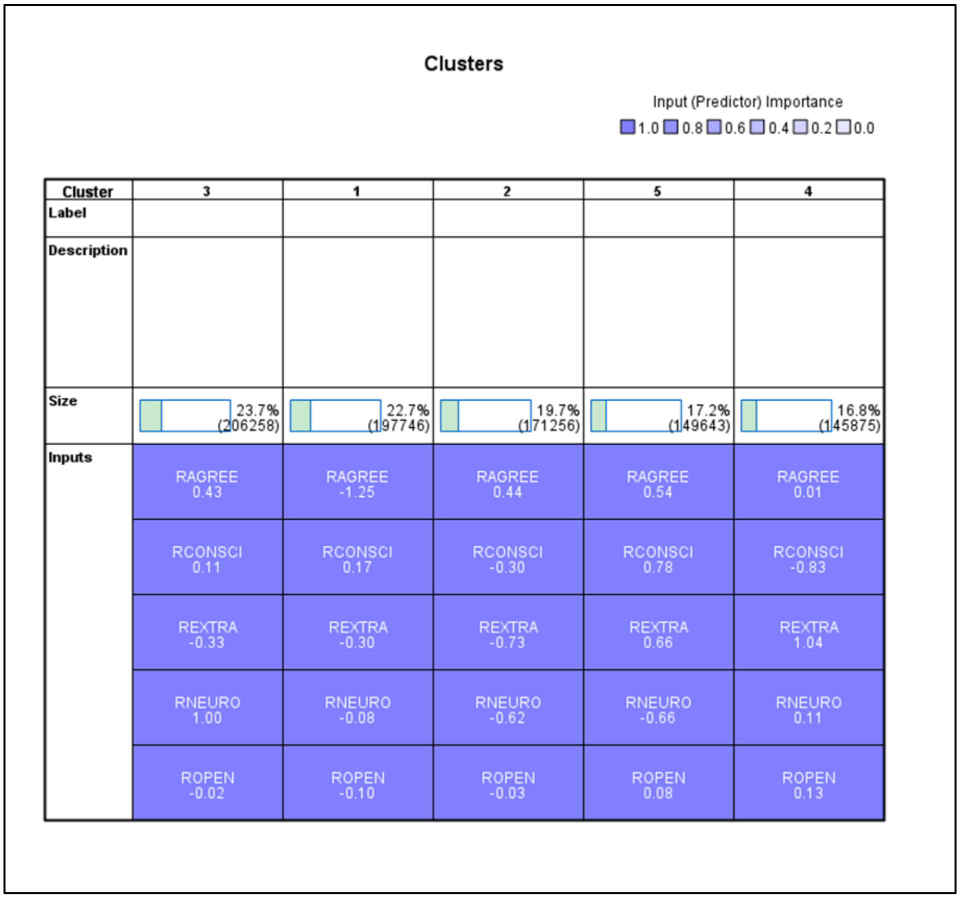
Table 126 Phase 2 Gaussian Mixture Modeling on Refined Scales: Cluster 9 Variance

Supplementary Figures



Size of Smallest Cluster	145875 (16.8%)
Size of Largest Cluster	206258 (23.7%)
Ratio of Sizes: Largest Cluster to Smallest Cluster	1.41

Figure 24 Cluster Sizes for the refined scales two-step cluster analytic solution, no fixed number of clusters.



Clusters

Input (Predictor) Importance
1.0 0.8 0.6 0.4 0.2 0.0

Cluster	3	1	2	5	4
Label					
Description					
Size	23.7% (206258)	22.7% (197746)	19.7% (171256)	17.2% (149643)	16.8% (145875)
Inputs	RAGREE 0.43	RAGREE -1.25	RAGREE 0.44	RAGREE 0.54	RAGREE 0.01
	RCONSCI 0.11	RCONSCI 0.17	RCONSCI -0.30	RCONSCI 0.78	RCONSCI -0.83
	REXTRA -0.33	REXTRA -0.30	REXTRA -0.73	REXTRA 0.66	REXTRA 1.04
	RNEURO 1.00	RNEURO -0.08	RNEURO -0.62	RNEURO -0.66	RNEURO 0.11
	ROPEN -0.02	ROPEN -0.10	ROPEN -0.03	ROPEN 0.08	ROPEN 0.13

Figure 25 Detailed clusters for the refined scales two-step cluster analytic solution, no fixed number of clusters.

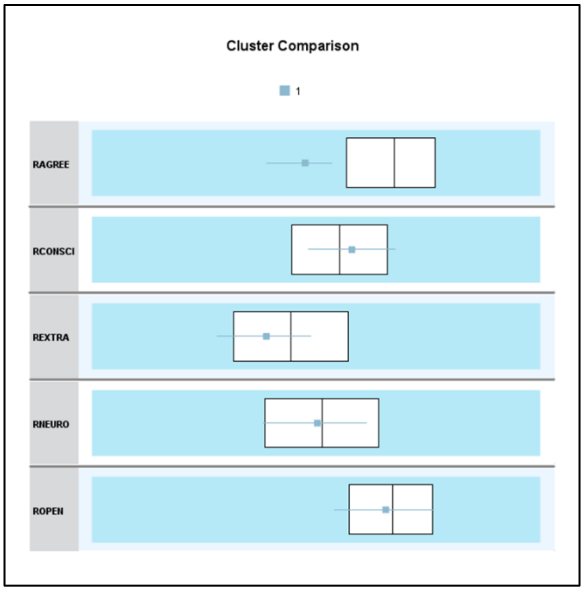


Figure 26 Cluster 1 of the refined scales two-step cluster analytic solution, no fixed number of clusters.

