



LUNDS
UNIVERSITET

DEPARTMENT of PSYCHOLOGY

***Beyond the Big Five Factors:
Using Facets and Nuances for Enhanced Prediction in Life
Outcomes***

Maiken Due Nielsen

Master's Thesis (30 hp)
Spring 2023

Supervisor: Petri Kajonius

Personal Acknowledgements

As I near the end of my journey as a student, I want to reflect on those with whom I share this accomplishment and extend my gratitude. First, I want to acknowledge my parents, who probably did not realize what they had set into motion when they first encouraged me to pursue a university degree. Seven years and two countries later, they continue to be my biggest supporters. I am especially grateful to my father for delivering the most spectacular pep talks and my mother for encouraging me to maintain a positive mindset even during times of frustration. For this gift, I can only say how deeply grateful I am.

Secondly, I want to thank my wonderful friends who have been on this journey with me. My great fortune was having their support, encouragement, and input throughout this process. I would also like to thank my supervisor Petri Kajonius for graciously contributing the data on which this thesis is based and for providing brilliant guidance and encouragement. Lastly, I would like to acknowledge the assistance of Martin Bäckström and Rene Mõttus, who were valuable contacts and invested time to help me with any questions about coding and analyses.

Abstract

Objective: Previous research using personality traits to predict life outcomes has typically utilized the Big Five factors and, occasionally, their facets. However, recent research suggests that using items (reflecting personality nuances) can account for greater predictive variance. The present study examines the predictive validity of the different levels of the personality trait hierarchy (factor, facet, and nuances).

Method: Confirmatory Factor Analyses (CFA) were performed on the data ($N = 440$) to confirm the structures of the Big Five levels prior to using Elastic Net Regression (ENR; with 10-fold cross-validation and shrinkage parameter) to predict outcomes at the factor, facet, and item level. Models were trained and applied for prediction in separate samples.

Results: The results showed that nuances, on average, provided greater explained variance (34%) than both facets (22.5%) and factors (12%) for all six outcome predictions, suggesting that narrower traits are more effective in predicting outcomes than the Big Five factors.

Conclusion: Findings suggest that there may be benefits to using narrower characteristics for predicting outcomes when predictive validity is the goal. Implications, limitations, and directions for future research are discussed.

Keywords: Personality traits, IPIP-NEO, facets, nuances, items, life outcomes, predictive validity

Beyond the Big Five Factors: Using Facets and Nuances for Enhanced Prediction in Life Outcomes

The field of personality psychology explores how individual personality differences relate to differences in attitudes, behaviors, and life outcomes. Obtaining a comprehensive understanding of how such individual differences impact the trajectory of life is paramount in gaining insights into human behavior and, subsequently, in promoting healthier and more fulfilling lives. At a practical level, this knowledge is applied in decision-making processes such as hiring and promoting and serves as the foundation for various interventions.

Personality-outcome associations are commonly studied using the Five Factor Model (FFM; McCrae & John, 1992) or the Big Five (Goldberg, 1990), which consists of five broad traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism. These broad traits have been associated with a variety of life outcomes, such as subjective happiness and well-being in late life (Gilberto et al., 2020), political affiliation (Furnham & Fenton-O'Creevy, 2018), smoking, drug abuse (Bogg & Roberts, 2004), volunteering behavior (Carlo et al., 2005), mortality, divorce, and career success (Roberts et al., 2007).

While research on factor-outcome associations is expansive and highly replicable (Soto, 2019), some researchers argue for using narrower traits (Seeboth & Möttus, 2018; Stewart et al., 2022) to improve predictive power and provide a more comprehensive description of the individual. This discussion on the optimal balance between the breadth of information and the precision at which this information can be processed, the so-called bandwidth-fidelity discussion, is by no means a new one (Cronbach & Gleser, 1965; Ones & Viswesvaran, 1996). However, it has recently gained renewed attention. This is partly due to new research demonstrating that trading the broad bandwidth of factors for increased fidelity from narrower traits allows for more accurate personality-outcome predictions (Seeboth & Möttus, 2018; Stewart et al., 2022).

Although broad-bandwidth models are practical and intuitive, they face limitations and challenges. One limitation is that factor-outcome studies tend to produce small effect sizes. While small effect sizes are accepted within personality research (Anvari et al., 2022; Götz et al., 2021), exploring the upper limits of effect sizes is necessary to avoid underestimating personality outcomes associations. Another limitation is the prominent trend in the literature of high scores in positively viewed traits being linked to favorable outcomes and, conversely, high scores in negatively viewed traits being linked to unfavorable outcomes (Allik et al., 2010). For instance, well-being is positively linked to extraversion and

conscientiousness but negatively related to neuroticism (Gilberto et al., 2020). As another example, those individuals high in neuroticism are more likely to get divorced, whereas individuals who are more conscientious and agreeable remain longer in their marriage (Roberts et al., 2007). The existence of comparable findings in the literature is abundant. However, there may be a more substantial and meaningful relationship underlying these associations. Traits that are more specific in scope present an opportunity to gain a more profound understanding of the relationship between personality and outcomes.

Big Five Facets and Nuances

The Big Five factors are composed of narrower traits known as facets. Research indicates that facets are heritable (Briley & Tucker-Drob, 2012) and capture unique variance on their own (Mõttus et al., 2014). Looking beyond factors and examining narrower traits may provide a solution to the limitations of factor-outcome associations. For instance, neuroticism comprises the facets anxiety, anger, depression, self-consciousness, immoderation, and vulnerability (IPIP-NEO-120; Johnson, 2014). While two people can obtain identical scores for neuroticism, their facet scores could be drastically different. For instance, Vainik et al. (2019) investigated the relationship between Body-Mass Index (BMI), as a measure of obesity, and personality, captured by factors and facets. While BMI was positively linked to neuroticism and negatively to conscientiousness, the analysis revealed significant relationships between BMI and 15 facets across all five factors. More importantly, it was found that facets explained 409% more variance than factors for obesity. Including facets as part of the analysis facilitated a more comprehensive understanding of the relationship between obesity and personality, demonstrating the ability of narrow traits to reveal more meaningful relationships.

Similarly, Espinoza et al. (2023) found that facets provide a more precise perspective on the relationship between personality and conflict management style. Beyond demonstrating that facets account for greater variance compared to factors, they also conducted formal tests for masking (the presence of a third variable is hiding the effect of one variable on another) and cancelation (two variables canceling each other out because they have opposing effects on a dependent variable). Evidence for both cancelation and masking effects were found for the factor models, demonstrating that factor-level predictions may obscure meaningful relationships. For these reasons, using facets in outcome prediction has become increasingly popular for enhanced discriminant validity and better interpretation of findings.

While the usefulness of facets in personality-outcome prediction has been demonstrated, it has been suggested that there is yet another indispensable level of traits below facets, labeled nuances (McCrae, 2015). Due to the lack of a classification, nuances are operationalized as individual items in a personality instrument. However, personality nuances and items may not be *exactly* the same. Nuances refer to the smallest unique aspects of an individual's personality (McCrae, 2015), which can be represented by a single item as well as sets of items that capture no distinct information from one another (Stewart et al., 2022). Items are standardized statements designed to capture tiny aspects of personality and are often treated as interchangeable with other items from the same facet group (Möttus et al., 2017). For instance, extraversion contains items such as "I have a lot of fun" and "I look at the bright side of life" (IPIP-NEO-120; Johnson, 2014). While these items are created to capture the facet cheerfulness and often correlate with each other, they contain unique information. For example, "I look at the bright sight of life" may capture a nuance labeled "positive thinking," whereas "I have a lot of fun" may reflect a nuance labeled "lively" or "playful." While treated as interchangeable in personality instruments, items capture distinct nuances of personality (Speer et al., 2022). Due to the lack of proper classification, items will be markers of nuances in the present study.

Previous Studies on Personality-Outcome Associations using Facets and Nuances

In a comprehensive study on the predictive value of nuances, Seeboth and Möttus (2018) surveyed a British sample ($N = 8719$) with 40 life outcomes and 50 items from the International Personality Item Pool (IPIP). They found that, on average, nuances explained 30% more variance than factors and outperformed factors in predicting 37 of the 40 outcomes. Nuance models out-predicted factor models even after dropping the ten most predictive items from the nuance model. However, there were two notable limitations of the study. Firstly, the study focused on the predictive accuracy of factors and nuances, excluding facets as a predictor. This made it impossible to gauge the actual value of using nuances over facets for predictions. Secondly, the instrument used in their study contained only a modest number of nuances ($N = 50$) specifically designed to measure the Big Five factors.

Building on the findings of Seeboth and Möttus (2018), Stewart et al. (2022) examined associations between the Big Five Inventory-2 (BFI-2; Soto & John, 2017) and 53 life outcomes using factor, facet, and nuance models in a US sample ($N = 6126$). Consistent with previous findings, nuances (20.9% explained variance) were better predictors of outcomes than factors (16.6%). Nuances were also found to be better predictors than facets

(18%) across all outcomes, regardless of the breadth of the outcome. This held true even after removing factor and facet variance from nuances, suggesting that the unique nuance-variance drove associations between personality and outcomes.

Stewart et al. (2022) utilized a personality inventory designed to balance bandwidth and fidelity while still attempting to provide an optimal measure of the Big Five factors. The BFI-2 captures personality using a limited number of facets ($N = 15$) and items ($N = 60$). An instrument with a more significant number of facets and items, such as the IPIP-NEO-120 (Johnson, 2014), may better capture the various nuances of personality. The IPIP-NEO-120 contains an impressive total of 120 items and is one of the few publicly available personality measures with a three-level structure. Moreover, it has demonstrated high internal consistency, reliability, and validity (Johnson, 2014), thus making it an appealing choice of instrument.

Challenges in Measuring and Using Nuances for Personality Outcome Research

Given that facets and nuances account for unique variance, it is reasonable to question why personality-outcome associations are commonly investigated using broad trait models. However, while there are calls for a bottom-up taxonomy and an instrument for measuring nuances (Condon et al., 2020), neither exists at present. Research on nuances as predictors of life outcomes is therefore carried out using instruments designed to maximize factor variance. Until a robust taxonomy is in place, researchers may prefer well-established measures of broad factors and forgo the complexity of using narrow traits for prediction. Developing a reliable and valid nuance instrument could be a meaningful supplementary tool for personality-outcome prediction. Until such a tool is developed, narrower traits are captured using existing instruments.

