Personality-obesity associations are driven by narrow traits

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Personality—obesity associations are driven by narrow traits: A meta-analysis

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Abstract

Obesity has inconsistent associations with broad personality domains, possibly because the links pertain to only some facets of these domains. Collating published and unpublished studies (*N* = 14,848), we meta-analysed the associations between body mass index (BMI) and 30 Five-Factor Model personality facets. BMI had a positive association with Neuroticism and a negative association with Conscientiousness domains. At the facet level, we found associations between BMI and 15 facets from all five personality domains, with only some Neuroticism and Conscientiousness facets among them. Certain personality—BMI associations were moderated by sample properties, such as proportions of women or participants with obesity; these moderation effects were replicated in the individual-level analysis. Finally, facet-based personality "risk" scores accounted for 2.3% of variance in BMI in a separate sample of individuals (*N* = 3,569), 409% more than domain-based scores. Taken together, personality—BMI associations are facet-specific and delineating them may help to explain obesity-related behaviors and inform intervention designs. Preprint and data are available at https://psyarxiv.com/z35vn/.

Keywords: prediction, personality, facet, risk score, moderator, body mass index

Obesity is a widespread (1) and broadly consequential health condition (2), characterised by excess body fat. Studies using body mass index (BMI, kg/m^2) as a proxy for body fat percentage have associated BMI with several personality traits (3–8). As personality traits summarise stable patterns in how people typically think, act, feel, and behave (9), they may prove instrumental in delineating how people with obesity differ from people with normal-weight status in their typical, weight-relevant behaviour. While cross-sectional studies on personality—BMI associations cannot imply causality, they can generate hypotheses on the association between psychological traits and physical health.

So far, the research on personality—BMI associations has focused on broad personality traits, such as domains of the Five-Factor Model (FFM). Each FFM domain, encompasses a wide range of behaviours, thoughts, and feelings. In a meta-analysis, Jokela et al. (5) found obesity to negatively associate with the Conscientiousness domain, a broad tendency for orderliness, diligence and goal-directed behaviour. If education was not controlled for, there was also an association with the Openness to Experience domain (5), which reflects intellectual curiosity and aesthetic sensitivity. The meta-analysis by Emery and Levine (3) also supported the link with Conscientiousness but additionally reported a positive association between BMI and the Neuroticism domain, a broad tendency to experience negative emotions. Reviews have also suggested that BMI may have a positive association with the Extraversion domain (4, 6), capturing responsiveness to positive emotions, and negative associations with the Agreeableness domain (4), a trait reflecting altruism and being sympathetic with others. However, the same reviews and meta-analyses have shown that these domain-obesity associations vary substantially across studies (3–5) and personality questionnaires (3).

Such inconsistencies in findings point to the possibility that the personality—BMI associations pertain only to subtraits of the broad domains that disparate measures sample differently (10–12). This possibility can be addressed by using personality questionnaires that divide broad personality domains into more specific facets, such as the Revised NEO Personality Inventory (NEO PI-R (13)) and its updated version, the NEO PI-3 (14). Because the NEO PI-R/3 facets of the same domains display only moderate intercorrelations (mean r = .38, SD = .12, 13), the questionnaire describes a considerably wider set of personality characteristics than the broad

FFM domains alone. For other phenomena, facet-level analyses have already provided more detailed accounts than domain-based analyses (e.g., 15–17). Indeed, BMI may be associated with only selected facets of broad personality domains such as the N5: Impulsiveness facet within Neuroticism (e.g., 10). This can explain the variability in domain-based personality-BMI studies: the associations only emerge when relevant facets happen to be covered by the questionnaire in use. Although not necessarily a limitation of broad domain-based analyses, a facet-based approach provides an opportunity to develop more detailed accounts of BMI—personality links.

A possible further cause of variability between studies are moderators of BMI—personality associations. For instance, the associations of Neuroticism and Extraversion with BMI may be moderated by sex (7): conceivably, women are more likely to engage in negative but men in positive emotional eating (18). Sutin and Terracciano (7) also discussed cultural difference such as Conscientiousness having weaker associations with BMI in Asia or Neuroticism having weaker associations in Latin America, but they omitted sample differences in age and prevalence of obesity as potential moderators; these variables have been tested as moderators in a meta-analysis on the associations between BMI and executive function (19).