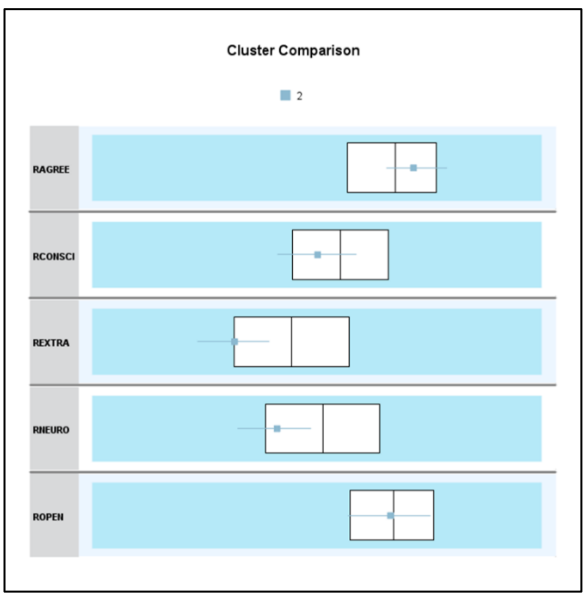


Figure 27 Cluster 2 of the refined scales two-step cluster analytic solution, no fixed number of clusters.

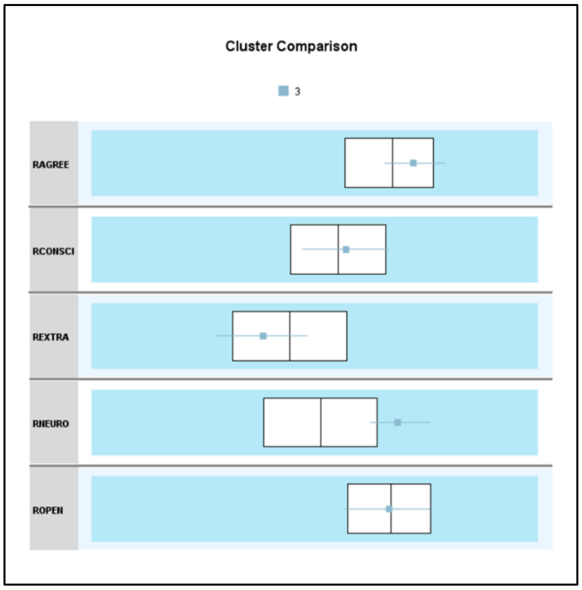


Figure 28 Cluster 3 of the refined scales two-step cluster analytic solution, no fixed number of clusters.

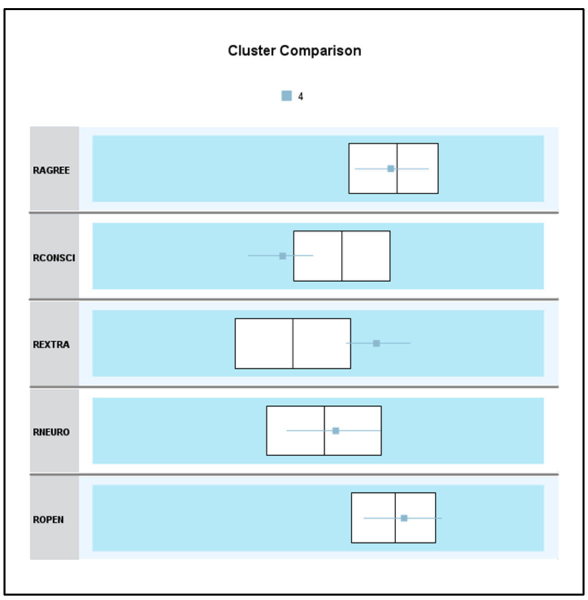


Figure 29 Cluster 4 of the refined scales two-step cluster analytic solution, no fixed number of clusters.

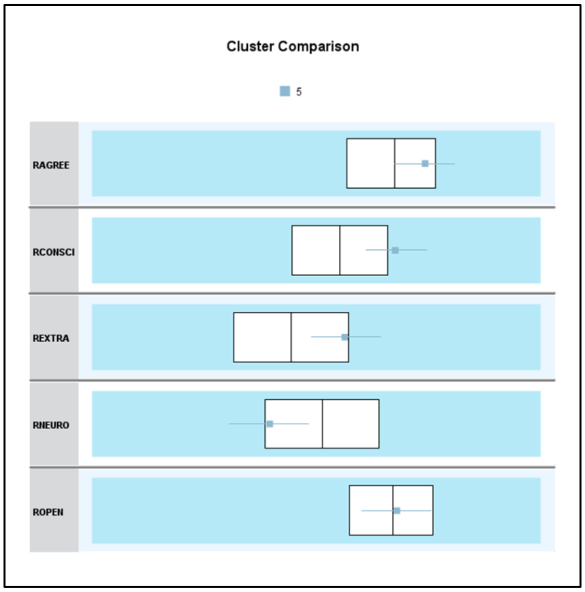


Figure 30 Cluster 5 of the refined scales two-step cluster analytic solution, no fixed number of clusters.

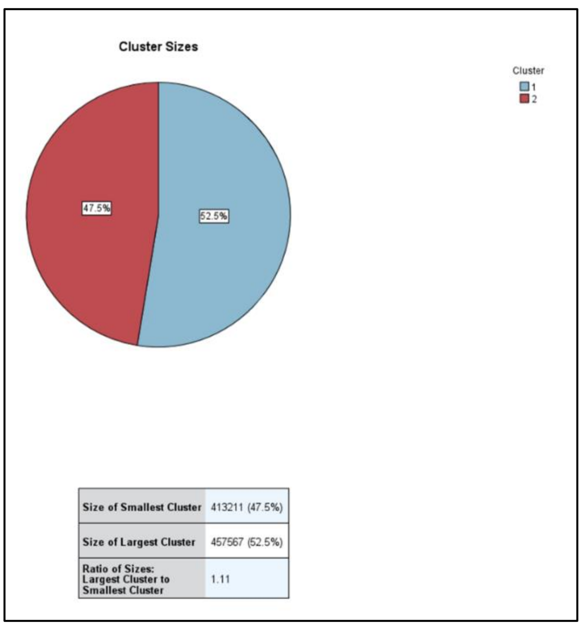


Figure 31 Cluster Sizes for the unrefined scales two-step cluster analytic solution, no fixed number of clusters.