Although some researchers have moved towards the consideration of using narrower traits (Elleman et al., 2020; Revelle et al., 2021; Speer et al., 2022), more research using different samples and instruments is needed to determine the potential benefits of using nuances for prediction. Specifically, there is a need to replicate previous studies using longer instruments, as it has been demonstrated that a substantial proportion of meaningful personality variance is left unaccounted for by shorter instruments (Sleep et al., 2021). Moreover, demonstrating the value of using narrower traits for making predictions may encourage researchers to construct a bottom-up nuance taxonomy with the goal of better predictive and discriminant validity in outcome-prediction research.

Present Study

The present study aims to compare the predictive validity of the different levels of the personality trait hierarchy - factor, facet, and nuance - in predicting life outcomes. Specifically, this study aims to model the methods of Stewart et al. (2022) and confirm their findings using different outcomes and a different dataset and personality instrument in a non-English sample. The study tests two hypotheses: (1) facet-level models will outperform factor-level models in predictions, and (2) item-level models (nuances), will outperform facet and factor-level models in life outcome predictions. Importantly, these hypotheses were tested with models containing either *all* factors, *all* facets, or *all* items rather than including individual traits based on their predictive power. This study contributes to a growing body of literature on the value of narrow traits in outcome prediction. Furthermore, it demonstrates the predictive validity of narrow traits across various life outcomes, seeking to shift personality research from correlational to predictive.

Methods

Participants

The data in the present study is secondary data collected from an online questionnaire for personality testing in Swedish. Participants filled out the IPIP NEO-120 (Johnson, 2014) and answered 16 additional questions regarding life outcomes. The advantages of using pre-collected data are the time and cost efficiency and access to a larger sample than would have been feasible to collect due to time and resource restrictions. All participants gave their informed consent prior to the start of the survey, and given the nature of the study, no ethical review was required.

The sample size of this study was $N = 549$ participants prior to data processing. As personality traits have been shown to stabilize in mid to late adulthood (Borghuis et al., 2017) and then remain remarkably stable (McCrae & Costa, 1994), participants below 25 years of age ($n = 76$) were excluded from the analysis. Furthermore, participants who failed to report their age or missed $\geq 10\%$ of items ($n = 52$) were excluded from the analysis. The final sample size was $N = 440$ (57% female), aged 25 to 65 ($M = 42$, $SD = 10.51$). See Appendix A for an overview of demographic variables.

Measurements

Five Factor Model of Personality (IPIP- NEO-120)

The IPIP-NEO-120 (Johnson, 2014) is a widely used self-report instrument that assesses the Big Five using 120 items. The instrument has good internal consistency, validity, and reliability (Johnson, 2014) and is one of the few large, publicly available instruments with a three-level structure. Moreover, the instrument is known for its simplicity and has been demonstrated to be robust for both research and practical purposes (Kajonius & Johnson, 2019). Respondents rate items on a five-point Likert scale ranging from 1 = *very inaccurate* to 5 = *very accurate*, with balanced (+ and -) keying. Example items from each factor are: “I make friends easily” (extraversion), “I love to help others” (agreeableness), “I usually leave a mess in my room” (reversed conscientiousness), “I am not bothered by difficult social situations” (reversed neuroticism), and “I have a lively imagination” (openness). Item scores are summarized into facet traits, with four items per facet, amounting to 30 facets. Facet traits are summed and averaged into factors, with six facet traits per factor. See Appendix B for a complete overview of the IPIP-NEO-120 scale.

Outcome Measures

Personal life outcomes were captured using 16 single-item constructs. A total of six outcome questions were selected for analysis based on the wording of the item, with ambiguously worded questions being excluded. Additionally, outcomes pertaining to the past were excluded due to potential memory bias. Questions were answered using a seven-point Likert scale ranging from 1 = *not at all* to 7 = *completely*. See Table 1 for questions and labels used in the present study.

Table 1

Life Outcome Measures

Outcome label	Item question
Job satisfaction	How much would you say you enjoy your current work/job
Social satisfaction	How much would you say you are satisfied with your current social life/friends
Empathy	To what extent do you empathize and take part in others' feelings
Bright future	How much would you say you believe your personal future will be bright
Intrinsic reward	To what extent is personal development your source of motivation for working
Extrinsic reward	To what extent is reward your source of motivation for working

Note. On the left: outcome construct labels used throughout the study to refer to the single-item questions. On the right: the item questions answered by the participants as they were

phrased in the study.

Statistical Analyses

All statistical analyses were performed using R (R Core Team, 2021). The packages Psych (Revelle, 2021), dplyr (Wickham et al., 2023), tidyr (Wickham et al., 2023), lavaan (Rosseel, 2012), semPlot (Epskamp, 2022), ggplot2 (Wickham, 2016), reshape2 (Wickham, 2007), caTools (Tuszynski, 2001), tidyverse (Wickham et al., 2019), glmnet (Friedman et al., 2010), lme4 (Bates et al., 2015), and caret (Kuhn, 2022) were utilized for analyses and plots.

Prior to all analyses, missing variables were dealt with using the R package mice (van Buuren & Groothuis-Oudshoorn, 2011). In this study, the mean value of each column was computed and inserted in the place of missing variables.

Descriptive analyses

Descriptive analyses were performed for facets and factors, examining Cronbach alpha, mean value, standard deviation, skewness, and kurtosis. Additionally, bivariate zero-order correlation analyses between the Big Five factors and outcome measures were performed. Furthermore, a descriptive analysis was performed for items, examining mean value, standard deviation, skewness, and kurtosis (see Appendix C). A correlational heatmap was generated for the 30 facets to allow for straightforward visual interpretation (see Appendix D).

Confirmatory Factor Analysis

A second-order Confirmatory Factor Analysis (CFA) was conducted to confirm the structural validity of the Big Five hierarchical levels. CFA models were computed for each Big Five factor, loaded by their respective facets, which in turn were loaded by their respective 24 items. No modification indices were used. Model fits were evaluated using point estimate values of the Standardized Root Mean Residuals (SRMR), robust Root Mean Squared Error of Approximation (RMSEA) $> .05$, and Comparative Fit Index (CFI) (Browne & Cudeck, 1992; Cheung & Rensvold, 2002).

Elastic Net Regression

An Elastic Net Regression (ENR) was performed to compare the predictive validity of factor, facet, and nuance models. ENR is a hybrid of two popular regression methods: Lasso and Ridge regressions. The Lasso regression adds a penalty term (L1) proportional to the absolute value of the coefficients, encouraging the model to use the most important features and reducing the coefficients of less important features to zero. The Ridge regression adds a

penalty term (L2) proportional to the square of the coefficients, encouraging the model to use all features but reducing their magnitudes (shrinking them towards zero). Ridge regression handles correlated features and multicollinearity in the data but is prone to overfitting the model to the training data. Conversely, Lasso regression produces modest models protected against overfitting but is sensitive to outliers and non-normality. ENR combines the best of both methods while addressing their individual limitations (Zou & Hastie, 2005).

The data set was randomly split into a training (67%) and a validation (33%) sub-sample, inspired by Stewart et al. (2022). Reserving a more considerable portion of the sample for training the model is common practice, as more information produces a more accurate model. The training sample was used to set up ENR models for each of the six outcomes, with either the Big Five factors, facets, or nuances as predictors. A 10-fold cross-validation and shrinkage parameters were applied to obtain the optimal parameter lambda (λ), which minimizes cross-validation error and prevents overfitting the data to the model¹. This helped to ensure that the model is more generalizable, as it will perform better on new data. Next, the trained models were fitted to the validation sample to predict each outcome. Finally, the predicted outcomes were correlated with the actual outcome scores to calculate prediction validity for each model. Each correlation was squared to show the percentage of explained variance.

Results

A descriptive analysis was performed for the Big Five personality structure. Table 2 displays mean value, standard deviation, skewness, kurtosis, and Cronbach alpha values for facets and factors. As shown in Table 2, the mean reliability for facets was $\alpha = .68$, with 14 facets $< .70$, and the data was acceptably symmetrical and normally distributed. Notably, the factor agreeableness and the facet altruism showed high kurtosis.

¹ 10-fold cross-validation means the training data is split into ten random sub-samples of equal size, called folds. Nine of those sub-samples are used for training, and one for testing. This process is repeated ten times, reserving a different fold for testing. Finally, the result of each run is averaged to produce an estimate of the model's performance.

Table 2*Descriptives for Facets and Domains*

Factor and facet traits	α	M	SD	Skewness	Kurtosis
Extraversion	.88	14.94	1.86	-0.57	0.97
E1_Friendliness	.73	16.70	2.55	-0.84	0.46
E2_Gregariousness	.70	14.64	2.93	-0.42	-0.26
E3_Assertiveness	.75	14.61	2.50	-0.30	0.37
E4_Activity	.53	13.55	2.51	-0.20	0.04
E5_Excitement	.77	13.64	3.04	-0.07	-0.29
E6_Cheerfulness	.79	16.56	2.35	-0.93	1.91
Agreeableness	.83	18.49	1.75	-1.19	3.55
A1_Trust	.83	15.79	2.82	-0.82	1.02
A2_Morality	.68	17.81	2.41	-1.32	1.61
A3_Altruism	.61	17.24	2.36	-1.38	3.41
A4_Cooperation	.44	16.10	2.15	-0.71	0.86
A5_Modesty	.70	11.37	2.88	0.18	-0.21
A6_Sympathy	.76	16.76	2.85	-0.95	-0.98
Neuroticism	.87	7.74	1.81	0.78	0.96
N1_Anxiety	.80	8.00	2.82	0.85	1.04
N2_Anger	.73	7.59	2.70	0.83	1.05
N3_Depression	.80	6.29	2.37	1.45	2.50
N4_Self-conscious	.51	8.51	2.74	0.38	-0.36
N5_Immoderation	.51	9.00	2.46	0.32	0.08
N6_Vulnerability	.61	7.05	2.11	0.76	0.59
Openness	.81	14.32	1.77	-0.03	-0.27
O1_Imagination	.81	12.51	3.51	0.04	-0.51
O2_Artistic	.67	15.13	3.16	-0.39	-0.44
O3_Emotionality	.53	16.22	2.24	-0.33	-0.32
O4_Adventurous	.71	14.03	2.82	-0.07	-0.32
O5_Intellect	.67	15.61	2.95	-0.29	-0.54
O6_Liberalism	.48	12.42	2.61	-0.22	0.27
Conscientiousness	.86	17.58	1.63	-0.68	0.58
C1_Self-efficacy	.81	17.56	2.16	-1.18	3.48
C2_Orderliness	.81	16.23	3.16	-0.86	0.49
C3_Dutifulness	.69	18.70	1.76	-1.81	3.62
C4_Achievement	.61	16.98	2.16	-0.51	-0.10
C5_Self-discipline	.73	16.53	2.46	-0.76	-0.60
C6_Cautiousness	.60	14.26	2.46	-0.07	0.16

Note. Overview of the facet and factor scores ($N = 440$). α = Cronbach alpha; M = Mean; SD = Standard deviation.