To empirically demonstrate the usefulness of a more detailed personality profile, we seek to compare the ability of domain- and facet-based personality profiles to predict BMI in a new sample. This can be achieved by calculating “poly-trait risk scores” for domains and facets, respectively called domain risk score (DRS) and facet risk score (FRS). To yield a DRS or FRS in every participant, a participant’s score on each trait is multiplied by the meta-analytic association between this trait and obesity and the products are then summed across domains or facets. It is important that the meta-analytic associations do not include the sample for which the risk scores are calculated. The poly-trait risk score represents as much variance in BMI that can be collectively predicted by the set of traits, be they domains or facets. This approach has already been successfully used in personality research (20–22), and it is conceptually very similar to polygenic risk scores widely used in genetics (23, 24). We expect FRS to explain more variance in BMI than DRS.

Using published and unpublished data from various countries and cohorts, we provide a comprehensive meta-analysis of how narrow personality traits derived from FFM facets are associated with obesity, operationalised as BMI. Given that personality—BMI associations may vary across samples, we test typical moderators used in other meta-analyses (e.g., 19), such as sex, age, and proportion of the sample exceeding the obesity cut-off (BMI > 30.00 kg/m^2). We attempt to replicate these moderation effects at participant-level data. Further, we compare the collective predictive power of the FFM personality facets to that of FFM domains by the ability of DRS *vs* FRS in predicting BMI in an independent sample.

Methods

Obtaining data

We were interested in the 30 facets defined by the NEO PI-R/3 manual (13, 14). However, we were open to alternative instruments targeting the same facets, such as the IPIP-NEO (25) or the National Character Survey (26). On February 5, 2019 we used Web of Science topic search for “obesity” OR “BMI” OR “body mass index” or “body-mass index”, yielding 454,396 articles. This search was then refined by further topics: “personality” and “facet” or "NEO PI" or "ipip-neo" or “national character survey”. The resulting 49 titles and abstracts were scanned for detailed personality facet-obesity associations across all 30 facets. We found six candidate studies, with four using full the NEO PI-R/3 (10–12, 27), one using a Korean shortened NEO PI-R (28), and one using the IPIP-NEO questionnaire (29). As this paper pool was dominated by the full NEO PI-R/3, we based the main meta-analysis only on this instrument for consistency. However, the profiles obtained with other instruments (28, 29) were compared with the meta-analytic NEO PI-R/3 facet profile.

We then scanned for potential gray literature on facet—obesity associations, such as dissertations and other unpublished works. As we decided to focus on the NEO PI-R/3 in the previous step, we limited our search to all papers which have either cited the NEO PI-R manual (N = 17,885) (13) or NEO PI-3 manual (N = 4,726) (30). Within this subset of papers, we carried out a keyword search for "obesity" or "BMI" or "body mass index" or "body-mass index" and "facet", resulting in 313+68 papers for NEO PI-R and NEO PI-3, respectively. No results that could be used for the meta-analysis ultimately emerged from this search.

NEO PI-R/3 domain/facet—BMI correlations were extracted from three papers (10, 11, 27). The fourth published paper (12) as well as two comparison papers (28, 29) reported group differences in personality traits and facets separately for each of the groups – people whose weight status was underweight, normal weight, overweight, or obese (12). In these cases, akin to the study by Vainik and colleagues (31), we extracted the mean, standard errors (converted to standard deviations), and sample sizes for the groups with normal-weight or obesity, used these summary statistics to perform a t-test between the groups for each trait and facet, and converted the t-statistics into correlation coefficients (see 31 for further details). As shown by Vainik and colleagues (31), personality—trait BMI correlations obtained from comparing participants with normal-weight or obesity are very similar to correlations with continuous BMI.