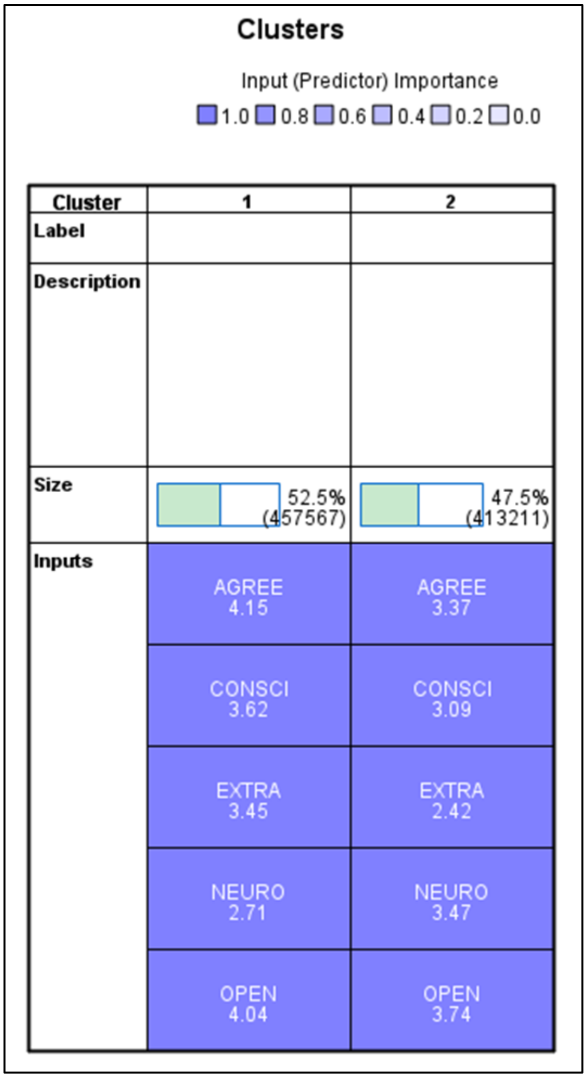


Figure 32 Detailed clusters for the unrefined scales two-step cluster analytic solution, no fixed number of clusters.

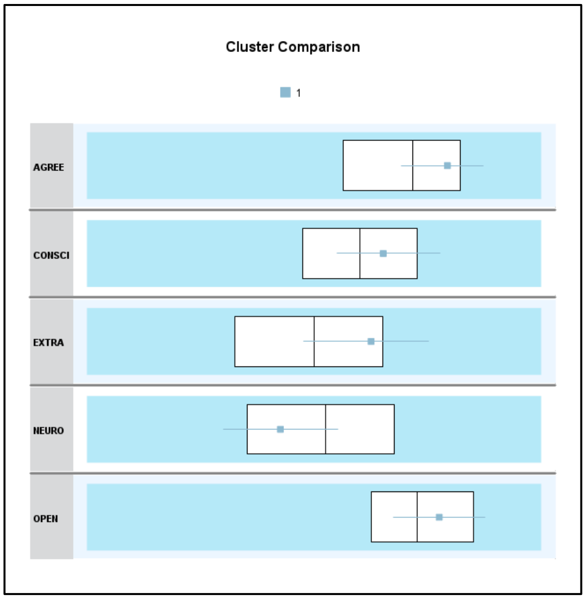


Figure 33 Cluster 1 of the unrefined scales two-step cluster analytic solution, no fixed number of clusters.

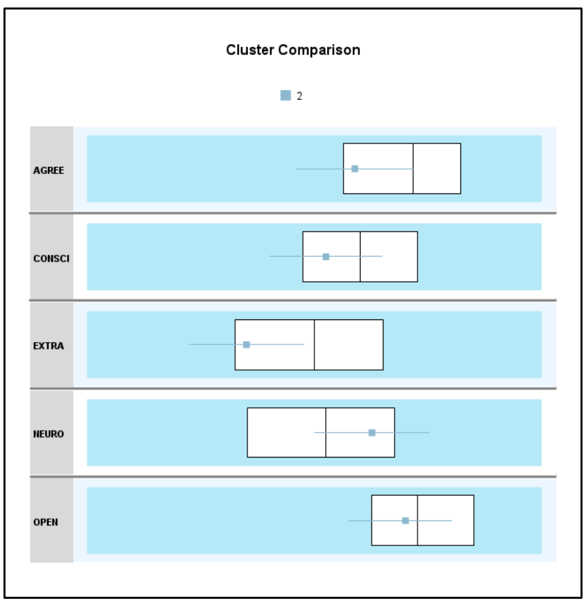


Figure 34 Cluster 2 of the unrefined scales two-step cluster analytic solution, no fixed number of clusters.

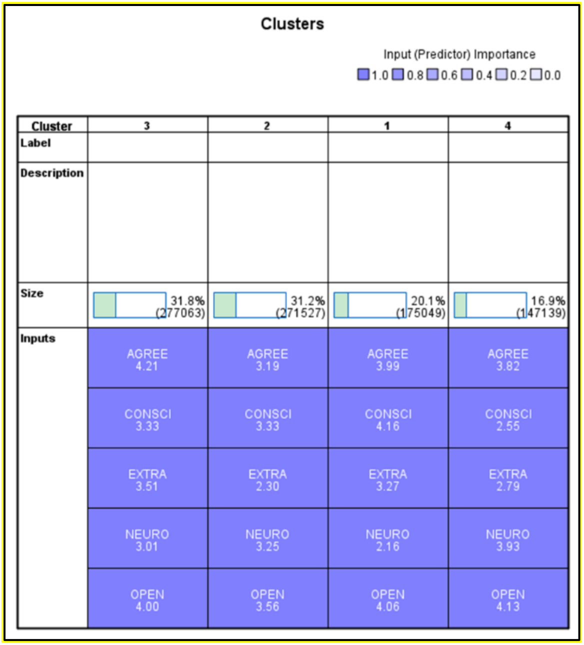


Figure 35 Detailed clusters for the unrefined scales two-step cluster analytic solution, fixed to 4 clusters.