A second-order CFA was conducted to confirm the relationship between lower-level latent variables and higher-order factors. Table 3 illustrates fit indices ($\chi^2(df)$, RMSEA, SRMR, and CFI) reported in the trait domain rows. Standardized item loadings are reported in the facet rows. As shown in Table 3, neuroticism was the best-fitting model, with an RMSEA of .05 and a CFI of .93. The remaining models had acceptable fits, with RMSEAs ranging from .06 to .07 and CFIs ranging from .81 to .85. All the models had SRMR values of .08 or less. Overall, the models were reasonably well-fitting. The standardized factor loadings were in the range of $\lambda = .16 - .95$, with an average of $\lambda = .61$ for extraversion, $\lambda = .55$ for neuroticism, $\lambda = .55$ for agreeableness, $\lambda = .46$ for conscientiousness and $\lambda = .57$ for openness. Only the facets cooperation and modesty failed to show acceptable loading estimates. Individual path diagrams for each construct, demonstrating covariances, regressions, and factor loadings, are found in Appendix E.

Table 3*S-CFA fit indices and Standardized Item Loadings*

Trait domain / facet trait	Item a	Item b	Item c	Item d
Extraversion $\chi^2(246) = 798.818$; RMSEA = .07; SRMR = .07, CFI = .85				
Friendliness	.57	.47	.56	.59
Gregariousness	.77	.56	.47	.66
Assertiveness	.63	.67	.55	.34
Activity level	.26	.70	.58	.36
Excitement-seeking	.74	.77	.50	.64
Cheerfulness	.54	.51	.51	.54
Neuroticism $\chi^2(246) = 494.221$; RMSEA = .05; SRMR = .06, CFI = .93				
Anxiety	.73	.66	.63	.52
Anger	.58	.69	.62	.43
Depression	.69	.38	.66	.41
Self-consciousness	.64	.65	.45	.29
Immoderation	.51	.22	.51	.56
Vulnerability	.41	.35	.46	.41
Agreeableness $\chi^2(246) = 762.107$; RMSEA = .07; SRMR = .08, CFI = .84				
Trust	.74	.70	.68	.47
Morality	.75	.55	.47	.23
Altruism	.50	.54	.40	.42
Corporation	.17	.44	.49	.36
Modesty	.27	.95	.82	.45
Sympathy	.74	.71	.48	.59

Trait domain / facet trait	Item a	Item b	Item c	Item d
Conscientiousness $\chi^2(246) = 762.736$; RMSEA = .07; SRMR = .08, CFI = .85				
Self-efficacy	.46	.46	.52	.50
Orderliness	.35	.80	.83	.90
Dutifulness	.42	.32	.34	.38
Achievement striving	.47	.38	.39	.46
Self-discipline	.42	.43	.63	.63
Cautiousness	.53	.16	.28	.71
Openness $\chi^2(246) = 691.853$; RMSEA = .06; SRMR = .07, CFI = .81				
Imagination	.81	.71	.80	.82
Artistic interests	.80	.59	.61	.60
Emotionality	.42	.39	.42	.42
Adventurousness	.58	.70	.52	.56
Intellect	.69	.74	.53	.43
Liberalism	.58	.36	.67	.24

Note. χ^2 = chi-square value; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Residuals; CFI = Comparative Fit Index; α = Cronbach alpha. Item a, Item b, Item c, and Item d denote the four items making up each facet trait.

Table 4 displays the result of the correlational analysis between the Big Five factors and the six life outcomes. Extraversion was positively associated with all six life outcomes, whereas negative associations were observed between neuroticism and most life outcomes. Notably, a significant negative relationship between agreeableness and the empathy life outcome was observed. Agreeableness is composed of facets such as altruism and sympathy, and it would be intuitive to assume that agreeableness and empathy would be positively linked. No relationship was observed between agreeableness and the other outcomes. Conscientiousness was positively related to social satisfaction, positive beliefs about the future, as well as both intrinsic and extrinsic reward. While openness was positively related to positive beliefs about the future, it was negatively linked to both extrinsic and intrinsic reward. Relationships between the life outcomes were also observed, with social satisfaction being related to all outcomes except for intrinsic reward. The remaining factors showed various patterns of relationships with the outcomes (see Table 4).

Table 4*Correlations Between Big Five Factors and Outcome Measures*

	1	2	3	4	5	6	7	8	9	10	11
1 Agreeableness											
2 Extraversion	-.01										
3 Neuroticism	-.13	-.57									
4 Conscientiousness	-.09	.46	-.61								
5 Openness	.00	.28	-.20	-.04							
6 Job satisfaction	.04	.21	-.16	.06	.10						
7 Social satisfaction	-.03	.45	-.44	.37	.01	.21					
8 Empathy	-.09	.10	.04	.04	.06	.14	.17				
9 Bright future	.06	.33	-.31	.20	.16	.08	.15	-.03			
10 Intrinsic reward	-.04	.31	-.29	.25	-.21	.09	.04	.05	.34		
11 Extrinsic reward	-.01	.12	-.06	.12	-.13	-.06	.19	-.03	.05	.21	

Note. Correlations between outcomes and the Big Five factors in the sample (N = 440). $r \geq .09$, $p < .05$, $r \geq .13$, $p < .01$, and $r \geq .16$, $p < .001$. Boldface indicates strong effect sizes, as recommended by Gignac and Szodorai (2016).

Using Facets and Nuances for Enhanced Prediction in Life Outcomes

The study aimed to investigate the predictive validity of factors, facets, and nuances for life outcomes. The hypotheses were that facets would outperform factors and that nuances would outperform both facets and factors. Figure 1 demonstrates the ENR analysis results, with variance explained by each model for all six life outcomes². As illustrated by Figure 1, support was found for both hypotheses. While the life outcomes varied in the degree to which the personality models predicted them, facets (blue dots) consistently explained more variance than factors (red dots) for all outcomes, and nuances (green dots) explained more variance than facets.

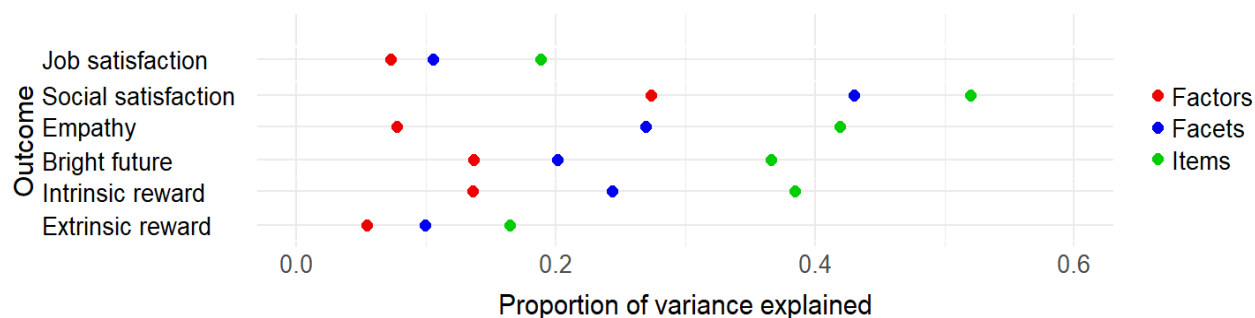
On average, factors, facets, and nuances accounted for 12%, 22.5%, and 34% of explained variance across all outcomes. As shown in Table 5, social satisfaction was the strongest outcome association, with nuances explaining 52% of variance. Conversely, extrinsic reward was the weakest outcome association, with nuances explaining 16% of variance. Although nuances consistently explained more variance than facets and factors, the amount of variance explained varied across outcomes. For instance, nuances explained 12%

² A multiple linear regression (MLR) was performed exploratorily to allow for easier interpretation of results across studies and to facilitate inter-methods comparisons. See Appendix F for the results of the MLR.

more variance than factors for job satisfaction, while nuances explained 35% more variance than factors for empathy.

Figure 1

Variance Accounted for in each Outcome.



Note. Results of the Elastic Net Regression. The figure shows variance (squared correlation coefficients) accounted for in each outcome by factors (red), facets (blue), and nuances (green).

Table 5

Proportion of Variance Explained for each Outcome Measure

Outcome	Factor	Facet	Nuance
Job satisfaction	.07	.11	.19
Social satisfaction	.27	.43	.52
Empathy	.07	.27	.42
Bright future	.14	.20	.37
Intrinsic reward	.14	.24	.38
Extrinsic reward	.05	.10	.16

Note. Explained variance for the six outcomes based on the Elastic Net Regression analyses. The data set ($N = 440$) was randomly split into training (67%) and validation (33%) sub-samples. The trained models were fitted to the validation sample to predict each outcome.

Discussion

The present study investigated the predictive validity of personality at the factor, facet, and nuance level for six self-assessed life outcomes. Using a sample collected in Sweden and a large personality instrument, this study demonstrated the value of utilizing narrow personality traits for predicting life outcomes. The result of my analysis was largely consistent with previous studies (Elleman et al., 2020; Espinoza et al., 2023; Revelle et al., 2021;

Seeboth & Möttus, 2018; Speer et al., 2022; Stewart et al., 2022) and support was found for both of my hypotheses.