Next, we approached several cohorts known to have the information on both the NEO PI-R/3 and BMI, and solicited access to five datasets. All these datasets contained sibling data. To avoid inflated effect sizes due to genetic and family environment overlap between participants (32), analysis was conducted within multi-level framework, using a random intercept for family. We controlled for age, age squared, and sex. BMI and personality scores were transformed into *z*-scores, so that the resulting regression weights could be interpreted as correlations. All data sources are summarised in Table 1. Transformed correlations, list of control variables used in each cohort, and results from individual cohorts are available in supporting Tables S1 and S2.

Data analysis

Altogether, we meta-analysed BMI data from 11 samples across 14,848 participants. We chose a random-effects model as implemented in metacor() function of meta R package (33), because the samples varied in cultural background and demographic characteristics (Table 1). We also estimated the extent to which the NEO PI-R/3 domain and facet—BMI associations profiles from different samples concurred. For this, we calculated the intra-class correlation estimates and their 95% confidence intervals, using the ICC() function from psych package (34), based on a mean-rating (k = 11), absolute agreement, 2-way random-effects model (*ICC* (2,k)). Random-effects absolute agreement models should generalize to any other similar personality study (35). The same ICC approach was used to compare the meta-analytic personality profiles with the profiles obtained with other instruments (28, 29).

For moderation analysis, we selected facets that had significant heterogeneity, such that I^2 confidence intervals did not span zero. We then applied meta-regression (36) to test whether sample properties tested in previous meta analyses (e.g., 19), such as proportion of people with obesity, proportion male, or age could explain variation in effect size across different samples. Because the number of samples was small, we tested each variable separately as a predictor.

We also sought to replicate the moderation effects at the participant-level using the NEO PI-3 and BMI data from the Estonian Biobank (37) (Table 1). The Estonian Biobank was chosen as it was the largest sample with raw data accessible to the first author, has wide age range, and contains both self- and informant-report personality data, allowing for cross-validation. After standardising all continuous variables ($M = 0$, $SD = 1$), we tested whether the personality—BMI effects were nonlinear. For each personality trait highlighted by meta-regression, we set the trait to predict BMI while controlling for age, age squared, education, and sex; we also set the trait to interact with weight group (BMI above 30 *vs* BMI below 30), sex, and age. Statistically significant interaction effects would demonstrate moderation.

We then compared the extent to which the NEO PI-R/3 domains *vs* facets allowed for the prediction of BMI in an independent sample, the Estonian Biobank. We first reran the meta-analysis, as above, without the Estonian Biobank contribution ($N = 12{,}536$). We then used the meta-analytic effect sizes for a) NEO PI-R/3 domains or b) facets as weights, with which each Estonian Biobank participants' respective a) domain and b) facet *z*-scores were multiplied. These weighted NEO PI-R/3 a) domain and b) facet scores were then averaged, yielding either DRS or FRS. We included all NEO PI-R/3 domains in DRS and all facets in FRS regardless of the magnitude or significance of their respective meta-analytic weights, as many papers working on polygenic risk scores have shown that the best prediction can generally be achieved when all predictors are included in risk scores, no matter the effect size (21, 23). The observed BMI was then predicted from the DRS and FRS (all expressed in *z*-scores), controlling for sex, age, age squared, and education. We emphasise that estimating the meta-analytic weights and applying them to calculate risk scores in independent participants mitigated against model overfitting.

Typically, published BMI—personality associations with NEO PI-R/3 control for education (5, 10–12). Therefore, we also controlled for education in our participant-level analyses. However, education is known to both influence BMI (38, 39) and be genetically intertwined with personality (20), and controlling for education may thus reduce the effect size (e.g., Openness effect in 5). To facilitate different approaches to interpretation, we also present our participant-level analyses without controlling for education in the supporting information (Figure S71 and Table S4).

All analysis was conducted in Microsoft R Open 3.5.1 (40) using the August 2018 version of several addon packages (33, 34, 41–46).