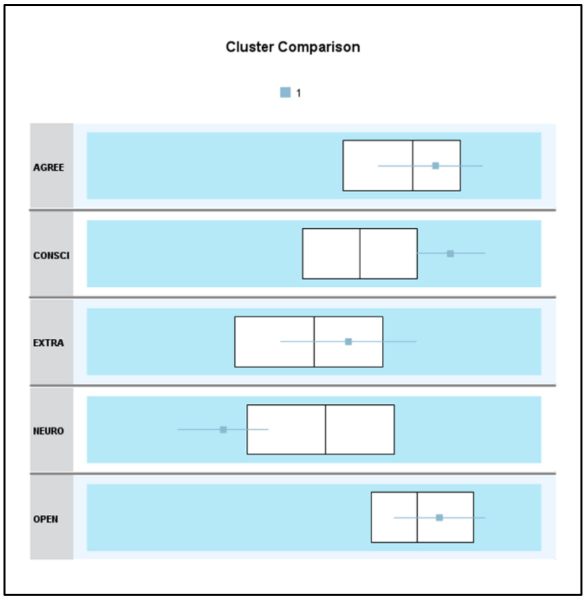


Figure 36 Cluster 1 of the unrefined scales two-step cluster analytic solution, fixed to 4 clusters.

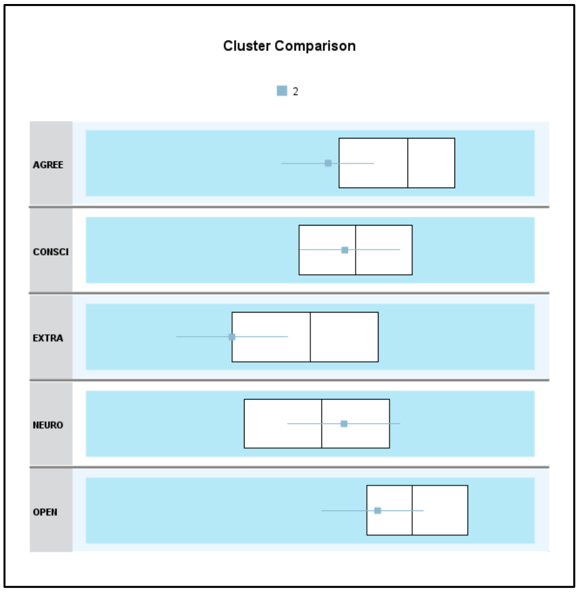


Figure 37 Cluster 2 of the unrefined scales two-step cluster analytic solution, fixed to 4 clusters.

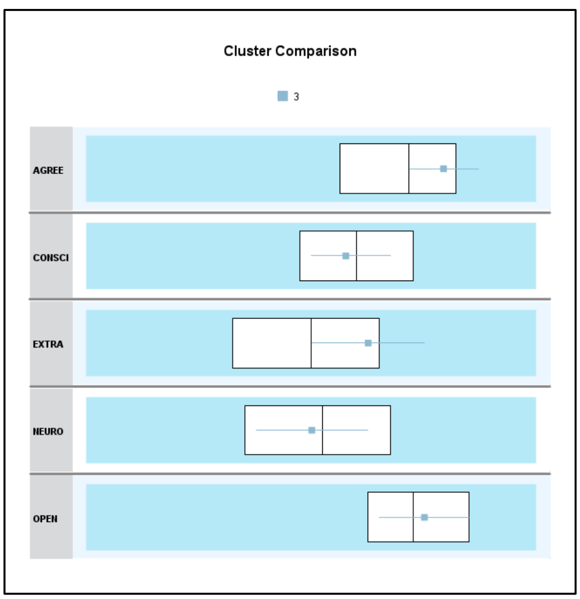


Figure 38 Cluster 3 of the unrefined scales two-step cluster analytic solution, fixed to 4 clusters.

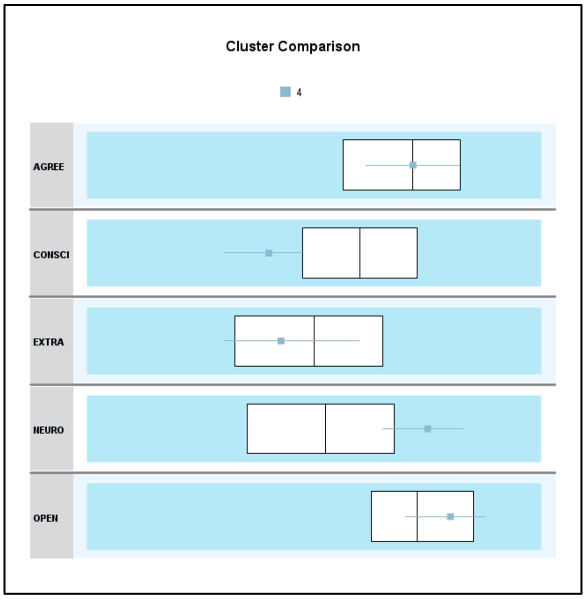


Figure 39 Cluster 4 of the unrefined scales two-step cluster analytic solution, fixed to 4 clusters.