This study modeled the methods of Stewart et al. (2022) but with a larger personality instrument, a different sample, and different life outcomes. The analysis produced comparable results to Stewart et al. (2022). However, the present study reported even greater differences between factors, facets, and item models in predicting outcomes. Stewart et al. (2022) did not find a large difference in explained variance between facets and nuances, whereas the present study demonstrated that nuances provide substantially better predictive validity. On average, this study found that nuances explained 13% more variance than facets, while Stewart et al. (2022) reported an increase of 2.9%. Such difference may be due to the relative size of the IPIP-NEO compared to the BFI-2, which was designed to be a more concise measure of the Big Five. As larger instruments capture substantially more variance than shorter instruments (Sleep et al., 2021), the use of the IPIP-NEO is one of the strengths of the present study.

While both hypotheses were supported, there were notable differences in the amount of variance that personality explained for each outcome. For example, among the outcomes, nuances accounted for the most variance for social satisfaction (52%). This was a 25% additional variance than was explained by factors. A possible explanation for this observation is that aggregating items into broad factors masks the actual relationship between personality and social satisfaction, resulting in a loss of predictive validity. Conversely, nuances explained the least variance for extrinsic reward (16% for nuances and 5% for factors). This may be because reward was not well-defined in the outcome question, leaving the interpretation of reward up to the individual participant. In contrast, the predictive validity was better for all levels of personality for intrinsic reward, where reward was explicitly defined as a sense of personal development.

The largest discrepancy in predictive validity between models was observed for the empathy outcome, with nuances explaining 35% more variance than factors. This can be argued to be either a result of nuances capturing additional information or due to overlap between outcome and measurement items. The IPIP-NEO contains the facet sympathy, which includes items such as “I feel sympathy with homeless” and “I feel sympathy with those with problems.” Moreover, it captures the facet emotionality, which includes items such as “I feel others' emotions.” It can be argued that the empathy outcome more closely reflects a nuance of personality, thus making the nuance-level prediction unrepresentatively better than factor-level.

On the Value of Narrow Traits for Predicting Outcomes

The present study suggests that nuance models are more effective than facet and factor models in predicting personality-outcome associations due to the unique variance accounted for by nuances. A possible way to interpret this is that nuances drive the personality-outcome associations, but when this information is aggregated into broad traits, some information is lost or masked. This has been observed in previous studies (Espinoza et al., 2023).

Embracing narrow traits may be unappealing to researchers accustomed to working with broad models such as the Big Five. Although generalized predictions derived from broad, intuitive models are practical and easy to communicate to the general population, narrow trait models may be more appropriate if the precision of prediction is the intended goal. To explore the precise predictive validity of nuances, the careful development of a comprehensive bottom-up nuance taxonomy is a necessary future step. Although researchers may have to think outside the box to design a reliable instrument, it is plausible that such an instrument can be developed. In the meantime, narrow traits captured with existing instruments can be a valuable tool for researchers to understand better how personality does not just correlate to but *affects* the trajectory of life.

Implications

There is a certain necessity in using simple models, especially when communicating findings to the general population. However, one must weigh the benefits of general face validity against the loss of specificity and prediction, especially when findings are intended for practical application. For instance, researchers may be interested in increasing the feelings of well-being of the general population. As neuroticism is negatively associated with well-being (Gilberto et al., 2020), interventions might include efforts to make people less neurotic. However, this is a very complex task. If, instead, it is found that only a handful of narrower traits drive this association, it follows that interventions become more targeted and tangible.

As another example, personality is often used as an indicator of job performance. However, job performance can pertain to many work-related behaviors and attitudes, such as how well one gets along with co-workers, ability to meet deadlines, and trustworthiness. These behaviors may not be easily captured and predicted by broad factors alone. Should the Big Five factors continue to be the prevalent model for predicting job performance if another more accurate option is available? It should be in the interests of researchers to strive for precision rather than merely linking traits to outcomes without offering explanation. This

study's findings imply that using nuance models may facilitate better insight into personality-outcome relationships.

Limitations and Future Research

While the study has several strengths, it also has some limitations which are important to mention. One consideration is the sample size. While there are no official guidelines for the sample size required for machine learning, aiming for a larger sample is generally recommended as prediction validity increases with the sample size (Cui & Gong, 2018). Additionally, a larger sample is more representative of the general population, increasing the generalizability of the findings (Cui & Gong, 2018). Future research can address this concern by applying the methods and instruments used in this study to a larger sample. Correspondingly, the data collection took place in Sweden through an internet webpage. As such, very little is known about the present sample and the findings may be limited to the Swedish population. While my findings are comparable to those of Seeboth and Möttus (2018), whose sample was collected in Great Britain, and Stewart et al. (2022), whose data was collected in the US, the external validity of the results of the study would be improved by extending the data collection to multiple countries.

Another suggestion for future research is to exercise caution when choosing outcome measurements. For example, it can be argued that the empathy outcome in this study too closely resembled some items of the IPIP-NEO-120. As such, it can be questioned whether the results represents a real relationship or if the amount of variance explained by nuances was overestimated.

Finally, the primary limitation of this study is the use of personality instruments designed to capture the Big Five factors best. Instruments such as the IPIP-NEO-120 are intended to maximize common variance using a limited number of items. While it is difficult to gauge how many nuances are captured by the IPIP-NEO-120, it is most likely less than 120, as the items overlap in content, and some are reverse-keyed duplicates. Thus, these instruments are restricted in their ability to demonstrate the predictive value of nuances fully. Having said that, larger instruments such as the IPIP-NEO-120 are demonstrated to capture substantially more variance for both factors and facets than shorter instruments (Sleep et al., 2021), making it both a strength and a limitation of the study. Future research incorporating narrow traits into their study design may benefit from using the IPIP-NEO-120. Additionally, future research should explore whether utilizing larger instruments, such as the IPIP-NEO-300, can provide an even more detailed and comprehensive understanding of personality.

Ideally, a complete and reliable nuance taxonomy would replace current instruments for prediction research.

Conclusion

The present study utilized the IPIP-NEO-120 to investigate the predictive validity of factors, facets, and nuances for six distinct life outcomes. The study results are largely consistent with previous research, suggesting that narrower traits can lead to better predictive validity in personality-outcome research. Additionally, there are grounds to believe that the proportion of variance explained by narrow traits, as compared to broad traits, partly depends on the specific outcome being examined. While Big Five factor models have produced countless personality-outcome associations and are often preferred for their practicality, I put forward the recommendation of using narrower traits, such as facets and nuances, when the intention is practical application or when enhanced prediction validity is desired over simplicity.

Data Accessibility Statement

The study materials, data and analysis scripts used for this article can be accessed at https://osf.io/8na4s/?view_only=07a010148e0147efb03252e5b1c08e4b

References

- Allik, J., Realo, A., Mõttus, R., Borkenau, P., Kuppens, P., & Hřebíčková, M. (2010). How people see others is different from how people see themselves: A replicable pattern across cultures. *Journal of Personality and Social Psychology*, *99*(5), 870–882. <https://doi.org/10.1037/a0020963>
- Anvari, F., Kievit, R., Lakens, D., Pennington, C. R., Przybylski, A. K., Tiokhin, L., Wiernik, B. M., & Orben, A. (2022). Not all effects are indispensable: Psychological science requires verifiable lines of reasoning for whether an effect matters. *Perspectives on Psychological Science*, *18*(2), 503–507. <https://doi.org/10.1177/17456916221091565>
- Bates, D., Maechler, M., Bolker, B., Walker, S. (2015). lme4: Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1-48. <https://doi:10.18637/jss.v067.i01>.
- Bogg, T., & Roberts, B. W. (2004). Conscientiousness and health-related behaviors: A meta-analysis of the leading behavioral contributors to mortality. *Psychological Bulletin*, *130*(6), 887-919. <https://doi.org/10.1037/0033-2909.130.6.887>
- Borghuis, J., Denissen, J. J., Oberski, D., Sijtsma, K., Meeus, W. H., Branje, S., Koot, H. M., & Bleidorn, W. (2017). Big five personality stability, change, and co-development across adolescence and early adulthood. *Journal of Personality and Social Psychology*, *113*(4), 641–657. <https://doi.org/10.1037/pspp0000138>
- Briley, D. A., & Tucker-Drob, E. M. (2012). Broad bandwidth or high fidelity? Evidence from the structure of genetic and environmental effects on the facets of the five factor model. *Behavior Genetics*, *42*(5), 743–763. <https://doi.org/10.1007/s10519-012-9548-8>
- Browne, M. W., & Cudeck, R. (1992). Alternative ways of assessing model fit. *Sociological Methods & Research*, *21*(2), 230-258. <https://doi.org/10.1177/0049124192021002005>
- Carlo, G., Okun, M. A., Knight, G. P., & De Guzman, M. R. (2005). The interplay of traits and motives on volunteering: Agreeableness, extraversion and prosocial value motivation. *Personality and Individual Differences*, *38*(6), 1293-1305. <https://doi.org/10.1016/j.paid.2004.08.012>

- Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, 9(2), 233-255. https://doi.org/10.1207/S15328007SEM0902_5
- Condon, D. M., Wood, D., Möttus, R., Booth, T., Costantini, G., Greiff, S., Johnson, W., Lukaszewski, A., Murray, A. L., Revelle, W., Wright, A. G. C., Ziegler, M., & Zimmermann, J. (2020). Bottom up construction of a personality taxonomy. *European Journal of Psychological Assessment*, 36(6), 923–934. <https://doi.org/10.1027/1015-5759/a000626>
- Cronbach, L. J. and Gleser, G. C. (1965). *Psychological tests and personnel decisions*. 2nd edn. University of Illinois Press, Urbana. IL.
- Cui, Z., & Gong, G. (2018). The effect of machine learning regression algorithms and sample size on individualized behavioral prediction with functional connectivity features. *NeuroImage*, 178, 622–637. <https://doi.org/10.1016/j.neuroimage.2018.06.001>
- Elleman, L. G., Condon, D. M., Holtzman, N. S., Allen, V. R., & Revelle, W. (2020). Smaller is better: Associations between personality and demographics are improved by examining narrower traits and regions. *Collabra: Psychology*, 6(1), 1–19. <https://doi.org/10.1525/collabra.17210>
- Epskamp, S. (2022). *semPlot: Path diagrams and visual analysis of various SEM packages' output*. R package version 1.1.6. <https://CRAN.R-project.org/package=semPlot>
- Espinoza, J. A., O'Neill, T. A., & Donia, M. B. (2023). Big five factor and facet personality determinants of conflict management styles. *Personality and Individual Differences*, 203, 112029. <https://doi:10.1016/j.paid.2022.112029>
- Friedman, J., Hastie, T., Tibshirani, R. (2010). glmnet: Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software*, 33(1), 1-22. <https://www.jstatsoft.org/v33/i01/>.
- Furnham, A., & Fenton-O'Creevy, M. (2018). Personality and political orientation. *Personality and Individual Differences*, 129, 88–91. <https://doi.org/.org/10.1016/j.paid.2018.03.020>