Results

Meta-analytic personality profile

The result of the meta-analysis (N = 14,848) are summarised in Figure 1. At the domain level, we found BMI to have small but significant associations with Neuroticism and Conscientiousness (false discovery rate $p < .05$). We also found effects of facets within each NEO PI-R/3 domain, but for none of the domains were all facets consistently (significantly and/or in the same direction) linked with BMI. That is, the associations were driven by specific facets. Most of these meta-analytic facet-level associations were suggested in at least one of the previously published studies. This included positive associations of BMI with N2: Angry Hostility, N4: Self-consciousness, N5: Impulsiveness, E1: Warmth, E3: Assertiveness, and E6: Positive Emotions; and negative associations with E4: Activity, A2: Straightforwardness, A4:

Compliance, C2: Order, C5: Self-discipline, and C6: Deliberation. As novel findings, we found additional negative associations with C3: Dutifulness (a facet of Conscientiousness), and with two Openness facets of O4: Actions and O6: Values. All effect sizes were small in magnitude, with $|r| \leq .06$, except for N5: Impulsiveness ($r = .13$). Forest plots (Figures S1-S35) and funnel plots (Figures S36-S70) for each personality trait separately can be seen in supporting information. No clear evidence for publication bias could be found in any of the funnel plots (Figures S36-S70).

The high reliability of the overall results was suggested by high between-sample absolute agreement for domains ($ICC(2,11) = .83$ 95% *CI* [.45, .98], $F(4,40) = 5.3$, $p = .002$) and for facets (ICC $(2,11) = .87$ 95% *CI* [.78, .93], F $(29,290) = 7.7$, $p < .001$). However, the meta-analytic profile was not in agreement with results obtained with IPIP-NEO ($ICC(2,2) = .04$ 95% *CI* [-.26, .37], $F(29,29) = 1.11$, $p = .393$) or 100-item Korean NEO PI-R (men: $ICC(2,2) = .38$ 95% *CI* [-.22, .69], $F(29,29) = 1.67$, $p = .086$; women: $ICC(2,2) = 0$ 95% *CI* [-1.08, .52], $F(29,29) = 1$, $p = .5$). Similar results were present for Korean sample at domain levels (men: $ICC(2,2) = .18$ 95% *CI* [-6.17, .91], $F(4,4) = 1.23$, $p = .424$, women: $ICC(2,2) = 0$ 95% *CI* [-8.6, .9], $F(4,4) = 1$, $p = .5$).

Moderation of personality—BMI associations

Despite the overall between-sample congruence in findings, heterogeneity analysis with I^2 indices (Figure 2) suggested that effect sizes for some traits varied across samples. The effect sizes of traits with I^2 confidence intervals not spanning zero were analysed with meta-regression. We found that the positive N5: Impulsiveness—BMI association strengthened as a function of the samples' proportion of people with obesity and participants' mean age, and weakened with increased proportion of women in the sample (Figure 3). On a smaller scale, prevalence of obesity status also increased the negative association between C2: Order and BMI, whereas the effects of some Extraversion facets were reduced by the proportion of women, and increased by the age of the group.

Most of the meta-regression results replicated at the individual-level in the Estonian Biobank (Figure 4). Both self and informant data provided robust evidence for a stronger N5: Impulsiveness—BMI correlation in participants with obesity. The C2: Order—BMI correlation only emerged in participants with obesity. Intriguingly, we found that the Extraversion domain to have *opposing* effects: in participants with BMI below 30, Extraversion has positive association with BMI, whereas the effect was reversed in participants with obesity. This may be one explanation to the lack of linear association between Extraversion and BMI at the meta-analytic level. In females, BMI had lower correlation with Extraversion and likely also with N5: Impulsiveness, when not accounting for education (Figure S71). We found no effects for age on personality—BMI relationship that would replicate across self-and and informant levels.

Domains and facets as predictors of BMI in new data

We then created DRS and FRS for BMI in the Estonian Biobank, applying them to both self-report (DRS_{self}, FRS_{self}) and informant-reported ($DRS_{informant}$, $FRS_{informant}$) NEO PI-3 personality trait scores. We found that after adjusting for typical covariates, such as age, age^2, sex, and education, FRS_{self} and $FRS_{informant}$ explained 409% and 465% more variance in BMI than DRS_{self} and $DRS_{informant}$ (see Table 2). Apart from age, the FRS outperformed other covariates, such as age^2 as sex and education, suggesting that facets offer an incrementally detailed understanding of BMI. To probe, whether the FRS results depended on the relatively large effect size of N5: Impulsiveness, we also built FRS-s excluding N5: Impulsiveness facet. These FRS-s still predicted 278% and 230% more variance in BMI than DRS-s (Table 2), suggesting that the cumulative small effects matter. Without controlling for education, the R^2 of all personality scores increased by 0.2% (Table S4).