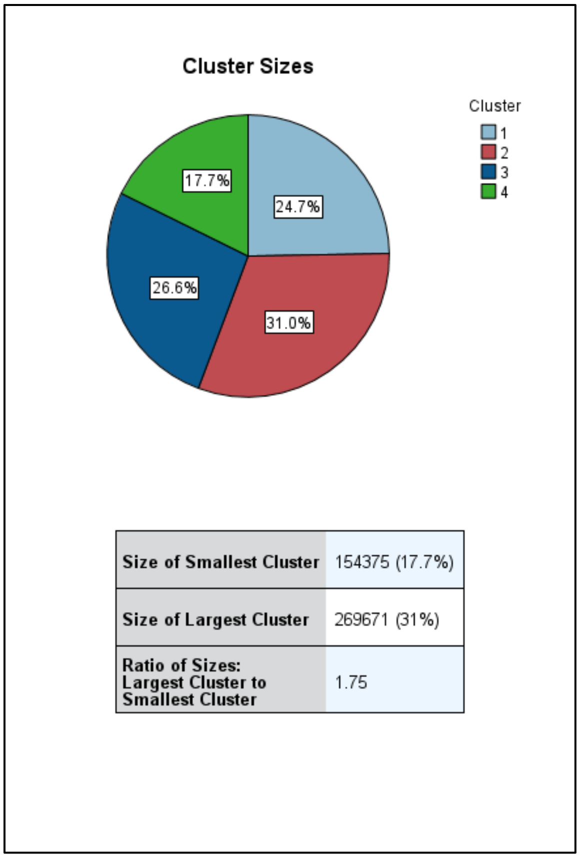


Figure 40 Cluster Sizes for the refined scales two-step cluster analytic solution, fixed to 4 clusters.

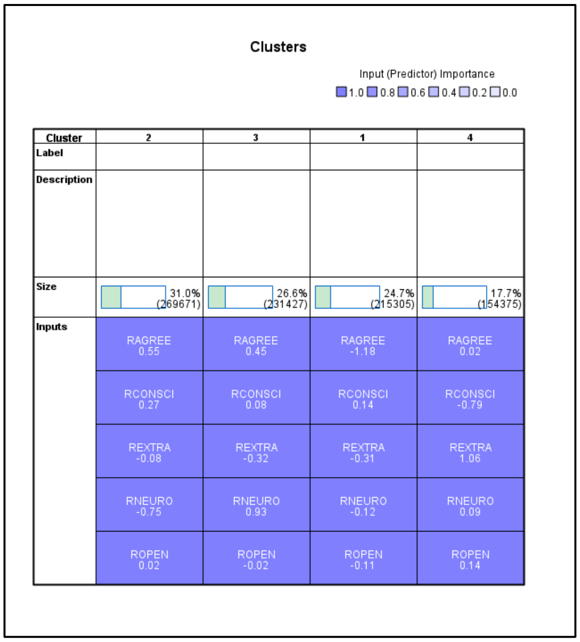


Figure 41 Detailed clusters for the refined scales two-step cluster analytic solution, fixed to 4 clusters.

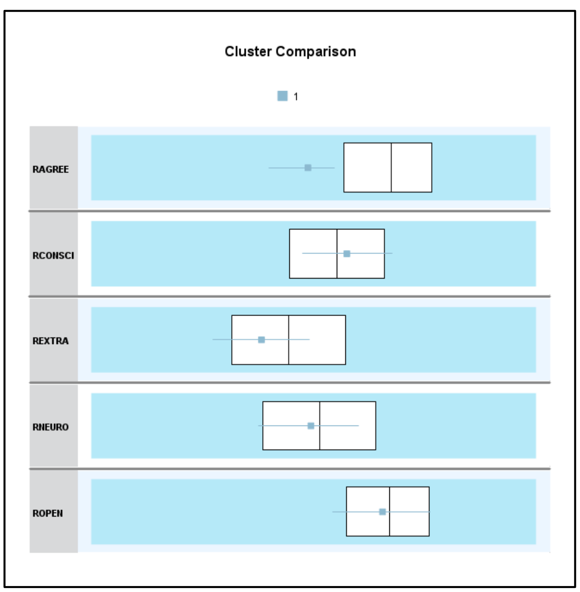


Figure 42 Cluster 1 of the refined scales two-step cluster analytic solution, fixed to 4 clusters.

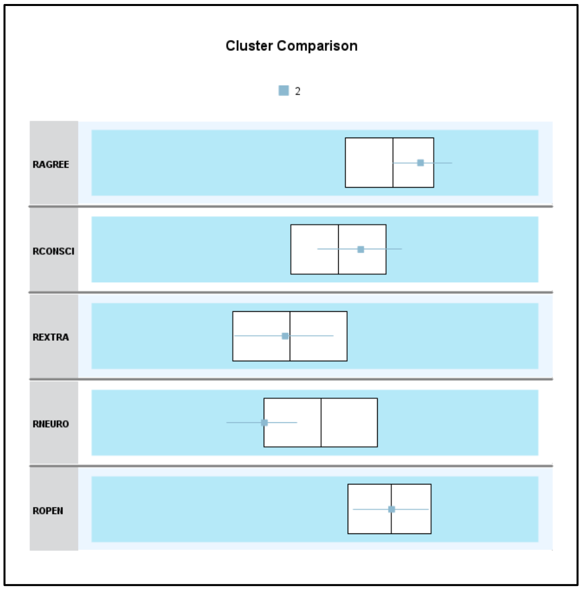


Figure 43 Cluster 2 of the refined scales two-step cluster analytic solution, fixed to 4 clusters.