- Gignac, G. E., & Szodorai, E. T. (2016). Effect size guidelines for individual differences researchers. *Personality and Individual Differences, 102*, 74–78.
<https://doi.org/10.1016/j.paid.2016.06.069>
- Gilberto, J. M., Davenport, M. K., & Beier, M. E. (2020). Personality, health, wealth, and subjective well-being: Testing a integrative model with retired and working older adults. *Journal of Research in Personality, 87*, 103959.
<https://doi.org/10.1016/j.jrp.2020.103959>
- Goldberg, L. R. (1990). An alternative "description of personality": The big-five factor structure. *Journal of Personality and Social Psychology, 59*(6), 1216-1229.
<https://doi.org/10.1037/0022-3514.59.6.1216>
- Götz, F. M., Gosling, S. D., & Rentfrow, P. J. (2021). Small effects: The indispensable foundation for a cumulative psychological science. *Perspectives on Psychological Science, 17*(1), 205–215. <https://doi.org/10.1177/1745691620984483>
- Johnson, J. A. (2014). Measuring thirty facets of the five factor model with a 120-item public domain inventory: Development of the IPIP-NEO-120. *Journal of Research in Personality, 51*, 78–89. <https://doi.org/10.1016/j.jrp.2014.05.003>
- Kajonius, P. J., & Johnson, J. A. (2019). Assessing the structure of the five factor model of personality (IPIP-NEO-120) in the public domain. *Europe's Journal of Psychology, 15*(2), 260-275. <https://doi.org/10.5964/ejop.v15i2.1671>
- Kuhn, M. (2022). caret: Classification and regression training. R package version 6.0-93.
<https://CRAN.R-project.org/package=caret>
- McCrae, R. R., & Costa, P. T. (1994). The stability of personality: Observation and evaluations. *Current Directions in Psychological Science, 3*(6), 173–175.
<https://doi.org/10.1111/1467-8721.ep10770693>
- McCrae, R. R., & John, O. P. (1992). An introduction to the five-factor model and its applications. *Journal of Personality, 60*(2), 175-215.
<https://doi.org/10.1111/j.1467-6494.1992.tb00970.x>

- McCrae, R. R. (2015). A more nuanced view of reliability. *Personality and Social Psychology Review, 19*(2), 97–112. <https://doi.org/10.1177/1088868314541857>
- Mõttus, R., Kandler, C., Bleidorn, W., Riemann, R., & McCrae, R. R. (2017). Personality traits below facets: The consensual validity, longitudinal stability, heritability, and utility of personality nuances. *Journal of Personality and Social Psychology, 112*(3), 474–490. <https://doi.org/10.1037/pspp0000100>
- Mõttus, R., McCrae, R., Allik, J., & Realo, A. (2014). Cross-rater agreement on common and specific variance of personality scales and items. *Journal of Research in Personality, 52*, 47-54. <https://doi.org/10.1016/j.jrp.2014.07.005>
- Ones, D. S., & Viswesvaran, C. (1996). Bandwidth-fidelity dilemma in personality measurement for personnel selection. *Journal of Organizational Behavior, 17*(6), [https://doi.org/10.1002/\(SICI\)1099-1379\(199611\)17:6%3C609::AID-JOB1828%3E3.0.CO;2-K](https://doi.org/10.1002/(SICI)1099-1379(199611)17:6%3C609::AID-JOB1828%3E3.0.CO;2-K)
- R Core Team. (2021). R: A language and environment for statistical computing. R foundation for statistical computing. <https://www.r-project.org/>
- Revelle, W., Dworak, E. M., & Condon, D. M. (2021). Exploring the persome: The power of the item in understanding personality structure. *Personality and Individual Differences, 169*, 109905. <https://doi.org/10.1016/j.paid.2020.109905>
- Revelle, W. (2021) psych: Procedures for psychological, psychometric, and personality research, R package version 1.7.8. <https://CRAN.R-project.org/package=psych>
- Roberts, B. W., Kuncel, N. R., Shiner, R., Caspi, A., & Goldberg, L. R. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes. *Perspectives on Psychological Science, 2*(4), 313–345. <https://doi.org/10.1111/j.1745-6916.2007.00047.x>
- Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*, 1–36. <https://doi.org/10.18637/jss.v048.i02>

- Seeboth, A., & Möttus, R. (2018). Successful explanations start with accurate descriptions: Questionnaire items as personality markers for more accurate predictions. *European Journal of Personality*, *32*(3), 186–201. <https://doi.org/10.1002/per.2147>
- Sleep, C. E., Lynam, D. R., & Miller, J. D. (2021). A comparison of the validity of very brief measures of the big five/five-factor model of personality. *Assessment*, *28*(3), 739–758. <https://doi.org/10.1177/1073191120939160>
- Soto, C. J., & John, O. (2017). The next big five inventory (BFI- 2): Developing and assessing a hierarchical model with 15 facets to enhance bandwidth, fidelity, and predictive power. *Journal of Personality and Social Psychology*, *113*, 117– 143. <https://doi.org/10.1037/pspp0000096>
- Soto, C. J. (2019). How replicable are links between personality traits and consequential life outcomes? The life outcomes of personality replication project. *Psychological Science*, *30*(5), 711–727. <https://doi.org/10.1177/0956797619831612>
- Speer, A. B., Christiansen, N. D., Robie, C., & Jacobs, R. R. (2022). Measurement specificity with modern methods: Using dimensions, facets, and items from personality assessments to predict performance. *Journal of Applied Psychology*, *107*(8), 1428–1439. <https://doi.org/10.1037/apl0000618>
- Stewart, R. D., Möttus, R., Soto, C. J., Seeboth, A., & Johnson, W. (2022). The finer details? the predictability of life outcomes from big five domains, facets, and nuances. *Journal of Personality*, *19*(2), 167-182. <https://doi.org/10.1111/jopy.12660>
- Tuszynski, J. (2021). caTools: Moving window statistics. R package version 1.18.2. <https://CRAN.R-project.org/package=caTools>
- Vainik, U., Dagher, A., Realo, A., Colodro-Conde, L., Mortensen, E. L., Jang, K., Juko, A., Kandler, C., Sørensen, T. I. A., & Möttus, R. (2019). Personality-obesity associations are driven by narrow traits: A meta-analysis. *Obesity reviews*, *20*(8), 1121–1131. <https://doi.org/10.1111/obr.12856>
- van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in r. *Journal of Statistical Software*, *45*(3), 1–67. <https://doi.org/10.18637/jss.v045.i03>

- Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L., François, R., Grolemond, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T., Miller, E., Bache, S., Müller, K., Ooms, J., Robinson, D., Seidel, D., Spinu, V., & Yutani, H. (2019). tidyverse: Welcome to the tidyverse. *Journal of Open Source Software*, 4(43), 1686. <https://doi.org/10.21105/joss.01686>
- Wickham, H., François, R., Henry, L., Müller, K., & Vaughan., D. (2023). dplyr: A grammar of data manipulation. R package version 1.1.0. <https://CRAN.R-project.org/package=dplyr>
- Wickham, H., Vaughan, D., & Girlich., M. (2023). tidyr: Tidy messy data. R package version 1.3.0. <https://CRAN.R-project.org/package=tidyr>
- Wickham, H. (2016). ggplot2: Elegant graphics for data analysis. Springer-Verlag New York. <https://ggplot2.tidyverse.org>
- Wickham, H (2007). reshape2: Reshaping data with the reshape package. *Journal of Statistical Software*, 21(12), 1-20. <https://www.jstatsoft.org/v21/i12/>.
- Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 67, 301– 320. <https://doi.org/10.1111/j.1467-9868.2005.00503.x>

Appendix A

Demographic Variables of the Sample

Variable	Total N = 440	Total in %
Gender		
Female	250	57
Male	186	42
Unspecified	4	1
Age		
25 - 35	140	32
36 - 45	129	29
46 - 55	113	26
56 - 65	58	13

Note. Characteristics of the sample.