As additional analysis, we entered DRS and FRS as predictors into the same model to test the incremental utility of FRS over DRS. We tested all four FRS-s mentioned above, and they conferred substantial incremental predictive value over DRS (Table 2). Intriguingly, the R^2 of FRS was even higher than in previous models with FRS without DRS. However, it should be noted that the DRS and FRS are strongly correlated ($r \approx .90$; VIF ≈ 4.5) and the regression weights of DRS and FRS became opposite of each other, suggesting difficulties in interpreting such combined models.

Discussion

We conducted a meta-analysis covering both the NEO PI-R/3 personality domains and facets associated with BMI, collating data from 14,848 participants. At the domain level, BMI was weakly positively associated with Neuroticism, and negatively with Conscientiousness. At the facet level, we replicated and extended the small but consistent effects of specific facets within each of the five domains. We also found that sample characteristics, such as prevalence of obesity and sex balance partly explained the heterogeneity in personality trait—BMI associations between 11 samples, and within a single sample. Finally, we demonstrated that despite the small effect sizes of the personality—BMI associations, they can be used to predict BMI in new data using the full version of NEO PI-3.

The domain-level associations of BMI with higher Neuroticism and lower Conscientiousness may suggest a role of increased anxious behaviour and decreased self-control capabilities (3, 4, 6, 7). However, many details remain hidden in broad domains based findings. The domain-level effects were not mirrored by all facets within their respective domains, suggesting that personality—BMI associations largely pertain to facet-level traits (11). Therefore, interpreting the effects of individual facets enables a more fine-grained understanding of personality—BMI associations.

Within Neuroticism, BMI associated foremost with higher N5: Impulsiveness indexing inability to control cravings and urges. The strongest effect size of N5: Impulsiveness is likely explained by the facet having two items directly refer to overeating, (#111—'I tend to eat too much of my favourite food' and #171—'Sometimes I am not able to control my appetite', 11). Therefore, the facet seems to be index uncontrolled eating, a behaviour already robustly associated with BMI (47, 48). There is some evidence that N5: Impulsiveness changes concurrently with BMI changes (49), further highlighting a strong link between them. At the same time, studies using other measures of uncontrolled eating suggest that BMI and uncontrolled eating are related but ultimately dissociable processes (reviewed in 48).

BMI also related positively to other facets of Neuroticism, such as N2: Angry Hostility, capturing a tendency to experience anger, frustration and bitterness, and N4: Self-consciousness, representing feelings of shame and embarrassment. These effects may reflect the negative connotations of discrimination experienced by people with obesity (50). Causal designs, including Mendelian randomisation and longitudinal studies suggest that increase in BMI could lead to lower well-being and higher depression (51–53), however stress levels have also seen to predict future BMI (54), suggesting bidirectional association. We were surprised not to see effects of N1: Anxiety, N3: Depression and N6: Vulnerability, which could have been expected from the known association of obesity and depression (55). Instead, obesity may predominantly be associated with more outward expression of negative affect.

Within Conscientiousness, higher BMI related negatively to orderliness-related facets, reflecting ability to plan and organise tasks and activities (56, 57). Facets supporting this conclusion are C2: Order, indexing organized and methodological behaviour, C3: Dutifulness, measuring adherence to ethical principles and obligations and C6: Deliberation, capturing thinking before acting. In addition, there was a negative effect of C5: Self-discipline, assessing the ability to complete tasks. Given that losing weight is a difficult task, the Conscientiousness facets may reflect troubles with adherence to weight loss regimens in people with obesity. The importance of planning and organising tasks conceptually supports the role that self-control plays in obesity, which has also been highlighted by research on executive functions and prefrontal cortex (3, 19, 21, 58). Scarce longitudinal evidence has suggested that obesity could have bidirectional associations with self-control capabilities (8, 58), while a Mendelian randomisation study suggested that higher education and cognitive ability could cause lower BMI (59).