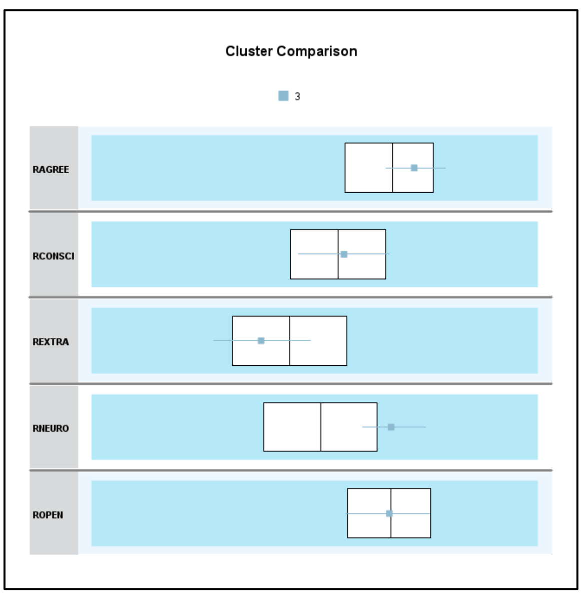


Figure 44 Cluster 3 of the refined scales two-step cluster analytic solution, fixed to 4 clusters.

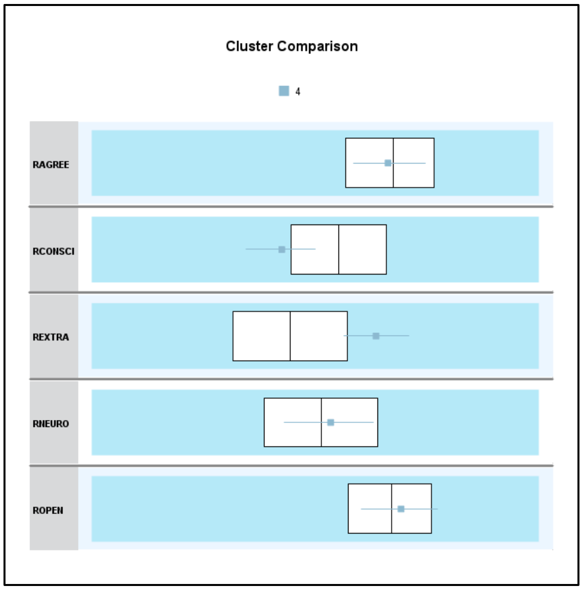


Figure 45 Cluster 4 of the refined scales two-step cluster analytic solution, fixed to 4 clusters.

SPSS Code

```
RECODE EXT2 EXT4 EXT6 EXT8 EXT10 EST2 EST4 AGR1 AGR3 AGR5 AGR7

CSN2 CSN4 CSN6 CSN8 OPN2 OPN4 OPN6  (1=5) (2=4) (3=3) (4=2) (5=1).

EXECUTE.


*Some items were negatively scored and needed to be reversed.*


RELIABILITY

  /VARIABLES=EXT1 EXT2 EXT3 EXT4 EXT5 EXT6 EXT7 EXT8 EXT9 EXT10

  /SCALE('ALL VARIABLES') ALL
```

```
  /MODEL=ALPHA.

RELIABILITY
  /VARIABLES=EST1 EST2 EST3 EST4 EST5 EST6 EST7 EST8 EST9 EST10
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA.

RELIABILITY
  /VARIABLES=AGR1 AGR2 AGR3 AGR4 AGR5 AGR6 AGR7 AGR8 AGR9 AGR10
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA.

RELIABILITY
  /VARIABLES=CSN1 CSN2 CSN3 CSN4 CSN5 CSN6 CSN7 CSN8 CSN9 CSN10
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA.

RELIABILITY
  /VARIABLES=OPN1 OPN2 OPN3 OPN4 OPN5 OPN6 OPN7 OPN8 OPN9 OPN10
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA.
```

Basic interitem reliability was looked at to make sure the 5 factor solution was legitimately found in the pre-cleaned data

```
DESCRIPTIVES VARIABLES=EXT2 EXT1 EXT3 EXT4 EXT5 EXT6 EXT7 EXT8
EXT9 EXT10
  /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.

DESCRIPTIVES VARIABLES=EST1 EST2 EST3 EST4 EST5 EST6 EST7 EST8 EST9
EST10
  /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.

DESCRIPTIVES VARIABLES=AGR1 AGR2 AGR3 AGR4 AGR5 AGR6 AGR7
AGR8 AGR9 AGR10
  /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.

DESCRIPTIVES VARIABLES=CSN1 CSN2 CSN3 CSN4 CSN5 CSN6 CSN7 CSN8
CSN9 CSN10
  /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.

DESCRIPTIVES VARIABLES=OPN1 OPN2 OPN3 OPN4 OPN5 OPN6 OPN7 OPN8
OPN9 OPN10
  /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
```

Descriptives of each item was looked at to make sure there was no egrigious errors. This was done pre-data cleaning

```
COMPUTE
EXTRA=MEAN(EXT1,EXT2,EXT3,EXT4,EXT5,EXT6,EXT7,EXT8,EXT9,EXT10).
EXECUTE.

COMPUTE
NEURO=MEAN(EST1,EST2,EST3,EST4,EST5,EST6,EST7,EST8,EST9,EST10).
EXECUTE.

COMPUTE
OPEN=MEAN(OPN1,OPN2,OPN3,OPN4,OPN5,OPN6,OPN7,OPN8,OPN9,OPN10).
EXECUTE.

COMPUTE
CONSCI=MEAN(CSN1,CSN2,CSN3,CSN4,CSN5,CSN6,CSN7,CSN8,CSN9,CSN10).
EXECUTE.
```

```
COMPUTE
AGREE=MEAN(AGR1,AGR2,AGR3,AGR4,AGR5,AGR6,AGR7,AGR8,AGR9,AGR1
0).
EXECUTE.
```