Appendix B

The IPIP-NEO-120 Instrument

Factor	Facet	Facet Key	Item
Extraversion	Friendliness	+ E1a	I make friends easily
		+ E1b	I feel comfortable around people
		- E1c	I avoid contact with others
		- E1d	I keep others at a distance
	Gregariousness	+ E2a	I love large parties
		+ E2b	I talk a lot to different people at parties
		- E2c	I prefer to be alone
		- E2d	I avoid crowds
	Assertiveness	+ E3a	I take charge
		+ E3b	I try to lead others
		+ E3c	I take control of things
		- E3d	I wait for others to lead the way
	Activity level	+ E4a	I am always busy
		+ E4b	I am always active
		+ E4c	I do a lot in my spare time
		- E4d	I like to take it easy and not do much
	Excitement seeking	+ E5a	I love excitement
		+ E5b	I seek adventure
		+ E5c	I enjoy being wild and reckless
		+ E5d	I act wild and crazy
	Cheerfulness	+ E6a	I radiate joy
		+ E6b	I have a lot of fun
		+ E6c	I love life
		+ E6d	I look at the bright side of life
Neuroticism	Anxiety	+ N1a	I worry about things
		+ N1b	I fear for the worst
		+ N1c	I am afraid of many things
		+ N1d	I get stressed out easily
	Anger	+ N2a	I get angry easily
		+ N2b	I get irritated easily
		+ N2c	I lose my temper
		- N2d	I am not easily annoyed
	Depression	+ N3a	I often feel down
		+ N3b	I dislike myself
		+ N3c	I am often depressed
		- N3d	I feel comfortable with myself
	Self-consciousness	+ N4a	I find it difficult to approach others
		+ N4b	I am afraid to draw attention
		+ N4c	I only feel comfortable with friends
		- N4d	I am not bothered by difficult social situations
	Immoderation	+ N5a	I drink too much
		- N5b	I rarely overdo things
		- N5c	I easily resist temptations
		- N5d	I am able to control my cravings
	Vulnerability	+ N6a	I panic easily
		+ N6b	I become overwhelmed

Factor	Facet	Facet Key	Item
Openness	Imagination	+ N6c	I feel that I am unable to deal with some things
		- N6d	I remain calm under pressure
		+ O1a	I have a lively imagination
		+ O1b	I enjoy wild fantasies
	Artistic interests	+ O1c	I love to daydream
		+ O1d	I like to get lost in my thoughts
		+ O2a	I believe in the importance of art
		+ O2b	I see beauty in things
	Emotionality	- O2c	I do not like poetry
		- O2d	I do not enjoy going to museums
		+ O3a	I experience emotions intensely
		+ O3b	I feel others' emotions
	Adventurousness	- O3c	I rarely notice my emotional reactions
		- O3d	I don't understand people who get emotional
		+ O4a	I prefer variety over routine
		- O4b	I prefer to do things I know
	Intellect	- O4c	I dislike changes
		- O4d	I am attached to traditional ways
		+ O5a	I love to read challenging books
		- O5b	I avoid philosophical discussions
	Liberalism	- O5c	I have difficulty understanding abstract ideas
		- O5d	I am not interested in theoretical talk
		+ O6a	I tend to vote for liberal/left candidates
		+ O6b	I believe there is no absolute right or wrong
Agreeableness	Trust	- O6c	I tend to vote for conservative/right candidates
		- O6d	I believe that we should punish criminals harder
		+ A1a	I tend to trust other people
		+ A1b	I believe others have good intentions
	Morality	+ A1c	I trust what people say
		+ A1d	I distrust people
		- A2a	I use others for my own goals
		- A2b	I cheat to get ahead
	Altruism	- A2c	I take advantage of others
		- A2d	I tend to manipulate others' plans
		+ A3a	I am concerned about how others are doing
		+ A3b	I love to help others
	Corporation	- A3c	I don't care about others' problems
		- A3d	I don't take time to care for others
		- A4a	I love a good fight
		- A4b	I sometimes yell at people
	Modesty	- A4c	I sometimes insult people
		- A4d	I usually get back at others
		- A5a	I believe I am better than most
		- A5b	I think highly of my importance
	Sympathy	- A5c	I have a high opinion of myself
		- A5d	I tell others about my success
		+ A6a	I feel sympathy with homeless
		+ A6b	I feel sympathy with those with problems
		- A6c	I am not interested in others' problems
		- A6d	I try not to think about people's needs

Factor	Facet	Facet Key	Item
Conscientiousness	Self-efficacy	+ C1a	I always complete tasks
		+ C1b	I have success in what I do
		+ C1c	I handle tasks smoothly
		+ C1d	I know how to get things done
	Orderliness	+ C2a	I like to have clean and tidy
		- C2b	I often forget to put things back in their place
		- C2c	I usually leave a mess in my room
		- C2d	I leave my stuff around
	Dutifulness	+ C3a	I keep my promises
		+ C3b	I tell the truth
		- C3c	I break rules
		- C3d	I sometimes break promises
	Achievement- striving	+ C4a	I do more than what is expected of me
		+ C4b	I work hard
		- C4c	I put very little time and effort into work
		- C4d	I do just enough
	Self-discipline	+ C5a	I am always prepared
		+ C5b	I finish my plans
		- C5c	I often waste my time
		- C5d	I have difficulty starting tasks
Cautiousness	- C6a	I often jump into things without thinking	
	- C6b	I make hasty decisions	
	- C6c	I rush into things	
	- C6d	I often act without thinking	

Appendix C

Descriptive Statistics for the IPIP-NEO-120 Personality Scale.

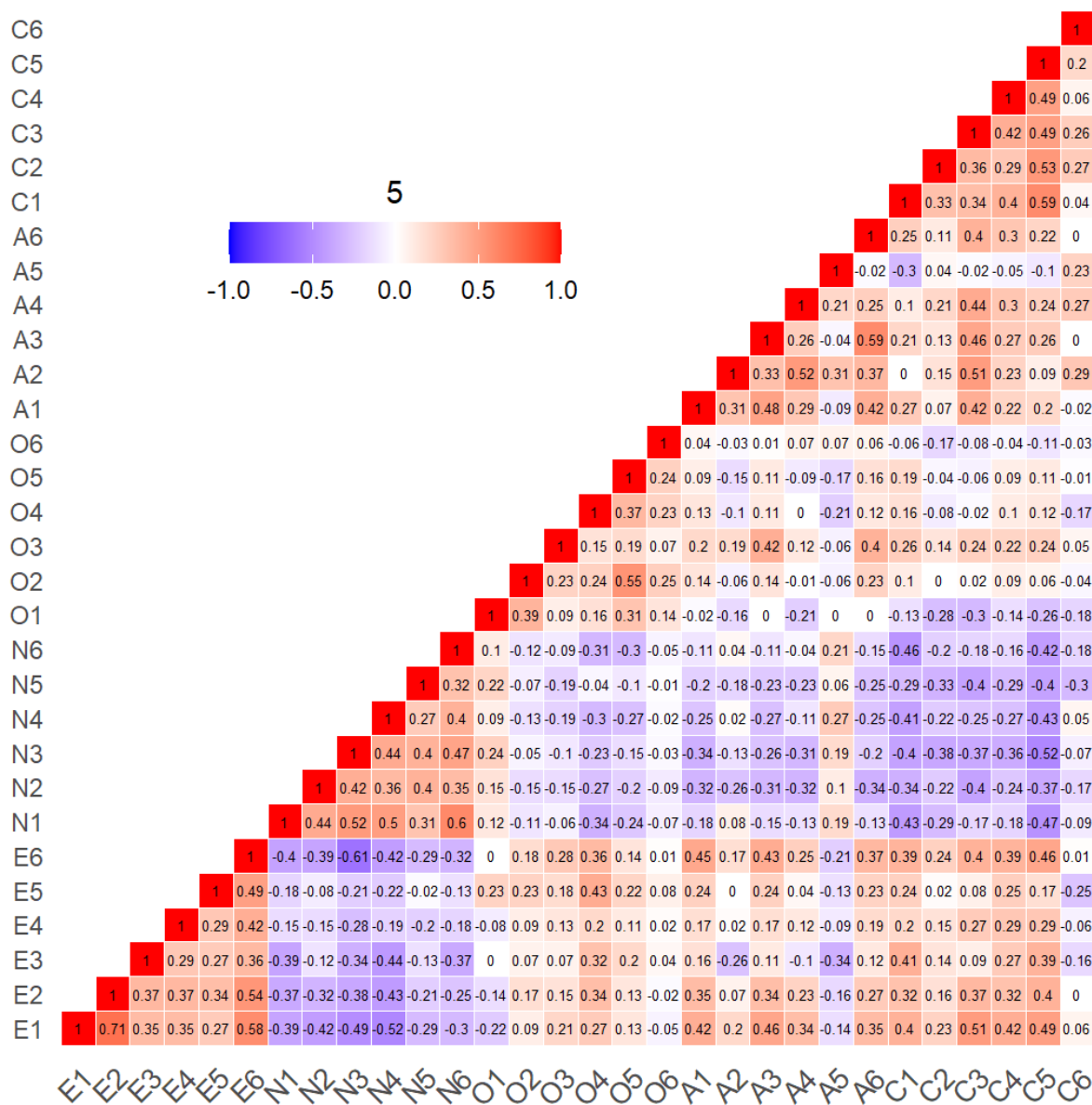
Item	M	SD	Skewness	Kurtosis	Item	M	SD	Skewness	Kurtosis
E1a	4.02	0.88	-0.88	0.70	O4a	3.51	0.97	-0.21	-0.37
E1b	4.23	0.81	-1.14	1.85	O4b	3.39	1.00	0.11	-0.73
E1c	4.41	0.78	-1.31	1.57	O4c	4.11	0.91	-0.76	-0.08
E1d	4.04	0.94	-0.87	0.44	O4d	3.04	0.97	0.18	-0.19
E2a	3.25	1.12	-0.14	-0.67	O5a	3.85	1.03	-0.71	-0.17
E2b	4.24	0.92	-1.25	1.25	O5b	3.91	1.07	-0.71	-0.31
E2c	3.48	0.86	0.07	-0.13	O5c	3.94	0.92	-0.50	-0.31
E2d	3.68	1.10	-0.46	-0.57	O5d	3.90	1.13	-0.81	-0.23
E3a	3.63	0.77	-0.27	0.23	O6a	3.52	0.94	-0.52	0.27
E3b	3.44	0.88	-0.34	-0.07	O6b	3.18	1.21	-0.23	-0.89
E3c	3.85	0.80	-0.47	0.19	O6c	3.60	1.04	-0.31	-0.46
E3d	3.68	0.83	-0.13	-0.35	O6d	2.11	0.96	0.61	-0.11
E4a	2.70	0.96	0.15	-0.53	A1a	3.96	0.88	-1.02	1.51
E4b	3.63	0.88	-0.24	-0.46	A1b	4.02	0.90	-1.05	1.41
E4c	3.65	0.96	-0.46	-0.28	A1c	3.77	0.83	-0.71	1.00
E4d	3.54	1.07	-0.24	-0.66	A1d	4.03	0.83	-0.56	-0.06
E5a	3.52	0.92	-0.09	-0.53	A2a	4.17	1.10	-1.17	0.33
E5b	3.36	0.98	-0.24	-0.34	A2b	4.49	0.81	-1.69	2.75
E5c	3.58	0.99	-0.45	-0.12	A2c	4.28	0.89	-0.91	-0.30
E5d	3.18	1.04	-0.26	-0.50	A2d	4.86	0.43	-3.55	13.88
E6a	4.14	0.77	-0.82	0.93	A3a	4.29	0.83	-1.16	1.33
E6b	3.78	0.81	-0.39	0.16	A3b	3.92	0.95	-0.99	1.11
E6c	4.42	0.70	-1.11	1.33	A3c	4.60	0.83	-2.32	5.14
E6d	4.21	0.73	-0.74	0.63	A3d	4.43	0.87	-1.69	2.70
N1a	2.31	0.95	0.32	-0.38	A4a	3.15	1.04	0.17	-0.45
N1b	1.76	0.93	1.14	0.66	A4b	3.73	0.91	-0.22	-0.52
N1c	1.85	0.86	0.85	0.41	A4c	4.69	0.61	-2.10	4.23
N1d	2.06	0.83	0.60	0.21	A4d	4.53	0.90	-2.30	5.16
N2a	1.68	0.76	1.09	1.20	A5a	2.20	0.91	0.64	0.51
N2b	1.87	0.82	0.92	1.00	A5b	3.07	1.08	0.29	-0.59
N2c	1.69	0.79	1.18	1.60	A5c	2.73	1.03	0.49	-0.22
N2d	2.36	1.19	0.75	-0.38	A5d	3.39	0.96	0.10	-0.49
N3a	1.59	0.76	1.45	2.59	A6a	4.04	0.96	-0.94	0.62
N3b	1.44	0.70	1.49	1.40	A6b	4.09	0.93	-1.07	1.06
N3c	1.53	0.75	1.61	3.26	A6c	4.34	0.88	-1.32	1.36
N3d	1.73	0.80	1.30	2.46	A6d	4.27	0.96	-1.28	1.07
N4a	1.67	0.93	1.46	1.73	C1a	4.49	0.68	-1.59	3.75
N4b	1.89	0.90	0.75	-0.15	C1b	4.43	0.65	-1.10	2.09
N4c	2.35	1.25	0.73	-0.55	C1c	4.25	0.68	-0.74	1.29
N4d	2.63	1.19	0.38	-0.70	C1d	4.38	0.70	-1.17	2.18
N5a	1.73	0.91	1.19	0.92	C2a	4.26	0.80	-1.15	1.76
N5b	2.68	1.10	0.38	-0.44	C2b	4.01	1.03	-0.86	0.11