The effect of domain level Extraversion on BMI was inconsistent, as facets differed in the directions of their associations with BMI. On the one hand, BMI related positively to E1: Warmth, indexing friendliness and affectionate behaviour, to E3: Assertiveness, measuring dominance, forceful actions, and social ascendance, and to E6: Positive Emotions, where high scorers are cheerful and optimistic. These results suggest, that perhaps people with obesity are also more sensitive to positive reinforcers. At the same time, high BMI related negatively to E4: Activity, which captures tendencies to be active and in vigorous movement, a result likely explained by morphometric constraints resulting from high BMI or lack of exercise intersecting with BMI. The unexpected moderation of Extraversion effects by obesity status may be explained by the different direction of facets, or hint at a possible curvilinear association between reward sensitivity and BMI (60). Facets of the same domain differing in the directions of their correlations with BMI highlights the value of more fine-grained analyses.

Finally, specific facets appeared from Openness and Agreeableness domains in relation to BMI. BMI associated negatively with two facets belonging to the Politeness aspect of Agreeableness: A2: Straightforwardness, representing frank, sincere, and ingenious social interaction, and A4: Compliance, where high scorers avoid interpersonal conflict. Politeness characterises more cognitive or reasoned respect for others' desires, as opposed to compassionate emotional affiliation (57). Lack of such behaviour can be speculated to be another response to the stigmatising social experiences related to weight. Within Openness, BMI related negatively to O4: Actions, capturing willingness to try different activities, and to O6: Values, measuring readiness to re-examine social, political, and religious values. Higher scores on Openness facets may protect from BMI by supporting eating healthier diets (61–63).

In case personality trait—BMI associations slightly varied from sample to sample, we found that the variation was partly explained by general sample characteristics, such as percent of participants with obesity and prevalence of females in the sample. Sex differences in Extraversion—BMI associations have been demonstrated previously (7) and were found again in the current study. As novel findings, we reported obesity status moderating the effects of N5: Impulsiveness, C2: Order, and Extraversion. Therefore, the previously observed effect size differences between samples attributed to culture (7) may also be attributed to differences in basic sample characteristics. In future, these basic characteristics should be accounted for, before attributing effect size differences to culture.

We were able to quantify the utility of facets over domains with the poly-trait risk score approach. Specifically, when the small effects of multiple traits were aggregated, a facet-based risk score outperformed the domain-based risk score in predictive power, either when the scores were tested one by one or when used together in a regression model. This is a direct support of the increased utility of using facets when explaining outcomes (15–17). In the current analysis, FFM facets accounted for five times as much variance in BMI as the broader domains. Even when the N5: Impulsiveness facet tapping into uncontrolled eating (11, 47) was removed, the facet-based risk scores were still able to predict extra variance in BMI, above and beyond the domains. Therefore, the personality—BMI associations include a considerably larger repertoire of behaviours than just uncontrolled eating (31).

On a practical level, the facet—BMI associations could provide starting points for designing interventions for obesity, whereas the ambiguous domain-level associations would be far less informative for this purpose. The large number facets highlights that increased BMI is a complex phenotype with multiple associated mental processes, which each could be targeted in a comprehensive intervention. Such approach has been proposed based on cognitive tests (64), and in the substance abuse domain, personality trait-specific interventions have been developed (65).

From a more theoretical perspective, the facet-level personality profile can be used to quantify the behavioural similarity that BMI has with other phenotypes not necessarily measured in the same sample. This can be achieved by comparing the similarity of current meta-analytic personality profile with the profile of other phenotypes of interest. For instance, BMI has moderate behavioural similarity with addictions, but also with certain other psychiatric conditions (31). Finally, the detailed personality profile can be used to make better predictions of

BMI in new samples using NEO PI-R/3, which may be useful for research purposes, such as trying to bring together behavioural, brain, and genetic factors (e.g., 21).