Creation of most basic scale scores by adding the items up and diving by the number of items in order to find the mean score for each potential factor

```
DESCRIPTIVES VARIABLES=OPEN CONSCI EXTRA AGREE NEURO
  /SAVE
  /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
```

descriptive statistics for each of the big five factor scales was taken to make sure all data was as expected

```
FACTOR
  /VARIABLES EXT1 EXT2 EXT3 EXT4 EXT5 EXT6 EXT7 EXT8 EXT9 EXT10
EST1 EST2 EST3 EST4 EST5 EST6 EST7
    EST8 EST9 EST10 AGR1 AGR2 AGR3 AGR4 AGR5 AGR6 AGR7 AGR8 AGR9
AGR10 CSN1 CSN2 CSN3 CSN4 CSN5 CSN6
    CSN7 CSN8 CSN9 CSN10 OPN1 OPN2 OPN3 OPN4 OPN5 OPN6 OPN7 OPN8
OPN9 OPN10
```

```
  /MISSING LISTWISE
  /ANALYSIS EXT1 EXT2 EXT3 EXT4 EXT5 EXT6 EXT7 EXT8 EXT9 EXT10 EST1
EST2 EST3 EST4 EST5 EST6 EST7
    EST8 EST9 EST10 AGR1 AGR2 AGR3 AGR4 AGR5 AGR6 AGR7 AGR8 AGR9
AGR10 CSN1 CSN2 CSN3 CSN4 CSN5 CSN6
    CSN7 CSN8 CSN9 CSN10 OPN1 OPN2 OPN3 OPN4 OPN5 OPN6 OPN7 OPN8
OPN9 OPN10
  /PRINT INITIAL EXTRACTION ROTATION
  /FORMAT SORT
  /PLOT EIGEN
  /CRITERIA FACTORS(5) ITERATE(25)
  /EXTRACTION ML
  /CRITERIA ITERATE(25)
  /ROTATION QUARTIMAX
  /SAVE REG(ALL).

*5-factor expected solution, before data cleaning procedures*

FACTOR
  /VARIABLES EXT1 EXT2 EXT3 EXT4 EXT5 EXT6 EXT7 EXT8 EXT9 EXT10
EST1 EST2 EST3 EST4 EST5 EST6 EST7
```

```
    EST8 EST9 EST10 AGR1 AGR2 AGR3 AGR4 AGR5 AGR6 AGR7 AGR8 AGR9
AGR10 CSN1 CSN2 CSN3 CSN4 CSN5 CSN6
    CSN7 CSN8 CSN9 CSN10 OPN1 OPN2 OPN3 OPN4 OPN5 OPN6 OPN7 OPN8
OPN9 OPN10
  /MISSING LISTWISE
  /ANALYSIS EXT1 EXT2 EXT3 EXT4 EXT5 EXT6 EXT7 EXT8 EXT9 EXT10 EST1
EST2 EST3 EST4 EST5 EST6 EST7
    EST8 EST9 EST10 AGR1 AGR2 AGR3 AGR4 AGR5 AGR6 AGR7 AGR8 AGR9
AGR10 CSN1 CSN2 CSN3 CSN4 CSN5 CSN6
    CSN7 CSN8 CSN9 CSN10 OPN1 OPN2 OPN3 OPN4 OPN5 OPN6 OPN7 OPN8
OPN9 OPN10
  /PRINT INITIAL EXTRACTION ROTATION
  /FORMAT SORT
  /PLOT EIGEN
  /CRITERIA FACTORS(8) ITERATE(25)
  /EXTRACTION ML
  /CRITERIA ITERATE(25)
  /ROTATION QUARTIMAX
  /SAVE REG(ALL).
```

8-factor solution was considered and dismissed for conceptual and interpretive reasons. Also the extra factors seemingly were created partially by having negatively scored items in our scales.

```
QUICK CLUSTER OPEN CONSCI EXTRA AGREE NEURO
  /MISSING=LISTWISE
  /CRITERIA=CLUSTER(4) MXITER(100) CONVERGE(0)
  /METHOD=KMEANS(NOUPDATE)
  /PRINT INITIAL.
```

4 clusters were looked at because of prior research using cluster analytic techniques on personality data, note this is the unrefined and unstandardized scales

```
QUICK CLUSTER ROPEN RCONSCI REXTRA RAGREE RNEURO
  /MISSING=LISTWISE
  /CRITERIA=CLUSTER(4) MXITER(100) CONVERGE(0)
  /METHOD=KMEANS(NOUPDATE)
  /PRINT INITIAL.
```

4 clusters were looked at because of prior research using cluster analytic techniques on personality data, note this is the refined scales

```
QUICK CLUSTER ZOPEN ZCONSCI ZEXTRA ZAGREE ZNEURO
  /MISSING=LISTWISE
  /CRITERIA=CLUSTER(4) MXITER(100) CONVERGE(0)
  /METHOD=KMEANS(NOUPDATE)
  /PRINT INITIAL.
```

4 clusters were looked at because of prior research using cluster analytic techniques on personality data, note this is the unrefined and standardized scales

```
TWOSTEP CLUSTER
  /CONTINUOUS VARIABLES=OPEN CONSCI EXTRA AGREE NEURO
  /DISTANCE LIKELIHOOD
  /NUMCLUSTERS AUTO 15 BIC
  /HANDLENOISE 0
  /MEMALLOCATE 64
  /CRITERIA INITHRESHOLD(0) MXBRANCH(8) MXLEVEL(3)
  /VIEWMODEL DISPLAY=YES.
```

two step cluster analysis of unrefined and unstandardized scales.

```
TWOSTEP CLUSTER
  /CONTINUOUS VARIABLES=ROPEN RCONSCI REXTRA RAGREE RNEURO
  /DISTANCE LIKELIHOOD
  /NUMCLUSTERS AUTO 15 BIC
  /HANDLENOISE 0
  /MEMALLOCATE 64
  /CRITERIA INITHRESHOLD(0) MXBRANCH(8) MXLEVEL(3)
  /VIEWMODEL DISPLAY=YES.
```

two step cluster analysis of refined scales.

```
QUICK CLUSTER ZOPEN ZCONSCI ZEXTRA ZAGREE ZNEURO
  /MISSING=LISTWISE
  /CRITERIA=CLUSTER(2) MXITER(100) CONVERGE(0)
  /METHOD=KMEANS(NOUPDATE)
  /PRINT INITIAL.
```