Item	M	SD	Skewness	Kurtosis	Item	M	SD	Skewness	Kurtosis
N5c	2.42	0.93	0.19	-0.31	C2c	3.94	1.05	-0.79	0.05
N5d	2.17	0.91	0.66	0.15	C2d	4.02	1.06	-1.05	0.44
N6a	1.28	0.57	2.34	6.15	C3a	4.71	0.53	-2.03	5.85
N6b	2.31	0.93	0.26	-0.43	C3b	4.68	0.62	-2.66	10.39
N6c	1.55	0.70	1.25	1.69	C3c	4.54	0.75	-1.68	2.44
N6d	1.92	0.86	1.08	1.55	C3d	4.77	0.51	-2.48	6.84
O1a	3.53	1.09	-0.43	-0.49	C4a	4.41	0.69	-1.23	2.36
O1b	3.23	1.02	-0.22	-0.35	C4b	4.01	0.76	-0.61	1.00
O1c	2.83	1.14	0.16	-0.72	C4c	4.10	0.91	-0.97	0.85
O1d	2.91	1.13	-0.05	-0.68	C4d	4.47	0.80	-1.79	3.55
O2a	3.82	1.12	-0.78	-0.09	C5a	3.84	0.81	-0.69	0.72
O2b	3.56	1.07	-0.41	-0.40	C5b	4.26	0.69	-0.73	0.57
O2c	3.69	1.15	-0.46	-0.73	C5c	4.20	0.85	-0.85	0.10
O2d	4.08	1.10	-1.08	0.40	C5d	4.22	0.92	-1.12	0.80
O3a	3.80	0.86	-0.65	0.55	C6a	4.05	0.85	-0.63	-0.15
O3b	4.00	0.78	-0.58	0.30	C6b	2.70	0.99	0.28	-0.16
O3c	4.12	0.91	-1.01	0.85	C6c	3.23	1.01	0.09	-0.37
O3d	4.30	0.93	-1.14	0.32	C6d	4.27	0.77	-0.93	0.52

Note. Descriptives for the 120 items in the IPIP-NEO-120. E1-E6 = Extraversion; N1-N6 = Neuroticism; O1-O6 = Openness; A1-A6 = Agreeableness; C1-C6 = Conscientiousness; with a, b, c and d being the individual items under the respective facets. *M* = Mean; *SD* = Standard Deviation. *N* = 440.

Appendix D

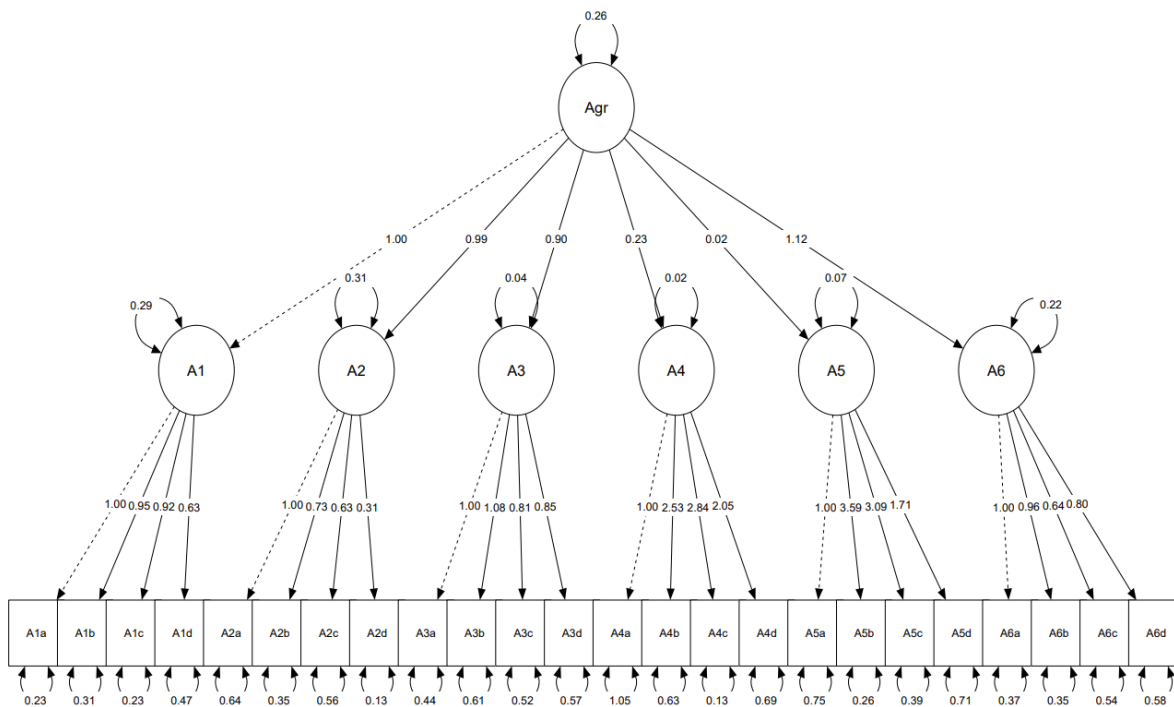
Correlational Heatmap of the IPIP-NEO-120 Facets



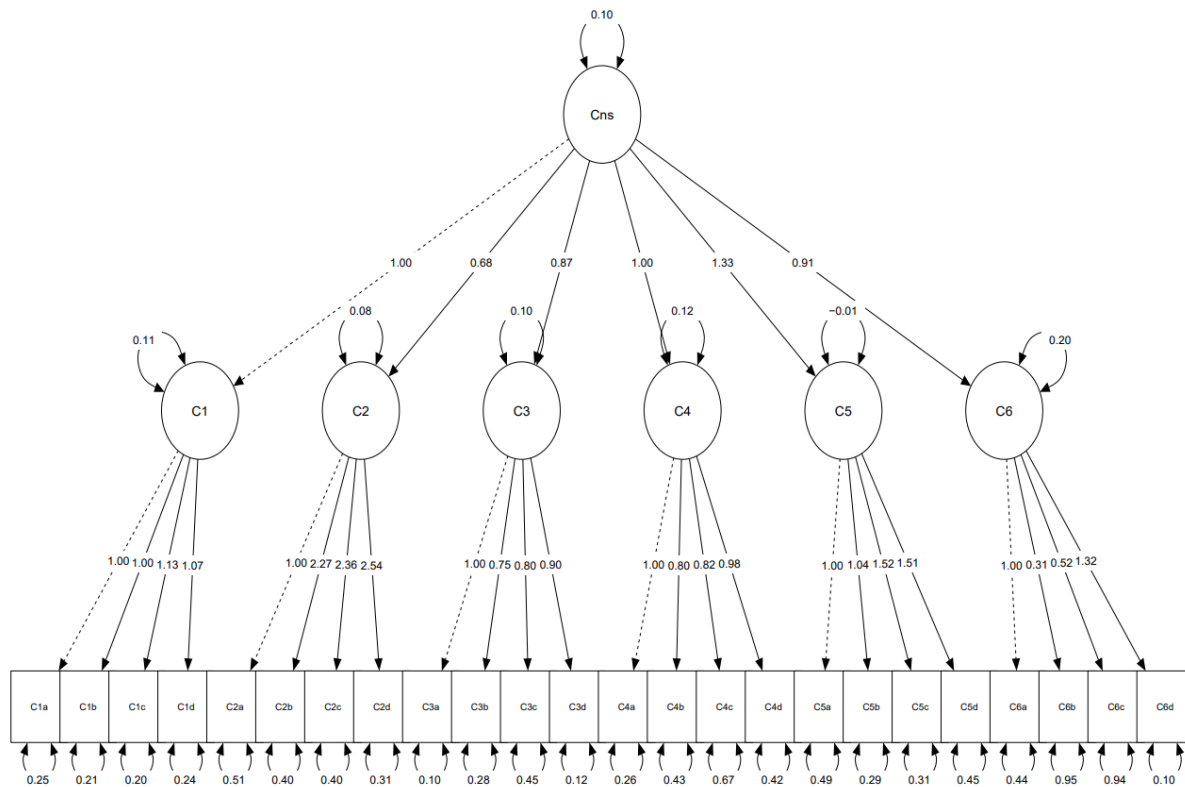
Note. Correlations between the 30 facet traits in the Five Factor Model IPIP-NEO-120 (N = 440). Red colors show positive relationships, and blue colors show negative relationships. The more saturated the color, the stronger the correlation is. E1-E6 = Extraversion; N1-N6 = Neuroticism; O1-O6 = Openness; A1-A6 = Agreeableness; C1-C6 = Conscientiousness.