As a limitation, both the theoretical interpretations and predictive ability are limited to concurrent BMI and not future BMI. Therefore, the facets highlighted here outline the behavioural profile of BMI, but do not offer evidence on the directionality of the association, that is, whether personality traits lead to higher BMI, or vice versa. Few studies have published personality profiles for predicting variability and change in BMI; these profiles look similar to the current results at domain level (5, 7, 54), but are different at the facet level (10). Due to limitations of current data, the current poly-trait risk scores assume additive effects in personality trait—BMI associations, as well as when aggregating individual personality traits into a combined score. Possibly, the prediction could be improved by integrating non-additive effects into the score. The current prediction accuracy prevents the use of the poly-trait risk scores for predicting individual BMI. This task is better achieved by traditional measures, such as childhood obesity or parental obesity (66) when this information is available. The meta-analytic profile did not generalise well to the IPIP-NEO or to the 100-item Korean version of NEO PI-R. The lack of overlap may be explained by differences between personality questionnaires, but also partly by the small sample size of the IPIP-NEO sample (n=84). Therefore, the IPIP-NEO overlap should be studied further with larger samples.

Another limit of the current meta-analysis pertains to the moderator analysis: we had only 11 samples available for the meta-regression. At the same time, most of the meta-regression results replicated at individual level self- and informant-derived personality data, suggesting the effects are real. Otherwise, different NEO PI-R/3 samples were generally in high agreement about more and less prominent personality traits, suggesting that the results hold across multiple cultures, and can be used to predict BMI in an unseen sample, with an effect size stronger than most control variables.

To conclude, the diverse set of narrower personality traits associated with BMI highlight, that personality—health associations may be too complex for broad personality trait models such as the FFM. This can be mitigated by more detailed descriptions of personality that can be derived from facets or nuances (67), potentially increasing understanding and intervening on health differences.

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Table 1. Summary of samples used in current analysis

Sample country	Cohort	Instrument	Total N	Female N	Included N	Age mean	Age *SD*	Age range	BMI mean	BMI *SD*	UW	NW	OW	OB	OB %
Argentina	(29)	IPIP-NEO	84	*67*	0	24.21	4.84	18-37	24/28	3.7/6	n/a	68	16		*23.5*
Australia*	(68–70)	NEO PI-R	866	502	761	22.47	3.47	17-33	23.4	4.4	55	507	151	48	*5.5*
Canada*	(71)	NEO PI-R	900	587	788	33.66	13.87	15-68	23.6	4.3	36	537	159	56	*6.2*
Denmark*	(72)	NEO PI-R	1191	603	1191	38.14	11.52	18-67	24.4	3.5	25	706	383	77	*6.5*
Estonia	(11)	NEO PI-3	2581	1398	2581	44	17.3	18-90	26.1	4.9	46	1169	874	49 2	*19.1*
Estonia full	(11)+ new data	NEO PI-3	3569	2133	0	46.82	16.99	18-91	26.2	5	64	1597	1183	72 5	*20.3*
Germany*	(73)	NEO PI-R	1700	1320	1700	31.12	12.78	14-80	22.2	3.3	148	1279	226	47	*2.8*
Italy	(12)	NEO PI-R	5693	*3291*	3621	42.8	17	14-94	n/a	n/a	156	2791	1916	83 0	*14.6*
Japan*	(74)	NEO PI-R	1286	846	1233	20.85	3.9	14-30	20.3	2.7	282	799	100	52	*0.9*
Korea men	(28)	Short NEO PI-R	1495	0	0	60	9.8	21-103	24.3	3	22	407	410	65 6	*43.8*
Korea women	(28)	Short NEO PI-R	2547	2547	0	47	15.5	19-93	22.8	3.4	273	1452	363	45 9	*18*
Mexico	(27)	NEO PI-R	282	*163*	282	21.09	4.27	n/a	n/a	n/a	n/a	n/a	n/a	*32*	11.5
USA, Mexicans born in	(27)	NEO PI-R	113	*65*	113	23.31	5.98	n/a	n/a	n/a	n/a	n/a	n/a	*10*	9