k means cluster analysis with 2 clusters recommended in the two step cluster analysis for unrefined standardized scales

```
QUICK CLUSTER ROPEN RCONSCI REXTRA RAGREE RNEURO
  /MISSING=LISTWISE
  /CRITERIA=CLUSTER(5) MXITER(100) CONVERGE(0)
  /METHOD=KMEANS(NOUPDATE)
  /PRINT INITIAL.
```

k means cluster analysis with the 5 clusters recommended in the twop step cluster analysis for refined scales

```
TWOSTEP CLUSTER
  /CONTINUOUS VARIABLES=EXTRA NEURO OPEN CONSCI AGREE
  /DISTANCE LIKELIHOOD
  /NUMCLUSTERS FIXED=4
  /HANDLENOISE 0
  /MEMALLOCATE 64
  /CRITERIA INITHRESHOLD(0) MXBRANCH(8) MXLEVEL(3)
```

```
  /VIEWMODEL DISPLAY=YES.
```

this the unrefined scales two step cluster analysis while restricting the number of clusters to 4.

```
TWOSTEP CLUSTER
  /CONTINUOUS VARIABLES=REXTRA RNEURO RAGREE RCONSCI ROPEN
  /DISTANCE LIKELIHOOD
  /NUMCLUSTERS FIXED=4
  /HANDLENOISE 0
  /MEMALLOCATE 64
  /CRITERIA INITHRESHOLD(0) MXBRANCH(8) MXLEVEL(3)
  /VIEWMODEL DISPLAY=YES.
```

this the refined scales two step cluster analysis while restricting the number of clusters to 4.

```
SHOW WORKSPACE

SET WORKSPACE= 1000000
```

```
DESCRIPTIVES VARIABLES=EXTRA NEURO OPEN CONSCI AGREE
  /SAVE
  /STATISTICS=MEAN STDDEV MIN MAX.
```

descriptive statistics for the 5 unrefined and unstandardized scales

```
COMPUTE ID=$CASENUM.
EXECUTE.
```

creating case #s to be able to keep better track of each participants data

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ID
```

```
  /METHOD=ENTER EXT1 EXT2 EXT3 EXT4 EXT5 EXT6 EXT7 EXT8 EXT9
EXT10
  /SAVE MAHAL COOK SDRESID.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ID
  /METHOD=ENTER EST1 EST2 EST3 EST4 EST5 EST6 EST7 EST8 EST9 EST10
  /SAVE MAHAL COOK SDRESID.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ID
  /METHOD=ENTER AGR1 AGR2 AGR3 AGR4 AGR5 AGR6 AGR7 AGR8 AGR9
AGR10
  /SAVE MAHAL COOK SDRESID.
```

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ID
  /METHOD=ENTER CSN1 CSN2 CSN3 CSN4 CSN5 CSN6 CSN7 CSN8 CSN9
CSN10
  /SAVE MAHAL COOK SDRESID.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT ID
  /METHOD=ENTER OPN1 OPN2 OPN3 OPN4 OPN5 OPN6 OPN7 OPN8 OPN9
OPN10
  /SAVE MAHAL COOK SDRESID.
```

extracting Mahalanobis distances, cooks d, and studentized deleted residuals for multivariate outlier analysis

```
COMPUTE EXTMAH=1- CDF.CHISQ(MAH_1,10).
EXECUTE.

COMPUTE ESTMAH=1- CDF.CHISQ(MAH_2,10).
EXECUTE.

COMPUTE AGRMAH=1- CDF.CHISQ(MAH_3,10).
EXECUTE.

COMPUTE CSNMAH=1- CDF.CHISQ(MAH_4,10).
EXECUTE.

COMPUTE OPNMAH=1- CDF.CHISQ(MAH_5,10).
EXECUTE.
```

for easier interpretation of Mahalanobis distance, the researcher turned it into a probability

R Code

```
set.seed(1)

Unrefined <- Final_Phase_1_Dissertation_Variables[,1:5]

Refined <- Final_Phase_1_Dissertation_Variables[,6:10]

Zunrefined <- Final_Phase_1_Dissertation_Variables[,11:15]

UnrefinedClust <- Mclust(data.frame(Unrefined), G=4)

RefinedClust <- Mclust(data.frame(Refined), G=4)

ZunrefinedClust <- Mclust(data.frame(Zunrefined), G=4)

summary(RefinedClust, parameters = TRUE)

summary(ZunrefinedClust, parameters = TRUE)

summary(UnrefinedClust, parameters = TRUE)

ZunrefinedClust2 <- Mclust(data.frame(Zunrefined))

UnrefinedClust2 <- Mclust(data.frame(Unrefined))

RefinedClust2 <- Mclust(data.frame(Refined))

summary(RefinedClust2, parameters = TRUE)

summary(ZunrefinedClust2, parameters = TRUE)

summary(UnrefinedClust2, parameters = TRUE)
```

```
set.seed(1)

Unrefined <- Final_Phase_2_Dissertation_Variables[,1:5]

Refined <- Final_Phase_2_Dissertation_Variables[,6:10]

Zunrefined <- Final_Phase_2_Dissertation_Variables[,11:15]

UnrefinedClust <- Mclust(data.frame(Unrefined), G=4)

RefinedClust <- Mclust(data.frame(Refined), G=4)

ZunrefinedClust <- Mclust(data.frame(Zunrefined), G=4)

summary(RefinedClust, parameters = TRUE)

summary(ZunrefinedClust, parameters = TRUE)

summary(UnrefinedClust, parameters = TRUE)

ZunrefinedClust2 <- Mclust(data.frame(Zunrefined))

UnrefinedClust2 <- Mclust(data.frame(Unrefined))

RefinedClust2 <- Mclust(data.frame(Refined))

summary(RefinedClust2, parameters = TRUE)

summary(ZunrefinedClust2, parameters = TRUE)

summary(UnrefinedClust2, parameters = TRUE)
```

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