Appendix E

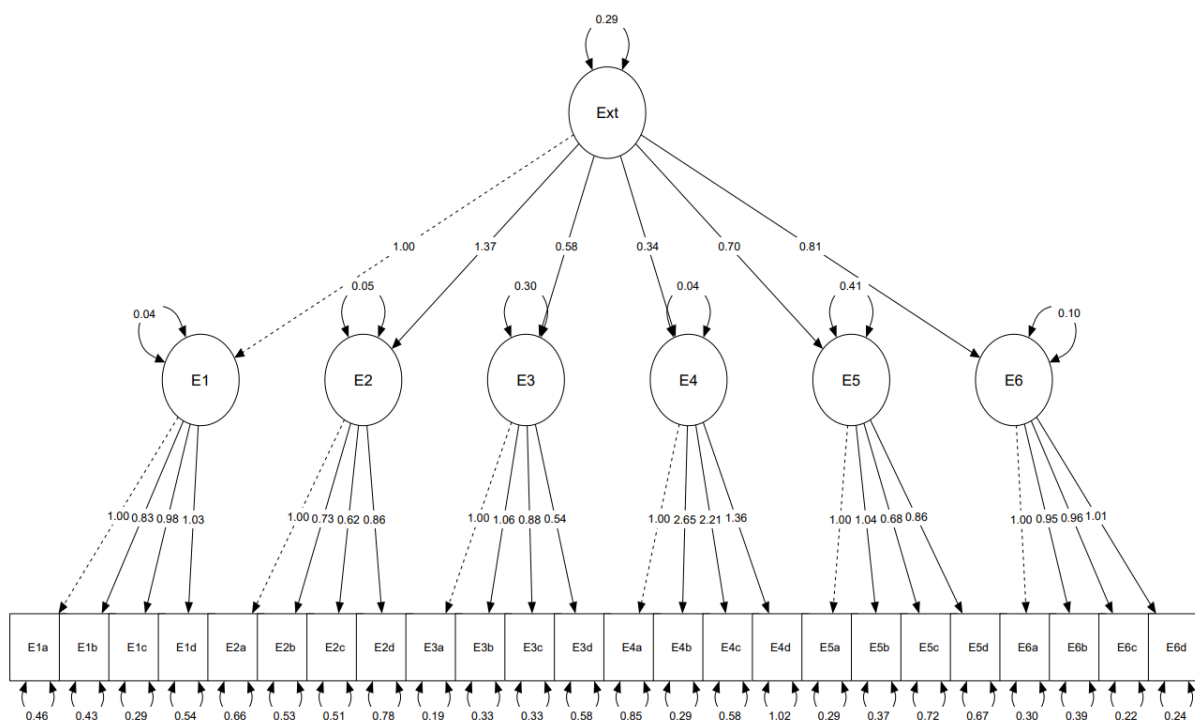
S-CFA Path Diagram for Agreeableness



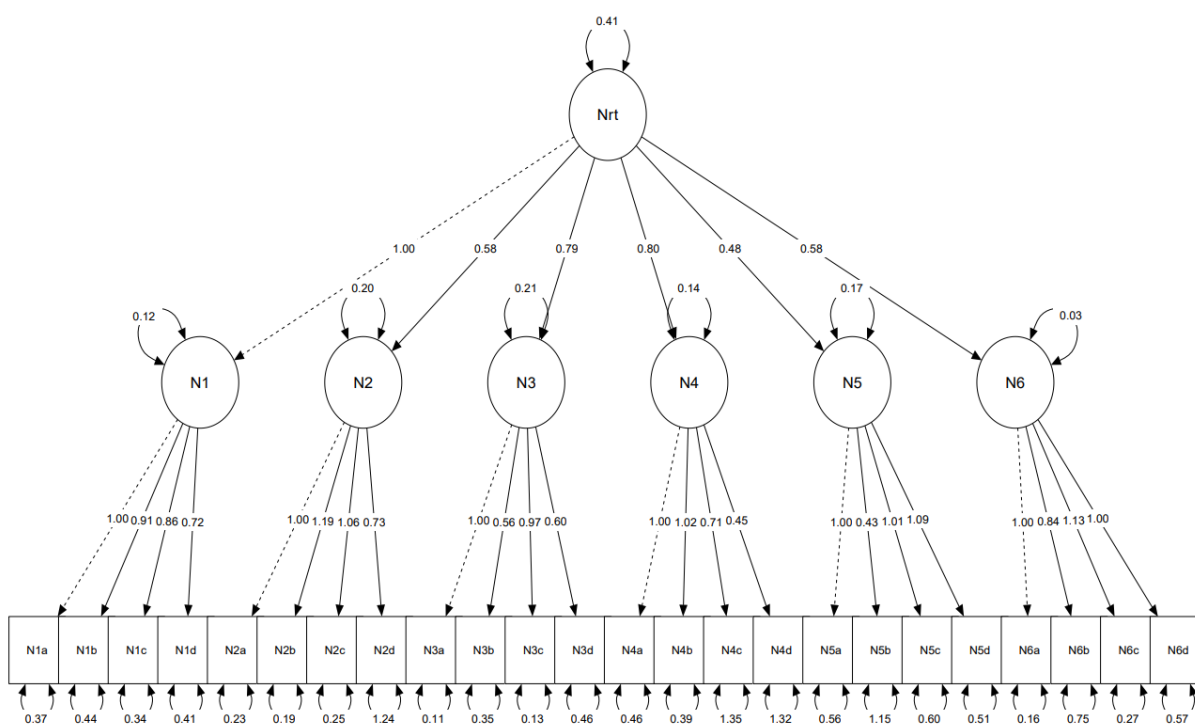
S-CFA Path Diagram for Conscientiousness



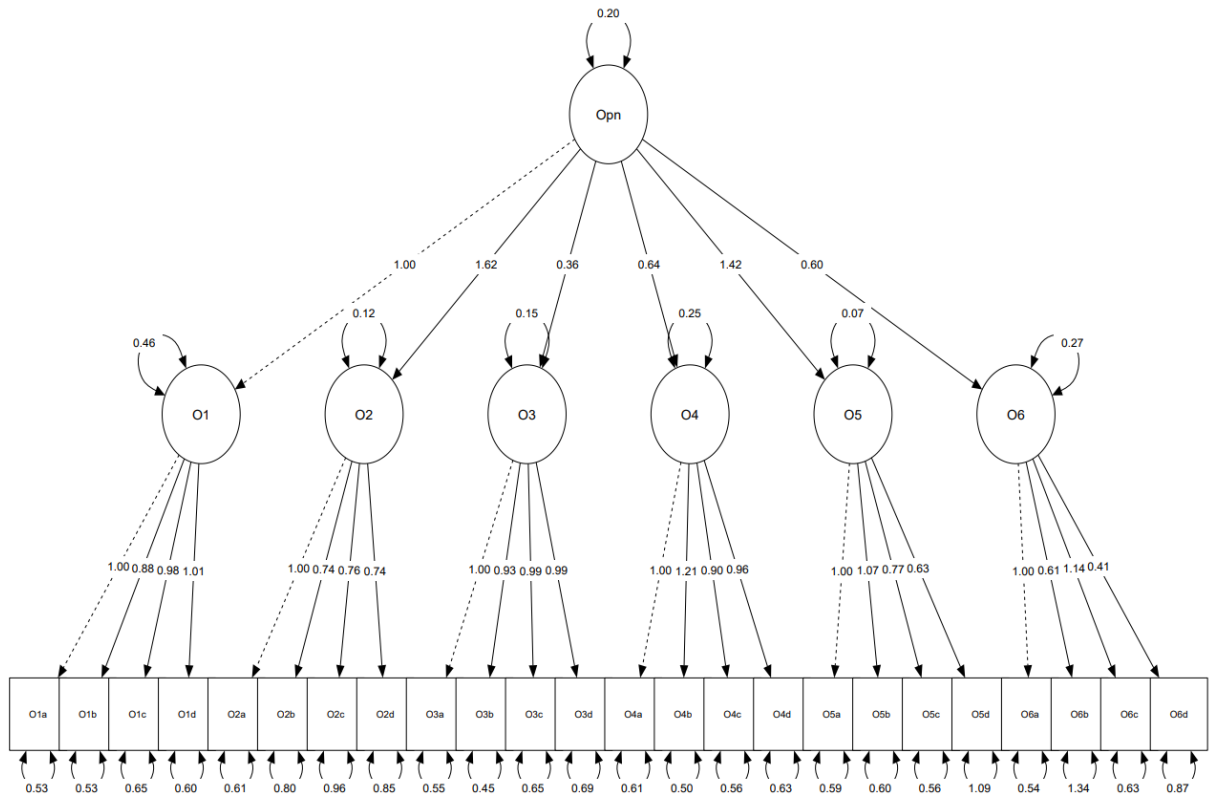
S-CFA Path Diagram for Extraversion



S-CFA Path Diagram for Neuroticism



S-CFA Path Diagram for Openness



Appendix F

Proportion of Variance Explained for each Outcome Measure

Outcome	Factor	Facet	Nuance
Job satisfaction	.07	.13	.37
Social satisfaction	.27	.45	.62
Empathy	.08	.28	.50
Bright future	.14	.23	.49
Intrinsic reward	.14	.27	.47
Extrinsic reward	.06	.14	.32

Note. Result of exploratory Multiple Linear Regression analysis. The proportion of variance explained for each outcome, by factors, facets, and nuance. On average factor, facet, and nuance accounted for 12.6%, 25% and 46% of variance explained across the outcomes.