Mexico															
USA, Mexicans born in USA	(27)	NEO PI-R	618	*357*	618	23.31	5.98	n/a	n/a	n/a	n/a	n/a	n/a	*126*	20.4
USA & Mexico pooled	(27)	NEO PI-R	1013	*719*	0	22.75	5.7	n/a	25.3	6.4	n/a	n/a	n/a	*162*	16
USA	(10)	NEO PI-R	1960	980	1960	56.9	17.02	19-96	26.1	4.9	n/a	885	740	335	*17.1*

Table 1. Note: * - personality—BMI associations contributing to the meta analysis that are available from cohorts referred to in this table but have not been previously published. Numbers in *italic* have been estimated, for instance number of females has been derived from percentage female. "Included N" summarises participants directly contributing to meta-analysis. The samples decreased due to occasional missing data, or just NW and OB groups being included from Italy. BMI = body mass index (kg/m^2); NW = normal-weight (BMI = 18.5 - 24.9, Asia:18.5 - 22.9); OB = obesity (BMI ≥ 30, Asia: ≥ 25); OW = overweight (BMI = 25 - 29.9, Asia 23-24.9); UW = underweight (BMI < 18.5).

Table 2. Percent of variance (R^2) in body mass index explained by control variables and personality risk scores

Model	Variable	Variable R^2	2.5% *CI*	97.5% *CI*
Baseline multiple regression				
	Age	16.84	14.71	19.17
	Age^2	0.99	0.52	1.63
	Sex	0.83	0.39	1.50
	Education	1.21	0.70	2.06
Baseline + Domain risk score (DRS)				
	DRS_{self}	0.46	0.13	0.92
	$DRS_{informant}$	0.37	0.08	0.86
Baseline + Facet risk score (FRS)				
	FRS_{self}	2.34	1.50	3.23
	$FRS_{informant}$	1.72	0.97	2.58
	$FRS_{self\ no\ N5}$	1.74	1.01	2.52
	$FRS_{informant\ no\ N5}$	1.22	0.60	1.9
Baseline + DRS + FRS				
	FRS_{self}	3.87	2.88	5.00
	$FRS_{informant}$	3.21	2.30	4.33
	$FRS_{self\ no\ N5}$	1.91	1.17	2.74
	$FRS_{informant\ no\ N5}$	1.36	0.73	2.15

Table 2. Note: Baseline model is a multiple regression model of covariates inserted together (age, age^2, education, and sex). Total baseline model R^2 = 19.87%, 95% *CI* [17.8,22.33]. After that, each polytrait risk score was added as a 5th predictor. In the last 4 models, two polytrait risk scores were the 5th and 6th variables, either only from self-report or only from other-report. For all

regression models, $p < 0.001$ for the variables reported. Confidence intervals have been bootstrapped 1,000 times. Results without controlling for education are presented Table S4.

Figures

Figure 1. Meta-analytic correlations between NEO PI-R/3 domains/facets and BMI. Error bars denote 95% confidence intervals. BMI = body mass index; FDR = False Discovery rate. Numeric values are presented in supporting Table S3.

Figure 2. I^2 heterogenity values. I^2 characterises the percentage of variation, that is attributable to effect-size variation between samples rather than chance. Error bars denote 95% confidence intervals. Black circles highlight traits where lower confidence interval (CI) did not touch 0. Numeric values are presented in supporting Table S3.

Figure 3. Meta-regression slope estimates for personality—BMI associations displaying heterogeneity in Figure 2. Slope can be interpreted as change in effect size due to a moderator. Intercepts are not displayed. Error bars denote 95% confidence intervals.

Figure 4. Demographic variables interacting with trait—BMI associations in the Estonian cohort. Leftmost panel displays the baseline trait—BMI association after accounting for control variables (age, age^2, education, sex) in males with BMI < 30, and mean age. Other panels display the difference in effect size evoked by each moderator. Age, BMI, and personality traits were scaled. Error bars denote 95% confidence intervals. C2 = C2: Order, E = Extraversion; E3 = E3: Assertiveness; N5=N5: Impulsiveness.